

Voice Attractiveness

Benjamin Weiss, Jürgen Trouvain, Melissa Barkat-Defradas, John J. Ohala

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- John J. Ohala
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Voice Attractiveness

- ²⁷ Studies on Sexy, Likable, and Charismatic
- ²⁸ Speakers

Springer



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78 Preface

At the Interspeech conference 2015, in Dresden, John (Ohala) asked Jürgen 79 (Trouvain) what he thinks about organizing a special session on attractive voices, 80 maybe for the next conference in this series. A former visiting researcher in 81 Berkeley, Melissa (Barkat-Defradas), had already expressed some ideas on such an 82 event on this topic. John has a long-standing interest in evolutionary aspects of 83 speech and voice. Melissa works in an interdisciplinary research team on all kinds 84 of aspects of evolution, and Jürgen has some background in paralinguistic char-85 acteristics of speech. At the same conference in Dresden, Jürgen introduced 86 Benjamin (Weiss) to John with Benjamin as the optimal complement to this team 87 since he has published several papers on social likeability of voices. 88

It was then at Interspeech in Stockholm 2017, that we were able to organize the 89 planned special session on voice attractiveness. We considered this event as the 90 perfect setting for presenting research dealing with many aspects: perceived vocal 91 preferences of men, women, and synthesized voices in well-defined social situa-92 tions, acoustic correlates of voice attractiveness/pleasantness/charisma, interrela-93 tions between vocal features and individual physical and physiological 94 characteristics, consequences for sexual selection, predictive value of voice for 95 personality and for other psychological traits, experimental definition of esthetic 96 standards for the vocal signal, cultural variation of voice attractiveness/pleasantness 97 and standards, and also the link between vocal pathology and vocal characteristics. 98 In Stockholm we agreed on a follow-up publication where the authors have more 99 space than in a conference paper with its strict limitations. Moreover, also those 100 colleagues could be reached that were not participants of this conference. 101

The special session was a success in our view. In total, we had nine accepted contributions. Authors from six papers of this session are also aboard in this volume. In addition to these, there are ten further contributions for this publication, having a total of seventeen papers when we add the introductory chapter. It is our belief that both collections, the nine conference papers, and the seventeen articles in this volume, can provide a useful overview on the state-of-the-art research on voice attractiveness, voice likeability, and vocal charisma. We also hope that these studies

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Preface

represent a fruitful fundament for further thoughts and investigations of an excitingfield of speech and voice research.

As many book projects of this size, the editing process took longer than expected. This delay is mainly but note entirely due to health reasons of some of the editors. We would like to thank all authors for their patience and the publishing house for the provided support.

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Benjamin Weiss Jürgen Trouvain Melissa Barkat-Defradas John J. Ohala

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Part I General Considerations

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Keywords

Chapter 1 Voice Attractiveness: Concepts, Methods, and Data



Jürgen Trouvain, Benjamin Weiss, and Melissa Barkat-Defradas

Abstract This book comprises contributions on vocal aspects of attractiveness,

- 2 social likability, and charisma. Despite some apparent distinct characteristics of these
- ³ three concepts, there are not only similarities, but even interdependencies to be con-
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- ⁵ and material selected in the contributions. Based on this structured summary, we
- 6 argue to increase interdisciplinary and even holistic efforts in order to better under-
- ⁷ stand the concepts for voice and speech in humans and machines.
- 8 Keywords Attractiveness · Charisma · Likability · Sexual selection ·
- ⁹ Interdisciplinary · Holistic view · Structured summary · Speech production ·
- 10 Speech perception

11 **1.1 Introduction**

- Probably, everybody has an idea of the meaning or meanings of *attractive* and *attractiveness* on the one side, and of voice and speaker on the other. It is also likely that everybody has their own ideas, which voices sound attractive—either in general or in specific contexts. But these ideas show by no means homogeneous structures and
- in specific contexts. But these ideas show by no means homogeneous structures and
 similar definitions.

A book on voice attractiveness attracts researchers, be it as authors and/or readers, who look at this topic from different angles as the subtitle of this book indicates. A *sexy* speaker is not the same as a *likable* speaker, and a *charismatic* speaker is different

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again. These differences of how attractiveness is considered are also reflected in the
 chapters of this book. Likewise, the definition of speaker and voice is heterogeneously
 used, too. For this reason, we first attempt to shed some light onto the diversity of
 concepts we face in the upcoming chapters.

There is a broad range of different methods used in the studies of this volume. 24 Many perform experimental research to investigate aspects of production, acoustics, 25 and perception of attractive speech. There are some studies with a focus on modeling 26 of data with respect to attractiveness, whereas other studies review how speech tech-27 nology can be applied taking the (missing) attractiveness of voices into account. The 28 data types that were used in the studies of this volume also show a large span. They 29 range from manipulations of monosyllabic stimuli over single words and sentences 30 in controlled settings up to many minutes of spontaneous conversational speech. The 31 recap of the diversity of methods and data in this collection is followed by some 32 concluding remarks on the emerging field of voice attractiveness, a research field 33 that attracts researcher from many disciplines. 34

35 1.2 Concepts

36 1.2.1 Voice, Speaker, and Speech

The contributions of this collection consider the *voice* and *voice attractiveness* in 37 different ways. Voice is not only seen in a narrow sense where it refers only to glottal 38 activity. Voice in a wider sense additionally includes supra-glottal activities such as 39 tongue raising, pharyngeal constriction, nasality or lip spreading (Laver, 1980), so 40 that for instance formants as acoustic correlates of supra-laryngeal resonances are 41 taken into account. For several studies, prosody plays an important role, reflected by 42 fundamental frequency (F0), intensity, pauses and duration from a suprasegmental 43 point of view. Further, timing parameters refer to entrainment in dialogs. 44

Naively, one would not assume that a voice that is considered as "normal", "stereotypical" or "average" would correlate to attractiveness. Nevertheless, three papers of
this volume look more closely to the acoustic parameters of the "mean" voice and
its perception of attractiveness—partially with somewhat surprising results.

Kreiman et al. (this volume) show that listeners differ regarding the question of 49 what it means for a voice to sound "normal". There seem to be individual, rather 50 consistent, strategies to label how normal or not normal a voice sounds. In their 51 study, listeners assessed a wide range of one second samples of female speakers. 52 From several acoustic parameters, the most relevant for explaining some amount of 53 variance in the labels are fundamental frequency and its variation, as well as the 54 first two formants, but not others that are typically associated with voice quality. 55 However, the authors could not find a simple or generally valid answer, the situation 56 is rather complex because several factors like the listener, the context, the purpose 57 of the judgment, and of course the individual voice have to take into account. 58

The topic of recalling a voice from memory, an everyday task for everybody of us, is analyzed in Babel et al. (this volume). They show in a set of experiments with monosyllabic words as stimulus material that subjective stereotypicality and attractiveness affect the performance to remember a voice. Overall, they found support for the statement that less stereotypical voices and less attractive voices were better memorized.

Belin (this volume) reports of findings of experiments where identical short syllables of multiple voices of the same sex were averaged. The more voices were averaged the 'speakers' of the averaged voice samples were perceived as more and more attractive. (similar to a visual effect concerning face attractiveness). Obviously, the main responsible factors for this effect are the reduced "distance-to-mean" for differences between F0 and the first formant, and an increased "texture smoothness" reflected by a raised harmonics-to-noise ratio.

There are also studies with stimuli to be rated that are longer than just one syllable 72 or just one second. These studies concentrate more on speech prosody. Quené et 73 al. (this volume), for instance, control for tempo and F0 in stimuli sentences, and 74 Bosker (this volume) analyzed amplitude modulation in authentic speech samples. 75 The review of charismatic speech of Rosenberg and Hirschberg (this volume) centers 76 at prosody in all possible aspects, whereas, for instance, Weiss et al. (this volume) 77 investigate acoustic parameters that reflect prosody (F0, intensity, rate), segmental 78 properties (formants, spectral features) but also the voice in a narrow sense (shimmer, 79 jitter, harmonics-to-noise ratio). These examples show that the vocal part in voice 80 attractiveness can be referred to very different aspects of voice and speech when 81 performing research in this field. 82

83 1.2.2 Sexual Selection and Voice Attractiveness

A sexy speaker can be seen as somebody who underlines her or his perceived sexual 84 attractiveness—often unconsciously—with her or his voice and speech behavior. 85 Though the voice is the privileged medium for interpersonal communication, it is 86 not solely useful for conveying semantic information to other people. As a matter of 87 fact, voice should also be regarded as a powerful social object, whose role is crucial in 88 the context of human relationships. Indeed, by using oral communication, speakers 89 are not only able to share their ideas and emotions, but they are also able to signal 90 some reliable sociobiological features to their interlocutors such as sex, age, health, 91 and social status, among others. There is a large body of scientific literature, for 92 instance Scherer (1978), which describe the links between voice characteristics and 93 personality traits, or the works by Laver and Trudgill (1979) and Bezooijen (1995), 94 who studied voice as a social and cultural marker, or either still, Banse and Scherer 95 (1996) whose work investigate how voice is used to express one's emotional state. 96 All of these authors, to name a few, have demonstrated that voice goes far beyond

All of these authors, to name a few, have demonstrated that voice goes far beyond
 its primary linguistic function. Yet, interestingly, researches in Humanities mostly

tackled the topic of vocal function independently of any evolutionary considerations.
 However, as early as 1890, Darwin addressed the issue within the frame of sexual
 selection by drawing intriguing parallels between animal vocalizations and the human
 voice:

The sexes of many animals incessantly call for each other during the breeding-season; and 103 in not a few cases, the male endeavors thus to charm or excite the female. This, indeed, 104 seems to have been the primeval use and means of development of the voice [...]. When 105 male animals utter sounds in order to please the females, they would naturally employ those 106 which are sweet to the ears of the species; and it appears that the same sounds are often 107 pleasing to widely different animals, owing to the similarity of their nervous systems, as 108 we ourselves perceive in the singing of birds and even in the chirping of certain tree-frogs 109 giving us pleasure. (Darwin, 1890, pp. 90-96). 110

Darwin's original idea according to which vocalizations allow the transmitter to 111 attract females' attention and express his reproductive intentions make it legitimate 112 to address the issue of human voice attractiveness in the specific context of human 113 mating. As a matter of fact, as it is developed in the first contribution of Suire, 114 Raymond, and Barkat-Defradas (this volume), it is reasonable to think that sexual 115 selection—the mechanism which promotes biological and social traits that confer a 116 reproductive benefit-has also intervened in the shaping of human vocal dimorphism; 117 the attractiveness of a voice being a proxy, or a reinforcing signal, for other physical 118 characteristics. By providing an overview of the research that lies at the crossroad 119 of the human voice and evolutionary biology, the authors aim at demonstrating that 120 sexual selection provides an interesting theoretical framework to understand the 121 functional role of the human voice from an evolutionary perspective. Indeed, several 122 studies have demonstrated the existence of a vocal attractiveness stereotype, which 123 suggests that voice is an honest signal¹ of phenotypic quality in the same way as 124 other physical features like, for example, the waist-to-hip ratio.² 125

Such an assumption raises the question of what makes a voice attractive? In 126 their survey of the literature, Rosenberg and Hirschberg (this volume) examine the 127 concept of vocal attractiveness itself. The authors consider the concept as highly 128 context-dependent and discriminate between several types of attraction (i.e., political 129 charisma, business leadership, nonsexual attraction and, last but not least, romantic 130 desirability) each one of them being associated with specific articulatory, acoustic, 131 and prosodic traits. They also show that though voice attractiveness is a complicated 132 and exceptionally subjective phenomenon, evidence suggests some shared cross-133 cultural patterns that must have been shaped in the course of evolution by the selective 134 pressure induced by the preferences of one sex for the vocal attributes of the other. 135 The topic of vocal preferences has given rise to a large body of literature on the 136 evolution of vocal preferences, which generally speaking, reveals that low-pitched 137

¹Signals are traits that have evolved specifically because they change the behavior of receivers in ways that benefit the signaler. For example, peacock resplendent tail feathers are honest since they truly signal reproductive fitness of their bearer to the receiver.

 $^{^{2}}$ The waist-to-hip ratio (WHR) is the dimensionless ratio of the circumference of the waist to that of the hip. WHR correlates with health and fertility (with different optimal values in males and females).

masculine voices are universally preferred by women, such voices being perceived 138 as related to a high quality phenotype. Conversely, men tend to prefer high-pitched 130 feminine voices that are perceptually associated with youth and fertility at least 140 in English. For more details of evolutionary mechanisms of attractive voices like 141 mate choice see the systematic review of vocal preferences in humans by Barkat-142 Defradas, Raymond and Suire (this volume). Quené et al. (this volume) also confirm 143 the expected pattern that men with lower-pitched voices tend to be rated as more 144 attractive by (heterosexual) female listeners. They also reveal the importance of fast 145 tempo in voice attractiveness evaluation. Indeed, their results based on manipulated 146 speech show that the female raters judged masculine voices as less attractive if the 147 F0 was artificially raised and the tempo decreased. 148

In their speed dating study, Michalsky and Schoormann (this volume) investigated
 the effects of perceived attractiveness and conversational quality on entrainment. In
 analyzing speed dating dialogs, prosodic disentrainment, in terms of pitch differ ences, is related to facial attractiveness for interlocutors of opposing sex. However,
 this result is inhibited by high conversational quality for females, and low conversa tional quality for males.

155 1.2.3 Likability and Social Attractiveness

A likable speaker is seen as somebody who underlines her or his perceived social 156 attractiveness or pleasantness with her or his voice and speech behavior. There are 157 several potential aspects that may constitute likability. For example, from the two 158 of the most stable interpersonal concepts for unacquainted persons, benevolence (or 159 warmth, communion) and competence (or agency, capability) (Abele, Cuddy, Judd, 160 & Yzerbyt, 2008; Schaller, 2008; Fiske, Cuddy, & Glick, 2006), the first dimension 161 (benevolence) is often assumed to resemble likability (DePaulo, Kenny, Hoover, 162 Webb, & Oliver, 1987; Fiske et al., 2006; Argyle, 1988). However, liking-aversion 163 may conceptually comprise the second dimension of competence as well (McCroskey 164 & McCain, 1974), even in speech (Putnam & Street, 1984). Actually, there is much 165 evidence from questionnaire analysis in a speech during dimension reduction that 166 evaluative questionnaire items, such as "likable", can be apparent in both dimen-167 sions, benevolence and competence, or neither (Cuddy, Fiske, & Glick, 2008; Brown, 168 Strong, & Rencher, 1973, 1985; Hart & Brown, 1974; Street & Brady, 1982; Weirich, 169 2010; Weiss & Möller, 2011). Given these empirical results, it can be argued that the 170 so-called benevolence is just one possible but a very likely attribution to a person, 171 which affects a speaker's social attractiveness, especially in a first impression. 172

Concerning voice acoustics, there are only few correlates of likability that show at
 least some robustness to changes in material, most notably increased pitch variability
 and tempo, while the results of average pitch reveal to be more complex, at least in
 German (Weiss et al., this volume).

While such results aim at correlates of averaged ratings on a scale, paired comparisons allow for a much finer measure of preference in likability. This method is, unfortunately, much more effort. Therefore, a crowd-based procedure is presented to collect such data efficiently, and it was used to train a model for predicting preferences of pairs of stimuli (Baumann, this volume).

In order to better take into regard the individual aspects of attractiveness, a method is presented that extracts overall voice attractiveness and listeners' preferences from paired comparisons, so that voices' likability can be estimated by the inner product of the two vectors of attractiveness and preferences (Obuchi, this volume).

186 1.2.4 Charisma and Leadership

A charismatic speaker is seen as somebody who underlines her or his perceived lead-187 ership, persuasive power, enthusiasm, and passion with her or his voice and speech 188 behavior. Charisma is, just like likability, a social evaluation. However, likability 189 typically refers to a dialogic situation, or in passive listening test, to the anticipation 190 of a dialog—without any predefined difference in social status. In contrast to this, 191 charisma is typically about an individual affecting a group of people, and thus implies 102 some kind of social superiority. Charismatic people stand out, formally by social sta-193 tus or rank, or situationally by other's acknowledgment of their specialty. Therefore, 194 the typical domains to study charisma in voice are speeches or talks of famous people, 195 such as politicians and managers. A passionate and motivating speech by such people 196 represents an often used, and sometimes even requested and anticipated, method of 107 leadership. A discursive overview of what a charismatic voice actually is, can be 198 found in Signorello (this volume). 199

The focus on public speeches and talks when dealing with charisma, complicates, 200 on the one hand, differentiating between effects of a speech's presentation from 201 those that originate in the fame, attributions, and social status. On the other hand, 202 instead of relying on ratings in the laboratory, there a plenty of potentially valid 203 indicators of charisma of those famous people including type of applause, (social) 204 media reaction, and election results. For example, during a party conference of the 205 German social democrats in 1995, the chairman was replaced by his vice-chairman— 206 atypically early at this specific date—after an inspiring and enthusiastic speech of that 207 vice-chairman. Given rather similar contents, sometimes even identical formulations, 208 this outcome of the election was analyzed not regarding rhetorics, but speaking 209 style instead (Paeschke & Sendlmeier, 1997). Such occurrences not only show that 210 charisma is blended with power and leadership, but also exemplify the relevance of 211 voice and speech for charisma. In this volume, the relevance of prosody and attire 212 is studied for speeches of leading senior managers (Brem & Niebuhr, this volume). 213 And in Bosker (this volume), a closer look on the modulation spectrum, which is 214 related to speech rhythm, is taken for speeches from the US presidential campaign 215 candidates Hillary Clinton and Donald Trump. 216

217 1.3 Methods

From a methodological perspective, we can divide studies on voice attractiveness in three fields. Investigations of the possible effects of different kinds of attractiveness and their vocal correlates are covered by *experimental research*. In addition to this research direction, *modeling* of processes how individual voices in audio samples attract listeners represents a further field of study. Finally, *technological applications* should be viewed as an own field of research in voice attractiveness.

224 1.3.1 Experimental Research

Human attractiveness is typically considered as a subjective concept. Therefore, 225 experimental research is dominated by collecting explicit and implicit human rat-226 ings and decisions. The simplest methodological approach is to present stimuli and 227 explicitly ask for ratings; on a scale if sequentially presented, or as a preference in 228 the case of comparing stimuli. Such listening and ratings are, for example, conducted 229 by Babel et al. (this volume). They collected a variety of subjective characteristics, 230 among them perceptual similarity, applying a comparison of pairs of stimuli on a 231 single scale, and perceptual attractiveness, collecting ratings in a sequential proce-232 dure for each stimulus individually. The latter method is also frequently used in the 233 studies evaluated by Belin (this volume). Quené et al. (this volume) explicitly argue 234 in favor of the sequential approach with absolute ratings instead of a forced prefer-235 ence choice of a direct comparison, as they want to avoid drawing attention to the 236 signal manipulations they have conducted. There are various variants applied, often 237 taken advantage of graphical computer interfaces, for example, to sort and assign 238 short stimuli of a set to labels (Kreiman et al., this volume). 239

Instead of explicitly asking for measures of attractiveness, implicit measures can 240 be attempted to collect, in order to avoid a social bias of the subjects. Such approaches 241 comprise observations of social decisions, for example, counting the number of 242 direct interactions in gaming or game-like tasks (Krause, Back, Egloff, & Schmukle, 243 2014). Other observations refer to the number of friends, or offspring (or explicitly 244 asking to disclose the number of sexual partners). Such long-term or retrospective 245 observations and surveys are, however, difficult to relate to specific traits, such as 246 vocal characteristics. 247

248 1.3.2 Modeling

Quantitative modeling of subjective human ratings, such a sexual or social attractiveness, serves in principle two purposes. One is to describe the relations, e.g., correlations, found with parameters of interest in a given data set. Such a model could
be a starting point for a prediction model, but does not provide explanatory power as

in a scientific theory. For the case of voice attractiveness, typical model parameters 253 are acoustic or articulatory measures. Another purpose is to actually explain inter-254 dependencies between parameters and ratings in a quantitative way. However, in the 255 latter case, the parameters chosen and the kind of relationship have to be confirmed 256 by methodological means ensuring a causal relationship. Synthesizing or resynthe-257 sizing speech represents the most popular approach to control for the variables in 258 question. It also aims at providing proof for a causal relationship. As the knowledge 259 base is enhanced by empirical studies incrementally, each study might fulfill both 260 purposes to some degree. For example, the linear models of social attractiveness of 261 Weiss et al. (this volume) build on hypotheses drawn from several scientific methods 262 in order to add evidence for acoustic-perceptual relations, but its main result is a 263 simple data description. 264

Baumann (this volume), present a methodological approach, that does comprises
not only the acoustic modeling part, but also a method to efficiently collect preference
ratings for stimulus pairs. Such pairwise preferences for German spoken Wikipedia
articles were acoustically correlated directly, and modeled as relative preferences by
means of a recurrent neural network.

In a related approach, Obushi (this volume) collected pairwise preferences for a Japanese greeting phrase. The ratings are multidimensionally analyzed, taking into account the listeners' differences as well, and modeled by multiple acoustics features applying machine learning.

274 1.3.3 Technological Applications

Voice attractiveness can play an essential role in human-machine interaction (HMI) 275 as two contributions in this volume show. There is a tendency that "people tend to 276 attribute personality traits to computers and robots as if they were human agents" 277 (Nass, Moon, Fogg, Reeves, & Dryer, 1995). That means that the human-sounding 278 voices of talking and conversational computers can also be considered as personalized 279 machines. In addition, machines can act for humans, for instance, when a speech 280 synthesizer is used as a speech prosthesis for people who cannot clearly and fluently 281 articulate anymore. From a view of listening to talking machines, we all know that it is 282 most of the time rather boring and less interesting when faced with an artificial voice 283 and synthesized speech, be it when street names are announced in car navigation 284 or when interacting with a dialog system. For conversational agents, e.g., intelligent 285 personal assistants, it is a particular challenge to show skills that are required for 286 smooth dialogs that span aspects of timing up to common grounding. Thus, voice 287 selection and voice modeling should be an integral part of the design in HMI tools. 288 The paper collected in this volume are not empirical studies with existent systems 289 but are reviews in which important thoughts are developed before experiments that 290 test the usability of certain aspects of voice attractiveness are performed. 291

Torre and White (this volume) focus on the characteristics of a robot's voice in human-robot interaction. They are particularly interested in how vocal elements can contribute to the impression of trustworthiness. They review studies in which a robot's voice was analyzed or manipulated, always with a particular view on trustworthiness. Naturalness and "machine-likeness", cognitive load, incongruity with the robot's behavior in general and the robot's appearance such as its size, gender, accent, and interaction context. Furthermore, they argue that the design of robot voices should come with an unambiguous appearance and function, because unrealistic expectations of robot performance in human users should be avoided.

The human evaluation in regard to different kinds of attractiveness represent 301 immanent social and cognitive processes. Such evaluations are, however, not limited 302 to other living persons. Instead, interactive systems, especially those using speech, 303 are known to evoke similar processes (Reeves & Nass, 1996; Nass & Brave, 2005). 304 And with the emergence of speech interaction with computers in the form of personal 305 smartphone assistants, smart home devices, virtual persons, and human-like (social) 306 robots, the users' appraisal of the verbal and nonverbal behavior of such interactive 307 computers are receiving much attention. 308

One observation specific to anthropomorphic computers is the so-called "uncanny 309 valley" effect. It describes an overall increase in familiarity (or attractiveness or lik-310 ability) with increasing human-likeliness (or level of details) of the systems features 311 and movements that is disrupted by a sudden decrease in familiarity close to perfect 312 human-likeliness (Mori, 2012). This awkward or eerie feeling for a close to human, 313 but obviously not natural synthesis is typically explained by a shift in reference 314 from artificial to human and can be circumvented by reducing the level of human-315 likeliness or choosing an artificial metaphor (e.g., a puppet or cartoon) instead of 316 a human. This effect is mostly studied for visual perceptions of the body and face 317 of a robot or virtual person and their animated movements. However, in Clark (this 318 volume), results for the evaluation of three linguistic strategies, politeness, relational 319 work, and vague language are discussed in their usage for speech interfaces and their 320 potential mismatch with the expectations in human users, and thus their potential to 321 cause an uncanny valley effect. 322

One important sub-concept of social attractiveness is trust (McAleer, Todorov, & Berlin, 2014; Weiss, Wechsung, Kühnel, & Möller, 2015). In Torre and White (this volume) the effects of robot voices' gender, naturalness, prosody, and accent on trust perception in users are presented and systematized. Overall, there are effects, but they depend on the context and user group. For example, a regional accent showed an increased credibility to a standard accent when being knowledgeable, but the opposite in the case of being unknowledgeable.

330 1.4 Data

The material used in studies on voice attractiveness varies widely, from monosyllabic stimuli recorded in the lab to large extracts of authentic speech material that was not produced for research. This stylistic diversity is also reflected in the contributions for this volume. Thus, it seems fair to separate three kinds of sources, controlled experimental data, naturalistic lab data, and natural field data "from the wild".

336 1.4.1 Controlled Experimental Data

One major source of the material stems from lab experiments, where new recordings 337 are conducted for a specific purpose with already defined acoustic and perceptual 338 analytic methods to be applied on. Such recordings are usually very short, for example 339 (sustained) vowels, syllables or words. They can also not be considered as socially 340 authentic, i.e., they do not aim to resemble real-life social communication situations. 341 Due to its short duration, such material lacks major prosodic aspects, e.g., intonation 342 contour or emphasis variation, as well as any natural situational grounding, affecting, 343 e.g., speaking rate. Controlling for such aspects, however, allows to focus on topics 344 like voice quality and person identification/similarity, while explicitly controlling for 345 the just mentioned effects. 346

Examples of experimental data are Belin (this volume), who uses averaged short syllables of multiple voices, for which attractiveness ratings are collected. Kreiman et al., (this volume) analyzes steady state vowels (one second duration) regarding "normal" voice quality, whereas Babel et al., and Obuchi (both this volume) used single (monosyllabic, respectively multisyllabic) words for perception tests.

On some occasions, full sentences, or even a paragraph, are read by speakers 352 in a lab with similar aims. The practical implications include potential laborious 353 manual work to extract specific segments for analysis, and to take into account richer 354 linguistic context, while the read speech style in a controlled environment allows to 355 analyze not only segmental and micro-prosodic, but also macro-prosodic parameters. 356 Therefore, it is not a coincidence to find a mixture of material types from experimental 357 data in the cited literature for our topics that refer to social attributions and traits 358 from speech (Suire et al.; Rosenberg & Hirschberg, both this volume). While some 359 decisions on the material duration are made because of the costs inflicted by the 360 prospective methods (see Sect. 1.3), other reasons to select material originate in the 361 aspects under research. 362

The syllables used by Belin (this volume) were recorded in the lab, and subse-363 quently post-processed to study the effect of acoustic averaging over speakers. Such 364 a manipulation of speech recordings is another kind of experimental data. Manipu-365 lations comprise post-processing of the acoustic speech signal, as well as outright 366 synthesis. Manipulated audio files can be in principle of any duration, but are con-367 sidered here still as experimental data due to its similarity in careful and specific 368 creation in a laboratory, but also due to the aim of controlling influencing factors— 369 this time by means of inducing a controlled number of manipulations. There are 370 different reasons for such manipulations, most importantly to verify analysis results 371 with even more controlled material, producing stimuli for experiments which are 372 hard or impossible to record, or to obtain speech signal qualities for the domain of 373 computer speech. 374

The papers in the part on technological applications are good examples, as they all refer to studies in which manipulated or synthesized material, typically shorter utterances in a dialog, are used, or they argue to conduct those (Torre & White; Clark et al., both this volume).

379 1.4.2 Naturalistic Data Recorded in the Lab

While strictly controlled speech material from the laboratory is a foundation of 380 basic research, there is always the aim to use naturalistic data in order to estimate 381 the strength of effects for real-life situations and to study situational and dialogic 382 aspects that cannot be simulated with—what we call—experimental data. Typically, 383 this means to elicit naturalistic situations and thus also spontaneous material in the 384 lab, often with the help of some supporting material. In contrast to the aforementioned 385 controlled experiments, the lab recordings of naturalistic data are not controlled to 386 the same degree. Here, experimenters aim to control a good acoustic quality, to 387 initiate conversations, and possibly to instruct conversational tasks. That means that 388 the linguistic and phonetic content is not (strictly) controlled for. However, very 389 specific instructions and support material is often provided to support the subjects 300 to elicit the situation, e.g., a game or task, but databases have been created with far 391 less information provided (Schweitzer, Lewandowski, Duran, & Dogil, 2015). 392

For obtaining attractiveness ratings, Quené et al., (this volume) used sentences from spontaneous interview speech as stimuli that were manipulated. They also used visual data. The situation of speed dating was applied by Michalsky and Schoormann (this volume) to allow for studying the effects of prosodic entrainment in dialog. Simulated telephone conversations on pizza ordering from the Nautilus database, but post-edit to exclude the callee were used by Weiss et al. (this volume).

399 1.4.3 Data from the Wild

The last category of the material refers to recordings from real situations. Obtaining 400 such data seems to be the easiest one on the first glance. However, it is often practically 401 impossible to ensure sufficient quality and sufficient amount of material given the 402 available resources, especially if there are requirements on the linguistic conditions 403 to be included. In addition, there is often more information on the speakers required, 404 which might be difficult to collect while or after recording, for example, additional 405 physiological measures. Finally, there might be ethical reasons to avoid taking data 406 from the wild. 407

In this collection, this kind of data was selected to solely study charismatic speakers. Bosker (this volume) selected speech fragments of c. 25 s from mass media recordings of US presidential debates. Brem and Niebuhr (this volume) used audiovisual data (video clips of charismatic management leaders). For natural data, this kind of material is the least uncontrolled, as the speakers are not only professional,
but also very aware of the fact of being recorded. Therefore, such field data might
not always be considered as truly "wild", but of course, it is as natural as it can be
when studying speeches of charismatic leaders.

Sometimes, it is not easy to assign data to one of the categories. For example, read Wikipedia articles used by Baumann (this volume) is comparable on the surface with other naturalistic speech paragraphs read in the lab, except for the varying recording quality. But still, the origin of this material is natural, as the speakers truly recorded themselves with the intention to be listened to by people interested in the Wikipedia articles.

422 **1.5 Conclusions**

The word "attractiveness" stems from Latin "ad trahere" and means "dragging or pulling to something". For our topic, people are dragged or pulled to the voice and vocal behavior of somebody else. This relationship unfolds in various dimensions: from sexuality and biology over social likability up to charisma and leadership. It is this diversity of voice attractiveness that we intended to cover in this book. It is our hope to raise awareness with this book for this diversity and the broad range of the various scientific fields involved.

What we see in the contributions to this volume is on the one hand a clear and intended separation of the above-mentioned concepts on the sexual, the likable, and the charismatic speaker. On the other hand, we recognize the interdependencies between the three concepts. The classical example is that a person perceived as beautiful is also regarded as a socially more attractive (Zuckermann & Driver, 1989).

In our view, we deal here with a contrast between simultaneous distinctive concepts that have not only mutual influences and mutual conditionality. We see a need for a unifying theory with respect to the concepts, but also the different methods and data used in the various scientific disciplines. Several contributions in this book provide useful suggestions for such a theory, which can be viewed as a starting point for a more systematic foundation to overcome the current limitations of knowledge.

As an example can serve the frequency code by Ohala (1984): Similarities between 441 languages, cultures, and even species in the use and effect of F0 was argued to orig-442 inate in biologically grounded separation between "smaller" and "larger" (vocal) 443 individuals. This does not only reflect the sexual dimorphism in terms of sexual 444 selection, but also social aspects of signaling and estimating relational power, sub-445 missiveness, even helplessness, and thus supports social roles and interaction. The 446 universal systematic in F0 observed by Ohala concerns charisma, attractiveness, and 447 likability alike. Following this road to connect biological and articulatory bases for 448 acoustic and perceptual effects can be seen as one of the most important elements of 449 a unifying theory. 450

Interestingly, we observe that *trust* occurs in many contributions and it seems to have an overarching character. Trust, obviously, represents a link between the 1 Voice Attractiveness: Concepts, Methods, and Data

concepts of the sexual, the social, and the charismatic attractiveness, as it represents a positive attitude towards another. Trust may be considered as an immediate
result of attractiveness, whatever the kind of attractiveness and social relation might
be. Therefore, it is an important characteristic of human relationships, but also an
important feature for Human-Computer Interaction.

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Abstract	A speaker's voice impacts listeners' perceptions of its owner, leading to inference of gender, age, personality, and even height and weight. In this chapter, we describe research into the qualities of speech that are deemed "attractive" by a listener. There are a number of ways that a person can be found attractive. We will review the research into what makes speakers attractive in the political and business domains, and what vocal properties lead to perceptions of trust. We then turn our attention to research into "likeability" and romantic attraction. While the lexical content of a speaker's speech is important to their attractiveness, we focus this survey on prosodic qualities, those acoustic properties that describe "how" the words are said rather than "what" the words are. Of course, attractiveness is subjective; what is attractive to one listener may not be to another. Properties of the listener and other contextual qualities can have a significant impact on the voices which are found to be attractive. The most comprehensive research in this topic includes analyses of both the speaker and the listener, since attraction is frequently a mutual phenomenon; when people are attracted to someone, they want to be found attractive in return. We will also summarize work that has investigated attraction dynamics in two-party conversations.	
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Chapter 2 Prosodic Aspects of the Attractive Voice



Andrew Rosenberg and Julia Hirschberg

Abstract A speaker's voice impacts listeners' perceptions of its owner, leading to 1 inference of gender, age, personality, and even height and weight. In this chapter, 2 we describe research into the qualities of speech that are deemed "attractive" by 3 a listener. There are a number of ways that a person can be found attractive. We Δ will review the research into what makes speakers attractive in the political and 5 business domains, and what vocal properties lead to perceptions of trust. We then 6 turn our attention to research into "likeability" and romantic attraction. While the 7 lexical content of a speaker's speech is important to their attractiveness, we focus this 8 survey on prosodic qualities, those acoustic properties that describe "how" the words 9 are said rather than "what" the words are. Of course, attractiveness is subjective; what 10 is attractive to one listener may not be to another. Properties of the listener and other 11 contextual qualities can have a significant impact on the voices which are found to be 12 attractive. The most comprehensive research in this topic includes analyses of both 13 the speaker and the listener, since attraction is frequently a mutual phenomenon; 14 when people are attracted to someone, they want to be found attractive in return. 15 We will also summarize work that has investigated attraction dynamics in two-party 16

- 17 conversations.
- 18 Keywords Likeability · Charisma · Political attractiveness · Business
- ¹⁹ attractiveness · Romantic attraction · Speech prosody · Vocal attractiveness

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20 2.1 Understanding Vocal Attractiveness

Attraction is central to human social bonding. It is an expression of whom we choose
to be close to and whom we choose to avoid. There are as many types of attraction
as there are types of interaction. In this chapter we will survey the prosodic qualities
of different types of attractive voices.

A person's speech communicates a wide variety of information about the speaker. 25 Not only information that they are trying to communicate, but information about the 26 speaker themselves is important in this regard. This information enables listeners to 27 assess the gender and age of a speaker, their emotional state, and aspects of both their 28 personality, and physicality, all while listening to a person speak. These qualities may 29 be more or less attractive to a listener based on their inherent preferences and other 30 situational factors. For example, in the case of political attractiveness, there are times 31 when anger in a speaker can resonate with a listener and will be perceived positively, 32 while in other contexts anger is deemed inappropriate and, therefore, unattractive. 33

We divide this survey into five sections, based upon different types of attrac-34 tiveness. In Sect. 2.2 we discuss political attractiveness. Political figures attract and 35 retain followers through their speeches, interviews, and other public performance. 36 Understanding what allows a speaker to gain political authority has been a source of 37 investigation in political science and sociology for many years. Of late, more com-38 putational approaches have been brought to bear in assessing what kind of speech is 39 perceived as charismatic. Also related to this is the kind of charisma that is found in 40 business leaders (cf. Sect. 2.3). The business community takes communication and 41 leadership very seriously. A significant amount of work has examined the speech 42 of entrepreneurs and established (and sometimes beloved) executives in hopes of 43 understanding what draws investors and employees to a business leader. Central to 11 both of these types of attractiveness is trust. In Sect. 2.4 we will survey research that 45 strives to identify what makes a voice sound trustworthy. Researchers also tend to 46 distinguish two more social types of attraction: likeability (Sect. 2.5) and romantic 47 attraction (Sect. 2.6). These types of attractiveness are not identical, but neither are 48 they orthogonal. Types of attraction may overlap with one another. Leaders who are 49 politically attractive may also be perceived as likeable. In addition, physical attrac-50 tion can impact the degree to which people are trusted. The types of voices that signal 51 qualities of business success may be attractive to some people as friends or romantic 52 partners, but may be unattractive to others. 53

In all of these analyses of vocal attractiveness, spoken communication is an important avenue to establishing the central social bond. People appear to have relatively consistent preferences regarding vocal attractiveness. Many of these vocal qualities are associated with other speaker properties that are considered attractive; for example, male body size in the case of romantic attractiveness, or enthusiasm and dynamism in the case of political and business leaders, are correlated with attractiveness.

⁶¹ Of course, attractiveness is not an objective phenomenon. Qualities of the listener ⁶² also contribute to their perceptions of attraction. These can include sexual preference

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in romantic attraction or political bias in assessing political attractiveness. Similarly,
 some voices and messages resonate more or less with a listener on the basis of any
 number of factors—memories, contextual relevance, broader business or political
 context, or other idiosyncrasies.

Another quality that adds a layer of complexity to understanding the attractive 67 voice is the interplay between inherent and performance qualities of the voice. In 68 general, studies are looking to assess what makes a voice inherently attractive, but 69 the same voice may be used in ways that are more or less attractive. Most studies 70 avoid direct assessment of this distinction. Some will look at the same speaker in dif-71 ferent venues or types of speech (cf. Sect. 2.2.1). Other work, particularly in studying 72 romantic attractiveness (cf. Sect. 2.6), will contextualize speech in two-party conver-73 sations and consider qualities and assessments of the two speakers. Distinguishing 74 the influence of the voice itself and the way it is used in a particular stimulus remains 75 an open question in these studies. Overall assessments of attractiveness in each of 76 these domains is a combination of both inherent qualities of the voice and how it is 77 being used in the specific utterance that is being assessed. 78

Moreover, attraction is often a dynamic process in which conversational partners 79 are simultaneously being attracted (or repelled) by an interlocutor while demonstrat-80 ing their own preference for their partner to be attracted to (or repelled by) them. 81 This contemporaneous perception and performance can make analysis challenging. 82 For example, male voices which are spoken lower in the speakers' pitch range and 83 with a relatively large formant dispersion tend to be found attractive by heterosexual 84 women. But men who are attracted and are signaling their attraction to a conversa-85 tional partner demonstrate the same qualities. So should we consider this voice to be 86 attractive or flirtatious? 87

While there are relatively few clear, consistent, and universal answers to what makes speech attractive even in a specific context, to a specific group, there are some broad conclusions in the literature centered around identifying prosodic properties of an attractive voice. This chapter is an attempt to summarize the current understanding, highlight gaps and inconsistencies, and provide some directions for future inquiry.

2.2 Political Attractiveness and Charisma

Charisma is defined as the ability to persuade and command authority by virtue of ٩ı personal qualities rather than through formal institutional (political, organizational, 95 or military) structures (Weber, 1947). Viewed from this perspective, charisma is a 96 challenge for institutional stability because it represents a path to leadership that 97 eschews standard institutional pathways to power. Alternately, charisma is an impor-98 tant driver of revolutionary change specifically because it does not require specific aa structures to grant power; rather, it is a quality attributed to a person by her or his 100 followers. 101

There is a wealth of political science and sociology research on charismatic leaders
 and movements, including importantly (Weber, 1947; Boss, 1976; Marcus, 1961). In

this section, we will survey research that has used empirical techniques to investigate
charismatic political speech. In Sect. 2.2.1, we will survey studies that have looked
at spoken correlates of charismatic speech. We will summarize work that has sought
to define charisma empirically in Sect. 2.2.2.

108 2.2.1 Vocal Correlates of Charisma

Rosenberg and Hirschberg (2005, 2009) describe the first set of studies that attempt 109 to measure the vocal and lexical correlates of charisma in American English. This 110 study presented 45 speech segments to eight subjects. Materials were chosen to 111 balance speakers, topics, and genres. A small set of speakers were chosen from those 112 whose public speech covered a similar set of topics, and for whom speech tokens 113 could be found in a wide variety of genres, or speaking styles. Since the experiment 114 was designed during the winter and spring of 2004, there was abundant speech 115 material available for the nine candidates running at that time for the Democratic 116 Party's nomination for President. Speakers were limited to Democrats in this study 117 to confine the range of opinions presented in the tokens, as it has been suggested 118 in the literature (Boss, 1976; Dowis, 2000; Weber, 1947) that a listener's agreement 110 with a speaker bears upon their judgment of that speaker's charisma. Segments were 120 selected from a variety of topics in order to test the influence of topic on subject 121 judgments of charisma. Five speech tokens were chosen from each speaker, one 122 on each of the following topics: health care, postwar Iraq, Pres. Bush's tax plan, 123 the candidate's reason for running, and a content-neutral topic (e.g., greetings). For 124 these five tokens, genre was also varied among the following types: interview, debate, 125 stump speech, campaign ad. 126

Subjects were presented with each of the stimuli twice, with a 2 s silence between
 presentations. They were asked to respond to 26 statements about the speaker includ ing "The speaker is charismatic." The order of presentation of stimuli and statements
 was randomized for each subject.

Using the subject responses, a mean score measuring the degree to which the 131 speech in each token was calculated in order to examine the extent to which the 132 subject believed that the speaker was charismatic. Colloquially this was referred to 133 this as "how charismatic" the utterance was-despite charisma being a quality of 134 the speaker rather than the speech itself. With this mean charisma score for each 135 token, it was possible to analyze acoustic-prosodic qualities of the speech to iden-136 tify correlates with charisma. These qualities were identified by measuring pitch, 137 intensity, speaking rate, and duration features of the tokens in the experiment and 138 then measuring the degree of correlation between these features and subject ratings 139 of the charismatic statement. Results of these analyses showed significant positive 140 correlations between charisma ratings and the duration of the speech, whether mea-141 sured in words, seconds, or number of phrases. These results also showed positive 142 correlations between enthusiastic and passionate ratings and mean and maximum F0, 143 intensity, and speaking rate. More colloquially this means, higher pitched, louder, 144

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and faster speech is considered to be more passionate and more enthusiastic (with
caveats that the perceptual properties of pitch and loudness are not identical to the
acoustic measurements of mean and maximum F0 and intensity). Additionally, a
positive correlation between standard deviation of F0 and ratings of enthusiastic and
passionate speech was observed in male speakers.

In a later study, Rosenberg and Hirschberg (2009) extended this analysis to include 150 ToBI labeling (Beckman & Hirschberg, 2005) of the segments. In this study, phrase 151 boundary prosody was classified into three types: rising pitch (L-H%; H-H%), falling 152 pitch (L-L%; L-), and plateau or flat pitch (H-L%; H-). Results showed that the rate 153 of rising tokens negatively correlates with charisma. Rising intonation is used in 154 questions, and can be associated with uncertainty. Neither of these qualities is con-155 sistent with "persuasiveness," a component of charisma. Consistent with this, the 156 L*+H pitch accent type, also associated with uncertainty, had a negative correlation 157 with charisma. The L*+H pitch accent is realized with low pitch on a prominent 158 syllable nucleus which rises, typically reaching a peak after the nucleus boundary. 159 In addition, prosody associated with "new" information (H* pitch accents) was pos-160 itively correlated with charisma, while prosody associated with "given" information 161 (downstepped contours: H* !H* L-L%) was negatively correlated. H* pitch accents 162 are high tone pitch peaks that are more or less time-synchronized with intensity peaks 163 occurring within syllable nuclei. Downstepped high pitch accents, !H*, are H* pitch 164 accents that occur after a previous high tone, and have a lower pitch height during 165 their high tone. The "downstepped" contour is a shorthand to describe a high tone, 166 followed by one or more downstepped high tones with a L-L% phrase ending. 167

Other notable efforts in measuring vocal correlates to charisma have investigated political speech in other languages and countries. From this work we can look for evidence of linguistic and or cultural biases in the perception or production of charisma. Disentangling these factors (linguistic vs. cultural; perception vs. production) is virtually impossible given the size of these studies and additional confounds (speaker/listener demographics and other biases, political, social, and temporal context to name a few) that all analyses in this space are subject.

Cullen and Harte (2018) analyzed a relatively large set (945 utterances) of longi-175 tudinal speech material from a single speaker, over seven years (2007–2012). This 176 material, compiled as the Irish Political Speech Database, has a number of useful qual-177 ities. By focusing on a single speaker, many political biasing elements are controlled 178 for. By including many recording contexts (talk shows, parliamentary speeches) dif-179 ferences in genre can be accounted for. The longitudinal aspect also allows polling 180 data to be associated with the politician's speech, facilitating investigation of how 181 popularity or standing impact communication. This work also included automatic 182 classification of charisma based on acoustic-prosodic features. The authors found 183 that prosodic features, based on pitch, intensity, and duration, outperformed spectral 184 features. The specific performance of this classifier is somewhat immaterial-the 185 broad applicability of a single speaker model for a paralinguistic task is *extremely* 186 limited. But the relative value of the acoustic signal is revealing-charisma is found 187 here to be a function of suprasegmental qualities more than voice quality (as captured 188 by spectral features). 189

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Biadsy, Rosenberg, Carlson, Hirschberg, and Strangert (2008) significantly 190 extended the studies described in Rosenberg and Hirschberg (2005, 2009. The orig-101 inal American English stimuli were additionally rated by native Swedish and Pales-192 tinian Arabic speakers, and a subsequent study presenting Palestinian Arabic speech 193 to speakers of the American English and Palestinian Arabic was conducted. Compar-194 ative analysis of the original study with these four new studies allowed the identifica-195 tion of some vocal correlates of charisma that appear to be robust to differences in the 196 language of the speaker or listener. Others appeared to be sensitive to the language 197 of the listener, regardless of the language of the speaker, and still others are specific 198 to the speaker/listening configuration. For example, across all experiments, mean 199 pitch, pitch range, mean and standard deviation of intensity, and stimulus duration 200 all positively correlated with charisma ratings regardless of the language spoken and 201 the native language of the rater. Conversely, the presence of disfluencies negatively 202 correlated with charisma in all experiments, though this correlation was weakest for 203 Swedish judgments of American English. 204

The studies also found that raters tended to pattern similarly in response to many aspects of the stimuli regardless of their native language. For instance, when assessing English stimuli, minimum F0 was positively correlated with charisma. However, when assessing Palestinian Arabic utterances, this feature was negatively correlated for Palestinian subjects, and not significant for American subjects. Also both groups judging Arabic data rated speech to be more charismatic that exhibits larger standard deviations in F0 but none of the groups judging English showed the same effect.

Finally, a third group of correlates appeared to be specific to the language of both speaker and listener. For example, the speaking rate was positively correlated with charisma judgments only for American and Swedish ratings of English: the faster the speech, the more charismatic the speaker was deemed to be. However, when Palestinians judged Arabic speakers, speaking rate approached a negative correlation with charisma, with no correlation between speaking rate and charisma when Palestinians judged American English or Americans judged Palestinian Arabic.

This is not the only work that has looked at cross-cultural biases in perceptions and
production of charisma. Though not every investigation found clear differences on the
basis of culture or nationality. For example, Cullen et al. (2014) also found that native
Irish raters and Amazon Mechanical Turk workers, who are largely American, were
quite consistent in their assessment of Irish Political speech with respect to charisma.
Pejčić (2014) investigated persuasiveness in Serbian and British political speech,

224 which appears clearly related to charisma. This study presented five samples of Ser-225 bian political speeches and five samples of British speeches to 113 Serbian subjects 226 asking them to respond to a subset of the 26 statements used in Rosenberg and 227 Hirschberg (2009) on a 5-point Likert scale. Acoustic analysis was performed on the 228 tokens from both languages considered as a common population, and also on each 229 language in isolation. When pooling both languages, relatively few statistically sig-230 nificant correlates with persuasiveness were observed. These were the standard devi-231 ations for F0 peaks in narrow-focused rising nuclear tones, their percentage in Tone 232 Units' F0 range and the maximum F0 of their Tone Units. Anecdotal observations 233

suggest roughly that larger F0 excursions were positively associated with persuasion
 in Serbian speech, but negatively associated with British speech, at least when rated
 by Serbian speakers.

In addition to these studies, there are a number of descriptive investigations of the 237 speaking style of politicians, particularly concerning the recognition of charisma. 238 Pèrez (2016) contrasted the speech of the Venezuelan politicians, Hugo Chávez and 230 José Luis Rodrìguez Zapatero, characterizing Chávez as using a "revolutionary" 240 style, consistent with charismatic authority, whereas Zapatero uses a more "tra-241 ditional" style, consistent with institutional authority. Ryant and Liberman (2016) 242 proposed a number of visualization techniques to investigate and compare prosodic 243 qualities of speech, using U.S. Presidents Barack Obama and George W. Bush as 244 examples. 245

246 2.2.2 Defining Charisma

Careful reading will reveal that the studies described in Sect. 2.2.1 side-step any
definition of "charisma." Specifically, subjects in Rosenberg and Hirschberg (2005)
were simply asked to respond to the statement "The speaker is charismatic," which
does very little to identify the personal or vocal qualities that lead to this perception.

Researchers in other fields have posited a number of factors that contribute to perceptions of charisma. Boss (1976) sees charismatic leaders emerging from an *important crisis* met by an *inspiring message* delivered by a messenger with a *gift* of grace. Marcus takes a more specific view identifying charisma as a product of the faith of a potential leader's *listener-followers* (Marcus, 1961). While these are useful perspectives on political attractiveness and authority, they provide little direction when we try to empirically quantify charisma and charismatic speech.

In Rosenberg and Hirschberg (2005), subjects were asked to respond to the state-258 ment "the speaker is charismatic." But the subjects also responded to 25 other state-259 ments about the speaker and his or her speech. Most of these were of the form 260 "The speaker is X," where X was one of the following: charismatic, angry, spon-261 taneous, passionate, desperate, confident, accusatory, boring, threatening, informa-262 tive, intense, enthusiastic, persuasive, charming, powerful, ordinary, tough, friendly, 263 knowledgeable, trustworthy, intelligent, believable, convincing, reasonable. These 264 attributes represent a subset of those often associated in the literature with charisma. 265 "The speaker's message is clear" and "I agree with the speaker" were also included as 266 statements to be rated. Using these ratings, along with the ratings of charisma, it was 267 possible to determine which *other* qualities were highly correlated with charisma, to 268 help in developing a "functional" definition of this term. Rather than offering a for-269 mal definition of charisma as a sociopolitical concept or a vocal characteristic, these 270 results indicate how the subjects themselves understood charisma and how they were 271 using the term. Specific results can be found in Table 2.1. These results confirmed 272 some of the conventional wisdom of what we mean when we say charismatic-273 specifically, a charismatic speaker is **charming**—and what we believe charisma to 274

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Statement	κ	
The speaker is enthusiastic	0.606	
The speaker is charming	0.602	A
The speaker is persuasive	0.561	
The speaker is boring	-0.513	
The speaker is passionate	0.512	
The speaker is convincing	0.503	

 Table 2.1
 Statements showing the most consistent subject responses with the statement "The speaker is charismatic"

be used for—a charismatic speaker is **convincing** and **persuasive**. However, they 275 also provide support for claims found in Dowis (2000) and Boss (1976) that charis-276 matic speakers should be passionate and enthusiastic and, by extension, not boring. 277 It was also interesting to see that responses to the *desperate*, *threatening*, *accusatory*, 278 and angry qualities showed no positive or negative ($|\kappa| < 0.15$) agreement with 279 the charismatic statement. Apparently, a charismatic speaker *can* demonstrate these 280 qualities, but, at least among the subjects in this study, they neither promote nor 281 inhibit perceptions of charisma. 282

A similar approach to defining charisma was undertaken in Signorello, D'Errico, 283 Poggi, and Demolin (2012). This study administered a free-form web survey, asking 284 58 French participants to provide adjectives that are consistent or inconsistent with the 285 term "charisma" as they understood it. Retaining only adjectives that were reported by 286 more than one subject, the authors identified 40 terms that were positively associated 287 with charisma and 27 that were negatively associated. To facilitate understanding, 288 the authors grouped these into five categories (1) Pathos, (2) Ethos Benevolence, 289 (3) Ethos Competence, (4) Ethos Dominance, and (5) Emotional Induction Effects. 290 Table 2.2 is reproduced from Signorello et al. (2012). Note that *charming*, *persuasive*, 291 enthusiastic, and 'boring' appear in both Signorello et al. (2012) and Rosenberg 292 and Hirschberg (2009) despite the studies using French and American participants, 293 respectively. 294

One divergent finding did appear however: while Rosenberg and Hirschberg (2009) found no correlation between *threatening* and *anger*, Signorello et al. (2012) identified through factor analysis an *Authoritarian-Threatening* factor which in their study **is** a factor, including the terms *determined*, *authoritarian*, *leader*, *confident* as well as the more aggressive terms *Who Scares*, *cold. dishonest* and *menacing*.

While not directly related to defining charisma, but related to political speech, an interesting idea presented in Cullen and Harte (2018) addresses vocal attractiveness more broadly. The Irish Political Speech Database is labeled for six attributes: *charisma, boring, enthusiastic, inspiring, likeable.* From these six, Cullen and Harte (2018), define Overall Speaker Appeal (OSA) as the average of these six ratings (including negative boredom ratings). The correlation of these attributes may limit

Dimension	Positive adjectives	Negative adjectives
Pathos	Passionate, empathetic, enthusiastic, reassuring	Cold, indifferent
Ethos benevolence	Extroverted, positive, spontaneous, trustworthy, honest, fair, friendly, easygoing, makes the others feel important	Untrustworthy, dishonest, egocentric, individualistic, introverted
Ethos competence	Visionary, organized, smart, sagacious, creative, competent, wise, enterprising, determined, resolute, who propose, seductive, exuberant, sincere, clear, communicative	Inefficient, inadequate, uncertain, faithless, unclear, menacing
Ethos dominance	Dynamic, calm, active, courageous, confident, vigorous, strong, leader, authoritarian, captivating, who persuade, who convince	Apathetic, timorous, weak, conformist, unimportant, who scare
Emotional induction effects	Charming, attractive, pleasant, sexy, bewitching, eloquent, influential	Boring

Table 2.2 The 67 positive and negative adjectives related to charisma. Reproduced from

the efficiency of this measure, but the attempt to summarize these signals into a single
 measure is potentially valuable, even if the specific formulation might benefit from
 modification.

309 2.3 Business Attractiveness

Business organizations are an area in which leadership and authority have clear 310 impacts. There are many organizational structures that are used in business activi-311 ties, but all instill participants with distinct, decision-making authority. Within these 312 structures, charismatic authority can be manifested the way (Weber, 1947) formulated 313 it—as an alternative to established, institutional authority. This would be revealed 314 by a situation where employees look to a co-worker who is not in a management or 315 reporting structure for direction rather than their direct manager. A more common 316 way to think about charismatic leadership in a business context is when charismatic 317 authority is aligned with institutional authority. This allows us to think about "how 318 charismatic" is one manager, one CEO, or one founder over another. 319

While there is always an element of "trust" in a leader–follower relationship, this is somewhat more quantifiable in business relationships. Investors are entrusting their capital to the efforts of a founder when they invest in a business. While the specific leadership of a founder may be more essential to a start-up, opinions about the CEO can have an impact on institutional investing in well-established corporations.

We previously noted some of the complications in defining charisma. The use of 325 a limited number of speakers who have a cultural consensus of being charismatic 326 is one way to get around a broader definition. One thread of work undertaken by 327 Oliver Niebuhr and colleagues has been to study Steve Jobs, former CEO and co-328 founder of Apple Inc., as an exemplar of a charismatic business leader. Niebuhr, 329 Brem, Novák-Tót, and Voße (2016b) posit a profile of charismatic speech based on 330 a reading of previous political studies (cf. Sect. 2.2). This is summarized as having 331 high and varied pitch, high and varied intensity, a fast speaking rate, few disfluencies, 332 a large number of emphatic words, but with varied realizations and high rhythmic 333 variation. By automatic analysis of two landmark speeches (launching the iPhone 4 224 and iPad 2) they find that Steve Jobs does in fact fit this profile. 335

This research direction is continued in a number of works via a contrastive analysis of Steve Jobs and Mark Zuckerberg, founder and CEO of Facebook (Mixdorff, Niebuhr, & Hönemann, 2018; Niebuhr, Voße, & Brem, 2016a, 2018b). The approach here is based on the common perceptions of Steve Jobs as a charismatic speaker and Mark Zuckerberg as a less charismatic speaker, though both were CEOs of major corporations at the time their speech was collected for analysis.

Niebuhr et al. (2016a) find that Jobs has shorter phrases, fewer and shorter hesi-342 tations, and a more dynamic use of pitch and rhythm than Zuckerberg. While Jobs 343 speaks quickly (compared to "normal" speech), Zuckerberg's speaking rate is even 344 higher. This contributes to strong phonetic reductions in his speech which may neg-345 atively impact perceptions of charisma. Applying the Fujisaki model of intonation 346 Fujisaki and Hirose (1984), Mixdorff et al. (2018) enable a more specific analysis 347 of how the two CEOs manipulate pitch in their speeches. In general, this analysis 348 brings insight into the earlier (and overly simplistic) findings that high pitch leads 340 to perceptions of charisma. These two speakers differ more in how they reset their 350 pitch ranges across phrases and the strength of their excursions. This work is then 351 expanded upon in Niebuhr et al. (2018b) where the timing and shape of pitch accents 352 are examined. Moreover, the authors find that a large vowel space, limited place of 353 assimilation, and a clear differentiation between voiced and unvoiced stops all dif-354 ferentiate Jobs from Zuckerberg. These factors all contribute to fast, dynamic speech 355 that is clearly pronounced. 356

While analysis of specific business leaders enables clear contrastive discussion, 357 there is more work that looks at business speech in entrepreneurship more gener-358 ally. Weninger, Krajewski, Batliner, and Schuller (2012) extracted speeches from 359 143 male business leaders that were shared on YouTube. They collected ratings of 360 charisma and attempted to automatically predict the human ratings with acoustic 361 and linguistic features. The raters were 10 psychology Ph.D. students, 5 male and 362 5 female.¹ This work investigated a large number (1,582) of acoustic–prosodic fea-363 tures, in addition to lexical features derived from automatic speech recognition tran-364 scripts of the speeches. This work finds that charisma can be automatically detected 365 with 61.9% accuracy, significantly over chance level, based on acoustic-prosodic and 366 lexical features. 367

¹No statistically significant gender effects in the ratings of charisma were discovered.

While the previous studies looked at established business leaders (Niebuhr, Brem, 368 & Tegtmeier, 2017) investigated start-up state entrepreneurs, since "a decisive part 360 of their strategy and daily work is to persuade others." Leaders of these early stage 370 businesses need to convince both investors, suppliers, and customers of the legitimacy 371 of their nascent technology, developing products and services, and of the likely market 372 demand. In this study, 45 participants gave the same elevator pitch, 15 practiced with 373 no feedback, 15 received visual feedback, and 15 received feedback based on the 374 Steve-Jobs-as-charismatic-exemplar acoustic model described above. They found 375 that speakers who received acoustic feedback about their speech were rated 41% 376 more charismatic following training, significantly more than those who received no 377 feedback (24% more charismatic) or those who received visual feedback (12% more 378 charismatic). 379

Extending this investigation of entrepreneurial speech into spectral qualities contributing to voice quality, Niebuhr et al. (2018a) found that a fuller and less breathy voice also led to higher speaker charisma ratings. This may be consistent with findings that suggest that clear or easily understood speech is an important element to charisma.

Much of the study of business attractiveness has been focused on analysis of 385 speech spoken by men. On one hand, this can limit variability to facilitate analysis. 386 On the other, it perpetuates patriarchal norms, implicitly treating charisma-and 387 specifically business leadership—as a quality only associated with male speech. 388 This thus limits our ability to understand charisma in female speakers. Novák-Tót, 389 Niebuhr, & Chen, 2017) investigated the bias in the perception of speeches delivered 390 by American female executives Oprah Winfrey and Ginni Rometti and male executive 391 Steve Jobs. No information as to the gender of the raters was provided. They found 302 that female speech that is judged to be as charismatic as male speech demonstrates 393 more and stronger acoustic cues to charisma. This suggests that this gender bias may 394 be compensated for by making a greater effort by the female speakers. Significantly 395 more work is necessary with regard to the charisma of female leaders both in business 396 and politics alike. 397

398 2.4 Vocal Correlates of Trust

Trust and attractiveness are closely related. Some studies have found that people 399 trust romantically attractive strangers more than unattractive ones, e.g., Wilson and 400 Eckel (2006). While others have found that the relationship is not so simple. Sofer, 401 Dotsch, Wigboldus and Todorov (2015) found that more "typical" faces elicited 402 more trust, rather than the most attractive faces. In this work, "typical" faces were 403 constructed as an averaged composite of 92 faces, while the "attractive" face was 404 an averaged composite of the 12 most attractive in the used data set. However, in 405 an investigation of responses to dating profiles, McGloin and Denes (2018) found 406 that attractive men were considered trustworthy, but attractive women were not. 407 It is worth noting that in both of these studies, the presented face was exhibiting 408

a "neutral" expression. Smiling or grimacing would likely impact impressions of 400 attractiveness, pleasantness, trustworthiness, and likeability in unanticipated ways. 410 When we think about attractiveness more broadly, as we have done in this chapter, 411 trust is a necessary component to political, business, and nonsexual attractiveness. 412 In the political and business roles, attractiveness can endow abilities to the person. 413 They can obtain political power via elections or they can obtain commercial power 414 through investment. Trusting the person is necessary when granting these abilities 415 and responsibilities to the person. 416

In an analysis of deceptive and truthful, trusted, and mistrusted speech in 417 the Columbia Cross-Cultural Deception (CXD) corpus, Levitan, Maredia, and 418 Hirschberg, Levitan et al. (2018) found significant differences in trusted and mis-419 trusted speech. The CXD corpus is a study of deceptive versus nondeceptive speech 420 from native speakers of Standard American English (SAE) and Mandarin Chinese 421 (MC), all speaking in English. The participants were balanced between male and 422 female speakers and native speakers of English and Chinese. It contains interviews 423 between 340 subjects in 122h of speech. A variation of a fake resume paradigm 424 was used to collect the data. All subjects were previously unacquainted, and pairs 425 of subjects played a "lying game" with each other. Each subject filled out a 24-item 426 biographical questionnaire and was instructed to create false answers for a random 427 half of the questions. They also reported demographic information including gender 428 and native language, and completed the NEO-FFI personality inventory. The speech 429 was recorded in a double-walled sound booth, where the two subjects were sepa-430 rated by a curtain to ensure no visual contact. For the first half of the game, one 431 subject assumed the role of the interviewer, while the other answered the biograph-432 ical questions, lying for half and telling the truth for the other; questions chosen in 433 each category were balanced across the corpus. For the second half of the game, the 434 subjects' roles were reversed, and the interviewer became the interviewee. During 435 the experiment, the interviewer was encouraged to ask follow-up questions to aid 436 them in determining the truth of the interviewee's answers. Interviewers recorded 437 their judgments for each of the 24 questions, providing information about human 438 perception of deception. Subjects were incentivized monetarily: for every response 439 to the 24 questions that the interviewer judged correctly, the interviewer received 440 an extra \$1, while every incorrect judgment cost them \$1. Every false answer the 441 interviewee persuaded the interviewer was true gained the interviewee \$1, while 442 every false answer the interviewer judged false lost the interviewee \$1. The intervie-443 wees annotated each of their statements during the interview by pressing a "truth" or 111 "false" key on a computer keyboard. We aligned these annotations with transcriptions 445 of the interviews obtained by speech recognition with crowdsourced corrections and 446 automatically aligned the transcripts with the speech recordings. 447

Overall, the researchers found that the mistrusted speech in their corpus (interviewee responses that were not believed by interviewers) was significantly more intense
(louder) and spoken in a higher pitch range, while the speech that interviewers tend to
trust was spoken more rapidly. However, they also found differences between male
and female and English and Mandarin Chinese native speakers in these features.
While male speakers did tend not be trusted when they spoke in a high pitch range,

ditor Proof

this was not true of female speakers (note that all features were z-score normalized, 454 so these findings were not influenced by a speaker's "normal" range or loudness 455 or speaking rate). Both genders were trusted more when they spoke more rapidly. 456 Female speakers, however, were trusted more when their voice quality exhibited 457 more jitter and shimmer-instabilities in their pitch and intensity associated with per-458 ceived "roughness" or "breathiness." There were also differences in trustworthiness 459 in speakers' native language backgrounds, although all speakers spoke in English. In 460 general, native speakers of Standard American English were more trusted when they 461 exhibited high jitter and shimmer while this was not a significant factor for native 462 speakers of Mandarin Chinese, who were more trusted when they spoke more rapidly. 463 These Chinese speakers were less likely to be trusted when they spoke in a high pitch 464 range and when their overall mean pitch was high; they were also mistrusted when 465 their maximum intensity was high and when their Harmonics-to-Noise (HNR) ratio 466 (another measure of voice quality disorders) was high. 467

The researchers also examined the gender and the native language of the inter-468 viewers that correlated with their judgments whether interviewers are lying or telling 469 the truth. Overall, all interviewers mistrusted speech with a high pitch range and a 470 high maximum intensity and trusted speech spoken rapidly. However, there were 471 major differences between genders. Male interviewers distrusted speech with high 472 mean pitch and maximum intensity and trusted fast speaking rate while females only 473 mistrusted high jitter and shimmer. Comparing native English speakers to native 474 Mandarin speakers, the researchers found fewer differences: both mistrusted high-475 intensity speech and trusted faster speaking rate, but only native English speakers 476 mistrusted high pitch range. 477

478 2.5 Likeability or Nonsexual Social Attractiveness

The distinction between finding a voice "pleasant" to listen to, and finding the speaker
to be socially attractive as in "I like this person" is difficult to distinguish in research
protocols. These two facets may overlap, they may even be identical for some listeners, but there may be differences that are elided in the research in this space.

There are several factors that have been found to contribute to likeability in speech. Strangert and Gustafson (2008) found that the speaker should be proficient. That is, the speech should include limited disfluencies and a reasonably high speaking rate. For clear speech, Weiss and Burkhardt (2010) found that warm/relaxed speech correlated significantly with likeability.² This included less pressed, more breathy voice quality and lower spectral center of gravity.

Weiss and Burkhardt (2012) performed a focused analysis of 30 speakers rated as highly likeable and 30 that were highly not-likeable, drawn from the material used in the 2012 Interspeech paralinguistics challenge (which is discussed in detail

²Note the difference in likeability correlating with *relaxed* speech, while charismatic speech (cf. Sect. 2.2.1 correlates with passion and enthusiasm.

⁴⁹² below). The presence of positive factors of likeability was found in all speakers. ⁴⁹³ These included minimal disfluencies and no discernible accent. However, unlikable ⁴⁹⁴ speakers show higher pitch, lower articulation rate, and lower pronunciation pre-⁴⁹⁵ cision. This suggests that these factors can make a speaker "unlikeable," although ⁴⁹⁶ perhaps the mere absence of negative attributes is sufficient for an unknown speaker ⁴⁹⁷ of a relatively short amount of speech to be viewed as "likeable."

Regarding the "no discernible accent" finding of Weiss and Burkhardt (2012), 498 there appears to be a more nuanced relationship between social factors like likeabil-499 ity and trust and a speaker's accent. For example, Tavernier (2007) examined per-500 ceptions of Flemish speaker's responses to English speech. They found the highest 501 social attractiveness and trust ratings to come from RP (Native British) speech, with 502 the lowest ratings coming from Flemish-accented English, despite the raters being 503 Flemish speakers themselves. Looking at American English, Preston (1999) found 504 broad differences in social assessments on the basis of the internal regional accent 505 of American speakers, including a finding that northern speakers are considered to 506 be less friendly than southern speakers by students in Michigan. 507

Baumann (2017) collected pairwise likability ratings from more than 220 speak-508 ers and over 160 raters. This work found very limited acoustic correlations with 509 rater preferences. Only measures related to the acoustic fidelity of the recording 510 showed significant correlations, while prosodic qualities showed trends that did not 511 reach statistical significance. However, the authors did find an interesting relation-512 ship between gender and likeability. Both male and female raters responded to male 513 speech similarly. However, female speech was rated as much more likeable by female 514 raters than by male raters. 515

As in the study of charisma, qualities of the *listener* do not receive as much research attention as qualities of the *speaker*. This is particularly true in the case of likeability. Social attractiveness necessarily involves two parties and is a subjective quality. We do not all want to be friends with the same people. The attitude and behaviors of the listener can impact the speaker and reveal the dynamics of establishing, maintaining, or undermining social attractiveness.

Schweitzer, Lewandowski, and Duran (2017) directly addressed this facet of like-522 ability. This work examined dialogs between pairs of German female speakers who 523 both rated their dialog partners following their conversation. This work treats like-524 ability as social and participatory. By investigating only dialogs between two female 525 participants, this study avoids the biasing on the part of speaker or listener based on 526 gender. While it was not explicitly measured, there is an assumption in this work that 527 the participants were all heterosexual, therefore, the potential for overlap between 528 likeability (social attractiveness) and sexual attractiveness is diminished. It is worth 529 mentioning that in work that investigates social and sexual attractiveness, the sexual 530 preferences of the participants are particularly relevant. As such, it is necessary to 531 collect or verify information about the sexual preferences of subject participants. 532

The experiment consisted of 46 two-party dialogs between 13 participants. Dialogs were collected in situations where the speakers could see each other, and where they were visually separated. Each dialog was spontaneous and unconstrained, and lasted approximately 25 min. After the conversation both participants responded
 to a questionnaire about how likeable, competent, friendly, and self-confident they
 found their conversational partner.

The authors found limited confirmation of pitch and voice quality correlates to 539 likeability in this study. Specifically, they found no effect of absolute pitch or pitch 540 range. Neither were effects of shimmer, jitter, or HNR observed. However, they 541 did find a number of entrainment or "convergence" based effects. These relate to 542 how the acoustic-prosodic and lexical qualities of two (or more) speakers either 543 become more or less similar over the course of a dialog. The authors found that 544 lexical entrainment, when interlocutors use the same words, is a reliable predictor of 545 likeability. In multimodal conversations, where the participants could see each other, 546 they found convergence of peak F0 height made a speaker appear less likeable. 547

The Interspeech Paralinguistics Challenge is an annual shared task with results 548 presented at the Interspeech Conference each fall. The organizers distribute speech 549 data sets labeled for some paralinguistic quality which are partitioned into train, 550 development, and evaluations sets. Previous tasks have included classification of 551 emotion, sleepiness, and intoxication among many others. The 2012 challenge 552 included a task to classify the likeability of a speaker on the basis of a short utterance. 553 Sentences were drawn from the aGender corpus (Burkhardt, Eckert, Johannsen, & 554 Stegmann, (2010), and originally collected for the prediction of age and gender. The 555 longest utterance for each speaker was selected. This resulted in 800 speakers bal-556 anced between male and female and divided into three age ranges (young: 15-24; 557 middle: 25-54; senior: 55-85). These were rated on a 7-point Likert scale of like-558 ability by 32 participants (17M; 15F) aged 20-42 years. Ratings were adjusted based 559 on evaluator reliability and discretized into Likeable and Not-Likeable classes for 560 classification. The organizers of the challenge found no impact of the rater's age 561 or gender on ratings, but the age and gender of the *speaker* did have a significant 562 impact. These challenges have served as a venue for the broader research community 563 to test the limits of automatic analysis of paralinguistics. In many situations, in part 564 because of the short time frame, and limited meta data available for the challenge 565 data sets, a good number of submissions associated with these challenges tend to be 566 applications of feature selection, e.g., Pohjalainen, Kadioglu, and Räsänen (2012), 567 Wu (2012) and classification approaches, e.g., Cummins, Epps, and Kua (2012), Lu 568 and Sha (2012), Brueckner and Schuller (2012), Sanchez, Lawson, Vergyri, and Bratt 569 (2012), Some of these are quite novel to these tasks yet include only limited analyses of the underlying phenomena. One exception can be found when participants develop 571 novel acoustic features for analysis. This was undertaken by Buisman and Postma 572 (2012) in this likability challenge. They found that spectral information extracted 573 via log-gabor-filter-based features were able to predict likeability with higher accu-574 racy than a much larger set of features included in the OpenSmile baseline (Eyben, 575 Wöllmer, & Schuller, 2010). 576

Additionally, Montaciè and Caraty (2012) developed specific pitch and intonation feature sets based on MOMEL (Hirst, 1987) and INTSINT (Louw and Barnard, 2004). MOMEL is a stylization technique which smooths out microprosody from a pitch contour, while INTSINT discretizes the contour into "key ranges" describ-

ing the speaker's pitch range, and "contextual labels" describing the relationship 581 between the pitch at a given target to the previous target. A set of features based on 582 the MOMEL and INTSINT processes were developed to help predict likability and 583 also personality traits (another task of the 2012 Interspeech Paralinguistics Chal-584 lenge). While the specific correlations between likeability and these novel features 585 are not presented, the use of intonational features was useful for the prediction of 586 likeability where they were not useful for predicting personality traits. This suggests 587 that these features may be particularly well suited to likeability, rather than being 588 generally valuable features for paralinguistic analysis. There are conflicting results 589 about correlations between pitch and likeability. These seem to suggest that either the 590 specific formulation of intonational features is critical, or the relationship is nuanced 591 and significantly influenced by other factors. 592

593 2.6 Romantic Attractiveness

Romantic attraction is a complicated phenomenon that involves the synthesis of a
wide array of signals to determine romantic interest. The current understanding of
this topic involves an interplay of influences too complicated to summarize here.
Here we will focus only on the work that has investigated qualities of the voice that
lead a listener to find a speaker romantically attractive, or not.

While romantic attractiveness is exceptionally subjective, research has been 599 undertaken to identify voices that are typically found to be more (or less) attrac-600 tive. In this work, compared to much of the work surveyed elsewhere in the paper, 601 characteristics of the listener are measured, and generally controlled for. However, a 602 significant number of studies in this area conflate the influence of gender and sexual 603 orientation in considering the qualities of the listener. Some studies investigate how 604 males react to female voices or faces and others will study how females respond to 605 male voices. In doing this, there is an assumption that all of the participants are, in 606 fact, attracted romantically or sexually to members of the opposite sex. When these 607 studies do not report the sexual orientation of the subjects, it stands to reason that 608 the question was not asked of the participants. This is a significant methodological 609 problem with this body of work. Through this section we will highlight whether a 610 study has in fact reported the sexual orientation of the subjects or not, and suggest 611 that future studies take this into consideration. We would also suggest that gender 612 questions in recruitment for these studies be broadened to gain an understanding of 613 how transgender, nonbinary, and intersex people assess attractiveness by the voice. 614 None of the surveyed papers address these populations. 615

In an example of this, Collins and Missing (2003) investigated subject ratings of attractiveness of female voices, and female faces. To account for sexual preference, they used only male raters. However, they do not report whether all participants were heterosexual. In this work, they found strong agreement as to what was an attractive voice, and what was an attractive face, and moreover, attractive voices belonged to attractive faces. They found that voices of younger women are typically

2 Prosodic Aspects of the Attractive Voice

higher pitched, as are voices of smaller women, while taller women demonstrate
a narrower formant dispersion. The authors' findings suggest that both the visual
and auditory signals are communicating complementary information regarding age
and body shape. The finding that men find high-pitched women's voices attractive
has been identified elsewhere as well, including by Feinberg, DeBruine, Jones, and
Perrett (2008b).

On the other hand, Feinberg, Jones, Little, Burt, and Perrett (2005), Collins and 628 Missing (2003), and Hodges-Simeon, Gaulin and Puts (2010) all found that women 629 find men with lower pitched voices to be more attractive. Feinberg, DeBruine, Jones, 630 and Little (2008a) found that both male and female subjects consistently rated the 631 masculinity of male faces and voices and demonstrated preferences for more mascu-632 line voices. The claim here is that testosterone information is similarly communicated 633 via the voice and the face. This supports a finding by Saxton et al. (2006) that men 634 with attractive voices also have attractive faces. Interestingly, this result was found 635 in adolescent and adult women, but not in female children. Of these, only Hodges-636 Simeon et al. (2010) reported the sexual orientation of the participants reported. 637

Many of these findings are predicated on the idea that attractiveness of a voice is 638 being used as a proxy or a reinforcing signal for other physical characteristics. While 639 there are plausible evolutionary justifications (cf. Puts, Doll, & Hill, 2014) for why 640 some secondary sexual traits are attractive, the value of an attractive voice is less 641 obvious. There is, however, some evidence that attractive voices are correlated with 642 other physical traits that are themselves attractive. For example, Bruckert, Liénard, 643 Lacroix, Kreutzer, and Leboucher (2006) found that male speech with low-frequency 644 formants correlate with age, height, and weight. However, female listeners were only 645 able to reliably estimate the age and weight of a male speaker based on enunciation 646 of vowels. González (2006) found that the pitch of human speech reveals very little 647 about body size when age and gender are controlled for. However, formant dispersion 648 does carry this information. Despite the fact that it is a poor signal, listeners do rely 649 on pitch information to estimate body size. Babel, King, McGuire, Miller, & Babel 650 (2011) investigated the vocal correlates of attractiveness particularly as it relates to 651 body size in the perception of opposite-sex voices by both male and female listeners. 652 They found that the ratings of both genders were highly correlated, though males 653 generally rated other males as less attractive than females did. They also found 654 that attractive female voices had high second formants in high vowels, breathy voice 655 quality, reduced pitch variance, and longer durations. However, attractive male voices 656 had shorter durations (consistent with faster speaking rate), higher vowels, lower first 657 formants overall, and higher second formant in /u/s. While this work was motivated 658 by a search for body size correlates, the authors found a much more complicated 659 relationship than expected. 660

In addition to pitch qualities, speaking rate also matters. Quené, Boomsma, and van Erning (2016) investigated the attractiveness of male voices by heterosexual female listeners as a function of both pitch and speaking rate. They found that faster and lower pitched speech was more attractive. However, tempo only matters if the pitch component is present. Fast but relatively high-pitched speech was not consistently rated as attractive. In general, there are relatively few published findings about the relationship between voice quality and attractiveness. Babel et al. (2011) found breathy voice to be an indicator of attractiveness in female voices. Barkat-Defradas te al. (2015) found that male voices that are slightly rough (R1 on the GRBAS scale, a measure of dysphonia) are rated as the most attractive by women. The sexual orientation of subjects was not reported in either study.

Given these findings that there are vocal correlates to attractiveness, Fraccaro 673 et al. (2013) investigated whether subjects could intentionally sound more or less 674 attractive. They asked male and females to intentionally raise and lower the pitch 675 of their voice. They found that when male speakers lowered their pitch and female 676 speakers raised theirs, these manipulations did not necessarily lead to increased 677 attractiveness. Additionally, when the male speakers raised their pitch and women 678 lowered theirs, their attractiveness was lowered. This suggests that it is difficult to 679 "fake" an attractive voice. Although we will return to the idea of intention when we 680 discuss entrainment and communication of interest (i.e., flirting). 681

These trends, that lower pitched (and therefore more masculine) men are consid-682 ered more attractive, are not independent of other qualities of the subject. Valentová, 683 Roberts, and Havlícek (2013) investigated ratings of attractiveness and masculin-684 ity of male voices and faces by homosexual men and heterosexual women. These 685 authors also collected information about the relationship status and sexual restrictive-686 ness. Homosexual male subjects also self-rated themselves on a masculine-feminine 687 scale. (Heterosexual female subjects were not asked to perform this self-rating.) They 688 found no consistent preference for masculine faces by either homosexual men or het-689 erosexual women. Moreover, a preference for masculine voices was only found in 690 coupled heterosexual women and single homosexual men, While a preference for 601 less masculine faces was observed in coupled homosexual men. Homosexual men 692 who considered themselves to be more masculine tended to prefer more masculine 693 voices, but more feminine faces. These findings highlight the complexity of iden-694 tifying romantically attractive voices. Perceptions of attractiveness are conditioned 695 not only on gender, but also sexual preference, and the gender expression of both 696 the listener and speaker, in addition to other subjective idiosyncrasies. While this 697 (and other) work by Valentova et al. goes further than most in acknowledging and 698 investigating these factors, there remains a wide range of unstudied questions and 699 interactions in this space. 700

The studies that we have surveyed so far have studied the perceptions of listeners 701 who are not also conversational participants. While there are, of course, situations 702 where this occurs, listening to the radio, an audiobook, a lecture, or other presentation, 703 romantic attraction is more commonly established in two-party conversations. Here 704 attraction is both assessed and performed and the voice is used to both express 705 attraction and promote attractiveness. While this is a more complicated process, a 706 number of efforts have been made to understand how romantic attractiveness works 707 in a conversational setting. 708

Leongómez et al. (2014) investigated this by examining how adult heterosex ual participants spoke when addressing attractive and unattractive potential partners
 (opposite-sex conversational partners) and potential competitors (same-sex conversa-

tional partners). The scenario followed a design similar to video dating and was con-712 ducted in both Czech and English. Subjects watched a stimulus video and recorded 713 a response video introducing themselves. In the case of opposite-sex stimuli, the 714 response video was to be played to the person who recorded the initial video. In the 715 case of same-sex stimuli, the response video would be played along with the stimulus 716 video to all opposite-sex subjects. Participants were instructed to explain whether 717 and why they would like to date the potential partner in opposite-sex stimuli, and to 718 explain why they should be chosen over the subject in same-sex stimuli. The stimuli 719 videos were rated for attractiveness by an independent set of raters and comprised the 720 three most and least attractive men and women drawn from a set of 40 participants 721 (20 male and 20 female). They found that male F0 varied most in speech toward 722 attractive women, but female F0 varied more in response to attractive competitors. 723 Also, male minimum pitch was lowered when addressing attractive women. In a 724 follow-up study, the experimenters also found that speech directed toward attractive 725 participants was itself considered to be more attractive. 726

Dating scenarios are especially useful for investigating romantic attractiveness. 727 The previous study used a video-dating paradigm. Another body of work looks at 728 speed dating. In speed dating, participants engage in short (approximately 5 min) 729 face-to-face conversations with potential partners and then fill out a questionnaire 730 about their partner including an opportunity to indicate whether they would like to 731 see the person again. In a speed-dating session, each participant may repeat this 732 experience 10 or more times. In this work, all participants have self-selected to be 733 interested in opposite-sex romantic partners. McFarland, Jurafsky, and Rawlings 734 (2013) recorded speed-dating participants, and analyzed their speech, the content 735 of their conversations, and their responses toward each other. While their analyses 736 are quite comprehensive, we focus on vocal qualities here. Both genders described 737 increased "connection" when they expressed excitement toward their partner. Male 738 participants expressed this excitement through laughter, varied loudness, and reduced 739 pitch variance. Female participants, however, raised and varied their pitch, spoke 740 softer, varied loudness, and took shorter turns. They also found that women felt they 741 "clicked" more with male partners who interrupted them. While this is somewhat 742 unexpected—conventional understanding of interruption is that it is rude—closer 743 inspection of these interruptions suggest that the overlapping speech that leads to a 744 sense of connection was used to demonstrate understanding, through backchanneling 745 and agreement. This is not to say that all interruption is "constructive" or used 746 to demonstrate connection. Interruption can also be rude or dismissive. However, 747 distinguishing the pragmatic effect of interruption can be challenging especially via a 748 reliable automated technique. The study also found that entrainment, the convergence 749 or divergence of vocal qualities between partners, is associated with attractiveness. 750 Specifically, they found that partners who described a connection mimicked each 751 others rate of speech, use of function words, and use of laughter. 752

Michalsky and Schoormann (2017) also looked at the role of entrainment in
 attractiveness, again investigated in a speed-dating setting. They focused on measures
 of pitch convergence. They found that speakers become more similar over time in
 both register and range, but that this degree of convergence was influenced by how

attractive subjects found their conversational partner. In a later study, Michalsky and
Schoormann (2018) found that listener reactions of attraction were sensitive to pitch
height relative to the speaker's natural pitch range rather than an absolute measure.
That is, attractive male voices are not simply low, but they are low in the speaker's
pitch range. Conversely, female voices that are considered attractive are high in the
woman's pitch range, not just naturally high pitched.

Examining vocal qualities in conversations forces experimenters to attempt to 763 disentangle those aspects that are perceptive (being attractive) from those which 764 are performative (expressing attractiveness). Puts et al. (2011) found that increased 765 pitch and increased formant dispersion in women is found to be attractive and to be 766 perceived as flirtations by other women. Jurafsky, Ranganath, and McFarland (2009) 767 found that women who are labeled as "flirting" by men on speed dates spoke faster 768 and with higher pitch and laugh more. These prosodic qualities overlap completely 769 men who are labeled as "flirting," but men also speak more quietly. When women 770 labeled their male partner as flirting (whether or not they actually were), they laughed 771 more and lowered their intensity. But when men labeled their female partner as 772 flirting, they raised their pitch. These analyses were developed and systematized in 773 Ranganath, R., Jurafsky, and McFarland Ranganath et al. (2009). This work attempted 774 to automatically detect flirting in speed-date speech. The most interesting qualities of 775 this work come from identifying which features are used in the perception of flirting 776 but are not used in the expression of flirting. For example, men are perceived to 777 flirt when they overlap less and use fewer appreciations, but this is not significant in 778 men who indicated that they were flirting. Similar faster speaking rate has a stronger 779 influence on the perception of flirting than the performance of flirting. For women, 780 laughing, taking fewer longer turns, and asking repair questions are strong indicators 781 of a woman intending to flirt, but are not perceived by their partners as flirtatious. 782

783 2.7 Conclusions

In this chapter, we have surveyed the literature on four types of attraction and trust 784 as it relates to a person's speech. We have used the term "charismatic" to describe a 785 speaker who is politically attractive. In general, charismatic speakers are dynamic, 786 passionate, and enthusiastic. These assessments are consistent across a range of 787 listeners. American, Irish, Swedish, and Palestinian subjects have come to similar 788 conclusions. However, the vocal realizations of this passion and dynamism vary by 789 speaker. In general, charismatic political speakers vary their use of pitch, intensity, 790 and speaking rate. Some research suggests that clear comprehensible pronunciation 791 with relatively few disfluencies is also important. 792

Considering attraction in the business domain, business leaders considered charis matic often demonstrate the same qualities as political leaders. They pronounce words
 clearly, are rarely disfluent, and demonstrate more varied speech.

In the cases of business and political attractiveness, male and female subjects
 tended to assess speakers similarly. However, across research in both of these

domains, far greater attention has been given to charisma in male speakers. One
area that needs further study is what qualities of the female voices lead listeners to
find them to be charismatic.

Regarding trust in a speaker, evidence suggests that listeners trust people who speak quickly. Male voices spoken with high pitch led to mistrust and female voices with more breathiness were more trusted. It is worth noting that these qualities are strongly linked to measures of political or business-based charisma.

⁸⁰⁵ Considering likeability, listeners tend to prefer voices that clearly enunciate—
 they have a higher pronunciation precision, but also a higher speaking rate. Other
 ⁸⁰⁷ prosodic properties have less of an impact on assessment.

Romantic attraction as it relates to the voice has received quite a bit of research 808 attention. The broad and most consistent finding here suggests than men with low 809 voices and greater formant dispersion are attractive as are women with higher voices 810 and more breathiness. The dynamics of romantic attraction in two-party conversa-811 tions create an interesting area for research. The voice is involved both as an object 812 of attraction and also a mechanism to demonstrate attraction. When heterosexual 813 male speakers flirt, they lower their pitch, while flirting heterosexual women raise 814 their pitch. Also, when participants are mutually attracted they tend to entrain on 815 a number of prosodic dimensions including speaking rate, the use of laughter, and 816 intensity. 817

One important caveat in the assessment of romantic attraction is that in many cases the gender of a listener is assumed to be a proxy for sexual preference. This is a methodological problem that can be found in a number of the reviewed studies.

While we have presented these types of attraction as related to each other, they have their own idiosyncrasies both in terms of how they operate socially and in how they are communicated via the voice. These forms of attraction may interact in unpredictable ways. The current research does not consider ways in which the qualities that make a voice attractive in one context may make it more or less attractive in another context or for a distinct social assessment. For example, are voices that are socially likeable more or less like voices that are attractive in business leaders?

In all, our understanding of what makes a voice attractive is fairly limited. There are a number of broad findings, but none of these in isolation is sufficient to either reliably predict attractiveness, or to provide overwhelmingly useful feedback to speakers. This ambiguity of findings can be found in individual studies but is even more clear through this survey. It is possible that it results from the fact that there is more interlistener variability in both what is attractive and what signals are being relied on to make this decision.

While there is clearly more work to be done on this subject, major areas for further study include (1) investigation of business and political charisma in female speakers, (2) likeability and romantic attraction in nonheterosexual participants, and (3) more thorough consideration of qualities of the listener in identifying not just what is attractive in the speaker's voice, but what particular types of listeners find attractive.

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Abstract	vision, emotions, and o Charisma is expressed culturally-acquired hat social environment wh observed here to unvei according to different s pitch, loudness, and ph attractiveness and cons intentionally and unint	a human leaders is defined as charisma, the set of leadership characteristics such as dominance used by leaders to share beliefs, persuade listeners, and achieve goals. through voice quality manipulations reflecting physiologically-based qualities and bits to display leadership. These manipulations are adapted by the speakers to the tere they intend to be perceived as charismatic. Charisma in political speech is il the biological abilities versus the culturally-mediated strategies in leaders' speech social contexts in which political communication takes place. Manipulations of vocal nonation types are shown to cause both cross-cultural and culture-specific social sequently, are key factors for charisma effectiveness. Charismatic voice is then tentionally controlled by the human leaders to carry the perlocutionary salience of influence listeners' choice of leadership.
Keywords	Vocal charisma - Polit	ical speech - Attractiveness of leadership - Biological abilities in vocal persuasion - charisma - Perceived charisma from speech

Chapter 3 The Vocal Attractiveness of Charismatic Leaders



Rosario Signorello

Abstract Social attractiveness in human leaders is defined as charisma, the set of 1 leadership characteristics such as vision, emotions, and dominance used by lead-2 ers to share beliefs, persuade listeners, and achieve goals. Charisma is expressed 3 through voice quality manipulations reflecting physiologically-based qualities and Δ culturally-acquired habits to display leadership. These manipulations are adapted 5 by the speakers to the social environment where they intend to be perceived as 6 charismatic. Charisma in political speech is observed here to unveil the biological 7 abilities versus the culturally-mediated strategies in leaders' speech according to dif-8 ferent social contexts in which political communication takes place. Manipulations of 9 vocal pitch, loudness, and phonation types are shown to cause both cross-cultural and 10 culture-specific social attractiveness and consequently, are key factors for charisma 11 effectiveness. Charismatic voice is then intentionally and unintentionally controlled 12 by the human leaders to carry the perlocutionary salience of persuasive speech and 13

¹⁴ influence listeners' choice of leadership.

15 Keywords Vocal charisma · Political speech · Attractiveness of leadership ·

- ¹⁶ Biological abilities in vocal persuasion · Cultural descriptors of charisma ·
- 17 Perceived charisma from speech

18 3.1 Introduction

3.1.1 Charisma Defined as the Social Attractiveness of Group Leaders

In modern literature, the term "charisma" was first popularized by sociologist Max
Weber (1920). According to Weber, "charismatic" leaders generally emerge in times
of great crisis for a nation, responding to the necessity of strong leadership to over-

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come the crisis. This author defines charisma as an "extraordinary quality" of a person who is believed to be endowed with superhuman properties, in such a way as to induce people to acknowledge him as a leader, to the point of making a cult of him. Weber calls this quality "charisma" (from Greek charis, grace), thus considering it a grace, a divine gift that only some enlightened people may possess. Weber does not describe this gift at length, and even considers it beyond human comprehension; yet, the very notion of charisma has been alternatively redefined and challenged.

Some first sketches of charisma may be retrieved from ancient philosophy. 31 According to Heraclitus, only a few individuals are endowed with particular physical 32 and mental skills and virtues, that include, in accordance with Socrates, fast learning 33 capacities, memory, open mind, and vision. These virtues are innate, according to 34 Plato, and make a chief the object of trust, faith, and veneration by other people, which 35 results in the cult of the leader (Cavalli, 1995). Such idea of the charismatic leader 36 was personified in the great dictators of the twentieth century: Hitler, Mussolini, and 37 Stalin. 38

Previously, research on charisma was mainly conducted in social psychology within the general framework of leadership studies. Some authors consider leadership as an internal trait of individuals (House & Howell 1992). For example, transformational leaders, which Burns (1978) and Bass (1985) consider to be charismatic, show high values in four of the Big Five factors: extraversion, openness, agreeableness, and conscientiousness (Bono & Judge 2004).

An opposing view—the contingency perspective, which also includes the contex-45 tual approach, contends that leadership and charisma are strongly determined by the 46 context: contextual factors trigger or inhibit particular leadership behaviors, and lead-47 ership is interactively constructed by the relationship between leader and followers 48 (Haslam et al., 2011). This contextualist view further develops into the transactional 49 leadership perspective, in which the strength and effectiveness of leadership is deter-50 mined by a cost-benefit computation, where followers agree to comply with the 51 leader's will to the extent they feel this is functional to their goals. Their behavior 52 is stimulated by rewards and punishments more than trust and identification. This 53 is not the case, however, for transformational leadership, which, introduced by the 54 so-called neo-charismatic school, views a true leader as an authentically charismatic 55 person (Lowe et al., 1996), endowed with vision and capacity for inspiring followers, 56 who works in their interest and aims at their growth (Burns, 1978; Bass, 1985). Neo-57 charismatic scholars stress the ethical impact of transformational leadership, and 58 warn of the "dark side" of charisma and the inauthentic or pseudo-transformational 59 leaders, who with self-serving aims act in bad faith, consciously or unconsciously. 60 Actually, the charismatic/transformational view integrates sociological and psycho-61 logical aspects since it sees charisma as a "social process" in which the perception 62 of followers becomes a very central aspect (Shamir, 2000). 63 The discussion among these diverse perspectives, based on personality or context,

The discussion among these diverse perspectives, based on personality or context, transaction or transformation, makes the definition of a charismatic leader and the singling out of charismatic attributes particularly complex. In fact, charisma is a multidimensional construct: it is certainly affected (and constructed) by the values, needs, motivations, and discourses of potential followers, but it also, indubitably

depends on the leader's skills, choices, and characteristics. External displays are the 69 perceivable expression of the internal features, and we can distinguish two kinds: 70 one which we call the "charisma of the body" and the other, "charisma of the mind" 71 (Signorello, 2014). Actually, the external features may stem either from the mind or 72 from the body of the leader. Aspects of the charisma of the mind, such as creative and 73 charming ideas or feelings, are displayed by a person's words or actions, while the 74 charisma of the body is displayed by specific aspects of their visual and/or acoustic 75 appearance, determined by their body's multimodal physical traits and behaviors 76 (Shamir, Zakay, Breinin, & Popper, 1993; Bull, 1986; Atkinson, 1984; Rosenberg & 77 Hirschberg 2009). 78

The athletic and proud gait of Barack Obama is a way of moving that conveys 79 dignity. But, take Mahatma Gandhi, who was a short, thin shy man, without a loud 80 voice, and who even sometimes stuttered: the features of his charisma did not emanate 81 from his voice or gait, but from the strength of his message, and what revolutionary 82 ideas came from his words and his political action. The first example is a case of the 83 charisma of the body, while the latter is an example of the charisma of the mind: the 84 meaning of a discourse by Gandhi (Bligh & Robinson, 2010). It is through words that 85 his charismatic qualities shine forth. These two forms of expression of charisma— 86 body and mind-may sometimes appear in combination, for example, Barack Obama 87 may be seen as charismatic both for the concepts he proposes and the way he exposes 88 them: he has charisma both of the body and of the mind (Bono & Judge 2004). 89

In sum, charismatic persons may have different kinds of charisma which depend 90 on the type of internal charismatic features they possess, the external features that 91 express them, and on their combinations. The aim of the present work is then to 92 highlight the multidimensionality of charisma, and to explore in detail a specific az display of political leaders' attractiveness: their voice. The hypothesis of this study is 94 that the charisma of a person can be disentangled into a set of "charismatic features", 95 and that in different persons, particular combinations of these features cluster into 96 peculiar kinds of charisma. So what are the internal features of charisma, and how 97 can we find them out? 98

⁹⁹ 3.1.2 Charisma and Voice Behavior: The Charismatic Voice

Group leaders use their voices to communicate their charisma, the set of leadership 100 characteristics, such as vision, emotions, and dominance used by leaders to share 101 beliefs, persuade, and achieve goals. Voice quality reflects leaders' physiologically-102 based vocal characteristics and culturally-acquired habits and strategies used to 103 shape those characteristics qualitatively. Political speech is studied in order to unveil 104 the biological abilities versus the culturally-mediated strategies of group leaders' 105 charismatic voices. Through voice acoustic analyses and perceptual studies, a cross-106 culturally similar use of vocal pitch, loudness levels, and ranges in political speech 107 and a culture-specific perceptual effect of overall vocal characteristics like phona-108 tion types, prosodic factors, and temporal characteristics were found. Charismatic 109

voices reflect individuals' (a) biological needs to have easy access to resources and(b) cultural needs to show skills that reflect high social status and power.

Voice quality results from speakers' biologically-derived differences in vocal 112 apparatus combined with learned linguistic and cultural habits used to convey their 113 personal identity (Garvin & Ladefoged, 1963; Kreiman & Sidtis, 2011). Voice quality 114 conveys individuals' physical (e.g., size, Ohala, 1994; Pisanski et al., 2014, attrac-115 tiveness, Zuckerman & Driver, 1989; Collins, 2000), psychological (e.g., personality 116 traits, Scherer, 1972; emotional status, Patel, Scherer, Björkner, & Sundberg, 2011) 117 and social characteristics (e.g., leadership; Surawski & Ossoff, 2006; Tigue et al. 118 2012; Klofstad, Anderson, & Peters, 2012; dominance, Ohala, 1984). These studies 119 raise the question about whether particular features characterizing political speak-120 ers' voices are biologically versus culturally determined, and which type of feature 121 is primary in distinguishing individuals chosen as group leaders from non-leaders. 122

Besides theoretical discussions on the nature of charisma, some studies investi-123 gated how charisma is perceived from voice. Tackling the relationship between the 124 acoustic-prosodic characteristics of a political leader's speech and the perception of 125 his/her charisma, Touati (1993) investigated the prosodic features of rhetoric utter-126 ances in French political speech in pre and post-elections discourses. Strangert and 127 Gustafson (2008) examined the relationship between prosodic features and the per-128 ception of a speaker as a "good communicator", while Rosenberg and Hirschberg 120 (2009), studied the correlation between acoustic, prosodic, and lexico-syntactic char-130 acteristics of political speech and the perception of charisma. 131

The overview above, introduced our conceptual definition of charisma focused 132 on its psychological multidimensionality that affects social attractiveness, as well as 133 a few theoretical insights, on the use of voice and speech as nonverbal behaviors to 134 convey vocal attractiveness in political speech. This chapter reports investigations on 135 the perceptual features that characterize vocal attractiveness in charismatic political 136 discourse. This work highlights the features of charisma conveyed by the speakers 137 and its social attractiveness on listeners speaking several languages. In the following 138 sections, I first present a tool developed to measure the differences between vocal 139 qualities of speaking individual political leaders. I later introduce studies that aimed 140 to distinguish various kinds of charisma while singling out the features of voice that 141 are responsible for their perception. 142

143 **3.2** Charismatic Voices

3.2.1 Cultural- and Language-Based Descriptors of Charisma

In contemporary literature about the perception of charisma from voice, scholars ask
 participants to rate voices in terms of adjectives that in previous studies had been
 connected to charisma (e.g., Rosenberg & Hirschberg, 2009). In our research, stud-

ies testing how people describe the charisma of group leaders in different languages 149 and cultures were carried out in order to make a scale for the rating of charisma 150 (Signorello et al., 2012a, 2012b). Through an empirical and non-biased approach, 151 positive and negative traits of charisma in several languages (American English, 152 French, Italian, and Brazilian Portuguese) were collected to develop the "Multi-153 dimensional Adjective-based Scale of others' Charisma Perception" (MASCharP) 154 (Signorello, 2014), a psychometric tool to be used in research on the perception 155 of charismatic traits from individuals' perceivable behaviors, such as voice. This 156 approach entailed three experimental phases. 157

The first phase involved the collection of lexical and semantic descriptions of charismatic traits communicated through an individual's perceivable behaviors from subjects of the languages being studied. This part entailed the gathering of adjectives that describe charismatic, as well as noncharismatic prototypes of leadership. It is fundamental to understand that the language in question is inseparable from its culture. These two factors act as filters in the attribution of an individual's traits.

The second phase involved dimensions of theoretical classification of the adjec-164 tives gathered. As in Di Blas and Forzi (1998), the adjectives were selected by their 165 frequency of usage. Only the most frequently used terms that are representative and 166 descriptive of charismatic traits in the participants' language were retained. In the 167 first stage of data sorting, adjectives with a frequency higher than 1 were retained, 168 indicating a cognitive commonality between at least two individuals who agree on 169 a semantic-representational connection that designates the adjective as a trait of 170 charisma. The adjectives used most frequently to describe charisma were then cat-171 egorized in dimensions that were deduced from aspects of the persuasive process 172 illustrated in the Sect. 3.2 of this chapter. The data were then organized according to 173 semantic closeness, as in the cases of Saucier (2009) and Di Blas and Forzi (1998), 174 corresponding to the dimensions of Poggi's theory of persuasion (Poggi 2005). An 175 example of the definitive selection of adjectives and dimensional classification con-176 stitutes the MASCharP as represented in Table 3.1 (American English). 177

The third phase involved the creation of a psychometric tool to perform the per-178 ceptual tests and measure the perception of charisma from voice. Each adjective 179 from MASCharP could be evaluated through a Likert scale (Likert, 1932). An inter-180 face based on the server-side software Limesurvey® (The LimeSurvey project team, 181 (2011)) was developed to collect the data. This software is written in PHP and 182 uses a MySQL database to store data. The interface features the combination of the 183 MASCharP with the 7-point Likert scale. The use of this tool has already been val-184 idated in several studies to measure the traits and types of charismatic leadership 185 conveyed by voice (Signorello et al. 2012a, 2012b, 2014b D'Errico et al., 2012, 186 2013). 187

Positive Charisma Traits	Negative Charisma Traits
Caring, Passionate, Kind, Enthusiastic, Understanding	Rude, Mean, Cold, Unkind, Egotistical
Extroverted, Optimistic, Trustworthy, Outspoken, Friendly, Genuine, Sociable	Introverted, Pessimistic, Dishonest, Selfish, Hostile, Aloof
Intelligent, Witty, Humble, Brave, Determined, Bold, Respectful, Assertive, Well-spoken	Ignorant, Stubborn, Closed-minded, Arrogant, Reserved
Dynamic, Confident, Energetic, Strong, Leader, Engaging, Persuasive	Aggressive, Angry, Apathetic, Shy, Weak, Overbearing, Dull, Obnoxious, Intimidating
Charming, Funny, Attractive, Humorous, Interesting, Relatable, Personable	Boring, Annoying, Uninteresting, Depressing

Table 3.1 Positive and negative interpersonal traits of perceived other's charisma in American English. Classification according to Signorello (2014)

188 3.2.2 Charisma Perception in Cross-Language Settings

The following study was conducted to understand what in the voice perceptual domain could be considered as universal versus language and culture-based. The perception of charismatic speaker identity from voice might be influenced unpredictably by one vocal characteristic or by a whole complex pattern resulting from source and filter characteristics, mode of vocal fold vibration, temporal characteristics, articulatory settings and characteristics, degree of nasality, prosodic line, and syllable structure (Kreiman & Sidtis, 2011).

To do so, this study first assessed how listeners use the vocal pitch as a biological 196 cue to detect speakers' charismatic traits from voice and how they use this cue 197 to assess leadership fitness and choose their leader. In several studies vocal pitch 198 has emerged as a feature that serves as an important biological cue that signals 199 social and physical dominance (e.g., Ohala, 1982, 1983, 1984, 1994, 1996; Puts et 200 al. 2007), conveys leadership (Klofstad et al., 2012; Anderson & Klofstad, 2012, 201 and that influences the choice of a leader (Darwin, 1871; Tigue et al., 2012). In 202 an experiment, 40 French listeners evaluated the dominance conveyed by different 203 voice quality patterns in the voice of an Italian speaker and political leader (Umberto 204 Bossi, former leader of the Lega Nord party from 1980 to 2012). The results showed 205 significant negative correlations between the perceived dominant type of charismatic 206 leadership and average F0 (r = -0.19, p < 0.05, linear regression), wide F0 range 207 (r = -0.18, p < 0.05), and maximum F0 (r = -0.18, p < 0.05). Meanwhile, higher 208 F0 mean (r = 0.52, p < 0.01), minimum F0 (r = 0.49, p < 0.01), maximum F0 (r = 209 (0.55, p < 0.01), and the F0 range (r = 0.53, p < 0.01) are significantly and positively 210 correlated with a nondominant type of charismatic leadership. 211

To confirm and extend these results, the investigations were repeated with the manipulation of F0 for vocal stimuli from two different leaders (Luigi de Magistris, an Italian leader; François Hollande, a French leader). Forty-eight Italians were then asked to rate vocal stimuli from the French leader and 48 French listeners were

asked to rate vocal stimuli from the Italian leader. Results show that French and Italian 216 listeners perceive leaders as having a less dominant charisma when they use a high F0 217 (average of 200 Hz for the French speaker; 212 Hz for the Italian speaker) and a wide 218 F0 range (16 semitones for French listeners; 12 semitones for Italian listeners). This 219 experiment studied the way in which listeners assess leadership fitness from voice. A 220 voice sounding more dominant (low frequencies of F0 and a narrow F0 range) would 221 be perceived as more effective by Italian listeners (r = 0.61, p < 0.0001; simple 222 linear regression), whereas French participants perceive effective leadership from 223 higher pitched voices (r = 0.41, p = 0.004). Results from the two experiments imply 224 that low frequencies of F0 and a narrow F0 range convey a dominant charismatic 225 leadership and that higher F0 average and wider F0 range, cause the perception 226 of a nondominant charismatic leader. These different types of leadership would be 227 perceived as more or less effective in different cultures. 228

Finally, the perception of specific charismatic traits from overall vocal charac-229 teristics was studied taking into account the role of the language and the culture 230 of listeners. The study first assessed the way in which different patterns of voice 231 quality convey the different charismatic traits of leaders. Forty French participants 232 assessed the charisma of the Italian leader Umberto Bossi from natural voice sam-233 ples. Detailed profiles based on the correlation between voice acoustics, perception 234 of charismatic traits, emotional states aroused, and choice of leader were created. 235 A profile with a voice pattern characterized by a medium pitch range (13 semi-236 tones), moderate falling pitch contour movements, modal phonation, phrase-final 237 harsh-high (middle-range) vowels and long inter-word pauses (~ 1 s) communicate an 238 Authoritarian-Threatening type of charisma where the leader is perceived as individ-239 ualistic, untrustworthy, influential, confident, organized, resolute, egocentric, deter-240 mined, authoritarian, menacing, scary, and cold (see Table 3.2), and moreover arouses 241 negative emotional states in the listeners like anxiety. A second profile shows that a 242 voice pattern characterized by a wide pitch range (16 semitones) from very low to very 243 high frequencies, abrupt pitch contour movements, harsh or modal phonation, and 244 sentence-final vowels in creaky phonation communicate a Proactive-Attractive type 245 of charisma. Listeners who perceived the Proactive-Attractive type of charismatic 246 leadership described the leadership of the speakers as vigorous, active, dynamic, 247 charming, and attractive (see Table 3.2), arousing positive emotions like amusement, 248 admiration, enthusiasm, reassertion, and calmness. French listeners would be most 249 likely to choose a leader perceived as Proactive-Attractive. The third profile shows 250 a voice pattern characterized by a narrow pitch range from low to medium-high fre-251 quencies (9–13 semitones), but not as high as the two vocal patterns above, smooth 252 pitch contour movements, harsh-low, harsh-mid, or modal phonation types, and an 253 increasing duration of the vocalization (from $\sim 1 \, s$ to 6.5 s). This pattern commu-254 nicates the Competent-Benevolent type of charismatic leadership, characterized by 255 participant-selected adjectives such as wise, prudent, calm, trustworthy, fair, intelli-256 gent, easygoing, honest, sagacious, and sincere (see Table 3.2), arousing amusement 257 but not calmness emotions. This type of leadership communicates the image of a

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Table 3.2 Charisma types and interpersonal traits. Speaker: Umberto Bossi. Assessed perceptually through the MASCharP tool. Exploratory Factor Analysis: Varimax Rotation that extracted three factors which explained 45% of the variance; significant Bartlett's test of sphericity (p = 0.000); Kaiser–Mayer Olkin (KMO) measure of Sampling Adequacy (0.83); high level of reliability (Proactive-Attractive: $\alpha = 0.92$, i.i. = 0.52; Calm-Benevolent: $\alpha = 0.87$, i.i. = 0.44; Authoritarian-Threatening: $\alpha = 0.90$, i.i. = 0.41)

Authoritarian-Threatening Proactive-Att		tractive	Calm-Benevolent		
Determined	0.508	Vigorous	0.837	Wise	0.825
Menacing	0.775	Active	0.767	Prudent	0.737
Who scares	0.767	Dynamic	0.766	Calm	0.731
Dishonest	0.762	Charming	0.738	Trustworthy	0.689
Cold	0.679	Attractive	0.709	Fair	0.645
Individualistic	0.642	Courageous	0.701	Intelligent	0.605
Authoritarian	0.585	Convincing	0.687	Easygoing	0.585
Leader	0.578	Captivating	0.676	Honest	0.576
Untrustworthy	0.563	Seductive	0.642	Sagacious	0.527
Influent	0.552	Bewitching	0.604	Sincere	0.514
Confident	0.523	Sexy	0.592	1	
Organized	0.509	Eloquent	0.553		
Resolute	0.506	Determined	0.54		
Egocentric	0.485	Who propose	0.54		
		Visionary	0.472		
Variance	22.52%		12.6%		10.83%

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leader competent enough to access vital resources and benevolent enough to share
those resources with other individuals. French listeners in the sample studied would
not choose this type of leadership.

261 3.3 Conclusions

262 3.3.1 Leaders' Social Attractiveness

Since Weber (1920), first launched the notion of charisma, the definition has gone 263 through various changes. The notion itself may have seemed too difficult to opera-264 tionalize, while the literature has fluctuated from serious investigation to skeptical 265 consideration. This may be partly due to the very nature of charisma, which lives 266 at the crossroad of various psychosocial dimensions and takes very different forms 267 (Shamir, 2000). This work has defined charisma as a set of internal and physical 268 qualities of a person that make him or her capable of influencing other people by 269 wakening their most positive emotions, and hence inducing them to do what she/he 270

wants very willingly and exploiting their internal motivation. These qualities are 271 related to various perceived aspects of the group leaders persona (moral, intellec-272 tual, affective), of power management, as well as esthetic and even erotic aspects. 273 Charisma is a multidimensional psychosocial notion: the studies presented in this 274 chapter tried to discover and disentangle its dimensions from participants' descrip-275 tion of charismatic and noncharismatic persons using a scale of charisma perception. 276 The present research found out that dimensions may combine to give rise to different 277 types of charisma. The type of perceived charisma depends on whether the esthetic 278 and dynamic dimensions prevail, resulting in a Proactive-Attractive charisma, or 279 whether they are moderated by the intellectual and ethical side, thus enhancing 280 a calm-benevolent charisma; or finally whether the dimensions of dominance and 281 deliberate influence cluster in an Authoritarian-Threatening charisma. 282

Besides discovering these internal features and their combinations, this investi-283 gation focused on a peculiar property of charismatic political leaders, their vocal 284 communication, showing that charisma resides in particular types of speech acts, but 285 also in particular parameters of the leader's voice that, depending on given variations, 286 may become less charismatic, or take up a different type of charisma. Two issues we 287 specifically investigated in this connection were the change in charisma caused by 288 a switch from modal to dysphonic voice, and the different perception of charisma 289 caused, in the French and the Italian culture, by a change in pitch and pause duration. 200

Results on the former issue—that the modal voice conveys a proactive-attractive, or even an authoritarian-threatening charisma, whereas the disordered one bears a calm-benevolent one—may be accounted for by an evolutionary perspective that views a dynamic leader as more functional to the effectiveness of the group.

As to the issue of whether charisma perception is universal or cultural, our results 205 may be interpreted as follows: The single traits attributed to a charismatic leader 296 tend to be different between cultures and may arise at two levels: first, the single 297 properties may cluster in different ways for two cultures, in that a type of charisma 298 may be more salient in one culture and dispersed in single properties in another; 299 second, as seen in the third phase of study, each specific type of charisma may be 300 evoked by some vocal parameters in one language or culture and by other parameters 301 in another. 302

These results may help answer some questions concerning charisma. For instance, 303 one possible objection to the very existence of such a notion is that a person may 304 appear as charismatic to some people but not to others. In other words, is it true 305 that -beauty is in the eyes of the beholder-? In our view, this is not so. Different 306 perceptions of charisma may well be accounted for by its multidimensionality. In 307 this sense, interactive accounts that view charisma as determined by the intertangling 308 between a leader and their followers may be sound. -Charismatic leadership- may 309 hold per se, but also, followers can contribute their perceptual preferences to its 310 emergence (Shamir, 2000). 311

In the same vein, the multidimensionality account might answer the question whether and why the perception of charisma varies across cultures. Since cultures definitely attribute different importance to different dimensions of life, cognitive functioning and social interaction, two cultures may well see the same leader as

charismatic or not, depending on the dimensions they value the most. Yet, this leads
to another question: aren't there any aspects of charisma that are universal, that is,
any characteristics of a leader (or of a person) that are perceived as charismatic by
people of all cultures?

An answer in line with the "emotional culture" approach above (Ekman & Friesen, 320 1971, Turner, 1976; Gordon, 1989; Matsumoto, 1990; Bagozzi, Verbeke, & Gavino, 321 2003) would be that leaders are perceived as charismatic to the extent to which they 322 adapt to the communicative norms of their culture. Yet, we might contend that, on the 323 contrary, the charismatic leader, does not "adapt to", but rather, "leads" his followers, 324 imposing new norms and values, and thus also changing the relative preference of 325 the charismatic dimensions. Therefore, a primary and possibly universal dimension 326 of charisma might be just the visionary skill that makes a leader point at something 327 new. 328

A final issue, among others, that is raised by our investigation is how the notion of charisma proposed here can be applied not only to political leaders but to a broader domain: not only social leaders can be charismatic, but actors, singers, managers, and teachers. Our theoretical explanation of charisma could be applied generally to all charismatic individuals.

334 3.3.2 The Charismatic Voice

The present research demonstrates how a specific vocal pattern used by leaders can convey different traits and types of their charisma, and also how several patterns can influence the perception of the same type of characteristic leadership when perceived by different individuals or social groups. The acoustics of voice in political speech is a cue to the perception of charisma in leaders. We used a cross-cultural approach to assess and distinguish the physiological/anatomical and cultural influence in the production and perception of voice in charismatic leadership.

In the perceptual domain, the research described above, first found evidence that 342 vocal pitch is a cross-cultural signal to distinguish dominant versus less dominant 343 charisma. This result is consistent with previous studies on the perception of domi-344 nance versus submission related to vocal pitch (e.g., Collins, 2000; Feinberg et al., 345 2006). Higher fundamental frequency and wider range are used by the speaker while 346 addressing a more diverse audience (in terms of sex, age and social status). Lower 347 fundamental frequency and narrower range are used by the leader-speaker when 348 addressing an audience of similar social status (other leaders). Healthy vocal range 349 is used by leaders in informal contexts of communication (during which no political 350 topics are addressed and the leadership is not questioned). 351

This work then found that certain vocal quality patterns used by the speaker-leader fit the listener's expectations about the vocal style that best conveys charisma in a given language and culture. The same vocal pattern can convey both an Authoritarian-Threatening and a Proactive-Attractive charisma that are perceptually distinguished in different languages and cultures. Competent-Benevolent charismatic leadership
 can be conveyed by several vocal quality patterns.

These results may help to better distinguish between the biological components 358 on the one hand, and language and cultural components on the other, present in voice 359 behavior that fit listeners' expectations and influences the choice of the social group's 360 leader. Listeners seem capable of accurately distinguishing these vocal features of the 361 charismatic leader and these results might explain why some leaders have been found 362 to be endowed with a cross-language and cultural charisma (e.g., Barack Obama was 363 found to be the most charismatic leader in the general sense in several cultures), 364 and some other leaders not endowed with effective speaking (Bligh & Robinson, 365 2010), are mostly endowed with a circumscribed charisma restricted within social 366 groups and languages (Gandhi is only charismatic if we understand English or if it 367 is translated). 368

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Abstract	biological function. Ye the functional role of s the very beginning of t its linguistic role, voice effect on the speaker's	of human voice evolution has long been conducted without any reference to its et, following Darwin's original concept, John Ohala was the first linguist to assume exual selection to explain vocal dimorphism in humans. Nevertheless, it is only at he millennial that the study of voice attractiveness developed, revealing that beyond e also conveys important psycho-socio-biological information that have a significant mating and reproductive success. In this review article, our aim is to synthesize 20 ated to the study of vocal preferences and to present the evolutionary benefits references.
Keywords	-	rception - Language evolution - Sexual selection - Evolutionary biology - Acoustics frequency - Formant dispersion - Voice attractiveness

Chapter 4 Vocal Preferences in Humans: A Systematic Review



Melissa Barkat-Defradas, Michel Raymond, and Alexandre Suire

Abstract Surprisingly, the study of human voice evolution has long been conducted

² without any reference to its biological function. Yet, following Darwin's original

³ concept, John Ohala was the first linguist to assume the functional role of sexual

selection to explain vocal dimorphism in humans. Nevertheless, it is only at the very
 beginning of the millennial that the study of voice attractiveness developed, revealing

⁵ beginning of the millennial that the study of voice attractiveness developed, revealing
 ⁶ that beyond its linguistic role, voice also conveys important psycho-socio-biological

⁷ information that have a significant effect on the speaker's mating and reproductive

⁸ success. In this review article, our aim is to synthesize 20 years of research dedicated

• to the study of vocal preferences and to present the evolutionary benefits associated

10 with such preferences.

Keywords Vocal preferences · Perception · Language evolution · Sexual

¹² selection · Evolutionary biology · Acoustics · Voice · Fundamental frequency ·

¹³ Formant dispersion • Voice attractiveness

14 4.1 Introduction

Darwin thought of mate choice as a purely aesthetic experience, a selection of beauty
for its own sake (Darwin, 1871). However, his view has not been embraced by
modern evolutionary biology, for which mate choice results from human adaptive
preferences, a mechanism that has evolved because of dimorphic physical features
or sexual ornaments (such as the female waist-to-hip ratio, the male shoulder-to-

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hip ratio, facial traits, breast size, voice, and so on) that are assumed to be reliable
indicators of mate quality (Arak & Enquist, 1993). Indeed, the mere sound of a
person's voice contains important, embedded biological information. Consequently,
a large amount of research has been dedicated to identifying men's preferences for
women's secondary sexual characteristics and vice versa, as well as the evolutionary
benefits associated with such preferences.

Preferences partly proceed from an unconscious mechanism: an individual may be 26 aware of the factors that have led him to choose one sexual partner instead of another, 27 but it does not necessarily mean s/he is conscious of the link existing between his or 28 her preference and the property conveyed by the cue itself. A good example to illus-29 trate this statement rests on women's preference for masculine low-pitched voices. 30 Though female subjects are often conscious of their attraction for this type of vocal 31 attribute in males, they are hardly aware that it indicates men's phenotypic quality as 32 well as part of their heritable genotypic value as potential mates (Apicella, Feinberg, 33 & Marlowe, 2007). In human species, mate's selective value includes several pheno-24 typic qualities among which: state of health, fertility, age, intelligence, social status, 35 and so on ... (Buss, 1989; Geary, Vigil, & Byrd-Craven, 2004; Sugiyama, 2015). All 36 these qualities are displayed through the face, the body, and the voice. For example, 37 health is indicated by skin complexion, the body shape is a proxy of nutritional status, 38 and the vocal height is determined by testosterone level. Therefore, it is reasonable 30 to assume that female typical preference for men exhibiting deep voices has been 40 shaped by evolution as an honest signal of masculinity related to an increased level of 41 androgens, a high physical strength, a good immune system, etc., all of these features 42 favoring men's-and thus women's-fitness. However, masculine versus feminine 43 preferences for the ornaments exhibited by the other sex are not the same since some 11 of the traits that are associated to desirable qualities in men may differ from those 45 linked to desirable phenotypic qualities in women. Consequently, men and women 46 do not grant the same importance to the different socio-biological cues driving mate 47 choice. Generally speaking, and at least in Western industrialized societies, men tend 48 to attach a great importance to women's beauty, and as early as Ancient Greece, the 49 concept of beauty has been closely associated with physical attractiveness, especially 50 feminine physical attractiveness (for a detailed review of the evolution of feminine 51 beauty see Bovet, 2018). But when choosing a mate, men and women also use non-52 physical features, such as smell, movements, behaviors, and voice. Although these 53 traits are not all equally weighted in mating decisions, they all likely contribute to 54 the general evaluation of a potential partner. 55

Our aim here is not to explore the diverse effects of physical attractiveness but 56 rather to examine the role of voice in the mating context by showing which vocal 57 features are considered attractive by men and/or women and why. Previous research 58 on vocal attractiveness (i.e., the perceived attractiveness of voices when isolated from 59 other cues, such as visual or olfactory cues) has suggested that vocal attractiveness 60 plays a role in mate choice in humans (e.g., Apicella et al., 2007; Hill et al., 2013; 61 Leongomez et al., 2014). For example, individuals possessing vocal characteristics 62 that are correlated with attractiveness report greater reproductive potential (as indexed 63 by reported number of sexual partners, Kordsmeyer, Hunt, Puts, Ostner, & Penke, 64

2018; Hill et al., 2013) and, at least in hunter-gatherers, have greater reproductive 65 fitness (Apicella et al., 2007). People also alter their vocal attractiveness in mating 66 contexts, such as when interacting with an attractive potential mate (Leongomez et 67 al., 2014; Pisanski, Bhardwaj, & Reby, 2018; Suire, Raymond, & Barkat-Defradas, 68 2018). In accordance to the runaway selection mechanism,¹ we assume preferences 69 may contribute to the shaping of attractiveness in human voices. Our goal therefore 70 is to show that preferences for some vocal attributes are likely the result of sexual 71 selection. Although the acoustic features associated with vocal attractiveness are 72 not exhaustively studied here (i.e., the prosodic dimension, in particular, could be 73 further developed), we propose an exhaustive review of the different studies (n =74 37, over a period of 40 years covering the years 1979–2020) that tackled the issue of 75 vocal preferences for men and women (see Table 4.1). Subsequently, we will focus 76 on the evolutionary mechanisms driving our preferences. Before fully entering our 77 topic, it should be noted that only the studies that have clearly identified the acoustic 78 correlates behind vocal preferences were considered. 79

Overall, a first remarkable point appears to be the importance ascribed to the study 80 of F0 and the formant position. Secondly, one will immediately notice that English 81 speakers are overrepresented in comparison with speakers of other languages. From a 82 methodological point of view, it appears that the number and the nature of vocal stim-83 uli used in the perceptual experiments are quite variable (i.e., spontaneous speech, 84 isolated words or vowels, reading versus oral speech ...). Likewise the number of 85 auditory judges is extremely heterogeneous from one study to another. As for the 86 acoustic analyses themselves, we distinguish between two types of approaches: on 87 the one hand, there are correlational studies, which basically aim at relating acoustic 88 characteristics and vocal attractivity from auditory judge's scores on Likert's scales 80 and on the other hand, there are experimental studies that try to establish causal 90 relations between acoustic features. All these studies help us pinpoint some general 91 trends about human vocal preferences. 92

A brief overview in Table 4.1 reveals that among the different measures that were investigated for qualifying vocal attractiveness across studies, it is undoubtedly vocal height (i.e., F0) that has most often aroused the authors' interest. Nevertheless some other articulatory and acoustic features have lead to interesting results suggesting vocal attractiveness is not confined to the realm of fundamental frequency but also extend to other aspects, which effects on perceived vocal attractiveness are also reviewed in the next sections.

¹Runaway selection is a mechanism whereby a secondary sexual trait expressed in one sex is correlated with a preference for the trait in the other sex. The genetic coupling of the trait and the preference leads to self-reinforcing loops of coevolution between the trait and preference for the trait (Travers, 2017).

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corresponds to the less attractive stimuli, the highest to the most attractive voice; when forced choice is used the judge has to choose between two stimuli the one he perceives the most attractive. By "manipulated speech" we mean that the subjects were recorded after they were asked to modify their voices following the experimentaters' instructions. Note that for studies based on modified stimuli (whether naturally or not) forced choice is often used since it allows judges to **Table 4.1** Studies are characterized by the language under study, the number and nature of tested the stimuli, the number and gender of auditory judges, the methodology (Likert's scale versus forced choice), results by gender and the direction of observed correlations. For Likert's scales, the lowest score (i.e., 1) select the most attractive stimuli between two versions of the same voice (i.e., natural versus modified). NB: CA stands for Canadian, AU for Australian, U.S. for American and U K for British variants of Enolish

References	Language(s) under No. of stimuli study		No. of auditory judges	Type of stimuli	Method and no. of evaluated stimuli	Acoustic features under study and direction of the observed correlations
Tuomi and Fisher (1979)	English (CA)	102 5ở	10ç 10ở	Spontaneous sentences	Likert's scale n = 15 (i.e., all)	– Low F0 +attractive φ and σ^{a} (n.s.)
Zuckerman and Miyake (1993)	English (U.S.)	62º 48°	8ç 9o ³	Speech reading	Likert's scale n = 110 (i.e., all)	- Low F0 +attractive σ - Low F0min +attractive σ - Low energy +attractive σ - Less pausing time +attractive σ - n.s. ♀
Oguchi and Kikuchi (i) Japanese – (1997) Experience 1		4ở	25ç	Read sentences	Likert's scale n = 4 (i.e., all)	 -Low F0 +attractive φ and σ⁷ -Low F0-SD +attractive φ and σ⁷
	(ii) Japanese -Experience 1	8ç 8ơ	42ç 20ở	Read sentences	Likert's scale n = 16 (i.e., all)	- Low F0 +attractive 2 and σ^{7} - Low F0-SD +attractive 2 and σ^{7}

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¥ 470006_1_E	References	Language(s) under study	No. of stimuli	No. of auditory judges	Type of stimuli	Method and no. of evaluated stimuli	Acoustic features under study and direction of the observed correlations
n_4_Chapter 🗹 TYPESET 🗌	Collins (2000)	Dutch	34°	540	Isolated vowels (natural speech)	Likert's scale n = between 10 & 14	- Spectral distribution in low frequencies +attractive of - Low formant spacing +attractive of
] DISK LE [✓ CP Disp.:7/9/20	Collins and Missing (2003)	English (U.K.)	309	300	Isolated vowels (natural speech)	Likert's scale n = 10	- Spectral distribution in high frequencies +attractive σ - High formants +attractive σ - High formant spacing +attractive σ
20 Pages: 85 Layout: 1	Feinberg et al. (2005)	English (CA)	10°	68 ₉	Isolated vowels (manipulated speech)	Likert's scale n = 10 (i.e., all)	– Low F0 +attractive م – Lower formant spacing + attractive م
î1-Standard	Bruckert et al. (2006)	French	26°	102 <u>2</u>	Isolated vowels (natural speech)	Likert's scale $n = 6$	– Low F0 +attractive م – High F0-SD +attractive م

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	R	90	54 ♀	Spontaneous then manipulated speech	Likert's scale n = 11	- High F0 -attractive o ⁷ - F0-SD n.s. o ⁷
Saxton et al. (2006) English (L	ish (U.K.)	12ở	40ç 7–10 y.o 40ç 12–15 y.o 40ç 20–34 y.o	Number counting (natural speech)	Forced choice $n = 6$ or 12	– Low F0 +attractive for 12–15 and 20–34 y.o.
Feinberg, DeBruine, –Experience Jones, and Little English (CA) (2008a, 2008b)		123 ♀	100	Isolated vowels (manipulated speech)	Likert's scale $n = 61$ or 62	- High F0 +attractive o ²
-Experience 2 English (CA)		15ở	263ç 342ở	Number counting (from 1 to 10)	Forced choice $n = 15$ pairs	– High F0 +attractive o ⁷
Hughes et al. (2008) English (U.S.)		31º 40°	50 ç 51 <i>ở</i>	Numbers recitation (from 1 to 10)	Likert's scale n = 71 (each voice being evaluated by 13 or 15 judges)	-Low F0min +attractive σ^* -F0, F0max, F0 range, median F0, Intensity, Duration, Jitter, Shimmer, HNR n.s. σ^* - n.s. q
(2008) English (U.S.)	_	١٩ ١٥	39ç 9 <i>ठ</i>	Sentences (manipulated speech)	Likert's scale n = 4	-Low F0min +attractive of and q

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References	Language(s) under study	No. of stimuli	No. of auditory judges	Type of stimuli	Method and no. of evaluated stimuli	Acoustic features under study and direction of the observed
Vukovic et al. (2008) Eng	English (U.K.)	36ď	582 Sentences (+contraceptive) 652 Imanipulated (-contraceptive) speech)	Sentences (manipulated speech)	 - Forced choice n = 16 pairs - Likert's scale for each preferred voice 	correlations –Low F0 +attractive ở – No effect of contraception on vocal mederences
Saxton et al. (2009)	English (U.K.)	62 60° 11–13 y.o 62 60° 13–15y.o 60° 13–15 y.o	148ç 177ở (same category of age)	Isolated vowels (manipulated speech)	 - Forced choice n = 6 pairs - Likert's scale for each preferred voice 	- High F0 +attractive \wp (for 11–13 y.o. σ only) - Low F0 +attractive σ (for 13–15 y.o. \wp only)
Jones et al. (2010)	English (U.K.)	42	30 ♀ 30♂	Spontaneous sentences (natural speech)	Forced choice $n = 16$ pairs	– High F0 +attractive q
Fraccaro et al. (2011)	English (CA)	¢¢	178°	Isolated vowels (manipulated speech)	Forced choice $n = 6$ pairs	 High F0 +attractive Q (long-term relationship condition only)

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Hodges-Simeon et al. (2010)	English (U.S.)	11103	142 <u>2</u>	Spontaneous speech	Likert's scale n = 30 or 31	-Low F0 +attractive σ' (no effect of short vs. long relationship condition, no effect of φ menstrual cycle phase) -Low F0-SD +attractive σ' (in long term + fertile context and in short term + unfertile context) - Spectral distribution in the low frequencies +attractive σ' (in short/long term + fertile conditions)
Hughes, Farley and Rhodes (2010)	English (U.S.)	25° 20ở	27º 12ơ	Truncated phone calls + speech manipulation	Forced choice n = 45 (i.e., all)	– Low F0 +attractive σ and ϕ
Jones et al. (2018)	English (U.K.)	6 <u>2</u> 6 <i>3</i>	100⊋ 100♂	Isolated vowels (manipulated speech)	Forced choice $n = 6$ pairs	- High F0 +attractive \$ - Low F0 +attractive
Borkowska and Pawlowski (2011)	Polish	58 ₉	144o°	Isolated vowels (manipulated speech)	Likert's scale $n = 13$ voices	 − High F0 +attractive ♀ (non linear relation)

References	Language(s) under study	No. of stimuli	No. of auditory judges	Type of stimuli	Method and no. of evaluated stimuli	Acoustic features under study and direction of the observed correlations
Pisanski and Rendall (2011)	English (CA)	22 6o ³	30ç 31°	Words list (natural then manipulated speech)	Likert's scale n = 40 voices	 Low F0 and formants +attractive ♂ (same trend observed for natural and manipulated speech) Low F0 and formants-attractive ♀ (same trend observed for natural and manipulated
Puts et al. (2011)	English (U.S.)	72ç	63م	Text reading (manipulated speech)	Likert's scale n = 18 pairs	 High F0 +attractive q Spectral distribution in the high frequencies +attractive q
Liu and Xu (2011)	English (U.K.)	Ot I	100*	3 repetitions of 1 single emotion-free sentence (natural then manipulated speech)	Likert's scale n = 81 (i.e., all)	 High F0 +attractive \$\vee\$ Small vocal length tract +attractive \$\vee\$
Simmons et al. (2011)	English (AU)	54°	15º	Isolated vowels (natural speech)	Likert's scale n = 54 (i.e., all)	-Low F0 +attractive

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Table 4.1

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References	Language(s) under study	No. of stimuli	No. of auditory judges	Type of stimuli	Method and no. of evaluated stimuli	Acoustic features under study and direction of the observed correlations
Barkat-Defradas et al. (2012)	French	620	92 ç	Text reading + Isolated vowel (natural speech)	Likert's scale n = 34	 - F0 n.s. - Mild roughness degree +attractive σ³ - Low breathiness +attractive σ³
Re et al. (2012)	English (CA)	1ç 1o'	9ç 10ở	Isolated vowels (manipulated speech)	Forced choice n = 50 pairs + supplementary pairs 6 \sigma and 42 \ge	- High F0 +attractive \$ - Low F0 +attractive \$ \$\dotsymbol{s}\$
Fraccaro et al. (2013)	English (CA)	4ç 4o°	104ç 110ơ	Isolated vowels (manipulated speech)	Forced choice $n = 16$ pairs	– High F0 +attractive ϕ – Low F0 +attractive σ
O'Connor et al. (2013)	English (CA)	4ç 4o'	128°	Words (manipulated Likert's scale speech) $n = 40$	Likert's scale $n = 40$	 High F0 +attractive φ - Low F0 +attractive
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470006_1	keterences	Language(s) under study	NO. OI SUITUI	No. of auditory judges	Type of stimul	Method and no. of evaluated stimuli	Acoustic reatures under study and direction of the observed correlations
En_4_Chapt	Xu et al. (2013)	English (U.K.)	- Experience 1 1 ²	10~	Sentences (manipulated speech)	Likert's scale n = 81 (i.e., all)	- Low F0 +attractive o ⁷ - Formants: n.s.
ter ☑ TYPESET □ DISK □ LE			- Experiences 2-5 1º 1ơ	16º 16ơ	Sentences (synthetized speech)	Likert's scale n = 81 (i.e., all)	- High F0 +attractive φ - Low F0 +attractive σ ² - High breathiness +attractive φ σ ³ - Low formants
✓ CP Disp.:7/9/2020 Pages: 85 Layout: T1-Standard	Babel et al. (2014)	English (U.S.)	30° 30° 3	15º 15 ở	Words (natural speech)	Likert's scale n = 15 (one single voice for each trial)	 Spectral Spectral distribution in high frequencies +attractive φ - Low F0 +attractive φ (n.s.) Breathy voices +attractive φ - Spectral distribution in low frequencies +attractive φ
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	References	Language(s) under study	No. of stimuli	No. of auditory judges	Type of stimuli	Method and no. of evaluated stimuli	Acoustic features under study and direction of the observed correlations
n_4_Chapter 🗹 TYPESET 🗌	Hughes et al. (2014)	English (U.S.)	20ç 20o ⁻	20ç 20ở	Number recitation (from 1 to 10) (manipulated speech)	Likert's scale n = 40 voices	- High hoarseness +attractive \$ n.s. \$\sigma'\$ - Longer duration +attractive \$\sigma'\$ \$ - Low F0 +attractive \$\sigma'\$ n.s. \$\sigma'\$ - Loudness n.s. \$\sigma'\$ \$ \$\sigma'\$
1	Skrinda et al. (2014)	Latvian	60°	290	Isolated vowels (natural speech)	Likert's scale n = unspecified	– Low F0 +attractive م – Low F2 values +attractive م – Other formants n.s. م
I	Tsantani et al. (2016) English (U.K.)		10 ç 9ơ ^a	183 <u>2</u> 57 <i>0</i> °	"Hello" (manipulated speech)	Forced choice $n = 40$ pairs	– Low F0 +attractive & n.s. 2
	Sebesta et al. (2017)	Cross-linguistic	45 ° (Cameroonians) 62 ° Czechs 48 ° (Namibians)	62 ç Czechs	Sentence (natural speech)	Likert's scale $n = 45 - 48$ pairs	 Low F0 +attractive Cameroonian o^c Low formant position + attractive Namibian o^c High breathiness +attractive Namibian

470006_1_Er	References	Language(s) under	No. of stimuli	No. of auditory judges	Type of stimuli	Method and no. of evaluated stimuli	Acoustic features under study and direction of the observed correlations
n_4_Chapter 🔽 1	Shirazi et al. (2018)	Cross-linguistic	60° (EN U.S)	20 breastfeeding + 20 nulliparous Filipinos q	Sentences (manipulated speech)	Likert's scale $n = 12$ stimuli	- High F0 +attractive σ [*] - n.s. between the 2 groups of φ
TYPESET DISK LI	Suire et al. (2018)	French	580	137 <u>2</u>	Sentence	Forced choice n = 11 pairs	-Low F0 +attractive of - High F0-SD +attractive of - Other acoustic measures n.s.
: CP Disp.:7/9/2020 Pages: 85 Layout: T1-Standard	Suire et al. (2019)	French	<u>ତ</u> ୦	1350 2 conditions: short- versus long-term relationship	Read sentences (natural speech)	Forced choice n = 13 pairs	 High speaking rate +attractive \$\overline{2}\$ -Low F0 +attractive \$\overline{2}\$ -Spectral distribution in high frequencies +attractive \$\overline{2}\$ -High roughness (high Jitter values) +attractive \$\overline{2}\$ -Low breathiness (high HNR values)

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Acoustic features under study and direction of the observed correlations	 High F0 +attractive of both for male and female raters High F0 +attractive of for male raters of for female raters of for female raters fout very low pitches are perceived less artractive > cue for laryngeal damage or below the intelligibility threshold)
Method and no. of evaluated stimuli	3 conditions: – habitual voice – raised in pitch (+20Hz) – lowered in pitch (-20Hz)
Type of stimuli	Isolated vowels (natural speech)
No. of auditory judges	88ç 79 <i>o</i>
No. of stimuli	809 35ở
Language(s) under study	Chinese
References	Zheng et al. (2020)

4.2 Preferences for Vocal Height

Most of the previous studies, whether they are correlational or experimental, have 101 revealed a negative correlation between vocal height and attractivity of men. Such a 102 regular trend shows that women, whatever their linguistic environments and/or cul-103 tural backgrounds, are predominantly attracted to men exhibiting deep low voices 104 (Bruckert, Lienard, Lacroix, Kreutzer, & Leboucher, 2006; Feinberg et al., 2005; 105 Hodges-Simeon, Gaulin, & Puts, 2010; Hughes, Farley, & Rhodes, 2010; Jones, 106 Feinberg, DeBruine, Little, & Vukovic, 2010; Pisanski & Rendall, 2011; Vukovic et 107 al., 2008; Xu, Lee, Wu, Liu, & Birkholz, 2013; Suire, Raymond, & Barkat-Defradas, 108 2019). Still, a few exceptions are to be considered. As a matter of fact, Babel, 109 McGuire, and King (2014) and Hughes, Mogilski, and Harrison (2014) reported 110 no significant correlation between vocal height and attractivity in American men. 111 Likewise, Barkat-Defradas et al. (2012) demonstrated F0 does not seem to be the 112 most salient perceptual feature to assess masculine voice attractiveness as com-113 pared to roughness at least in clinical context when patients range into a comparable 114 vocal height category (i.e., $\pm 125 \,\text{Hz}$) irrespective of their global dysphonic grade. 115 Lastly, Shirazi, Puts, and Escasa-Dorne (2018) obtained an unexpected opposite 116 result with Filipino women judging male vocal samples produced in English by 117 American speakers. As for women vocal attractiveness, the vast majority of studies 118 reach the same results with men being consistently attracted by high-pitched fem-119 inine voices (Borkowska & Pawlowski, 2011; Collins & Missing, 2003; Feinberg 120 et al., 2008a, 2008b; Jones et al., 2010; Puts, Barndt, Welling, Dawood, & Burriss, 121 2011; Re et al., 2012). But here again, the results obtained by Leaderbrand, Dekam, 122 Morey, and Tuma (2008), Oguchi and Kikuchi (1997) go in the opposite direction 123 when those by Hughes et al. (2010, 2014) reveal interesting trends. In Hughes et 124 al. (2010), the authors show that women tend to lower their voices when interacting 125 with men they consider as particularly attractive while they significantly raise their 126 pitch when facing men they are not attracted to. The same kind of unexpected result 127 is observed for men who judge those low-pitched women as sexier. More recently, 128 Pisanski et al. (2018) replicated the same results. In a second study, in which female 129 subjects were asked to modify their voice so as they might be perceived as more 130 attractive by male auditory judges, it has been shown that in such an evoked seduc-131 tive context, women are also inclined to deepen their voices, and interestingly the 132 subsequent perceptual study revealed that the female voices attesting the lower pitch 133 values are also those that were perceived as the most attractive by the group of male 134 auditory judges (Hughes et al., 2014). The results launched by Zheng, Compton, 135 Heyman, and Jiang (2020) in what must be to our knowledge the most recent avail-136 able study tackling the subject aimed at determining more precisely the effect of 137 raised versus lowered pitch on voice perceived attractiveness. In order to answer 138 this question, the authors used a method based on voluntarily pitch-shifted voices. 139 Their findings suggest that indeed pitch shifts do affect voice attractiveness in the 140 sense that female voices are perceived—both for male and female raters—as more 141 attractive when vocal pitch is raised (+20Hz from a digitally computed average 142

pitch at 237 Hz). As for male voices, they typically show that lowered pitch lead to 143 better evaluations by female raters (up to certain limits beneath which low voices are 144 perceived either as pathological or unintelligible). But surprisingly, they also come 145 to the result that their male raters consider high-pitched masculine voices as more 146 attractive. According to the authors this may be explained by the fact that in real-life 147 conditions, men are more often placed into the position of evaluating sex-opposite 148 attributes using morphological signals, like waist-to-hip ratio,² but also vocal cues so 149 as to find information of phenotypical compatibility, which makes their perceptual 150 evaluation biased either by a lack of experience or by the unconscious usage of a 151 perceptual grid of evaluation that is structured around feminine vocal references and 152 which is consequently quiet unsuitable for the evaluation of male voices. 153

4.3 Preferences for Vocal Modulation

If studies dealing with the effect of mean F0 on vocal attractiveness are relatively 155 numerous, those based on the measure of FO-SD (i.e., the increased versus reduced 156 mean fundamental frequency variations, which the listener perceives, respectively, as 157 rather flat versus highly modulated speech) are rather scarce. Yet, Hodges-Simeon et 158 al. (2010) have shown that male speakers producing speech with very little variations 159 in F0 are perceived as more masculine and attractive by female raters. Given that 160 the extent of F0-excursions is affected by attitudinal and emotional factors (Traun-161 möller & Eriksson, 1995), such a trend appears to be kind of difficult to explain at 162 first glance. Indeed, as it is well admitted the non-verbal characteristics of voices 163 can play a significant role in signaling emotional as well as health state, like for the 164 latter, major depression that is regularly reflected through reduced vocal modulation, 165 female preferences for small melodic variations in male voices may be explained both 166 by vocal dimorphism (since it has been regularly shown lively speech is related with 167 feminine talking style (Polce-Lynch, Myers, Kilmartin, Forssmann-Falck, & Kliewer 168 1998; Hall, 1978) and social factors (as the extensive vocal expression of emotions 169 is more often associated with female behavior (Fischer & Manstead, 2000). There-170 fore, assuming pitch variations are perceived along a continuum (from monotonic 171 to highly expressive speech), the receivers may have assigned monotonous voices to 172 masculinity and, reversely, dynamic speech to feminity. Besides, Suire et al. (2020) 173 have shown males' sexual orientation can be inferred more accurately from F0-SD 174 than mean F0, suggesting vocal modulation is a more reliable acoustic cue for gays' 175 vocal feminization than vocal height. Moreover, though previous studies assessed 176

²The WHR has been used as an indicator of health and the risk of developing serious health conditions. WHR correlates with fertility (with different optimal values in males and females). The concept and significance of WHR as an indicator of attractiveness has been theorized by Singh (1993) who argued the WHR is a consistent estrogen marker, and thus a reliable proxy of fertility. Women with a 0.7 WHR are usually rated as more attractive by men from Indo-European cultures (Singh & Young 2001), but preferences may vary according to the culture under study (Fisher & Voracek, 2006).

that reduced fundamental frequency variations are rather linked to vocal masculin-177 ity, two other studies lead to unexpected opposite results. According to Bruckert 178 et al. (2006), monotonous voices are judged as significantly less attractive for men 179 while Leongómez et al. (2014) found modulated voices are rated as more attractive 180 for both sexes. Further researches are thus needed to disentangle these inconsistent 181 results. But yet for now, it is interesting to notice that the same criterion may lead 182 to different auditory impressions, which valences are somehow contradictory. For 183 example, although perceived as more attractive, those masculine speakers exhibit-184 ing monotonous, low-pitched voices are also perceived as being less cooperative 185 (Tognetti et al., 2019), more threatening, and their likelihood to have extramarital 186 affairs is considered as higher. This claim does not result from unfounded subjective 187 impressions since there is also evidence that suggest men with masculine voices 188 report a higher number of extra-pair sex partners and are more often chosen by 189 women as extra-pair partners (Hughes et al., 2004). 190

The above suggests that men with relatively more masculine voices-that are 191 negatively correlated with testosterone levels (Evans, Neave, Wakelin, & Hamil-192 ton, 2008)—may present a greater infidelity risk to their partners, though it is still 193 unclear whether observers assess infidelity risk via vocal cues to underlying testos-194 terone levels. Likewise, women with relatively high-pitched, modulated voices-that 195 are linked both with youth, higher fertility, and increased perceived attractivity—are 196 also seen as more conspicuous and more likely to commit adultery (O'Connor, Re, 197 & Feinberg, 2011). But, while there is substantial evidence for a positive relationship 198 between testosterone, deep voice, and "unbridled" sexuality among men, the rela-199 tionship between women's sexuality and feminine vocal features is more complex 200 (for a review, see Bancroft, 2005). We should therefore be cautious and presume that 201 women with attractive voices may be more likely to be unfaithful due to a greater 202 opportunity for extra-pair sex given their desirability as a mate as their attractive 203 voices are more often chosen by paired men as extra-pair partners (Hughes, Dis-204 penza, & Gallup, 2004). 205

206 4.4 Preferences for Timbre

Sounding vocalizations are the product of multiple acoustic parameters, including 207 formant position and formant dispersion. Formant dispersion is a measure of the 208 average spacing between the formants (Fitch, 1997). It is a function of the length and 209 shape of the vocal tract and corresponds to the space through which sound waves must 210 travel from the vocal folds to the oral cavity. Until sexual maturity, vocal tract length 211 grows without any sexual dimorphism between boys and girls (Vorperian et al., 2005), 212 but at puberty, under the influence of androgens, males' larynges descend farther than 213 females' (Fitch & Giedd, 1999). Indeed, working through hormone receptors in the 214 epithelial cells of the laryngeal tissue, testosterone enlarges the larynx on the one 215 hand and lengthens and thickens the vocal folds on the other. The consequence of 216 these remarkable anatomic modifications is a longer vocal tract and the acoustic 217

result is a lower vocal height and a deeper and more resonating voice in adult males.
On average, the vocal tract is about 15% longer in men than women (Fant, 1960) and
this results in perceptible sex differences in formant dispersion, with males exhibiting
formants of lower frequency (measured through formant position) as well as lower
formant dispersion (Hanson, 1997).

Studies trying to correlate vocal resonances and perceived attractiveness have 223 lead to controversial results. For instance, Hodges-Simeon et al. (2010), Pisanski 224 and Rendall (2011) showed that the lower the formant dispersion, the more attractive 225 the masculine voices. The same tendency was observed by Sebesta et al. (2017) for 226 whom the formant position was the acoustic variable of interest. Conversely, Skrinda 227 et al. (2014) and Xu et al. (2013) found no correlation between low resonances and 228 male voice attractiveness. Interestingly, two other studies led to original results. 229 Using formant dispersion, Babel et al. (2014) showed that only tall women tend to 230 prefer low resonances in males' voices. Likewise, Feinberg et al. (2005) observed 231 the same preferences but only for the two high vowels /i/ and /u/, which are perceived 222 more attractive when the spacing between F1 and F2 is reduced. Such a result may 233 be explained by basic acoustic principles. Indeed, Holmberg et al. (1995) showed 234 that the relative amplitude of the harmonics is closely related with the adduction 235 of the vocal folds, with the higher the adduction, the lower the harmonics at the 236 glottal exit. Moreover, using fiberscopy to characterize vocal closure as function 237 of speakers' gender, Södersten, Lindestad, and Hammarberg (1991) showed female 238 speakers' higher degree of incomplete closure is correlated with increased harmonics. 239 Therefore, the results of Feinberg et al. are in line with theoretical analysis and 240 observations in experimental acoustics, since sounds with greater low-frequency 241 and weaker high-frequency components are recognized to result from more adducted 242 glottal considerations that are, themselves, more typical of male speakers (Hanson, 243 1996). 244

Collins and Missing (2003) investigated the relationship between male human 245 vocal characteristics and female judgments about the speaker and showed that, in 246 general, women found men's voices with harmonics that are closer together and 247 lower in frequency more attractive. This corroborates the findings of earlier studies 248 where less masculine sounding speakers were described as having higher formant 249 frequencies (Avery & Liss, 1996). In their study aiming in testing listeners' weighting 250 of F0 and/or formant frequency for the rating of vocal attractiveness, Pisanski and 251 Rendall (2011) reached the same conclusion, that is, voices with relatively low F0 252 and/or low formant frequencies rated as more attractive if male and less attractive if 253 female. Interestingly, the authors also showed that, in assessing attractivity, listeners 254 appeared to weigh formant frequency cues more heavily than F0, an unpredicted 255 result which suggests female listeners might interpret lower frequency cues as indi-256 cating greater masculinity and thus greater attractiveness in male voices. Finally, the 257 results obtained by Xu et al. (2013) also showed male voices sounded more attractive 258 when they are low pitched and with densely distributed formants associating such 259 characteristics with the large body size projected. 260

Editor Proof

4.5 Preferences for Voice Quality

Among the various complex acoustic features that give a voice its quality, the varia-262 tions of the glottal source waveform hold a special place. The values of the parameters 263 that describe the glottal waveform can vary depending on the glottal configuration 264 and/or the quality of the vocal fold vibrations, and it is expected that these variations 265 may lead to different voice qualities. Some voice qualities are usually associated with 266 disordered voice, such as harshness (also referred to as vocal roughness or hoarse-267 ness), but since our main concern here is vocal attractiveness, we will focus on those 268 that may occur for voices that are not perceived to be pathological. Voice qualities that 260 occur frequently in normal speech are described to be "modal," that is, smooth and 270 acoustically brilliant voices (Laver, 1980; Titze, 1994), but there are also some voice 271 qualities that are commonly related to dysphonia but may also occur in normal (i.e., 272 non-pathological) conversational speech and still be perceived attractive (Barkat-273 Defradas et al. 2012). It is typically the case for both moderately breathy and rough 274 voices. According to Fairbanks (1960: 179), "breathy quality" (also called murmured 275 voice or whispery voice) is described as an inefficient laryngeal vibration: "(...) In 276 the coordination of normal voice quality the vibrating vocal folds approximate in the 277 midline once per cycle, closing the glottis and interrupting the airflow. In breathy 278 quality the vocal folds vibrate, but the intermittent closure fails and the airflow is con-279 tinuous." Interestingly, the author also underlines breathy voice lowers voice pitch 280 and is almost invariably accompanied by limited vocal intensity. As for vocal rough-281 ness, or "harsh quality," it is defined as an "irregular, aperiodic noise in the vocal fold 282 spectrum caused by an excessive laryngeal tension" (Fairbanks, 1960: 179; Laver, 283 1980: 133, 1994: 477). Though the indication of psychological attributes conveyed 284 through voice quality has aroused researchers' attention since ancient times (Laver, 285 2009: 38), this belief has long found rather eccentric and impressionistic assertions. 286 For example, a breathy quality was supposed to show that men were "aesthetic" 287 and women "pretty and callow"; flat that men are "distant" and women "hard and 288 lethargic"; nasal that men are "unattractive and self-effacing" and women the same; 289 tense that men are "cantankerous" and women "high-strung"; throaty that men are 290 "stable" and women "oafish"; orotund (or loud) that men are "suave" and women 291 "aggressive"; and so on. The idea that personality characteristics are correlated with 292 voice quality has recently been tested more scientifically, and although some con-293 troversy remains, it must be admitted some correlations do exist. Among the few 294 studies that have tackled the topic of vocal breath and/or vocal roughness and their 295 effects on perceived voice attractiveness, it has been shown that harsh voices are 296 regularly correlated with more aggressive, dominant, and authoritative personalities 297 while breathy ones are more frequently associated with self-effacing, submissive, 298 and weak temperaments. A way to quantify breathiness-which is caused by glottal 299 air leakage—is to measure harmonics-to-noise ratio (henceforth HNR), a measure 300 that quantifies the relative amount of additive noise.³ As for vocal roughness, it 301

³At the physiological level, low HNR values are believed to be related to insufficient vocal fold adduction during the so-called "closed" interval of the phonatory cycle. Insufficient closure would

results from irregular vocal fold vibrations. These vibratory perturbations have come 302 to be more commonly referred to as vocal jitter. As a matter of fact, a number of 303 investigators have demonstrated a significant correlation between increased levels 304 of jitter and perceived roughness (Lieberman, 1963; Moore & Thomson, 1965). For 305 example, Babel et al. (2014) and van Borsel et al. (2009) found female voices were 306 perceived more attractive when breathy. Unexpectedly, Sebesta et al. (2017) and 307 Xu et al. (2013) showed significant relations between vocal breath and attractivity 308 for both sexes. A plausible explanation for male vocal attractiveness unexpectedly 309 enhanced by breathiness in this particular study lies in the fact that this predomi-310 nantly feminine vocal feature may presumably soften the aggressiveness regularly 311 associated with low deep voices. 312

Though some other phonetic characteristics could be addressed so as to characterize vocal attractiveness (e.g., preferences for speech tempo), the above overview offers an exhaustive assessment of the state of the art regarding the topic and underlines the necessity to question both understudied acoustic parameters that may be relevant for vocal pleasantness and the effect of language/culture on perceived attractiveness.

4.6 Sources of Variations in Vocal Preferences

Though some general tendencies emerge from studies dealing with vocal preferences, some sources of variations should be mentioned. These are mainly of two different natures. Some sources of variation seem to be due to physiological matters (i.e., variations in hormonal levels) while some others are more concerned with cultural arguments (i.e., social representations).

4.6.1 The Effect of Menstrual Cycle on Females' Vocal Preferences

It has been suggested that women's preferences maybe affected both by menstrual cycle (i.e., whether they are in their ovulatory versus follicular and/or luteal phase) and the context of mating they are looking for (i.e., short- versus long-term relationships). Feinberg et al. (2006), Pisanski et al. (2014), and Puts (2005) have put forward the hypothesis of "*good genes ovulatory shift*" which suggests that women in ovulatory phase tend to prefer more masculine men (higher masculinity being associated with a better genotypic quality according to the theory of immunocompe-

allow excessive airflow through the glottis, giving rise to a turbulence noise component in the quasi-periodic source signal. This friction noise would result in a higher noise level in the spectrum, especially in the higher frequencies.

tence handicap⁴) more particularly in the context of short-term relationships (Jünger
et al., 2018). Conversely, in the context of long-term relationships, women in their
follicular and/or luteal phases tend to prefer men exhibiting less masculine traits,
indicating they are more likely to invest themselves in parental care. Such variability
in females' preferences would account for an adaptive strategy allowing women to
optimize their fitness (i.e., reproductive success) in function of their menstrual cycle.

As for vocal preferences specifically, Puts (2005) noted that for the same vocal 340 stimulus, women in their ovulatory phase judge low-pitched masculine voices (i.e., 341 low F0) more attractive when looking for a short-lived relationship. Likewise, Fein-342 berg et al. (2006) and Pisanski et al. (2014) observed this choice is even more marked 343 for women in their fertility window. Hodges-Simeon et al. (2010) also investigated 344 the effect of vocal resonance (i.e., formant dispersion) on females' vocal preferences 345 and, though they could not find any effect of the type of relationship (i.e., short 346 or long) specifically linked to this feature, they showed women are more likely to 347 judge attractive masculine voices that exhibit a low dispersion of formants (i.e., deep 348 voices). They also notice a shift in women's preferences as function of both menstrual 349 cycle and duration commitment: monotonous masculine voices (low F0-SD) being 350 judged as more attractive by unfertile women in the context of short-term liaisons 351 while the same vocal stimuli are perceived as more attractive for fertile women who 352 are engaged in a long-term relationship. Those somehow inconsistent results lead 353 some authors to question the validity of menstrual cycle as a reliable explanatory 354 factor for women's variations in their attractiveness preferences. For example, Jones 355 et al. (2018) and Marcinkowska, Galbarczyk, and Jasienska (2018) found no effect 356 of female's menstrual cycle on body and face attractiveness evaluations of men. 357 Likewise, Jünger et al. (2018)-using a robust methodology-could not confirm 358 any effect neither of cycle phases nor of steroids to explain females' variations in 359 their choices. As for feminine voices, since laryngeal epithelial cells are known to 360 be highly sensitive to hormonal variations (Haselton, Mortezaie, Pillsworth, Bleske-361 Rechek, & Frederick, 2007; Miller et al., 2007; Higgins & Saxman, 1989; Abitbol 362 et al., 1999; Amir & Biron-Shental, 2003; Bryant & Haselton, 2009; Fischer et al., 363 2011), women's voices undergo perceivable variation in their quality. As a matter 364 of fact, Pipitone and Gallup (2008) have shown that feminine voices—which are 365 higher pitched when women approach their fertile period—are perceived as more 366 attractive by men whereas they sound lower pitched outside the ovulatory phase and 367 are, consequently, judged less appealing (Bryant & Haselton, 2009; Fischer et al., 368 2011). These variations in females' vocal quality are essentially due to changes in 369 estrogens and progesterone levels across the menstrual cycle, which lead to physio-370

⁴The theory of immunocompetence handicap (Zahavi, 1975) suggests that androgen-mediated traits accurately signal condition due to the immunosuppressive effects of androgens. This immunosuppression may be either because testosterone alters the allocation of limited resources between the development of ornamental traits and the immune system or because heightened immune system activity has a propensity to launch autoimmune attacks against gametes, such that suppression of the immune system enhances fertility. Therefore, only healthy individuals can afford to suppress their immune system by raising their testosterone levels, which also augments secondary sexual traits and displays (among which low deep voices for men).

logical modifications in the mass, the tension, and the viscosity of the vocal folds,
which in turn modify their oscillatory properties. It has been suggested these cyclic
vocal quality variations could have been adaptive since they could contribute to the
enhancement of women's attractiveness and facilitate mating when the risk of conception is higher and, therefore, the chance to conceive higher (Fischer et al., 2011;
Pipitone & Gallup, 2008; Puts et al., 2013).

4.6.2 The Effect of Sociocultural Environment on Vocal Ouality

Though they are remarkably scarce, the few existing studies that have investigated 370 the effect of sociocultural environment on vocal preferences have shown they are 380 not universal but language/culture dependent. For example, van Bezooijen (1995) 381 demonstrated that Japanese women exhibited the highest vocal pitch among a large 382 sample of natural languages (i.e., 232 Hz) while the mean fundamental frequency 383 of American women is around 214 Hz and that of Dutchwomen close to 196 Hz. 384 Vaissière (2015) found French women's voice are even lower pitched with a mean 385 F0 close to 190 Hz. It has been suggested that these significant differences in female 386 vocal height could be constrained by specific cultural requirements that are them-387 selves shaped by social values and expectations that are linked to the roles allocated 388 to women versus men and, more generally, to the stereotypes of feminity versus 389 masculinity defined by the culture in question. Stereotypes of gender therefore vary 390 among different cultures as well as among different ethnic groups (Landrine, 1985; 391 Harris, 1994). In this way, the figure of feminity in Japanese culture is traditionally 392 related to modesty, innocence, gentleness, subordination, physical fragility, and psy-393 chological submission (Sughira & Katsurada, 1999); these personality traits being 394 vocally signalized to Japanese men who share the same cultural background through 395 that famous "voix de petite fille" which has been subtly described by Léon (1981). 396 Conversely, in the Netherlands—a country described as more egalitarian—women 397 exhibit more masculine (i.e., low pitched) voices since their culture favors psycho-398 logical traits that are associated with female independence. In conclusion, it seems 399 that the acoustic features that are typical of feminine versus masculine voices are 400 not only due to anatomical and/or physiological criteria (i.e., vocal length tract and 401 hormonal level) but also to cultural aspects depending on the social values attributed 402 to sex roles in a given society. Besides, the studies conducted by Sebesta et al. (2017) 403 and Shirazi et al. (2018) have shown that cultural expectations do not only con-404 cern vocal height. For example, in a Namibian population, male attractiveness is 405 not predicted by F0 but by the degree of vocal breathiness they exhibit. Likewise, 406 in the Philippines, females tend to prefer men with higher pitched voices. Though 407 the effect of sociocultural representations on voice has been focused on, there is, to 408 our knowledge, no study that aimed at identifying the factors of this variation. Yet, 409 it does not seem to occur randomly in the same way as it has been observed for 410

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the evolution of the waist-to-hip ratio (Bovet & Raymond, 2015; Bovet, 2019), the 411 body mass index, or the stature, in which variations have been shown to be partly 412 due to the ecology (see Pisanski & Feinberg, 2013 for a discussion), and that is why 413 cross-cultural surveys are still needed to evaluate the weight of culture on vocal pref-414 erences. The scope of research dealing with voice attractiveness should also consider 415 the issue of preferences limitations. As a matter of fact, there are very few studies that 416 tackle the topic of superior and/or inferior limits above/below which a voice is no 417 longer perceived as attractive. Among these, Re et al. (2012) have shown women's 418 preferences do not vary when male vocal pitch is below 96 Hz, but when they have to 419 choose between two stimuli above this value, they regularly prefer the lower voice. 420 As for men, to our knowledge, two studies were interested in determining a vocal 421 height threshold (in the range 160–300 Hz) below/above which female voices would 422 no longer be perceived as attractive (Feinberg et al., 2008a, 2008b; Re et al., 2012). 423 Results show men always consider high-pitched voices as more attractive for women. 424 Moreover, Borkowska and Pawlowski (2011) reported a non-linear relation between 425 vocal height and attractivity, the latter starting to decrease when F0 is close to 260 Hz. 426 According to the authors, this may be due to the fact that high-pitched voices are 427 commonly associated to sexually immature females. Though works dealing with the 428 determination of perceptive thresholds from which vocal attractiveness is affected are 429 still in the pipeline, several studies have shown that straight after a voice is perceived 430 as too distant from the norm, it is often categorized as pathological and associated 431 with negative personality traits (Barkat-Defradas et al., 2015; Revis, 2017). 432

Conversely, vocal attractiveness has a profound influence on listeners-a bias 433 known as the "what sounds beautiful is good" vocal attractiveness stereotype—with 434 tangible impact on a voice owner's success at mating, job applications, and/or elec-435 tions (Zuckerman & Driver, 1989). This led some authors, like Bruckert et al. (2010), 436 to test the effect of averaging voices via auditory morphing on perceived attractiv-437 ity. Overall, their results reveal that the larger the number of voices averaged, the 438 more attractive the result. This is partly because composite voices have a smoother, 439 more regular texture and also because they sound more like the average voice and 440 reflect norm-based encoding of vocal stimuli. Preferences for some voices may also 441 be explained by the principle of sparseness. It has been demonstrated that human 442 perceptual systems (visual, auditory, and olfactory) have been selected so as to code 443 the information efficiently that is to say quickly and as parsimoniously as possible 444 to be in line with the principle of least effort (Renoult, Bovet, & Raymond, 2016). 445 Such a cognitive process relies on the elimination of the redundant components of a 446 signal, by which processing is consequently more accurate and less costly while the 447 storage and the retrieval of relevant information is more efficient. Nevertheless, the 448 neuropsychological mechanisms driving the coding of acoustic signals in relation 449 with vocal attractivity has received little scientific attention and, to our knowledge, 450 there is no study investigating these aspects specifically. Yet, since clear evidence for 451 interference between facial and vocal information has been observed (Aben, Pflügera, 452 Koppensteiner, Coquerellee, & Grammer, 2015), it seems reasonable to claim that 453 vocal and facial cues convey redundant information about a speaker's mate value 454 and thus may serve as a backup signal for human mate choice decisions. 455

4.7 How Evolution Shaped Human Voice via Opposite 457 Sex's Preferences

Though it is easy to understand how morpho-anatomical, physiological as well as 458 behavioral differences between species result from natural selection and environmen-450 tal adaptations, in some famous cases, those well-known mechanisms fail to explain 460 the existence of certain remarkable features (Darwin, 1871). The iconic example 461 that is traditionally invoked to illustrate this point is the male peacock's tail (Pavo 462 cristatus), which is adorned with iridescent feathers. Darwin himself recognized this 463 extravagant ornament contradicted his theory of natural selection. As a matter of 464 fact, no doubt the male peacock's tail represents a critical bulk for his flight, and its 465 outstanding colors has the disadvantage to attract his predators' attention. Besides, 466 noting their absence in females and juveniles, the author concludes such an orna-467 ment cannot serve the animal's survival. Indeed, if peacocks' tail feathers were useful 468 against predators then females and juveniles would exhibit the same. Therefore, he 469 suggests the presence of some morphological characteristics cannot be explained 470 solely by the advantages they provide to their bearers in terms of survival (which 471 refers to "natural selection" itself) but also in terms of mating and fitness (which 472 refers to a complementary concept, he defines as "sexual selection"). According 473 to Darwin, sexual selection is restricted to secondary sex characteristics⁵—among 474 which body size—and explains why many species exhibit sexual dimorphism at sex-475 ual maturity through the spectacular feathers of the birds-of-paradise, the impressive 476 antlers of the male members of the deer family and, last but not least, vocal dimor-477 phism in humans, among other dimorphic traits. The theory of Ohala's frequency 478 code (1984)—inspired by Morton $(1977)^6$)—indicates that despite the development 479 of highly complex language capable of conveying fine subtleties in meaning, humans 480 still use an encoding strategy similar to the one widely used by nonhuman animals, 481 namely, (i) by using relatively low-frequency sounds to indicate they are likely to 482 attack versus (ii) more high-frequency sounds to indicate they are submissive, appeas-483 ing, or fearful. Here pattern (i) is to project a large body size so as to threaten the 484 receiver, because a larger animal has a better chance at winning a physical con-485 frontation. Pattern (ii) is to project a small body size to attract the receiver, because a 486 smaller animal is less likely to be a threat (Morton, 1977). Following this reasoning, 487 Ohala (1984) argues the longer vocal folds of human males may have evolved under 488

⁵Secondary sex characteristics are features that appear during puberty in humans, and at sexual maturity in other animals. Secondary sex characteristics include, for example, the manes of male lions, the bright facial and rump coloration of male mandrills, and horns in many goats and/or antelopes. In humans, visible secondary sex characteristics include public hair, enlarged breasts and widened hips of females, facial hair, Adam's apples on males, etc.

 $^{^{6}}$ In a famous article dealing with vocal communication in animals, Morton (1977) introduces his \ll motivation-structural rules \gg theory, which suggests physical proprieties of acoustic signals (sounds of high versus low frequencies) are motivated since they reflect the vocalizer's body size and inform about his/her intentions and/or emotional state. He argues a large number of birds and mammals use low-frequency sounds to express hostility, threat, and aggression whereas high-frequency sounds are rather used to express fear, submission, and "amicability.".

a selection pressure to compete with other males in achieving dominance for the 489 sake of gaining access to female mates (i.e., intra-sexual selection). Likewise, the 490 longer vocal tract of males may have evolved under the same pressure, as it may also 491 reflect a larger body size and attract females (i.e., inter-sexual selection, see Puts 492 et al., 2006 for an exhaustive presentation of the role of intra-selection in males). 493 Extending the mechanism further, the shorter vocal folds and vocal tract of females 101 may have developed under a pressure in the opposite direction, i.e., to project a small 495 body size in order to attract male mates. To sum it up, by making an analogy between, 496 on the one hand, the appearance of antlers in male deers, which develop when they 497 attain sexual maturity and, on the other hand, voice change in pubescent boys, Ohala 498 was a pioneer in assessing the functional role of sexual selection for the emergence 499 of vocal dimorphism in humans. 500

I think the enlargement of the vocal apparatus also occurs to enhance aggressive displays. Males, by their role in the family unit and the fact that they compete for the favors of the female—i.e, they are subject to what Darwin called sexual selection would be the ones to develop such deviations from the 'norm'. However, they would only need these aggressive decorations when they are ready to compete and retain the favors of a female, that is, at the time of sexual maturity (Ohala, 1984: 14).

507 4.8 Conclusion

This contribution aimed at showing the mechanism of sexual selection formalized by 508 Darwin as early as 1871 constitutes a crucial force in the evolution of voice, which 509 directly intervenes in reproductive strategies. Though such an argument has been 510 considered as obvious for many species, it is only at the very beginning of the 2000s 511 that the phenomenon of vocal dimorphism has been tackled in relationship with Dar-512 win's theory. As a matter of fact, it is surprising that the study of language activity has 513 long been conducted without any reference to its biological function. Traditionally, 514 humanities (anthropology, linguistics ...) used to consider language as a pure cultural 515 product, which had been created by humans in the same ways as writing or art (Levi-516 Strauss, in Charbonnier, 1959: 48; Noble and Davidson, 1996: 214; Tomassello, 517 1999: 94), and which developed irrespective of any selective pressure (Chomsky, 518 1975: 75). In this purely cultural conception, the study of ultimate (or distal) causes 519 explaining the existence of vocal dimorphism in terms of evolutionary forces has 520 been left aside for the benefit of extensive analyses of proximal mechanisms, which 521 explain its biological function in terms of immediate physiological or environmental 522 factors. Yet, a transdisciplinary approach—at the crossroad of linguistics and evolu-523 tionary biology—is of a great interest to better understand the whys and wherefores 524 of the evolution of articulated language in the human lineage. Indeed, beyond its 525 evidenced social function (Dunbar, Duncan, & Nettle, 1995), vocal behavior should 526 undoubtedly be regarded as a reliable way to display one's phenotypic value (Puts, 527 2010). Moreover, the existence of a low laryngeal configuration—an indispensable 528 condition for language—in many non-speaking species undermines the hypothesis 529

ditor Proof

- of a specific adaptation to language in humans (Fitch & Reby, 2001). Reversely, con-
- sidering such a disposition is present in several animals of different species clearly
- ⁵³² indicates it has evolved during phylogenesis to respond to other functions.

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Part II Voice

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Abstract	"voice quality" in gen 100 female speakers, l were undergraduate st	at is meant by "normal" voice quality, just as it is often unclear what is meant by eral. To shed light on this matter, listeners heard 1-sec sustained vowels produced by half of whom were recorded as part of a clinical voice evaluation and half of whom udents who reported no vocal disorder. Listeners compared 20 voices at a time in a trials, ordering the samples on a line according to the severity of perceived

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Keywords	Voice quality - Normal voice - Dysphonia - Voice perception - Voice disorders - Listener - Agreement

Chapter 5 What Does It Mean for a Voice to Sound "Normal"?



Jody Kreiman, Anita Auszmann, and Bruce R. Gerratt

Abstract It is rather unclear what is meant by "normal" voice quality, just as it 1 is often unclear what is meant by "voice quality" in general. To shed light on this 2 matter, listeners heard 1-sec sustained vowels produced by 100 female speakers, half 3 of whom were recorded as part of a clinical voice evaluation and half of whom were Δ undergraduate students who reported no vocal disorder. Listeners compared 20 voices 5 at a time in a series of sort-and-rate trials, ordering the samples on a line according to 6 the severity of perceived pathology. Any voices perceived as normal were placed in 7 a box at one end of the line. Judgments of "normal" versus "not-normal" status were 8 at chance. Listeners were relatively self-consistent, but disagreed with one another, 9 especially about what counts as normal. Agreement was better, but still limited, 10 about what counts as "not normal." Strategies for separating "normal" from "not 11 normal" differed widely across individual listeners, as did strategies for determining 12 how much a given voice deviated from normal. However, acoustic modeling of 13 listeners' responses showed that several acoustic measures—F0, F1 and F2, and F0 14 coefficient of variation—appeared more often than others as significant predictors of 15 both categorical judgments and of scalar normalness ratings. These variables did not 16 account for most of the variance in these analyses, and did not appear together in the 17 perceptual models for even half of the listeners, but they did appear individually in 18 most analyses, suggesting that in practice the concept of "normal" may have some 19 small core of meaning based on F0 and vowel quality. Thus, the answer to our initial 20 question of what it means for a voice to sound normal is a complex one that depends 21 on the listener, the context, the purpose of the judgment, and other factors as well as 22 on the voice. 23

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Keywords Voice quality · Normal voice · Dysphonia · Voice perception · Voice
 disorders · Listener · Agreement

²⁶ 5.1 Introduction

The voice literature provides surprisingly little insight into what it means for a voice 27 to be "normal," despite the fact that much depends on the concept of a normal voice. 28 Many studies have shown that a listener's perception of vocal abnormality may 29 lead to negative assessments of the personality, health, intelligence, or social desir-30 ability/social attractiveness of the speaker. For example, Amir and Levine-Yundof 31 (2013) found significant differences between speakers with voice disorders and non-32 dysphonic speakers with respect to listeners' judgments of attractiveness, agreeable-33 ness, reliability, potency, aggressiveness, and tenseness. Similarly, Maryn and Debo 34 (2015) found a correlation of r = 0.85 between clinicians' ratings of severity of dys-35 phonia and naïve listeners' ratings of healthiness. Similar results have been reported 36 for adult or child listeners, and for expert and naïve judges (Table 5.1). Results also 37 appear to apply to both child and adult speakers, and are robust cross-culturally (e.g., 38 Altenberg & Ferrand, 2006; Irani et al., 2014). These kinds of effects can cause 30 embarrassment and interfere with job performance; in the worst case, they can lead 40 to reduced career opportunities and social isolation. 41

In clinical settings, a clear understanding of "normal" voice would seem to underlie the entire diagnosis-and-treatment enterprise. A sense that a voice does not sound normal leads patients to initiate treatment, and "normal" serves as a target for determining when therapy is complete. Studies of treatment efficacy logically depend on defining a normal voice as a target, and the practice of establishing normative values for instrumental measures of voice assumes that "normal" has at least a relatively constant meaning.

Despite the importance of "normal" in understanding voice and voice disorders, 49 authors discussing the nature of normal voice have typically emphasized the difficulty 50 of pinning down exactly what it is, echoing Sundberg's (1988) lament that everyone 51 knows what voice is until they try to be specific. Discussions of normal quality 52 have focused on two main themes. The first and more common one describes a 53 normal voice as one that properly presents the person speaking-their age, sex, 54 emotional state—and that adequately meets the speaker's occupational and social 55 communication needs (e.g., Behlau & Murry, 2012; Dehqan et al., 2010; Greene & 56 Mathieson, 1992; Johnson et al., 1965; Aronson & Bless, 2009). Such definitions 57 emphasize the functionality of a voice. For example, Greene and Mathieson (1992) 58 wrote: 59

The simplest definition of normal voice is it is 'ordinary': it is inconspicuous with nothing out of the ordinary in its sound. To achieve this standard of acceptability, the voice must be loud enough to be heard, and appropriate for the age and sex of the speaker. It must be reasonably pleasing to the ear of the listener, modulated and clear, not droning and flat or hoarse and breathy. It must be appropriate to the context and not too loud or assertive. (p. 43)

Speakers	Listeners	Attribute judged	Result	References
Normal and hypernasal children	Children	Social acceptance	Negative responses increased with increasing hypernasality	Blood and Hymen (1977)
Normal and hypernasal children	Children	Social acceptance	Even mild-to-moderate hypernasality decreased social acceptance	Watterson et al., (2013)
Normal and dysphonic female adolescents	Teachers	Personality	Voice disorders increased negative perceptions	Zacharias et al., (2013)
Normal and dysphonic adult females	Adults; monolingual and bilingual, younger and older	Personality	Even mild voice disorders led to negative impressions, for all listener groups	Altenberg and Ferrand (2006)
Normal and dysphonic adult females	Adults	Personality, attractiveness	Nasality and breathy/harsh quality both associated with worse perceptions	Blood et al., (1979)
Normal, dysphonic, and hypernasal females	Students with and without information about voice disorders	Social desirability	Ratings were more negative for speakers with voice disorders	Lallh and Rochet (2000)
Normal and dysphonic adults and children	Adult SLPs; naïve listeners	Healthiness	Even slight dysphonia produced the perception of unhealthiness	Maryn and Debo (2015)
Normal and dysphonic speakers of Hebrew	Young and older adults	Personality	Dysphonia associated with negative perceptions, for women more than for men	Amir and Levine-Yundof (2013)

 Table 5.1 Representative studies showing perceptual and social sequelae of perceived disordered voice or speech

⁶⁵ It follows from this definition that standards and judgments will vary across lis-⁶⁶ teners and contexts. For example, Moore (1971) wrote:

It is apparent that the voice is abnormal for a particular individual when he or she judges it to be so regardless of the circumstances. Judgment implies a set of standards that are learned through experience and that are related to the judge's own aesthetic and cultural criteria. Judgment also implies that standards are not fixed, that there is opportunity for more than one conclusion. This flexibility in determining the defectiveness of voices does not alter the validity of the basic definition of voice disorders, but it does underscore the observation that vocal standards are culturally based and environmentally determined. (p. 535)

However, to our knowledge the nature and extent of this variability have not been 74 studied, nor have the factors conditioning variability in perceived vocal abnormality. 75 A second definitional approach emphasizes physical normalness, without partic-76 ular concern for vocal quality or for use of the voice in communication. For example, 77 normal voice can be characterized as the acoustic product of a normal vocal tract 78 that is functioning normally (Mathieson, 2000) or as a voice produced by a speaker 70 with no current or previous voice complaint and that passes a perceptual evaluation 80 by a speech-language pathologist (Bonilha & Deliyski, 2008). 81

To our knowledge, no empirical data exist in support of either of these views. In the 82 face of the importance a perceived voice disorder can have for a speaker, clinicians 83 and scientists have proceeded as if "normal" unambiguously exists. For example, 84 numerous studies propose algorithms devised to automatically separate normal from 85 pathological phonation, arguing that such algorithms bring needed objectivity to 86 clinical voice evaluation (e.g., Arias-Londoño et al., 2011; Orozco-Arroyave et al., 87 2015; Wang et al., 2011; Moro-Velázquez et al., 2016). "Normal" in these studies 88 remains an unexamined concept, and algorithms typically show good classifica-89 tion accuracy (usually >90% correct), suggesting this approach is not unreasonable. 90 Similarly, many more studies have reported normative values for acoustic (e.g., Goy, 91 Fernandes et al., 2013; Wuyts et al., 2002), physiological (e.g., Xue & Hao, 2006), 92 and/or aerodynamic measures of voice (e.g., Lewandowski et al., 2017), again imply-93 ing that it is possible to define "normal" as a quality with clear boundaries. The voice 94 literature thus presents a paradox. Clinical concerns combined with the demonstrated 92 social and personal importance of sounding normal lead researchers to design studies 96 that assume a clear boundary between normal and not-normal phonation, while at the 97 same time arguing that no such boundaries exist in theory, all of this in the absence 98 of empirical evidence about what sounds normal or not normal to listeners. 99

This study is intended to address this situation. Our goals are to gather listeners' assessments of the extent to which voices sound normal, and to seek insight into the factors that determine whether a voice sounds better or worse to a particular listener.

103 5.2 Methods

104 5.2.1 Speakers and Voice Samples

The voices of 100 female speakers were used in this experiment. Females (as opposed 105 to males) were selected for this preliminary study because of recent research interest 106 in the perception of normal versus abnormal female voice quality, particularly with 107 respect to vocal fry and "creaky voice" (Yuasa, 2010; Anderson et al., 2014; Oliveira 108 et al., 2016). Fifty voice samples were drawn from an existing database of recordings 109 of speakers who had a diagnosis from an otolaryngologist ("not normal"). Voices 110 were unselected with respect to diagnoses, which included functional and neurogenic 111 disorders, mass lesions, reflux, and age-related dysphonia. Samples ranged from 112 extremely mild to very severe vocal pathology. An additional 50 voices were drawn 113 from the UCLA Speaker Variability Database (Keating et al. 2018), which includes 114 multiple voice samples from over 200 male and female UCLA undergraduate stu-115 dents, all of whom reported no history of voice or speech complaints ("normal"). 116 Note that although voices were categorized as \pm normal based on diagnostic status, 117 no assumptions were made about the normal or abnormal quality of the voices, and 118 no attempt was made to select "normal" or "not-normal" voices that sounded more or 119 less normal, beyond informally ensuring that the "not-normal" samples represented 120 a broad range of severity of perceived pathology. 121

All speakers sustained the vowel /a/ as part of their recording sessions, and all 122 were recorded with a Brüel and Kjær 1/2" microphone. Steady-state vowels were 123 studied rather than continuous speech, to allow listeners to focus on voice quality 124 and not on articulation or native/nonnative status of the speakers. Previous studies 125 (e.g., Gerratt et al., 2016) have shown negligible effects of stimulus type on quality 126 assessment. Samples were directly digitized at a 20 kHz (clinical samples) or 22 kHz 127 (normal samples) sampling rate, edited to 1 s duration, and then downsampled to 128 10kHz prior to acoustic analyses and testing. 120

130 5.2.2 Listeners and Listening Task

Stimuli were assembled into blocks of 20 voices each, which in turn were assembled
into five sets of nine trials (each trial comprising one 20-voice block), such that
across the five sets of trials, every voice was compared at least once to every other
voice and every voice received a total of 90 ratings. Each listener heard 9, 20-voice
trials, for a total of 180 judgements/listener: each stimulus voice was judged at least
once/listener, with 80 voices repeated in 2 different trials so that test-retest reliability
could be assessed. (No voices were repeated within a single trial.)

All experimental procedures were approved by the UCLA Institutional Review Board. Ten UCLA students and staff (aged 18–68; mean age = 21.5; sd = 9.67) heard each set of trials, for a total of 50 listeners. All listeners reported normal



Fig. 5.1 The testing interface for the sort-and-rate task. Listeners played each voice by clicking its icon, and then dragged the icon to indicate (1) whether the voice sounded normal, in which case the icon was placed in the box on the right and (2) if it did not sound normal, how close to normal it sounded. The most abnormal-sounding voices were placed toward the left end of the line; those that approached normal were placed near the box

hearing and received course credit in return for their participation. Clinicians were
not targeted separately during subject selection because evidence indicates they do
not differ significantly from naïve listeners when judging the severity of dysphonia
(Eadie et al. 2010).

Subjects heard the stimuli over Etymotic insert earphones (model ER-1) at a 145 comfortable constant listening level. The testing interface is shown in Fig. 5.1. Each 146 icon in the figure represents a single voice token, randomly assigned to that icon. 147 Listeners played each voice by clicking its icon, then dragged the icon to a line to 148 indicate (1) whether the voice sounded normal, in which case the icon was placed in 149 the box on the right end of the line and (2) if it did not sound normal, how close to 150 normal it sounded (a visual sort-and-rate task; Granqvist, 2003). The most abnormal-151 sounding voices were placed toward the left end of the line; those that approached 152 normal were placed near the box. Voices judged as equally dysphonic were to be 153 stacked on the line. Because the box for "normal" voices appeared rather small on 154 the screen, listeners were explicitly instructed that box size did not mean that there 155 were only a few normal voices in the set, and that they could place as many or as few 156 icons as desired in the box. Listeners were encouraged to play the voices as often 157 as required, in any order, until they were satisfied with their sort, after which testing 158 advanced to the next trial. The experiment was self-paced and listeners were allowed 159 to take breaks as needed. They were not told how many total speakers were included 160 in the experiment. Total testing time was less than 1 h. 161

Variable	Definition and reference
H1*-H2*	Relative amplitudes of the first and second harmonics, corrected for the effects of formants on amplitude (Hanson, 1997; Iseli & Alwan, 2004)
H2*-H4*	Relative amplitudes of the second and fourth harmonics, corrected for the effects of formants on amplitude
H4*-H2kHz*	Relative amplitudes of the fourth harmonic and the harmonic nearest 2 kHz, corrected for the effects of formants on amplitude
H2kHz*-H5kHz	Relative amplitudes of the harmonic nearest 2 kHz and that nearest 5 kHz; H2kHz is corrected for the effects of formants on amplitude
Cepstral peak prominence (CPP)	The relative amplitude of the cepstral peak in relation to the expected amplitude as derived via linear regression; a measure of aperiodicity (Hillenbrand et al., 1994)
Energy Root Mean Square (RMS)	Energy, calculated over five pitch pulses.
Subharmonic-to-harmonic ratio (SHR)	The amplitude ratio between subharmonics and harmonics; characterizes speech with alternating pulse cycles (period-doubling; Sun, 2002)
Fundamental frequency (F0)	The frequency of the first harmonic
F1, F2, F3, F4	Center frequencies of the first four formants

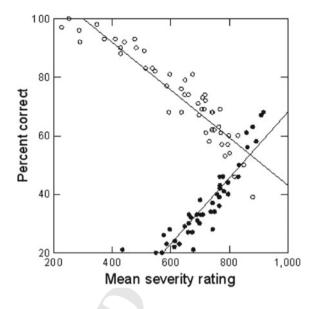
 Table 5.2
 Acoustic variables. Means and coefficients of variation were calculated for all measures using VoiceSauce software

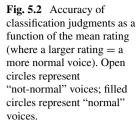
162 5.2.3 Acoustic Analyses

Acoustic measurements (Table 5.2) were made on all stimuli to facilitate interpretation of listeners' perceptual strategies. As a set, these measures constitute a psychoacoustic model of voice quality (Kreiman et al., 2014) and were chosen because as a set they are sufficient to model the perceived quality of virtually any sustained phonation. Variables were measured every 5 ms using VoiceSauce software (Shue et al., 2011), and then averaged across the entire utterance. Coefficients of variation were also calculated as estimates of signal variability.

170 5.3 Results

Analyses fall into two groups, corresponding to the two approaches to defining "normal" discussed in the Introduction. The first analyses treated "normal" (i.e., placed in the box by a listener; Fig. 5.1) and "not-normal" (placed on the line outside the box) responses as straightforwardly categorical, consistent with definitions of nor-





mal as "lacking a diagnosis." The second set of analyses treated ratings as forming a
continuum from most severe (=0), to normal (=1000), consistent with the idea that
perceived normalness varies continuously as a function of listening context (Gerratt
et al., 1993), social and/or communicative context, and other such factors. Both sets
examined (1) listener agreement about (the degree of) perceived deviation and (2)
the acoustic cues that explained listeners' judgments.

Figure 5.2 shows the relationship between these two measurement approaches in 181 a plot of categorization accuracy as a function of mean normalness ratings. In this 182 figure, a priori "normal" voices are plotted as filled circles and a priori "not-normal" 183 voices are plotted as open circles. Note that accuracy is greater for "not-normal" 184 voices than for "normal" voices: It is apparent from this figure that many voices 185 with diagnoses sound quite normal, and many nominally normal voices sound rather 186 abnormal on average. The majority of "normal" voices were judged normal less than 187 50% of the time, while only a few "not-normal" voices were incorrectly categorized 188 more than 50% of the time. Also note that the range of severity ratings for "normal" 189 voices completely overlaps that for "not-normal" voices, but not vice versa. This 190 pattern occurs because the normal end of the scale has an absolute ending point—a 191 voice cannot be more normal than normal-but one can always imagine a worse 192 voice, so that the left end of the scale can extend infinitely. 193

Editor Proof



5.3.1 Categorical Judgments of "Normal" Versus "Not-Normal" Voice Quality

5.3.1.1 Can Listeners Accurately Separate Nominally Normal from Nominally Not-Normal Voices?

If the boundary between normal and not-normal voice quality is ill-defined, as sug-198 gested by the papers reviewed in the Introduction, then it should be difficult for 199 listeners to make categorical decisions regarding the status of a voice sample. This 200 proved to be the case. For voices deemed normal a priori, listener performance 201 ranged from 1.1 to 67.8% correct classification, with a mean of 34.1% correct (sd 202 = 14.64%), where chance is 50%. Performance was somewhat better for a priori 203 not-normal voices, which were correctly classified an average of 73.6% of the time 204 (sd = 14.99%), with a range of 45.6–100%. Chi square analyses indicated that lis-205 teners heard only 2/50 a priori normal voices as normal at above chance levels, but 206 agreed at above chance levels that 30/50 normal voices were not normal. For a priori 207 not-normal voices, 35/50 were significantly often classified as not normal, and none 208 was incorrectly classified as normal. 209

Finally, d' analysis (e.g., Green & Swets, 1966) was used to assess overall cate-210 gorization accuracy across the entire group of listeners. In this context, d' measures 211 listeners' ability to correctly identify voices as normal or not normal, independent 212 of response biases in favor of "normal" or "not-normal" responses. Ratings on the 213 normal/not-normal scale were quantized to range from 1 to 10, where 1 represented 214 the worst voice quality and 10 meant the voice had been classified as normal. These 215 rescaled values were then used to calculate d' for each listener and for the group as a 216 whole (Macmillan & Creelman, 2005). Results for both the pooled listeners and for 217 individuals indicated that performance was at chance levels. For the pooled listeners, 218 d' equaled 0.21, while across individual listeners, values averaged 0.24, with a range 219 of -0.27-0.81 (sd = 0.28). We conclude from these data that listeners were unable 220 to distinguish nominally normal from nominally not-normal voices at above chance 221 rates, due to misclassifications both of normal voices as dysphonic and of not-normal 222 voices as normal. 223

5.3.1.2 Do Listeners Agree with One Another in Their Categorical Judgments?

Although listeners were inaccurate in their categorical responses, it is possible that this occurred because some of the clinical voice samples were very mildly deviant, and some of the nominally normal voices were characterized by high or low F0, vibrato, vocal fry, and/or breathiness, which could be interpreted as abnormal. This is especially possible when not normal is defined entirely in terms of physiology, because abnormal-appearing vocal folds can sometimes occur without any perceptual consequences. If this is the case, listeners might agree in their normal/not-normal judgments, even though these do not correspond to the clinically defined state ofaffairs.

To assess this possibility, we examined listener agreement about vocal status, 235 independent of the existence of a diagnosis. Listeners did not agree unanimously 236 that any voice was normal; they were unanimous regarding only a single not-normal 237 voice. Significant agreement was almost as uncommon as unanimous agreement. 238 Chi square analyses showed that listeners agreed at above chance levels that only 239 2/100 voices were normal (both of which were in fact normal; p < 0.05); they 240 agreed at above chance levels that 65/100 voices were not normal (30 of which were 241 nominally normal, as noted above; p < 0.05). We conclude that listeners are no more 242 in agreement than they are accurate when asked to judge whether or not a voice is 243 normal. 244

245 5.3.1.3 Are Listeners Self-consistent in Their Judgments?

Two possibilities emerge from the findings that listeners are highly inaccurate and 246 disagree widely when asked to judge whether a voice is or is not normal. First, it is 247 possible that "normal" is truly meaningless in practice. However, it is also possible 248 that every listener has his/her own consistent idea of what "normal" is, but that these 240 ideas differ from listener to listener. To examine these possibilities, we calculated 250 intrarater agreement in normal/not-normal judgments for the 80 repeated ratings 251 each listener provided. Average intrarater agreement equaled 75.8%, with a range 252 from 57.5 to 94.4% (sd = 9.22%; chance = 50%). Three of 50 listeners were self-253 consistent at rates below 60%; 30/50 were self-consistent at rates of 75% or above. 254 These results indicate that most listeners are reasonably reliable when they report 255 that a voice is or is not normal, but suggest that the basis for these judgments may 256 vary across listeners, leading to self-consistency but low interrater agreement. We 257 pursue this possibility in the next section. 258

5.3.2 Can We Predict Listeners' Categorical Responses from Voice Acoustics?

Linear discriminant (LD) analysis was used to determine how well listeners' cat-261 egorical "normal" versus "not-normal" judgments could be predicted from voice 262 acoustics (regardless of the existence/non-existence of a diagnosis). All variables 263 from the psychoacoustic model were entered simultaneously into the analysis. One 264 eigenfunction accounted for 100% of the variance in the data (canonical correlation 265 = 0.263; Wilks' lambda = 0.931; chi square = 642.72, df = 14, p < 0.001). 70% 266 of stimuli were correctly classified as perceptually normal or not normal. Predictors 267 with weights ≥ 0.3 (~10% variance accounted for) included F2 (weight = -0.52), 268 F0 (weight = 0.33), and F0 cv (weight = -0.30). These results suggest that, even 269

Primary predictor variable	Additional significant predictors	Number of listeners
Variability		14
Vowel quality		7
Vowel quality	Variability	2
Vowel quality	Noise	5
Vowel quality	F0	5
F0		1
F0	Noise	3
F0	Spectral shape	5
Noise		6
Spectral shape		2

 Table 5.3 Patterns of weights on eigenfunctions resulting from LD analyses relating individual listeners' categorical normal/not-normal judgments to acoustic variables

when considered as a group, listeners are not responding randomly, but also show
that only a few rather simple variables (vowel quality, pitch, and pitch variability)
are apparently shared across listeners.

To examine differences among listeners, we repeated the LD analyses for each 273 of the 50 individual listeners. Results showed significant classification based on 274 acoustic measures for all but 1 listener; across individuals, voices were correctly 275 categorized as "perceived to be normal" or "perceived to be not normal" 81.35% of 276 the time (sd = 6.64; range = 67.8-96.7%). However, listeners differed widely in the 277 measures that emerged from these analyses. For brevity of presentation, the acoustic 278 parameters were grouped into five categories: variability (coefficients of variability 279 for all measures), vowel quality (F1, F2, F3, F4); spectral noise (CPP, energy, SHR), 280 F0, and source spectral shape (H1*-H2*, H2*-H4*, H4*-H2kHz*, H2kHz*-H5kHz). 281 Variables that weighted at 0.3 or higher on the eigenvector for each listener are 282 tallied in Table 5.3. As in the group analyses just described, F0 and vowel quality 283 were important for explaining individual listeners' normal/not-normal decisions, but 284 overall acoustic variability and noise also emerged as important predictors. 285

Finally, context effects are well known to affect ratings of vocal severity. For 286 example, a given voice will sound rougher in the context of normal voices, and less 287 rough in the context of voices with severe vocal pathology (Gerratt et al., 1993). To 288 examine the influence such effects might have had on perceptual strategies in the 289 present task, we repeated the LD analyses separately for each of the five groups of 290 listeners. Recall that all listeners heard all the voices, but voices were grouped into 291 different sets of 20, so the context in which each voice was judged varied from group 202 to group. Results appear in Table 5.4. Groups did differ somewhat in the acoustic 293 variables that predict overall categorical response patterns. Notably, spectral shape 294 parameters appear in the solutions for two groups, and CPP appears in two other 295 solutions. However, the increased complexity of the sets of predictor variables did 296

Listener group	Variables (weights)	% Correct classification
1	CPP (0.46), CPP cv (-0.41), F2 (-0.35), F1 (0.34)	70.3
2	F2 (-0.50), H4*-2kHz* (-37), H2*-H4* (0.31), F0 cv (-0.30)	66.7
3	F2 (-0.49)	70.8
4	F0 (0.52), CPP cv (-0.48), F0 cv (-0.44)	77.8
5	F2 (-0.66), H4*-2kHz* (-0.30)	64.0

Table 5.4 Discriminant analysis results for the five groups of listeners. All analyses p < 0.001; only weights exceeding 0.3 are listed

²⁹⁷ not result in improved correct classification rates, which generally remained well ²⁹⁸ below those observed for individual listeners. This suggests that, although context ²⁹⁹ effects exist, individuals in even small groups (n = 10) vary enough in perceptual ³⁰⁰ strategies that controlling context effects does not improve correct classification to ³⁰¹ any measurable extent.

To summarize, across all listeners, parameters associated with F0, F0 variability, 302 and vowel quality appear to be important for separating normal from not-normal 303 voices for many, but not most, listeners, and thus provide at best moderate prediction 304 of how a voice will be judged. Listeners' strategies vary with listening context, but 305 modeling this aspect of variation does not improve overall prediction. However, 306 LD analyses indicated that individual listeners' strategies can be well predicted from 307 acoustics, but that listeners differ widely from one another. We conclude that listeners 308 disagree because they are using rather different perceptual strategies, which are more 309 idiosyncratic than they are context dependent. We examine this possibility further in 310 the next section. 311

312 5.3.3 Do Listeners at Least Sort Voices in Similar Fashions?

A final possible explanation for our findings is that listeners rank the voices similarly 313 on a scale from normal to maximally not normal, but differ in where they place the 314 dividing line between categories. This could also have occurred if listeners differed 315 in their interpretation of the size of the "normal" box in the experimental interface. To 316 investigate these possibilities, we calculated Spearman correlations between scalar 317 ratings for all pairs of listeners within a group. Rank-order correlations averaged only 318 0.267 (sd = 0.107; range = -0.093-0.583), indicating that listeners do not agree 319 even about the relative normalness/not-normalness of the voices. 320

5.3.4 Can We Predict the Extent to Which a Voice Sounds Not Normal? What Parameters Are Associated with Increasing Perceived Vocal Deviance for Individual Listeners?

Analyses in previous sections have demonstrated that listeners are individually self-325 consistent but inaccurate and in disagreement when separating normal from not-326 normal voices. To investigate this further, we modeled each listener's perceptual 327 strategy with a series of correlation and multiple regression analyses using only the 328 voices categorized as not normal. First, for each listener, we calculated a multiple 320 regression between the scalar not-normal ratings and the complete set of acoustic 330 measures, entered into the equation in five blocks (F1, F2, F3, and F4; the coefficients 331 of variation; F0; CPP, energy, and SHR; and the four spectral shape parameters). 332 Order of entry was determined by the overall importance of the sets of variables in the 333 LD analyses (Table 5.3). Next, for each listener, we calculated Pearson's correlation 334 between each acoustic measure and the scalar rating on the normal/not-normal scale 335 for that listener, again including only the voices that the listener categorized as not 336 normal. Finally, we calculated additional multiple regressions again relating ratings 337 to acoustic measures for each listener, but this time using only the variables that 338 were significant predictors in the first regression for that listener plus any additional 339 variables that were significantly correlated with that listener's not-normal ratings. 340

Results are shown in Table 5.5. All the regressions were statistically significant (p 341 < 0.01), but all accounted for rather small amounts of variance in listeners' judgments 342 (mean r = 0.477; sd = 0.126; range = 0.227-0.699). As Table 5.5 shows, every 343 variable contributed significantly to predicting ratings for at least one listener, but 344 F0, F1, F2, and F0 cv stand out as more important across listeners than the rest. 345 Recall that these same variables were associated with categorical normal/not-normal 346 judgments for many listeners, as described above. This suggests that, for at least 347 some listeners, deciding whether or not a voice sounds normal and establishing 348 exactly how not normal it sounds depend on the same cues and thus are essentially 349 the same process. 350

5.4 Discussion and Conclusions

To summarize our findings, judgments of diagnostically "normal" versus "not-352 normal" status were at chance. Listeners were relatively self-consistent in their 353 judgments, but disagreed with one another, especially about what counts as nor-354 mal. Agreement was better, but still limited, about what counts as "not normal." This 355 may have occurred because of differences in the possible ranges of the two labels. 356 As noted above, the range of perceived not-normal quality can extend essentially 357 limitlessly. As a result, there will always be voices that are so far from the boundary 358 between normal and not normal that little or no ambiguity exists with respect to 359

Table 5.5 The frequency with which each acoustic variable emerged as a significant predictor in multiple regressions relating acoustic variables to the degree of perceived not-normalness. The most important predictors are listed in **bold type**. The maximum possible value is 50 (=the number of listeners)

Variable	# listeners for whom that variable was a significant predictor of perceived
	not-normalness
H1*-H2*	4
H2*-H4*	7
H4*-H2kHz*	3
H2kHz*-H5kHz	5
СРР	8
Energy	3
SHR	5
FO	19
F1	14
F2	24
F3	3
F4	3
H1*-H2* cv	1
H2*-H4* cv	4
H4*-H2kHz* cv	8
H2kHz*-H5kHz cv	3
CPP cv	9
Energy cv	7
SHR cv	3
F0 cv	26
F1 cv	2
F2 cv	2
F3 cv	10
F4 cv	4

their status. In contrast, logically a voice cannot be more normal than "normal," and
 any deviation in quality, however slight, creates ambiguity (and hence disagreement)
 about the voice's status. The surprising aspect of our results was how completely the
 category "normal" was compromised by this process.

The overall picture that emerges from the present data is one of differences between listeners, but less so within listeners, in the attributes they pay attention to when deciding that a voice is or is not normal. Strategies for separating "normal" from "not normal" differed widely across individual listeners, as did strategies for determining how much a given voice deviated from normal, and all variables in the psychoacoustic model played a role in decisions for at least one listener. However, several variables—F0, F1 and F2, and F0 cv—appeared more often than the others as
significant predictors of both categorical judgments and of scalar normalness ratings.
These variables did not account for most of the variance in these analyses, and did not
consistently appear as a set in the perceptual models for even half of the listeners, but
they did appear individually in most analyses, suggesting that in practice the concept
of "normal" has some small core of meaning based on F0 and vowel quality.

We note that the "core" variables are also important determinants of individual 376 voice quality (see Kreiman & Sidtis, 2011, for review), which is judged in terms of 377 a central category member and idiosyncratic deviations from that "average" voice. 378 Thus, it is possible that (at least some of the time), listeners assess normalness much 379 as they assess individual voice quality in general, with respect to a central pattern and 380 the deviations from that pattern that appear in the particular voice sample at hand. 381 Thus, the answer to our initial question—What does it mean for a voice to sound 382 normal?—is a complex one that depends on the listener, the context, the purpose of 383 the judgment, and other factors as well as on the voice. 384

A few limitations to this research should be noted. First, stimuli were steady-state 385 vowels rather than connected speech. This means that many details that can char-386 acterize disordered speech were not available for consideration, including prosody, 387 articulation, pausing, and other vocal attributes. However, it seems unlikely that 388 inclusion of more complex stimuli would improve overall listener agreement, par-380 ticularly with respect to which voices sound normal. This study was also restricted 390 to female speakers. While it is likely that different parameters will emerge from 391 studies of normal versus not-normal male voices, the fact that listeners' behavior is 392 consistent with broader models of voice perception makes it unlikely that the over-393 all pattern of results would differ substantially. Studies of male voices are currently 304 underway in our laboratory. Finally, the relatively small size of the response box 395 for "normal" voices in the testing interface (Fig. 5.1) may have discouraged some 396 listeners from categorizing too many voices as normal, despite instructions that any 397 number of voices could be placed in the box. However, we note that correlation 398 analyses showed very poor agreement among listeners, suggesting that the effect of 399 this design issue on the overall pattern of results is minimal. 400

In conclusion, these results have implications for ongoing efforts to identify acous-401 tic measures to screen for vocal pathology or the provision of normative values for 402 single acoustic measure. The finding that listeners are self-consistent but highly indi-403 vidual in their perceptual strategies for determining what is and is not normal suggest 404 that automatic protocols or screening based on normative values may be of limited 405 clinical or theoretical use. Clear communication between clinicians and patients in 406 a context of cultural awareness would seem to be the straightest path to satisfactory 407 treatment outcomes. 408

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Abstract	voice typicality, gende —in a set of 60 Ameri predict listeners' abilit been studied from a ra	s the relationship among a suite of voice evaluation metrics—vocal attractiveness, er categorization fluency, intelligibility, acoustic similarity, and perceptual similari ican English voices with the goal of understanding how these evaluation metrics ties to accurately recall voices. This question of what makes a voice memorable hat nge of perspectives, as it raises critical theoretical issues about auditory memory at addition to having applied concerns in the context of acruitmess testimony. We fin				

phonetic encoding, in addition to having applied concerns in the context of earwitness testimony. We find

that the more subjective voice evaluation measures of stereotypicality and attractiveness predict listeners' ability to recall voices more so than the more objective measures related to voice similarity and processing. These results suggest that listeners' cognitive organization of voices is influenced by social assessments of voices.

Keywords

Voice recall - Talker recognition - Voice evaluation - Voice typicality - PCA - Voice organization

Chapter 6 The Role of Voice Evaluation in Voice Recall



Molly Babel, Grant McGuire, and Chloe Willis

Abstract This chapter examines the relationship among a suite of voice evalua-

² tion metrics—vocal attractiveness, voice typicality, gender categorization fluency,

³ intelligibility, acoustic similarity, and perceptual similarity—in a set of 60 Amer-

ican English voices with the goal of understanding how these evaluation metrics
 predict listeners' abilities to accurately recall voices. This question of what makes a

predict listeners' abilities to accurately recall voices. This question of what makes a
 voice memorable has been studied from a range of perspectives, as it raises critical

voice memorable has been studied from a range of perspectives, as it raises entrear
 theoretical issues about auditory memory and phonetic encoding, in addition to hav-

⁸ ing applied concerns in the context of earwitness testimony. We find that the more

subjective voice evaluation measures of stereotypicality and attractiveness predict

¹⁰ listeners' ability to recall voices more so than the more objective measures related

to voice similarity and processing. These results suggest that listeners' cognitive

¹² organization of voices is influenced by social assessments of voices.

Keywords Voice recall \cdot Talker recognition \cdot Voice evaluation \cdot Voice typicality \cdot

PCA \cdot Voice organization

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15 6.1 Introduction

This chapter examines the relationship between vocal attractiveness, voice typicality, and other related vocal evaluation metrics along with listeners' ability to recall voices from memory. What makes a voice memorable has been studied from a range of perspectives as it raises critical theoretical issues about auditory memory and phonetic encoding, in addition to having applied concerns in the context of earwitness testimony. In this work, we explore some of the qualities of the voices that improve and detract from voice recall performance.

Talker recognition or listeners' ability to recall voices they have been previously 23 exposed to is highly affected by what is referred to as the language familiarity effect. 24 Listeners are more accurate at recalling voices that speak the same language as the 25 listener population (Goggin, Thompson, Strube, & Simental, 1991; Perrachione & 26 Wong, 2007; Thompson, 1987; Winters, Levi, & Pisoni, 2008; Perrachione, Del 27 Tufo, & Gabrieli, 2011; Xie & Myers, 2015; Orchard & Yarmey, 1995; Bregman 28 & Creel, 2014) or speak with a familiar accent (Goggin et al., 1991; Stevenage, 29 Clarke, & McNeill, 2012; Senior et al., 2018; Thompson, 1987; Perrachione, Chiao, 30 & Wong, 2010). The mechanism behind these findings is generally considered to be 31 one of listeners' familiarity with the phonetic distribution of sounds in the language 32 or accent. When listeners are familiar with a language or accent, they are better able 33 to determine which acoustic-phonetic features in the speech stream are language-34 specific and which are attributes of a particular speaker's voice (Winters et al., 2008; 35 Perrachione, in press). 36

While this literature has established that voices with familiar languages and accents are generally more accurately recalled, voices within a language variety are not equally memorable. Within a language variety, what makes a voice more or less memorable? Several studies have found that subjective listener ratings of distinctiveness, typicality, memorability, among other evaluative qualities can predict which voices have better recall accuracy (Papcun, Kreiman, & Davis, 1989; Kreiman, & Papcun, 1991; Yarmey, 1991; O'Toole et al., 1998).

For example, Papcun et al. (1989) exposed listeners to 10 voices that had been 44 previously rated on a scale from easy- to hard-to-remember and tested voice recall 45 in an open set task with 1-, 2-, and 4-week delays. Subjects were generally better 46 at rejecting novel voices rather than correctly identifying the voices that they had 47 been exposed to. Specifically, the voices did not differ greatly in accuracy of recall, 48 but did differ in false identifications, such that "hard" voices engendered more false 49 positives. Papcun and colleagues invoke a prototype model to explain these results, 50 hypothesizing that listeners characterize and remember voices in terms of a prototype 51 and deviations therefrom. Thus, more prototypical voices are hard-to-remember as 52 they are more similar to other voices and are more likely to be misidentified as a pre-53 viously heard voice. Papcun and colleagues propose that easy-to-remember voices 54 are less stable in memory because the voice-specific traits that make a voice easy-55 to-remember fade as a function of time, as the voice coalesces toward the prototype, 56 resulting in more false alarms in the longer test delays. The authors attribute this 57

to "a psychological analog to statistical regression to the mean" and suggest that 58 hard-to-remember (prototypical) voices are more stable in memory than easy-to-50 remember (atypical) ones (Papcun et al. 1989, p. 923). In a follow-up study, Kreiman 60 and Papcun (1991) examined the discrimination and recognition accuracy of voices 61 from Papcun et al. (1989). Overall, results were similar to the previous experiment: 62 voices that were rated easier to remember were less likely to be confused with other 63 voices while hard-to-remember voices were easily confused. Of special interest in 64 this study is that the accuracy results were compared with various acoustic and sub-65 jective quality predictors (made by a separate group of listeners) that were assessed 66 via a multidimensional-scaling solution. The authors interpret the most predictive 67 dimensions for the discrimination results to be roughly equivalent to "masculinity," 68 "creakiness," "variability," and "mood" while the recognition results were best pre-69 dicted by what was interpreted as dimensions relating to"masculinity," "breathiness," 70 and "liveliness." These descriptors and their relationship to voice discrimination and 71 recognition are applicable only to the set of 10 voices used in Kreiman and Papcun's 72 studies, but the applicability of these dimensions illustrates the features in which 73 listeners cognitively organize this set of voices. 74

Voice typicality was the explicit subject evaluation under consideration in 75 Mullennix et al. (2011). Mullennix and colleagues asked listeners to evaluate 40 76 voices for typicality, using these judgments to prune the larger set for a memory 77 task. The voices with the highest (4 male, 4 female) or lowest (4 male, 4 female) 78 typicality ratings were selected. An independent group of listeners were exposed 79 to the 16 subset voices in a vowel identification task, and were then given a sur-80 prise memory task. Overall, listeners were more accurate with the voices they had 81 previously trained on, but showed a bias to make recognition errors when typical 82 voices were used as foils, especially listeners exposed to typical voices. A recur-83 ring theme across these studies is that unique or distinctive voices are more easily 84 remembered. What listeners rate when evaluating voices in terms of distinctiveness 85 or typicality is not clear, but it appears to be a measureable quality that listeners 86 exhibit agreement on. Typicality and distinctiveness may be connected to speech 87 clarity and the predictability of phonetic variation. Voices vary in how clearly they 88 produce linguistic contrasts, and this variation in contrast clarity has implications for 89 how listeners process and recognize the speech stream (Bradlow, Torretta, & Pisoni, 90 1996; Newman, Clouse, & Burnham, 2001). How an individual manifests a phonetic 91 contrast is a talker-specific feature that listeners track and exploit in subsequent pro-92 cessing, spilling over into perceptual events beyond the moment of comprehension 93 (Theodore, Myers, & Lomibao, 2015). Too much phonetic variation can affect lis-94 teners' confidence in their categorization of speech sounds (Clayards, Tanenhaus, 95 Aslin, & Jacobs, 2008). Unexpected or unfamiliar phonetic variation associated with 96 accents or dialects that are different from one's own makes comprehension and recog-97 nition more challenging (Clopper & Pisoni, 2004; Bradlow & Bent, 2008), and this 98 is often attributed to lack of exposure and experience. While this may be intuitive 99 when thinking about nonnative speakers, the evidence is mixed as to whether non-100 native speakers are more variable in their acoustic-phonetic realizations than native 101 speakers (Vaughn et al., 2020; Wade, Jongman, & Sereno, 2007). Talker variability 102

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occurs within an accent or speech community as well (Strand, 1999; Bradlow et al., 103 1996; Babel & McGuire, 2015), resulting in intelligibility and memory benefits for 104 familiar speakers (Nygaard & Pisoni, 1998). Accents that may be less familiar, but 105 are the standard variety, often, however, show similar processing benefits to famil-106 iar varieties (Clopper, 2014; Clopper, Tamati, & Pierrehumbert, 2016), suggesting 107 that the cognitive organization of voices is not exclusively tailored to the quantity 108 of experience, but may involve some preferential encoding of socially prestigious 109 exemplars (Babel, 2012; Babel, McGuire, & King, 2014b; Sumner, Kim, King, & 110 McGowan, 2014). 111

How does the social evaluation of voices affect processing or the cognitive orga-112 nization of voices? As is clear from the topic of this book, there is extensive evidence 113 that listeners assess voices in terms of their attractiveness. The patterns by which 114 voices are deemed attractive seem to be a combination of culturally acquired (Babel, 115 McGuire, Walters, & Nicholls, 2014a; Bezooijen, 1995) and more strongly evolution-116 arily encoded (Zuckerman & Miyake, 1993; Puts, Gaulin, & Verdolini, 2006; Riding 117 et al., 2006; Saxton et al., 2006; Feinberg, DeBruine, Jones, & Perrett, 2008; Apicella, 118 Feinberg, & Marlowe, 2007) preferences that tap into acoustic-phonetic dimensions 119 that are related to sexually dimorphic traits. Many of the culturally acquired compo-120 nents appear to stem from what is typical or standard within a speech community. 121 While there may be initial appeal in thinking of typicality or standardness in terms 122 of the pattern that is the most common or at the peak of a community's acoustic-123 phonetic distribution, linguistic standardness is much more of an imposed concept. 124 Listeners tend to show stronger recognition patterns for pronunciation variants that 125 are standard, despite a different pronunciation variant being far more frequent in the 126 input (Sumner & Samuel, 2005) and listeners exhibit more false memories for a less 127 socially prestigious accent compared to a more prestigious accent, despite equiva-128 lence in experience with the two (Sumner & Kataoka, 2013). Media is one means 129 through which standardness and socially conditioned social preferences appear to 130 be formed for speech communities (Kinzler & DeJesus, 2013; Lippi-Green, 2012). 131 Overall, this body of literature makes clear that not all voices are treated equivalently 132 in terms of processing and that both exposure and social preference play a role in 133 voice evaluation. 134

To better understand the dimensions on which listeners may organize voices and 135 how this organization may affect voice recall, we first report on a set of experiments 136 and analyses intended to quantify the typicality of a set of voices from 60 American 137 English speakers. These experiments provide two response time-based measures— 138 Intelligibility and Categorization Fluency—designed to better reflect exposure by 139 tapping into online frequency effects. Previous research has shown that response 140 latency to voices is a proxy for familiarity; words are more likely to be recognized 141 quickly if heard in a familiar voice rather than an unfamiliar voice (Goldinger, 1996). 142 For the intelligibility task, listeners were asked to shadow voices embedded in noise 143 and in the Categorization Fluency task, listeners identified voices as male or female 144 in a speeded fashion. In both cases, faster responses indicate easier processing for a 145 given voice. Additionally, we provide two subjective assessments, perceived Attrac-146 tiveness and perceived Stereotypicality. For both of these assessments listeners were 147

asked to subjectively rate the voices on either their attractiveness or typicality. We 148 expect these measures to better tap into social preference. Because previous stud-149 ies demonstrate that more similar voices are less likely to be remembered and are 150 more likely to be considered a previously heard voice, we also include two measures 151 of similarity, one based on auditory-acoustic measures, Acoustic Similarity, and 152 one based on comparative listener ratings, Perceptual Similarity. After reporting the 153 methods and results of each of these experiments, we examine to what extent these 154 measures tap into similar dimensions in Sect. 6.2.7. Following this, Sect. 6.3 reports 155 on a voice recall experiment, which we analyze with the voice evaluation metrics to 156 assess which voice metrics best predict voice recall performance. 157

6.2 Voice Evaluation Experiments

159 6.2.1 Materials for All Experiments

The voice stimuli used in all the experiments reported here were from participants recruited as part of a previous study (Babel, 2012). They consist of 30 female (mean age 24, range 18–57) and 30 male (mean age 24, range 18–47) native speakers of American English reading 50 low-frequency monosyllabic words. For the present study a subset of 15 words which contain /i a u/ as the syllable nucleus were selected for each voice, 5 words per vowel (Table 6.1).

166 6.2.2 Intelligibility

To quantify the intelligibility of the voices, we used a speeded shadowing task where the response time to the onset of vocalization is taken as a proxy for how easy it was for listeners to understand the utterance.

	the off the tender of te						
/i/		/a/	/u/				
deed		cot	boot				
key		pod	dune				
peel		sock	hoop				
teal		sod	toot				
weave		tot	Z00				

Table 6.1	Words used in the e	periments organized by	the vowel category	for each item

170 6.2.2.1 Participants

Thirty participants (15 male, 15 female) were recruited from the University of California, Santa Cruz, undergraduate population and were compensated with course
credit. All were native speakers of American English from the state of California.
Ages ranged from 18 to 23, mean 20.4 years.

175 **6.2.2.2 Materials**

The same voices and words used in the gender categorization fluency task were used in this task. Each individual sound file was embedded in pink noise at +6 dB signal to noise ratio (SNR). The noise began at the onset of each word and ended at the offset of each word.

180 **6.2.2.3 Procedure**

Participants were seated in a sound-attenuated booth at a computer workstation wear-181 ing AKG HSC271 model headset with integrated condenser microphone. The stimuli 182 were presented in a randomized order at a comfortable listening volume (approxi-183 mately 70 dB). Subjects were asked to repeat each word, initiating their repetition as 184 quickly as possible without compromising accuracy. Response times were measured 185 from the onset of the stimulus to the onset of the subject's production as registered 186 by a microphone connected to a PST serial response box. The response time for each 187 trial was displayed on the computer monitor to participants to help motivate fast 188 response times. This feedback screen was displayed for 1000 ms, after which a new 189 trial began. Each word production was recorded as a unique .wav file. 190

191 6.2.2.4 Results

Response time was automatically calculated for each production, and the accuracy of each shadowed production was determined by manual coding. A custom-written program brought up each individual sound file and provided an orthographic transcription of the intended word. Each production was categorized as correct or incorrect. Productions with disfluencies, missing phones, or the wrong lexical item were considered incorrect.

Accuracy of the repeated item is a measure of recognition. Female (M = 81%correct, SD = 39) voices achieved higher recognition rates than the male (M = 76%correct, SD = 42) voices [t (51.67) = 2.47, p = 0.02], indicating that female voices were overall more intelligible than the male voices. Correct responses for reaction times within two standard deviations of the group mean were then aggregated across words for each voice. Using response time to correctly identified items as a proxy for intelligibility, we found no significant differences between male and female voices

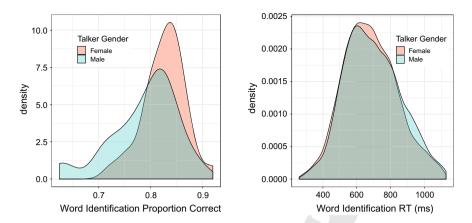


Fig. 6.1 Density plots showing the distribution of accuracy of correctly identifying each item (left panel) in a speeded shadowing task and the distribution of voice intelligibility, as measured by response lag (right panel) in a speeded shadowing task

 $_{205}$ [t (56.04) = 1.68, p = 0.098]. When items were accurately recognized, there was no difference in the intelligibility of those items for female and male voices. These aggregate measures mask the talker-specific variability of these measures. Figure 6.1 provides density plots to illustrate the range of recognition scores (left panel) and intelligibility (right panel).

210 6.2.3 Gender Categorization Fluency

In order to have an online estimate of typicality, the voices were assessed using a gender categorization fluency task. This is a speeded classification task where subjects heard a single word and quickly decided the gender of the voice. Previous work has used this for evaluation of typicality for faces (Orena, Theodore, & Polka, 2015) and voices (Strand, 1999).¹

216 6.2.3.1 Participants

Thirty participants (15 male, 15 female) were recruited from the University of California, Santa Cruz, undergraduate population and were compensated with course
credit. All were native speakers of American English from the state of California.
Ages ranged from 18 to 24 years, with a mean of 21.

¹The data from this experiment were originally reported in Babel and McGuire (2015).

221 6.2.3.2 Materials

In order for the task to be feasible for the participants to complete in 45 min, the word list was pruned to nine words for each talker (9 words \times 60 voices = 540 stimuli). The original word list was presented to an independent group of university students (n = 23) who rated how likely each word was to be used by males or females. The words *teal, weave, pod, sod, toot,* and *dune* were identified as the most gender-valenced of the word set and were removed from the list.

228 6.2.3.3 Procedure

Listeners were presented with the individual words, one per trial. Words and voices
were randomized across all voices, and participants were prompted to respond to
each word by selecting whether the voice that said the word was male or female.
Reaction time feedback was given after each trial and listeners were asked to respond
in less than 500 ms. Each trial timed out after 1500 ms if no response was given.

234 6.2.3.4 Results

Response times for correct responses (98% of the data) made within two standard deviations of the mean were then aggregated across words for each voice. The speed at which listeners identified male (M = 523 ms, SD = 17.5) and female (M = 525 ms, SD = 14) voices differed was nonsignificant [t(55.93) = 0.56, p = 0.58].

239 6.2.4 Acoustic Similarity

To assess the voices in terms of their raw acoustic-auditory similarity, we calcu-240 lated voice similarity using mel-frequency cepstral coefficients (MFCCs). While 241 MFCCs have no straightforward perceptual interpretations, they provide a global and 242 unbiased acoustic assessment of the speech signal. This type of unbiased acoustic 243 measurement is useful when trying to determine the extent to which listeners' orga-244 nization of sound patterns are faithful to acoustic-auditory parameters or whether 245 they are influenced by listeners' experiences (Cristiá, Mielke, Daland, & Peperkamp, 246 2013; Mielke, 2012). The choice to use MFCCs, as opposed to resonant frequen-247 cies or other spectral properties more readily connected to listeners' perception of 248 phoneme categories, allows us to side-step any explicit decision about which aspects 249 of the speech spectrum to explicitly measure. 250

251 6.2.4.1 Materials

²⁵² The set of 15 words produced by the 60 talkers was used in this analysis.

253 6.2.4.2 Procedure

The MFCC acoustic similarity algorithm implemented in Phonological CorpusTools 254 (PCT; Hall, Allen, Fry, Mackie, & McAuliffe, 2018) was used to quantify acoustic 255 vocal distinctiveness within the voice set. In this analysis, twenty-six mel-scaled tri-256 angular filters are applied to a windowed signal, and the resulting spectrum is the log 257 of the power of each filter. The mel-frequency cepstrum is calculated using a discrete 258 cosine transform, resulting in twelve coefficients. MFCCs are then compared using a 259 dynamic time warping algorithm, which ultimately returns the summed distances of 260 the best path through the data matrix. This comparison was done between matched 261 words and each voice in the data set. While dynamic time warping may eliminate 262 durational differences among tokens, and thus one cue to gender, it is a reliable 263 way to directly compare the tokens. We chose this method over correlation-based 264 approaches to quantifying spectral similarity because of precedent in the speech lit-265 erature (Mielke, 2012) and the challenges of correlating signals of different lengths. 266

267 6.2.4.3 Results

To compare the acoustic vocal distinctiveness in the voice set, the similarity values for 268 each voice comparison were averaged and used to create a distance matrix. Distance 269 matrices were created separately for male and female voices as a combined analysis 270 resulted in a first dimension that simply separated male and female voices. For both 271 female and male voice sets, a scree plot of stress suggested an elbow at the fourth 272 dimension, therefore a four-dimensional multidimensional-scaling solution was fit 273 to each matrix using isoMDS() from the MASS package in R (Venables & Ripley, 274 Venables and Ripley (2002)). For the female set, the stress of the four-dimensional 275 solution was 8.28, while the stress of the four-dimensional solution was 6.78 for the 276 male set.² The visualization of the first two dimensions for both the female and male 277 voices sets are presented in the left panel of Fig. 6.2. We have made no attempt to 278 identify the dimensions. 279

To use the similarity scores alongside the other voice evaluation metrics, we created a distance score for each voice. Given that talker gender was a robust dimension on which the voices were separated in the MDS space, the voice distance score was calculated separately for female and male voices. Following methods of calculating vowel dispersion (e.g., Ménard et al. 2013), acoustic voice similarity was calculated using the four dimensions of the MDS solution for each gender by taking the

²Note that these stress values are not indicative of a particularly strong fit, indicating that more dimensions might ultimately provide a better characterization of the data.

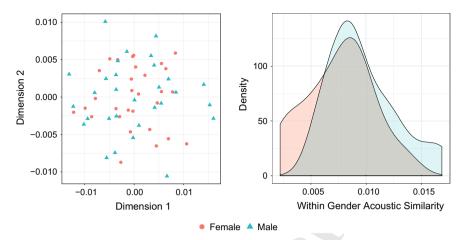


Fig. 6.2 The first two dimensions of the four-dimensional scaling solutions for the MFCC acoustic similarity of the 60 voices (left panel) and a density plot showing the distribution of within-gender acoustic variability for the 60 voices (right panel). Higher values along the x-axis in the density plot indicate more acoustically dissimilar voices. Female data are in red, and male in cyan

Euclidean distance of a voice from the average four-dimensional values for all other
voices of that voice's gender. The distribution of these values was relatively normal,
and is shown in the right panel in Fig. 6.2.

289 6.2.5 Perceptual Similarity

Even when measures of acoustic similarity use a transformation that models the human auditory system (like the mel-scale used in Sect. 6.2.4), such analyses may not adequately weigh or represent the cues that perceivers rely on when assessing voices. To address this, we conducted a similarity rating experiment using the voice corpus.

295 6.2.5.1 Participants

A research assistant who was a female native speaker of West Coast English (age = 19) completed this task with all 60 voices.³

³While having just a single listener does affect the potential generalizability of our conclusions, we ultimately feel this single data point is better than no data point.

298 6.2.5.2 Materials

²⁹⁹ The 15 words spoken by the 60 voices were used as stimuli in this task.

300 6.2.5.3 Procedure

On a given trial, a random selection of nine words (three from each vowel group) 301 from a voice were presented in randomized order with 500 ms interstimuli interval, 302 followed by 1000 ms break, then a second voice comprising the same nine words. 303 After the presentation of the second voice, the participant rated the similarity of 304 the voices on a scale from 1 (very dissimilar) to 9 (very similar) using a computer 305 keyboard. All possible nonidentical pairs were presented in both orders resulting in 306 3480 trials (60 voices, 602 pairs = 3600, minus $60 \times 2 = 120$ identical pairs). Given 307 the tedious and repetitive nature of this task, it was conducted at the participant's 308 convenience over the course of several months. 309

310 6.2.5.4 Results

The ratings matrix was simplified in a similar way to the acoustic similarity data. 311 Again, a combined analysis demonstrated that the first dimension was based on 312 voice gender, so separate within-gender analyses were fit. A scree plot of stress 313 suggested an elbow at four dimensions for both analyses and thus a four-dimensional 314 nonmetric multidimensional-scaling solution was fit to each matrix using isoMDS() 315 from the MASS package in R (Venables and Ripley, 2002). The stress of the four-316 dimensional solution was 8.36 for the female set and 7.48 for the male set of voices.⁴ 317 The visualization of the first two dimensions for both the female and male voices 318 sets are presented in the left panel of Fig. 6.2. 319

For comparison with the other measures, perceptual voice similarity was calculated in an identical way to the similarity data. That is, separate distance scores were created for male and female voices by using the four dimensions from the MDS solutions and finding the mean Euclidean distance for each voice by gender. The distribution of these values is shown in right panel of Fig. 6.3.

325 6.2.6 Subjective Voice Ratings

To examine how listeners' subjective impressions of a voice's attractiveness and stereotypicality affect voice memory alongside the more objective measures described above, we collected the metrics described below.⁵

⁴Again, these high stress values suggest that more dimensions could provide a better fit to the data. ⁵These subjective voice ratings were previously reported in Babel and McGuire (2015).

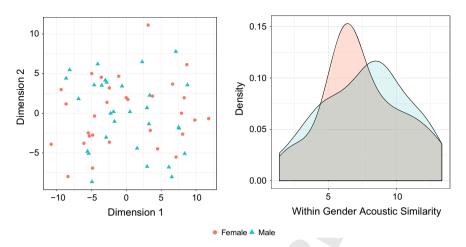


Fig. 6.3 The first two dimensions of the three-dimension multidimensional-scaling solution for the perceptual similarity of the 60 voices (left panel) and a density plot showing the distribution of within-gender perceptual variability for the 60 voices (right panel), where higher values along the x-axis indicate more perceptually dissimilar voices. Female data are in red, and male in cyan

329 6.2.6.1 Participants

Sixty participants were recruited for explicit rating tasks from the student population
 of the University of California, Santa Cruz and received course credit or \$10 for their
 participation. Participants were divided into two groups of thirty (15 male, 15 female,
 each) and assigned to either the Stereotypicality rating group or the Attractiveness
 rating group.

335 6.2.6.2 Materials

The full set of 15 words for the 60 talkers were used in the tasks that elicited ratings of stereotypicality and attractiveness.

338 6.2.6.3 Procedure

For both experiments, subjects heard each voice say each of the 15 words followed by a pause where they were prompted to rate the voice using a 1–9 scale where 1 was "Very Unattractive" or "Very Atypical" and 9 was "Very Attractive" or "Very Typical." All voices and words were presented in a randomized order. "Attractiveness" was not defined for the participant; they were free to evaluate the voice for sexual attractiveness or pleasantness.

Table 6.2 Mean and standard deviations of the Attractiveness and Stereotypicality Ratings for the male and female voices are shown in the leftmost columns. The Kendall's *W* values for the ratings are in the rightmost columns

	Female voices	Male voices	Female voices (W)	Male voices (W)
Attractiveness				
Female raters	5.05	4.67	0.274***	0.274***
Male raters	5.07	4.05	0.476***	0.185***
Stereotypicality				
Female raters	6.8	6.62	0.311***	0.255***
Male raters	6.54	6.52	0.325***	0.261***

Values marked with *** indicate p-values <0.001

345 6.2.6.4 Results

Female voices were overall rated as more Attractive and Stereotypical than male voices. Listeners' ratings were assessed for reliability using Kendall's *W*, and listeners showed a range of agreement levels. These values are given in Table 6.2.

349 6.2.7 Global Voice Assessment

While the six voice evaluation metrics are based on unique perception tasks posed 350 to unique groups of listeners or, in the case of the acoustic similarity metric, an inde-351 pendent acoustic-auditory measurement, the metrics may indeed tap into common 352 means of cognitively organizing voices. To assess this, we conducted a principal 353 components analysis (PCA) on a centered and scaled data matrix using the averaged 354 values for each talker's voice using a singular value decomposition strategy.⁶ The 355 loadings of the PCA are shown in Table 6.3 and the model summary is presented in 356 Table 6.4. The first principal component accounts for only about 32% of the variance 357 in the data, and the loadings of this component illustrate the positive relationship 358 between perceived attractiveness and stereotypicality along with the negative rela-359 tionship of these two dimensions with categorization fluency (Babel & McGuire, 360 2015). The second principal component appears to show a negative relationship 361 between acoustic similarity and intelligibility of the voices. The third component 362 seems to be driven by perceptual similarity. 363

Somewhat surprisingly, it takes until the fifth principal component for the 95% of the variance to be accounted for. This suggests that not much is achieved through this process of dimensionality reduction and these dimensions, while not completely independent, are not wholly interconnected.

⁶This was done using the prcomp() command in base R.

	PC1	PC2	PC3	PC4	PC5	PC6
Attractiveness	0.5774	-0.3100	0.2280	-0.1354	0.2472	0.6625
Stereotypicality	0.6074	-0.03364	0.1849	-0.3875	-0.0630	-0.6645
Categorization fluency	-0.4454	-0.3349	0.4282	-0.2232	0.6449	-0.2021
Intelligibility	-0.2520	-0.6179	-0.1913	-0.4972	-0.5133	0.0863
Perceptual similarity	0.1189	-0.1101	-0.8328	-0.1379	0.5039	-0.0848
Acoustic similarity	0.1466	0.6298	0.0165	-0.7170	0.0456	0.253

 Table 6.3
 Rotation of the six voice evaluation metrics and the principal component loadings

Table 6.4 Summary of the PCA on the six voice evaluation metrics

	PC1	PC2	PC3	PC4	PC5	PC6
Standard deviation	1.3931	1.1541	1.0860	0.8931	0.6911	0.5222
Proportion of variance	0.3234	0.2220	0.1966	0.1329	0.0796	0.04546
Cumulative proportion	0.3234	0.5454	0.7420	0.8750	0.9545	1.000

Given this, these metrics will be used below to predict performance in the voice memory task.

370 6.3 Voice Memory Experiment

The previous sections summarized data evaluating voices using several subjective 371 measures (Stereotypicality, Attractiveness), online processing measures (Categoriza-372 tion Fluency, Intelligibility), and similarity (Acoustic-Auditory, Perceptual). In this 373 section, we turn to the original goal of the paper and use these measures to predict 374 listeners' ability to recall individual voices. Following previous literature, we expect 375 that less typical voices will be easier to recall than more typical voices, and the 376 following experiment will elucidate which of our measures are best at predicting 377 this. 378

379 6.3.1 Methods

380 6.3.1.1 Participants

There were 42 listeners in four counterbalanced groups. All were native speakers of American English and had lived in California since toddlerhood. They were recruited at the University of California, Santa Cruz, and received partial course credit for their
 participation.

385 **6.3.1.2** Procedure

The voices were divided into two lists of 30 and two word sets for the purposes of 386 balancing. The two voice lists were designed to have an equal number of male and 387 female voices in each and to be roughly equivalent in stereotypicality. The words 388 were randomly assigned to two lists with the constraint that each list had two words 389 for each vowel. In the exposure phase, listeners were presented with one list of 30 390 voices each saying six words and asked to type each word as accurately as possible. 391 This was similar to Mullennix et al. (2011) in that the exposure phase was a linguistic 392 task rather than a talker-focused one. After a brief self-paced break listeners were 393 given a surprise memory task where they were again presented with voices. This 394 procedure was identical to the exposure phase except that (1) the full set of 60 voices 395 was used and (2) rather than type in the words spoken, subjects were asked to identify 396 each voice as either Old (i.e., previously heard) or New (i.e., not previously heard), 397 logging their response on labeled buttons on a serial response box. Participants were 398 run in groups of up to three at a time in a sound-attenuated booth. 300

400 6.3.2 Results

401 6.3.2.1 Listener-Focused Analysis

To model listeners' decisions regarding the voices, a mixed-effects logistic regression 402 model was used to analyze the probability that listeners could correctly identify the 403 voices as New or Old. Given that the dimensionality reduction of the PCA was not 404 particularly effective (e.g., it took five principal components to account for 95% of 405 the variance when six variables were entered into the model), we also assessed the 406 collinearity of the six voice evaluation metrics via condition number and a variance 407 in inflation (VIF) calculation prior to including these metrics in the model. The 408 condition number analysis, following Baayen (2008), gave a kappa statistic of 22, 409 and the highest VIF value was 2.5. These are both generally considered moderate in 410 terms of collinearity. Given this and the results of the PCA, we opted to include the 411 six metrics in the model. To assist in the interpretability of the model output, however, 412 the six metrics were entered into the model as fixed effects with interactions with 413 New/Old, but not as interactions with each other. New/Old was entered into the 414 model as a fixed effect with dummy coding; New was the reference level. There 415 were random slopes for listeners, along with the random intercepts for New/Old and 416

	Estimate	Standard error	z-value	p-value
Intercept	-0.1841	0.1678	-1.097	0.2726
New/Old	0.72821	0.29796	2.444	0.01453*
Attractiveness	-0.1719	0.0999	-1.721	0.08517
Stereotypicality	-0.5680	0.09735	-5.835	< 0.001***
Categorization fluency	-0.0886	0.0781	-1.135	0.2563
Intelligibility	0.02133	0.07426	-0.287	0.7739
Perceptual similarity	0.0379	0.07043	0.539	0.5901
Acoustic similarity	-0.2146	0.07218	-2.97	0.0029**
New/Old:Attractiveness	0.1562	0.12655	1.234	0.2170
New/Old:Stereotypicality	0.7499	0.1279	5.863	< 0.001***
New/Old:Categorization fluency	-0.0071	0.10647	-0.067	0.9468
New/Old:Intelligibility	0.19416	0.0991	1.959	0.0501
New/Old:Perceptual similarity	-0.11858	0.0966	-1.226	0.2201
New/Old:Acoustic similarity	0.24846	0.0980	2.535	0.0603

Table 6.5 Model output for the listener-focused voice memory analysis

P-values marked with * indicate values <0.05, ** indicates values <0.01, and *** indicates values <0.001

the voice evaluation metrics. All of the voice evaluation metrics were centered and scaled prior to the regression analysis.⁷

The results of this analysis are summarized in Table 6.5. The lack of a significant 419 intercept indicates that listeners were not very accurate at identifying previously 420 unheard or novel voices as New. The effect of New/Old illustrates that listeners 421 were more accurate at correctly recalling old voices as old than new voices as new. 422 In terms of the voice metrics, Stereotypicality was a significant predictor, and it 423 also surfaced in a significant interaction with New/Old. New voices that had been 424 independently rated as less stereotypical were more accurately identified as new than 425 more stereotypical new voices, and old voices which were more stereotypical were 426 more accurately identified as old than older voices that were less stereotypical. This 427 relationship is shown in the left panel of Fig. 6.4. Acoustic Similarity was also a 428 significant predictor. Listeners were less accurate on new voices that were further 429 from the Euclidean mean of the voice set. That is, listeners were more accurate 430 with voices that were more acoustically typical, somewhat in contradiction with the 431 Stereotypicality results. This relationship is shown in the right panel of Fig. 6.4. 432

⁷The following code was used: glmer(Accuracy New/Old + Attractiveness + Stereotypicality + Categorization Fluency + Intelligibility + Perceptual Similarity + Acoustic Similarity + New/Old:Attractiveness + New/Old:Stereotypicality + New/Old:Categorization Fluency + New/Old:Intelligibility + New/Old:Perceptual Similarity + New/Old:Acoustic Similarity + (1 + New/Old + Attractiveness + Stereotypicality + Categorization Fluency + Intelligibility + Perceptual Similarity + Acoustic Similarity IListener)).

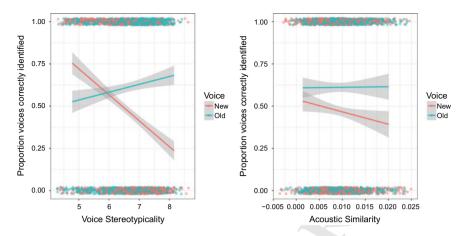


Fig. 6.4 The relationship between voice recall accuracy for Old and New voices and Stereotypicality (left panel) and Acoustic Similarity (right panel). The jittered points represent listener responses

433 6.3.2.2 Talker-Focused Analysis

To model voice memory with a focus on the talkers' voices, the signal detection 434 theory measures of d' (sensitivity) and c (bias) were calculated across listeners for 435 each voice (Macmillan & Creelman, 2004). For this analysis the data were averaged 436 across listeners for each voice and correct responses to Old voices were assigned as 437 hits and incorrect Old responses to New voices were assigned as false alarms. This 438 calculation results in positive values of d' indicating that listeners correctly identified 430 voices as Old or New, while negative values indicate listeners had more false alarms 440 than hits and, thus, incorrectly classified the voices. The assignment of correct Old 441 responses as hits also means that negative values of c, indicate a bias to respond Old 442 and a positive number indicates a bias to respond New. These d' and c values were 443 used as the dependent measures in simple linear regression models where each voice 444 evaluation measure was entered as an independent variable along with talker gender. 445 Because of the small number of observations one is left with in this style of analysis 446 (n = 60, one data point per talker), we chose to run separate regression models for 447 each voice evaluation metric. 448

⁴⁴⁹ Model results for the d' analysis are summarized in Table 6.6. They indicate ⁴⁵⁰ voices which were lower in attractiveness and stereotypicality had higher d' values, ⁴⁵¹ indicating listeners were more sensitive to the New/Old decision for voices that ⁴⁵² were previously rated as less attractive or less stereotypical. The R^2 values indicate ⁴⁵³ that this pattern was more robust along the Stereotypicality than the Attractiveness ⁴⁵⁴ dimension. Figure 6.5 illustrates these patterns.

The *c* results complement these findings and are summarized in Table 6.7. There was a bias to respond Old to voices that had been rated as Attractive and Stereotypical. Again, there was a larger effect size for the Stereotypicality voice evaluation metric, compared to Attractiveness. These results are visualized in Fig. 6.6.

	Estimate	Standard error	z-value	p-value	Adjusted R ²
Intercept	1.22	0.32	3.83	< 0.001***	
Attractiveness	-0.20	0.07	-3.11	0.003**	0.13
Intercept	2.41	0.48	5.06	< 0.001 ***	
Stereotypicality	-0.33	0.07	-4.57	<0.001***	0.25
Intercept	-1.37	2.31	-0.59	0.56	/
Categorization fluency	0.003	0.004	0.70	0.49	-0.009
Intercept	-1.98	1.30	-1.52	0.13	
Intelligibility	0.003	0.002	1.71	0.09	0.03
Intercept	-0.049	0.08	-1.01	0.08	
Perceptual similarity	2.508	0.10	0.89	0.32	-0.07
Intercept	0.48	0.17	2.87	0.0057**	
Acoustic similarity	-25.68	16.77	-1.531	0.13	0.022

Table 6.6 Model summaries for the d' sensitivity talker-focused voice memory analysis. The Adjusted R^2 for each model's fit is reported in the final column

P-values marked with ** indicate values <0.01 and *** indicates values <0.001

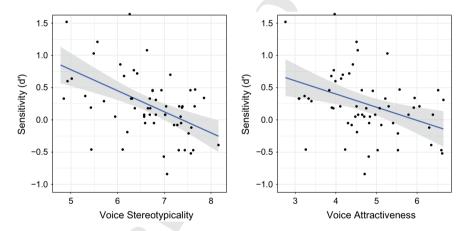


Fig. 6.5 Sensitivity by Stereotypicality (left panel) and Attractiveness (right panel) in the Voice Recall task. Each point represents a talker in the experiment

Together, these results indicate that listeners were more accurate in the voice memory task with voices that were less Attractive and Stereotypical, and there was a strong bias for listeners to respond Old to voices that were more Attractive and Stereotypical.

	Estimate	Standard error	z-value	p-value	Adjusted R ²
Intercept	0.77	0.24	3.21	0.002 * *	
Attractiveness	-0.18	0.05	-3.68	< 0.001***	0.18
Intercept	1.89	0.34	5.54	< 0.001***	
Stereotypicality	-0.30	0.05	-5.86	<0.001***	0.36
Intercept	-2.23	1.77	-1.26	0.21	7
Categorization fluency	0.004	0.003	1.21	0.23	0.008
Intercept	0.02	1.03	0.02	0.99	
Intelligibility	-0.0002	0.002	-0.11	0.92	-0.02
Intercept	-0.092	0.412	-0.091	0.76	
Perceptual similarity	0.022	0.07	0.71	0.42	-0.01
Intercept	0.0095	0.133	0.071	0.943	
Acoustic similarity	-11.197	13.15	-0.85	0.39	-0.004

Table 6.7 Model summaries for the *c* bias talker-focused voice memory analysis. The Adjusted R^2 for the model fit is reported in the final column

P-values marked with ** indicate values <0.01 and *** indicates values <0.001

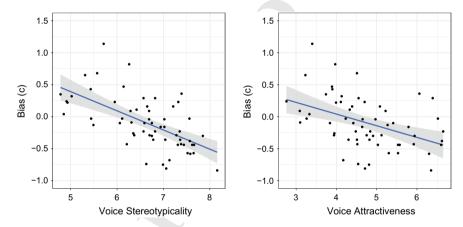


Fig. 6.6 Bias by Stereotypicality (left panel) and Attractiveness (right panel) in the Voice Recall task. Negative values indicate a bias to respond Old, while positive values indicate a bias to respond New

463 6.4 General Discussion

Listeners process the communicative linguistic signal of a voice while they evaluate it socially (Sumner et al., 2014). In this chapter, we used a combination of online intelligibility and processing measures, measures of acoustic–auditory and perceptual similarity, and subjective voice evaluations to predict voice memory. For decades, it has been established that voice evaluation related to distinctiveness or typicality was a strong predictor of listeners' ability to recall voices (Papcun et al., 1989; Kreiman & Papcun, 1991; Mullennix et al., 2011). In line with these earlier
claims, we find that our subjective measures of voice evaluation—perceived Stereotypicality and Attractiveness, two related dimensions for this set of voices (Babel &
McGuire, 2015)—predict performance in a voice recall task, as did our measure of
Acoustic–Auditory similarity. Notably, the more online measures of intelligibility
and gender categorization fluency do not. Perceptual similarity also did not predict
performance, but it is difficult to draw conclusions from one listener.

In this corpus of voices, we can conceive of voices that are more stereotypical 477 and more attractive as being analogous to the voices that Papcun et al. (1989)'s 478 listeners identified as hard-to-remember voices. In our study, these stereotypical and 479 attractive voices are more accurately identified as old voices (i.e., voices previously 480 heard in the experiment) when they are indeed old. Listener accuracy on stereotypical 481 and attractive new voices that listeners were not exposed to was poor. The signal 482 detection theoretic analyses illustrate that listeners had decreased sensitivity to more 483 stereotypical and attractive voices and this was due to listeners having a strong bias 484 to respond "old" to these stereotypical and asesthetically pleasing voices. Papcun, 485 Kreiman, and colleagues (Papcun et al., 1989; Kreiman & Papcun, 1991) argue that 486 their results support a prototype model of voice memory: voices that are typical are 487 well-represented and thus trigger the illusion of experience. Our results complement 488 these findings by providing insight into what voice attributes these prototypes are 480 structured around. In the context of voice memory, it appears that more subjective 490 voice evaluations are at the core of the prototype structure, particularly perceived 491 stereotypicality, as opposed to more objective, online measures like intelligibility 492 or categorization fluency or measures of voice similarity taken from the acoustic-493 auditory or perceptual space. 101

The results do raise a contradiction in that listeners were less accurate at identi-495 fying acoustically atypical voices as New while voices judged less stereotypical are 496 more accurately identified. These two voice measures, Stereotypicality and Acoustic 497 Similarity are not correlated for our data set [r = -0.02, p = 0.25]. Moreover, our 498 measure of acoustic similarity is based on MFCCs, which while usefully exploited for 499 automatic talker recognition systems, may not at all adequately capture the phonetic 500 detail around which human listeners organize and distinguish voices. Our attempt to 501 use an online measure of listener-derived voice similarity is stymied by the duration 502 of the task, thus providing us with the perceptual space of a single listener. While the 503 previous research aligns well with our results regarding stereotypicality and attrac-504 tiveness, more research is necessary to understand the role of voice similarity in the 505 acoustic and perceptual domains. 506

Sociocultural influences shape listeners' interpretation and social assessment of 507 voices and accents (Hay, Jennifer, Warren, Paul, & Drager, Katie, 2006; Babel & 508 Russell, 2015), in addition to shaping the, for example, gender-specific realization 509 of spoken language (Johnson, 2006; Foulkes, Docherty, & Watt, 2005). Listeners' 510 assessments of what is typical appear not to be based on veridical interpretation of 511 the statistical distributions that listeners are exposed to, but rather are a reflection of 512 a cognitive reorganization that is based on community standards and norms (Sum-513 ner et al., 2014; Babel & McGuire, 2015). The results of the voice memory task 514

ditor Proof

reported here provide a concrete example of where this has implications: attractive
and especially stereotypical voices are recalled less accurately because of a bias
to assume they have been previously experienced. Individuals with more typical or
attractive voices may thus receive a social benefit in terms of processing advantages
that familiar accents experience.

520 6.5 Conclusion

These results generally support previous research that less typical and more unusual 521 voices are more easily recalled from memory (Papcun et al., 1989; Kreiman & Pap-522 cun, 1991; Mullennix et al., 2011). Using several different evaluations of voices we 523 find that stereotypicality and, to a lesser extent, attractiveness and acoustic similar-524 ity predict listeners' ability to recall voices, such that less stereotypical voices are 525 recalled more easily, but there is a strong bias to determine that highly stereotypical 526 voices have been previously heard. In contrast, online response time measures do 527 not predict voice recall. 528

While further research is certainly necessary, a broader conclusion that can be 529 gleaned from this study is that voices are organized and perceived fairly abstractly, 530 with considerable reliance on social factors. This conclusion is a natural extension 531 of the results. If online response time measures, which are typically diagnostic of 532 experiential information and speed of processing, do not predict voice recall, then 533 this negative result suggests that experience plays a more minimal role, or is dwarfed 534 by the social factors that are tapped by asking listeners about attractiveness and 535 stereotypicality. This is perhaps unsurprising as a voice is an aggregate of experiences 536 and words. Many, if not most, exemplar models of speech (Pierrehumbert, 2001; 537 Johnson, 1997) propose words as a basic unit of storage. In this study, participants 538 were asked to recall voices holistically, after hearing six words produced by a voice, 539 not respond "old"/"new" to individual words. Thus, when participants are asked 540 about a voice as a whole, they rely more on abstracted, subjective information. 541

However, as is clear from diverse work in the speech sciences (Goldinger, 1998, 1996; Nielsen, 2011; Palmeri, Goldinger, & Pisoni, 1993; Theodore & Miller, 2010;
Dahan, Drucker, Sarah & Scarborough, 2008) individual instances in memory matter
for speech perception. A full theory of voice organization will need to rectify such
instances with more abstracted memories. Further research should elucidate this
issue.

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Abstract	Beyond the linguistic content it conveys, voice is one of the fundamental aspects of human communication. It conveys an array of bio-psycho-social information about a speaker and enables the expression of a wide range of emotional and affective states so as to elicit a whole range of auditory impressions. Such aspects are of a great importance in determining the outcomes of competitive and courtship interactions as they influence the access to mating partners and thus reproduction. Sexual selection, the mechanism that promotes biological and social traits that confer a reproductive benefit, provides an interesting theoretical framework to understand the functional role of the human voice from an evolutionary perspective. This chapter aims to provide an overview of the research that lies at the crossroad of the human voice and evolutionary biology.
Keywords	Sexual selection - Reproductive success - Mate choice - Contest competition - Voice - Attractiveness

Chapter 7 Voice, Sexual Selection, and Reproductive Success



Alexandre Suire, Michel Raymond, and Melissa Barkat-Defradas

Abstract Beyond the linguistic content it conveys, voice is one of the fundamental

² aspects of human communication. It conveys an array of bio-psycho-social informa-

³ tion about a speaker and enables the expression of a wide range of emotional and

⁴ affective states so as to elicit a whole range of auditory impressions. Such aspects

are of a great importance in determining the outcomes of competitive and courtship
 interactions as they influence the access to mating partners and thus reproduction.

Sexual selection, the mechanism that promotes biological and social traits that confer

Sexual selection, the mechanism that promotes biological and social traits that confer
 a reproductive benefit, provides an interesting theoretical framework to understand

⁹ the functional role of the human voice from an evolutionary perspective. This chapter

aims to provide an overview of the research that lies at the crossroad of the human

voice and evolutionary biology.

¹² Keywords Sexual selection · Reproductive success · Mate choice · Contest

¹³ competition · Voice · Attractiveness

14 7.1 Evolutionary Background

15 7.1.1 Sexual Selection

¹⁶ Sexual selection is an evolutionary process by which a specific trait, either biological

17 or social, is selected depending on the advantages it confers to the individual that bears

it in order to access sexual partners for reproduction (Darwin, 1871). Reproductive

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selection can be divided into two distinct selection processes: intra- and intersexual
 competition (Andersson, 1994).

On one hand, intrasexual competition refers to contest competition that occurs 25 between same-sex individuals. When competition implies a physical confrontation, 26 sexual selection will favor the evolution of any characteristic that strengthens the 27 force and endurance of individuals, or any characteristic that diminishes the physical 28 prowess of competitors. This leads to the evolution of specific "weapons" designed to 29 repel and fight conspecifics. For instance, the antlers of male red deers are important 30 physical attributes in duels during the mating season (Clutton-Brock, Guinness, & 31 Albon, 1982), likewise the impressive body size of male sea lions, a key determinant 32 of male-male fights to access harem of females (Ralls & Mesnick, 2009). 33

On the other hand, intersexual competition refers to the process of competition 34 that depends on the choice made by opposite sex members, a mechanism commonly 35 termed mate choice. This mechanism depends on sexual attractiveness (Sect. 7.2b 36 deals with it). Evolutionary theory predicts that the sex that invests the more in 37 reproduction (in the form of anisogamy and parental care) should have the scrutiny 38 upon choosing a mate. This type of selection explains the origin of many extravagant 39 characteristics, such as vivid colors, excessive plumage, and complex songs in male 40 bird species (Bennett & Owens, 2002). Such traits are usually termed "ornaments". 41 The most classical example is the tail of the blue peafowl, with its elongated upper 42 tail which bears colorful eyespots. 43

In humans, many specific traits, such as height, the body size, and the immune system have been well studied under sexual selection theory and have provided a better understanding of their function within human mating systems (Miller, 1998; Puts, 2010). As we will see, contest competition and mate choice are two important evolutionary mechanisms that can also shed light on the evolution of the human voice.

50 7.1.2 Vocal Dimorphism

Humans display one of the most important vocal acoustic sexual dimorphism across
 anthropoids (Puts et al., 2016).

Differences in acoustic characteristics between the voices of men and women have
long been recognized and studied (Titze, 1989). Men's vocal tract is about 15–20%
longer than women because of their larger larynx and lower placement in the neck.
Men's vocal chords are also about 50% longer and significantly more massive than
those of women. These anatomical differences, which develop during puberty under
the influence of the estrogen/testosterone ratio, explain the lower vocal resonant
frequencies of male voices (Fitch & Giedd, 1999). Most notably, the fundamental

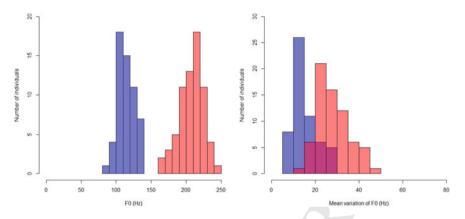


Fig. 7.1 Distribution of F0, F0-SD, and mean values of formant frequencies (F1–F4) for the vowels |a|, |i| and |u| for men (blue) and women (red). Purple values represent overlap between sexes. Acoustic data drawn from spontaneous speech; $n_{men} = 60$, $n_{women} = 68$ (Suire, unpublished data)

frequency shows relatively little to no overlap between the two sex: women's fundamental frequency is typically double that of men (Fig. 7.1). Additionally, men display lower formant frequencies from F1 to F4 compared to women, and such differences are consistent across different types of vowels (Simpson, 2009). Although less understood, the variation of F0 (generally noted as F0-SD) also appears to be sexually dimorphic, with men having a more monotonous voice than women (Puts et al., 2012).

Although the proximate mechanisms (i.e., physiology and anatomy) explain the 66 observed difference between men and women, it does not tell which evolutionary 67 factor has led to this phenomenon. When a trait shows a strong dimorphism between 68 the two sex, it is reasonably well grounded to see sexual selection as a potential 69 explaining factor. Although vocal attractiveness and dominance may be less relevant 70 to human mating success in modern life than it has been during most of human evo-71 lution, the underlying logic of the following studies is that past contest competition 72 and mate choice would have favored signals of threat potential and mate attraction 73 (Puts, 2010). 74

75 7.2 The Functional Role of the Human Voice

76 7.2.1 Contest Competition and Vocal Dominance

Within same-sex competition, dominance is a key perception to assess. It can be
defined as the capacity of one individual to repel competitors. Several studies have
highlighted the importance of the fundamental and formant frequencies in the per-

⁸⁰ ception of both social and physical dominance, especially in men.

For instance, it has been regularly shown that men with a more masculine voice, 81 i.e., lower F0 and formant frequencies, are perceived as more dominant by same-sex 82 individuals, in both experimental settings (Feinberg, Jones, Little, Burt, & Perrett, 83 2005; Feinberg et al., 2006; Puts et al. 2006; Puts et al. 2007; Jones, Feinberg, 84 DeBruine, Little, & Vukovic, 2010; Watkins et al. 2010; Wolff & Puts, Wolff & 85 Puts 2010) and correlational studies (Aronovitch, 1976; Hodges-Simeon, Gaulin, 86 & Puts, 2010). Moreover, in a competitive setting, men who perceived themselves 87 as more dominant speak in a lower voice pitch and in a more monotonous manner 88 when speaking to competitors. Conversely, men who feel non-confident or more 89 "submissive" speak in a higher voice pitch (Puts et al., 2006). Interestingly, aggressive 90 and dominant communicative behavior can possibly go beyond simple acoustics, by 91 differentially producing phonetic variants relevant to the perception of masculinity 92 (Kempe, Puts, & Cárdenas, 2013). For instance, taller and more masculine men with 93 higher levels of circulating testosterone levels used less the alveolar stop consonant 94 /t/, as a mean to display threat potential. Effects of side observer or context-dependent 95 displays of aggression may be equally important to signal power and authority to an 96 audience, as it has been reported that observers seeing a man speaking aggressively 97 to other men are perceived as more dominant (Jones, DeBruine, Little, Watkins, & 98 Feinberg, 2011). 99

Another consequence of having a deeper voice is that it can lead to higher social 100 positions in men. For instance, it has been shown that people prefer to select a leader 101 with a more masculine voice (Anderson & Klofstad, 2012; Klofstad, Anderson, 102 & Peters, 2012), which can also influence voting behaviors (Tigue et al., 2012) 103 and predict actual presidential election outcomes (Klofstad, 2016; Banai, Banai, 104 & Bovan, 2017). Interestingly, voice pitch can be linked to leadership's positions 105 within companies: CEOs with lower pitch voices managed larger companies, earned 106 more money, and enjoy longer tenures (Mayew et al., 2013). More generally, voice 107 pitch and formant frequencies seem to signal potential threat and aggression, higher 108 social status (including social dominance), all of which may have been particularly 109 important in past human environments (Puts, 2010). 110

For women, there are relatively few studies that have looked at the acoustic cor-111 relates of dominance. One study from Borkowska & Pawlowski (2011) showed that 112 men and women perceived women with lower voice pitch as more dominant, with 113 women being more sensitive to this vocal cue than men. Another study showed that 114 feminine voices were perceived as more flirtatious and more attractive to men, and 115 women were most sensitive to formant dispersion (i.e., the relative distance of two 116 adjacent formants) than the fundamental frequency, suggesting that women may track 117 competitors' femininity using this vocal cue (Puts et al., 2011). 118

The lack of studies for women's vocal dominance can be partly explained by the fact that past research has shown that competition among women, at least during human evolutionary history, relies very little on physical combat or aggression; women are assumed to be more prone to use indirect aggression. Such attempts may include social manipulation, for instance, by spreading false information about one's reputation or interfering with friendships and group inclusion of competitors (Fisher, 2015). Therefore, this kind of competition does not lead to larger, taller, and stronger

7 Voice, Sexual Selection, and Reproductive Success

statures in women, and thus women do not need to convey impressions of dominance
 or largeness through their vocal features against competitors.

Several authors have recently argued that intrasexual competition has mainly
driven the evolution of several morphological traits in men, including voice pitch
and its resonant frequencies (Puts, 2010; Hill et al., 2013; Kordsmeyer, Hunt, Puts,
Ostner, & Penke, 2018), but mate choice should not be regarded as an insignificant
evolutionary force in shaping vocal acoustic features (Suire et al., 2018).

133 7.2.2 Mate Choice and Vocal Attractiveness

Attractiveness, which can be defined as the capacity of one individual to attract opposite sex members, is an important component of voice perception in seductive and romantic settings. Other perceptions, such as the propensity to fidelity or trustworthiness, are also possibly important indexical cues to assess (Vukovic et al., 2011; O'Connor, Pisanski, Tigue, Fraccaro, & Feinberg, 2014a).

In men, consensus toward the attractiveness of relatively more masculine voices 139 has been well established, that is, a relatively lower voice pitch (Collins, 2000; Fein-140 berg et al., 2005, 2006, 2008; Ridings et al., 2006; Jones et al. 2010, but see Shirazi, 141 Puts, & Escasa-Dorne, 2018). Additionally, simultaneously masculinizing pitch and 142 formant frequencies increases men's vocal attractiveness (Feinberg et al. 2005, 2006; 143 Puts, 2005). However, preferences for vocal monotonicity are contradictory (Ridings 144 et al., 2006; Hodges-Simeon et al., 2010) and further studies are needed. Nonethe-145 less, women's visual object memory seems to increase after hearing masculine male 146 voices, but not after hearing feminine male voices or female voices, suggesting that 147 women may be particularly attuned to masculine voices (Smith, Jones, Feinberg, 148 & Allan, 2012). Voice pitch and formants are well-studied acoustic correlates of 149 voice attractiveness, but multiple components of voice quality have not been studied 150 within an evolutionary context and are known to potentially affect vocal attractive-151 ness, such as vocal roughness and breathiness (Suire et al., 2018). In addition, as for 152 vocal dominance, attractiveness can go beyond the acoustics' limits, as it appears that 153 specific sociolinguistic dialects, combined with a lower voice pitch, are preferentially 154 selected by women (O'Connor et al., 2014b). 155

Interestingly, women's preferences for vocal masculinity seem to shift during 156 the ovulatory cycle. Given that hormonal profiles (i.e., levels of progesterone and 157 estradiol) vary during the ovulatory cycle, women may prefer less masculinized 158 voices in men during the luteal phase as opposed to preferring masculinized voices 159 in men toward ovulation peak (Puts, 2005; Feinberg et al. 2006). This result can be 160 interpreted by the fact that women observe a trade-off when choosing a partner: a more 161 cooperative and submissive individual during the luteal phase, with relatively lower 162 testosterone levels, and a strong, testosterone-filled masculine men when approaching 163 ovulation. Choosing the former can be understood by the fact that a more cooperative 164 men is preferred when a woman seeks a long-term partner, particularly important so 165 as to provide shelter and resources, and choosing the latter may be important when 166

a woman seeks a short-term partner (i.e., one-night stand) to maximize reproductive
success (Buss & Schmitt, 1993). However, recent evidence has found no significant
shift of women's preferences over the ovulatory cycle for both vocal and facial
masculinity (Jones et al., 2018; Jünger, Kordsmeyer, Gerlach, & Penke, 2018).

Regarding men's preferences for women's voices, both experimental and corre-171 lational studies have found a consistent positive relationship between attractiveness 172 and F0, that is, men are attracted in average to relatively higher voice pitch (Collins 173 & Missing, 2003; Feinberg et al., 2008; Jones et al., 2010; Borkowska & Pawlowski, 174 2011; Puts et al., 2011, however, see Tuomi & Fisher, 1979; Hughes et al., 2010, 175 2014). However, this relationship might not be linear (Borkowska & Pawlowski, 176 2011), suggesting a possible optimum for women's vocal attractiveness. Moreover, 177 relatively higher formant dispersion (i.e., Df, the relative distance between two con-178 secutive formants, which correlates to the vocal tract length and perceived timbre) is 179 also perceived as more attractive by men (Puts et al., 2011; Babel et al., 2014). Addi-180 tionally, the variation of the F0 has also been hypothesized to play upon the perception 181 of indexical cues relevant in human competing and mating contexts (Leongómez et 182 al., 2014; Hogdes-Simeon et al., 2010, 2011) but has so far received scant atten-183 tion. Although sexually dimorphic, it has only been tested for women's preferences 184 (Bruckert et al., 2006; Hodges-Simeon et al., 2010), but one study suggests that men 185 may be attracted to higher F0-SD profiles in women as it may be a cue of femininity 186 (Leongómez et al., 2014). 187

Nonetheless, it is possible that vocal preferences for both men and women may not 188 be culturally universal. As a matter of fact, physiological and anatomical differences 189 do not explain the full variation in mean F0 between men and women, as individuals of 190 both sexes exhibit considerable variation from one language to another (Rose, 1991; 101 Traunmüller & Eriksson, 1995; Yamazawa & Hollien, 1992; Keating & Kuo, 2012; 192 Andreeva et al., 2014; Pépiot, 2014). For instance, even under the same speaking 193 conditions and balanced in age, American women exhibit a lower F0 than Japanese 194 women (mean F0: 211 versus 224 Hz, Yamazawa & Hollien, 1992), while Bulgarian 195 and Polish women exhibit a higher F0 than German and English women (mean F0: 196 272 and 266 Hz versus 210 and 217 Hz, Andreeva et al., 2014). As males and females 197 vary in mean F0 across various languages, this strongly suggests that some of the 198 differences must be accounted for learned behavior or specific sociocultural practices 199 (Simpson, 2009, e.g., Loveday, 1981). For instance, Dutch women display a lower 200 F0 than Japanese women, and interestingly, Dutch and Japanese men tend to prefer 201 female voices that exhibit culturally congruent vocal heights that is: low female 202 voices versus high female voices for Dutch versus Japanese men, respectively (Van 203 Bezooijen, 1995). Even in men, vocal attractiveness may not be solely predicted by 204 voice pitch. For instance, the harmonics-to-noise ratio (a proxy of vocal breathiness) 205 can predict Namibian men's vocal attractiveness (Sebesta et al., 2017). 206

7.3 Reproductive and Mating Successes

208 7.3.1 Its Quantification

Giving such observations, it is interesting to know how much variance can voice explain for an individual's overall reproductive success.

Investigating reproductive success within hunter-gatherer societies is of a par-211 ticular interest because it is argued that such societies better reflect past human 212 environments, practices, and cultures. However, studies are scarce. Hadza men with 213 relatively lower F0 had higher reproductive success (Apicella et al., 2007). However, 214 it has been recently reported that this relationship does not hold when controlling for 215 reputation (Smith et al., 2017). In women, it has been shown that F0 significantly 216 predicted several measures of reproductive success in a group of Namibian females: 217 higher voice pitch was associated with overall higher reproductive success (Atkinson 218 et al., 2012). 219

An easier measure of reproductive success is to measure mating success, and 220 mostly the number of past-year sexual partners. Although less powerful, this mea-221 sure is interesting because it represents a time window over which participants' 222 recollections are expected to be accurate (contrary to asking the lifetime number 223 of sexual partners) and the measured acoustics' characteristics are likely to be sta-224 ble (Hodges-Simeon et al., 2011). Moreover, human mating success should be an 225 important component of expected reproductive success in past environments, as it 226 represents their potential fertility (Perusse, 1993). 227

Through a simulated dating game, lower F0 negatively correlated to men's mating 228 success (Puts 2005), but another study found that it was not significant (Puts et al., 229 2006). Using a similar approach, men who spoke in a more monotonous manner 230 (i.e., lower F0-SD) and faster when confronted to a competitor declared more sexual 231 partners over the past year (Hodges-Simeon et al., 2011; Suire et al., 2018). Lastly, it 232 has been reported that female and male vocal attractiveness (when rated by members 233 of the opposite sex) could predict their mating success, their declared number of 234 extra-pair copulations, and their age at first sexual intercourse (Hughes et al., 2004). 235

However, methodologies varied concerning speech samples used in previous stud-236 ies; some studies used the recordings of spoken vowels and read speech without any 237 contextual background (Apicella et al., 2007; Atkinson et al., 2012; Hughes et al., 238 2004; Smith et al., 2017). This approach of read speech has been also intensively 239 used in perceptual studies when attractiveness and dominance need to be judged. 240 This is problematic as it does not properly reflect how an individual vocally behave 241 in ecological settings. Indeed, it has been regularly shown that studies conducted 242 on read/reciting versus spontaneous speech produce quite different results (Howell 243 & Kadi-Hanifi, 1991; Blaauw, 1992; Daly & Zue, 1992). As spontaneous speech 244 is more difficult to analyze experimentally, it has been little used. Nonetheless, the 245 simulated dating game studies have attempted to use it. These studies also provide an 246 interesting way to quantify the relative contribution of both types of sexual selection 247 in shaping vocal acoustic features (Hodges-Simeon et al., 2011; Suire et al., 2018). 248

249 7.3.2 The Underlying Biological Quality of Voice

To understand the ultimate reasons behind the correlations between vocal acoustic
 features, attractiveness, dominance, and reproductive success, the "honest signaling
 theory" offers an interesting explanation.

Regarding communication systems (i.e., the exchange of information through 253 different mechanisms involving at least two parties), this theory posits that, giving 254 conflicting interests between and within sexes, an individual should give an honest 255 signal to the receiver rather than cheating. This is due to the fact that cheating will 256 select over time for skeptical individuals who, in turn, have no benefits in "listening." 257 Thus, a communication system cannot emerge if false or manipulative information 258 is exchanged actively. Here, voice has long been considered as an honest signal 259 of overall biological quality, given the physiological and anatomical constraints in 260 speech production (Feinberg et al., 2005; Evans et al., 2006; Puts et al., 2006). This 261 means that voice should reflect another trait particularly relevant in contest and mate 262 choice competitions, which are correlated to the aforementioned perceptions. 263

It has first been suggested that voice should be a reliable signal of body size, a 264 feature particularly important in physical competitions between same-sex individu-265 als. Correlations between vocalizations' frequencies have been well established in 266 numerous species (Bowling et al., 2017) but surprisingly, such correlations are very 267 weak within the human species. A meta-analysis showed that F0 did not explain 268 more than 2% of the variation in body size, and formant frequencies only explained 269 up to 10% (Pisanski et al., 2014a). This is interesting as both men and women still 270 perceptually associate lower pitch voices to larger and taller individuals, and con-271 versely higher pitch voices to thinner and smaller individuals (Rendall, Vokey, & 272 Nemeth, 2007, but see Pisanski et al., Pisanski et al. 2014b). 273

An alternative hypothesis is the immuno-handicap principle (Zahavi, 1975). It 274 has been suggested that voice should reflect immuno-competence of individuals. 275 As testosterone is a sexual hormone that is immunosuppressive, individuals with 276 higher testosterone levels could bear the costs of impacting their immune system, 277 and are thus supposedly in a better biological shape. Although lower F0 may be 278 linked to higher testosterone circulating levels (Dabbs & Mallinger, 1999; Evans, 279 Neave, Wakelin, & Hamilton, 2008), the immuno-handicap principle has yielded 280 mixed results in humans (Roberts, Buchanan, & Evans, 2004; Boonekamp et al., 281 2008). Nonetheless, it has been reported that men plasma testosterone levels were 282 positively correlated with sexual language and the use of swear words in the presence 283 of their partners (Mascaro et al., 2018). Additionally, bioavailable testosterone was 284 also found to be associated with the sound pressure level of the normal speaking 285 voice in men and the softest speaking voice in women (Jost et al. 2018). The most 286 convincing study to date has shown that some masculinized vocal characteristics 287 were correlated to a specific antibody (Arnocky et al., 2018). The authors showed 288 that men with lower voice pitch and formant position had higher concentrations of 289 immunoglobulin A, an antibody produced by the mucus and constituting the first 290 line of immune defense against toxins and infectious agents. 291

7.4 Conclusion and Future Perspectives

Since the beginning of the 2000s, research has provided a better understanding on
 the functional role of the human voice from an evolutionary perspective. Although
 considerable efforts have been dedicated, further studies are needed to understand
 understudied aspects.

For instance, although acoustic features seem to be heritable (Przybyla, Horii, & 297 Crawford, 1992; Debruyne, 2002) and possibly related to the prenatal and/or pre-208 pubertal androgen exposure (Fouquet, Pisanski, Mathevon, & Reby, 2016), little is 299 still known of its biological foundations. Other understudied acoustic components 300 part of voice quality, such as roughness and breathiness, have also been little studied 301 and are known to potentially affect attractiveness perceptions (Šebesta et al., 2017; 302 Suire et al., 2018). Sociocultural variation in vocal preferences is also one important 303 avenue for research. Additional efforts should also be devoted to study the interaction 304 between linguistic material and vocal acoustic features to project indexical cues 305 relevant to mating and competing contexts. Lastly, another interesting avenue for 306 further research is to investigate vocal modulation, a capacity described as a volitional 307 control of nonverbal vocal features evolutionarily linked to traits important in the 308 context of sexual selection. However, context-dependent vocal modulation patterns 309 have been little relatively studied so far, but provides evidence that individuals of 310 both sexes alter several acoustic characteristics to signal traits relevant to contest 311 competition and mate choice (see Pisanski et al. 2016 for a review). 312

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Abstract	Several experiments investigating the perceptual, acoustical and neural bases of the 'voice attractiveness averaging phenomenon' are briefly summarized. We show that synthetic voice composites generated by averaging multiple (same gender) individual voices (short syllables) are perceived as increasingly attractive with the number of voices averaged. This phenomenon, independent of listener or speaker gender and analogous to a similar effect in the visual domain for face attractiveness, is explained in part by two acoustical correlates of averaging: reduced 'Distance-to-Mean', as indexed by the Euclidean distance between a voice and its same-gender population average in f0-F1 space and increased voice 'texture smoothness' as indexed by increased harmonics-to-noise ratio (HNR). These two acoustical parameters covary with perceived attractiveness and manipulating them independently of one another also affects attractiveness ratings. The neural correlates of implicitly perceived attractiveness consist in a highly significant negative correlation between attractiveness and fMRI signal in large areas of bilateral auditory cortex, largely overlapping with the Temporal Voice Areas, as well as inferior prefrontal cortex: more attractive voices elicit less activity in these regions. While the correlations in auditory areas were largely explained by distance-to-mean and HNR, inferior prefrontal areas bilaterally were observed even after covarying out variance explained by these acoustical parameters, suggesting a role as abstract voice attractiveness evaluators.		
	Averageness - Aperiodicity - Distance-to-mean - Distinctiveness - Pitch - Formant dispertion		

Chapter 8 On Voice Averaging and Attractiveness



Pascal Belin

Abstract Several experiments investigating the perceptual, acoustical and neural 1 bases of the 'voice attractiveness averaging phenomenon' are briefly summarized. 2 We show that synthetic voice composites generated by averaging multiple (same 3 gender) individual voices (short syllables) are perceived as increasingly attractive Δ with the number of voices averaged. This phenomenon, independent of listener or 5 speaker gender and analogous to a similar effect in the visual domain for face attrac-6 tiveness, is explained in part by two acoustical correlates of averaging: reduced 7 'Distance-to-Mean', as indexed by the Euclidean distance between a voice and its 8 same-gender population average in f0-F1 space and increased voice 'texture smooth-9 ness' as indexed by increased harmonics-to-noise ratio (HNR). These two acoustical 10 parameters co-vary with perceived attractiveness and manipulating them indepen-11 dently of one another also affects attractiveness ratings. The neural correlates of 12 implicitly perceived attractiveness consist in a highly significant negative correlation 13 between attractiveness and fMRI signal in large areas of bilateral auditory cortex, 14 largely overlapping with the Temporal Voice Areas, as well as inferior prefrontal cor-15 tex: more attractive voices elicit less activity in these regions. While the correlations 16 in auditory areas were largely explained by distance-to-mean and HNR, inferior pre-17 frontal areas bilaterally were observed even after co-varying out variance explained 18 by these acoustical parameters, suggesting a role as abstract voice attractiveness 19 evaluators. 20

²¹ Keywords Averageness · Aperiodicity · Distance-to-mean · Distinctiveness ·

²² Pitch · Formant dispertion

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23 8.1 Introduction

ditor Proof

The faces shown in Fig. 8.1a are computer generated: they are the pixel-wise aver-24 age of a large number of pictures of different faces after conformation to a same 25 configuration (eyes and mouth in the same position). Observers typically find these 26 faces more attractive than most of the individual constituting faces. This so-called 27 'averaging attractiveness phenomenon' has been observed since the nineteenth cen-28 tury and the beginnings of photography when experimenters such as Sir Francis 20 Galton noticed that by superimposing portraits of different individuals on a same 30 photographic plate one obtained a quite attractive picture (Galton, 1878; Jastrow, 31 1885). Since those pioneering times the averaging attractiveness phenomenon has 32 been replicated many times with more sophisticated computer graphics techniques 33 such as in Fig. 8.1a (Langlois et al., 2000; Langlois & Roggman, 1990; Perrett, May, 34 & Yoshikawa, 1994; Thornhill & Gangestad, 1999). 35

There are two main accounts for the face averaging attractiveness phenomenon. 36 One account from evolutionary psychology—the 'good genes' explanation— 37 proposes that we tend to prefer averaged faces because if they were real faces they 38 would signal a potential mate with particularly high fitness. Indeed, facial features 39 such as proximity to the population average, facial symmetry, or face texture smooth-40 ness appear to signal high fitness in real faces (Grammer, Fink, Moller, & Thornhill, 41 2003; Langlois & Roggman, 1990; Thornhill & Gangestad, 1999). The averaging 42 procedure enhances all three of these features, artificially signalling high fitness 43 in a synthetic face, and hence their attractiveness. Another account from cogni-44 tive psychology-the 'perceptual fluency' account-proposes that observers prefer 45 averaged faces because they are closer in face space, i.e. more similar to a central 46 face prototype based on which all face identities are coded, and so they are eas-47 ier to process, and hence more attractive (Winkielman, Halberstadt, Fazendeiro, & 48 Catty, 2006). These two accounts are not mutually exclusive: the 'perceptual flu-49 ency' account can be viewed as an explanation at the proximate level, in terms of 50 cognitive mechanisms implementing the effect, while the 'good genes' account is an 51 explanation at a more ultimate level, in terms of the selective evolutionary pressures 52 that gave rise to such a phenomenon in our ancestors. 53

Crucially, both the cognitive and evolutionary accounts suggest that a similar phenomenon could exist for voices. Thanks to the development of voice morphing technology, and the excellent and generous contribution of Professor Hideki Kawahara at Wakayama University, we were able to test that hypothesis for the first time in Bruckert et al. (2010).

59 8.2 Voice Attractiveness Increases with Averaging

To start addressing the complex problem of voice averaging, we decided to focus on the simpler problem, more manageable in an experimental setting, of averaging of brief, quasi-stationary vocalizations, and opted to use short syllables as stimuli. We reasoned that such stimuli, for which time plays minimal role, would be easier
to process through averaging than longer, more complex and variable utterances.
Quasi-static syllables are also analogous to the static photographs with which most
face attractiveness research has been performed so far.

We selected from a database of high-quality recordings of English syllables 67 (Hillenbrand, Getty, Clark, & Wheeler, 1995) as set of recordings of the syllable 68 /had/ spoken in isolation by 32 different male and 32 female American speakers 69 (duration: mean \pm s.d.: female voices: 320 ± 51 ms; male voices: 267 ± 42 ms). We 70 then identified in each stimulus a set of spectro-temporal landmarks to be put in 71 correspondence across speakers during averaging. As shown by the black dots in 72 Fig. 8.1b, these landmarks consisted of first three formant frequencies at onset and 73 offset of phonation, and at the beginning of the formant transition of the final /d/. We 74 then used the Straight software (Kawahara & Matsui, 2003) to generate voice com-75 posites consisting of an interpolation of the aperiodic and spectral temporal density 76 components of varying numbers of individual voices of the same gender (arbitrarily 77 chosen, such that not all possible composites have been generated). For each speaker 78

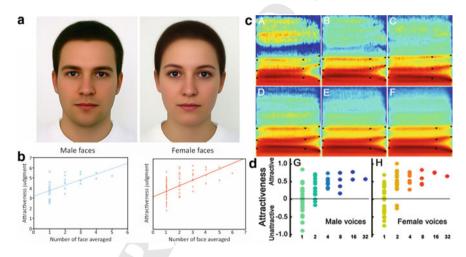


Fig. 8.1 Face and voice attractiveness judgments as a function of averaging. **a** Face composites generated by averaging 32 male faces (left) and 64 female faces (right). **b** Attractiveness ratings as a function of number of faces averaged. Note the steady increase in attractiveness ratings with increasing number of averaged faces, for both male (left) and female (right) faces. Reproduced with permission from Braun et al. (2001). **c** Spectrograms of voice composites generated by averaging an increasing number of voices of the same gender (different speakers uttering the syllable 'had'). Top left panel: 1-voice composite; middle top panel: 2-voice composite; right top panel: 4-voice composite; bottom left panel: 8-voice composite; bottom middle panel: 16-voice composite; bottom right panel: 32-voice composite. **d** Attractiveness ratings as a function of number of voices averaged in the composites (individual points). Note the steady increase in attractiveness ratings with increasing number of averaged voices, for both male (left) and female (right) voices. Reproduced with permission from Bruckert et al. (2010)

⁷⁹ gender, this procedure resulted in thirty two 1-voice composites (the individual voices
⁸⁰ resynthesized), sixteen 2-voice composites, eight 4-voice composites, four 8-voice
⁸¹ composites, two 16-voice composites, and a single average of all voices of the same
⁸² gender, the 32-voice composite. Example composite stimuli are shown in Fig. 8.1c.

We then played these stimuli in a pseudorandom order to 25 listeners (13 females) 83 who were asked to rate the perceived attractiveness of each stimulus using a visual 84 analogue scale ranging from 'not at all' to 'extremely' attractive. Analysis of the 85 data provided striking results (Bruckert et al., 2010). As shown in Fig. 8.1d, for the 86 1-voice composites (the resynthesized original voices) we found as expected a normal 87 distribution of attractiveness ratings around the average: for both male and female 88 speakers, most of the voices were rated with average attractiveness while a few voices 89 were perceived as more attractive than average and others as less. But as soon as two or 90 more voices where averaged together, we witnessed a marked progressive increase 91 of average attractiveness ratings, similar for the male and female voices. 4-voice 92 composites were already perceived as markedly above average and 16- and 32-voice 93 composites all resulted in very high ratings. The correlation between attractiveness 94 z-scores and number of voices in the composite was highly significant (p < 0.001) 95 for both male and female voices (Bruckert et al., 2010). 96

Thus, we could observe for the first time a 'voice averaging attractiveness phenomenon' that was directly predicted by analogous studies in face perception: the more speakers are included by averaging in a synthetic voice, the more attractive it is perceived. Two implications of these results are worth discussing.

First, there is a highly striking similarity between the attractiveness ratings 101 obtained in face and voice averaging experiments. Despite the very different nature 102 of the sensory input (vibrations of the tympanic membrane versus light on the retina) 103 the effects of averaging gave rise in the two sensory modalities to highly similar and 104 gender-independent averaging-induced attractiveness increases (compare Fig. 8.1b 105 and d). This beautifully illustrates the notion of similar functional architectures for 106 face and voice processing in the human brain. Indeed, many sources of evidence from 107 patient observation to neuroimaging studies converge to the notion that the compu-108 tational problems posed by face and voice processing, being of very similar nature, 109 and subjected in our ancestors to comparable evolutionary pressures, are addressed 110 by the brain using similar neurophysiological solutions (Yovel & Belin, 2013). 111

Second, and more relevant to voice attractiveness, the voice averaging attractiveness phenomenon opens an exciting window onto the acoustical underpinnings of this complex percept. Indeed, the averaging procedure had at least two independent acoustic effects on the synthesized composites. Including an increasing number of different voices in the composite's resulted in: (i) a progressive decrease in the distance-to-mean (increased similarity to the average) and (ii) a progressive decrease in the amount of aperiodicity (increased harmonicity or voice texture smoothness).

119 8.3 Effects of Distance-to-Mean

Because of the linear combination of individual spectral temporal landmarks in the 120 composites during averaging, at each successive averaging step the resulting com-121 posites mathematically became closer in acoustical space to the average: their fun-122 damental frequency and formant frequency values became increasingly similar to 123 those of the 32-voice average, resulting at each step in decreasing average 'distance-124 to-mean', as defined by the Euclidean distance between a voice and the same-gender 125 average in f0-F1 (first formant frequency) space. In other words, the more voices 126 are averaged together, the more the resulting composite sounds like the population 127 average. This suggests that distance-to-mean could potentially provide an acoustical 128 parameter relevant for voice attractiveness. We tested that hypothesis in two differ-129 ent ways: (i) by examining the relationship between distance-to-mean and perceived 130 attractiveness in our set of natural and synthetic voices and (ii) by explicitly manip-131 ulating distance-to-mean (but not other parameters such as aperiodicity) in synthetic 132 voices. 133

We first tested, independently for male and female voices, whether distance-to-134 mean in our set of voice composites would correlate with their average perceived 135 attractiveness. For both voice genders, we found highly significant negative correla-136 tions between distance-to-mean and attractiveness: the higher the distance-to-mean, 137 the lower the perceived attractiveness. As including composites of all levels in this 138 analysis, known to be both closer to the average and more attractive involves some 139 level of circularity, we repeated the analysis by only including the 1-voice compos-140 ites, resynthesized versions of the original recordings (indistinguishable by ear): the 141 results remained strongly significant, for both male and female voices. Thus, in our 142 set of 32 male and 32 female voices, those that were naturally closer to the same-143 gender average were also perceived as more attractive (Bruckert et al., 2010)—a 144 result that should be tested on larger samples (Fig. 8.2). 145

Does modifying distance-to-mean also modify perceived attractiveness? We tested 146 the hypothesis by using morphing to generate, for each of the 32 individual voices 147 of each gender, a pair of synthetic voices that differed from the original by having 148 been moved either towards the average or away from the average by the exact similar 149 amount of acoustical change (50% of the natural distance-to-mean). We predicted 150 that although the new synthetic voices were acoustically equally dissimilar to the 151 original, the one closer to the average would be perceived as more attractive. Results 152 confirmed that prediction for both voice genders (Bruckert et al., 2010). 153

Thus, not only are voices naturally closer to the same-gender average perceived as more attractive, but acoustically modifying voices to move them closer to the average also makes them more attractive than moving them away. Distance-to-mean thus appears as one important acoustical correlate of voice attractiveness. Interestingly, distance-to-mean can be consciously modified, if not by altering formant frequencies (largely dependent on vocal tract size) but by consciously modifying one's pitch of voice so that our average fundamental frequency is closer to the gender-typical value

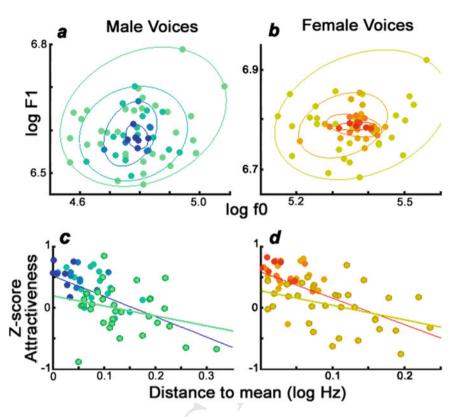


Fig. 8.2 Effects of distance-to-mean. **a.** Male voice composites are represented as coloured dots in logf0-logF1 space. Colour indicates degree of averaging with darker colours indicating more voices in the composite. Lines indicate the smallest elliptic contours containing all composites of a same degree of averaging. Note how composites progressively become closer to the average with increasing number of constituting voices. **b.** Female voice composites, legend as in (**a**). **c.** Relation between distance-to-mean and attractiveness ratings for each male voice composite (coloured dots). Lines indicate the regression line when all composites are considered (blue line) or when only the 1-voice composites are considered (green line). **d.** Relation between distance-to-mean and attractiveness. Legend as in (**c**)

(about 125 Hz for men and 215 Hz for women Hillenbrand et al., 1995), not too
low and not too high, as a means of 'vocal make-up' to enhance one's perceived
attractiveness.

164 8.4 Effects of Voice Texture Smoothness

Another important effect of averaging on the acoustical structure of voices, largely independent from the effect of distance-to-mean in f0-formant frequency space, is a

progressive decrease in the amount of aperiodicity with the number of voices aver-167 aged, as the morphing procedure averages out aperiodic noise in the signal. This effect 168 can be plainly seen in Fig. 8.1c as the spectrograms become progressively smoother 169 with the increasing number of voices in the composite from the top left panel (1-voice 170 composite, showing much spectro-temporal irregularities) to the bottom right panel 171 (32-voice composite) with a very smooth structure. This effect is analogous to the 172 increase in face texture smoothness (see Fig. 8.1a) caused by averaging as individual 173 local variations in luminance and reflection (the 'villainous irregularities' of Galton, 174 1878) are averaged out across individual faces. This effect of smoothing of the 'voice 175 texture' can be quantified using measures such as the harmonics-to-noise ratio (HNR) 176 that captures the amount of regularity in the sound. When the harmonic-to-noise ratio 177 of each composite is plotted as a function of its number of constituent voices (Bruck-178 ert et al., 2010), there is a clear and highly significant progressive increase in HNR 179 along with number of voices in the composite that nearly mirrors the increase in 180 attractiveness ratings. Thus, the amount of energy in the aperiodic component of 181 voice could constitute another acoustical correlate of voice attractiveness. 182

We tested this hypothesis by generating for each of the 32 male and 32 female 183 voices of our sample, a 'smoother' and 'rougher' version of each voices. Those were 184 generated by moving stimuli away or closer to the average by equal amounts of 185 acoustic change, as for the manipulation of distance-to-mean above, but this time 186 modifying only the aperiodic component of voice. We verified that the 'smoother' 187 synthetic voices had greater harmonics-to-noise ratio than the 'rougher' for both 188 voice genders. We then presented listeners with voice pairs made of the smoother 189 and rougher version of a same original voice and asked them to decide the one 190 they found the more attractive. Subjects overwhelmingly preferred the smoother 101 version with reduced periodicity and increased HNR to the rougher version (Bruckert 192 et al., 2010). 193

Overall, the increase in voice attractiveness induced by averaging highlights 194 distance-to-mean and voice textures smoothness as two largely independent and 195 important acoustical correlates of voice attractiveness. They can potentially be used 196 to predict listeners' ratings and can be manipulated in synthetic, but also in natural 197 voices, to artificially increase perceived attractiveness. Note, however, that while 198 distance-to-mean already correlated with attractiveness ratings in natural, unaver-199 aged voices, this was not the case for HNR that showed essentially no relation with 200 attractiveness ratings for the natural voices. This suggest that, while both parameters 201 contribute to the attractiveness averaging effect, distance-to-mean is more important 202 than HNR in determining the attractiveness of natural voices. 203

8.5 Neural Correlates of Perceived Voice Attractiveness

We then turned to the question of the neural correlates of voice attractiveness. Indeed neuroimaging studies have shown linear or quadratic relations between perceived facial attractiveness and neural activity in orbitofrontal cortex as well as in amygdala

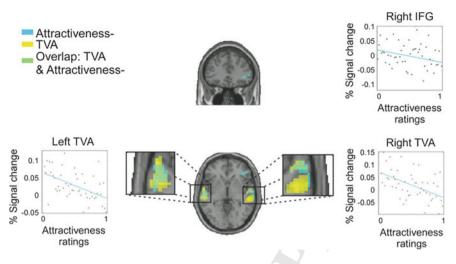


Fig. 8.3 Neural correlates of perceived attractiveness. Cerebral regions modulated by implicitly perceived attractiveness during passive listening to voices. Cortical areas in blue showed significant negative correlation between BOLD signal and attractiveness (graphs in insets showing regression lines for three regions of interest): more attractive voices elicited less neural activity in those regions. They largely overlap with the voice-sensitive temporal voice areas (in yellow) but also involve right inferior prefrontal cortex (top central panel)

(Winston, O'Doherty, Kilner, Perrett, & Dolan, 2007). To address this question in the 208 domain of voice perception, we performed a functional magnetic resonance imaging 209 (fMRI) study in normal participants (Bestelmeyer et al., 2012). They were scanned 210 while passively listening to our set of voice composites presented in a pseudorandom 211 order. We used a so-called 'cluster volume acquisition' fMRI protocol with brief 212 silent intervals during fMRI volume acquisitions allowing the presentation of voice 213 stimuli during silent periods for optimal stimulation. Subjects were not informed of 214 our focus on voice attractiveness and were simply instructed to listen to the voices 215 and press the button when they would hear an infrequent pure-tone stimulus. 216

In the fMRI analyses, we first asked whether there would be regions of the brain 217 in which stimulus-induced activity would co-vary with the average attractiveness 218 rating obtained offline for each voice. Indeed a well-defined network of cortical 219 region showed significant correlations between fMRI signal and attractiveness ratings 220 (Fig. 8.3). Most prominently, negative correlations were observed in large areas of 221 bilateral superior temporal gyrus and sulci, overlapping with the voice-selective 222 temporal voice areas (TVA) of auditory cortex (Belin, Zatorre, Lafaille, Ahad, & 223 Pike, 2000; Pernet, Charest, Belizaire, Zatorre, & Belin, 2007) of secondary auditory 224 cortex. But such negative correlation was also observed in the inferior frontal gyrus 225 (IFG) of the right hemisphere, outside of voice-sensitive regions (Bestelmeyer et al., 226 2012). 227

We asked whether part of these strong negative correlations could be partly explained by one or the other acoustic parameters highlighted above—distance234 auditory cortex overlapping with the TVAs bilaterally showed a positive correlation 235 with distance-to-mean (voices farther away from the mean-also less attractive on 236 average—eliciting greater signal). This phenomenon has since been replicated and 237 extended in subsequent work (Latinus & Belin, 2011; Latinus, McAleer, Bestelmeyer, 238 & Belin, 2013). The positive correlation between distance-to-mean and neural activ-239 ity constitutes a hallmark of 'norm-based coding' as evidenced in visual cortex for 240 face identity processing (Leopold, Bondar, & Giese, 2006): individual voices appear 241 to be coded in the TVAs as a function of their difference with the average voice: 242 whether the negative correlation with attractiveness in those areas is a consequence 243 of, or drives, the positive correlation with distance-to-mean remains to be established. 244 Other, more anterior parts of the TVAs instead showed a negative correlation with 245 HNR, with more aperiodic voices eliciting higher activity. Thus, the large negative 246 correlation between attractiveness and fMRI signal is in part explained by a sensitiv-247 ity of auditory cortex to the two underlying acoustical features shown as determinant 248 for perceived attractiveness. 240

But could we detect attractiveness-related changes that would be independent of 250 the underlying acoustics? We addressed that question by performing another anal-251 ysis in which measures of distance-to-mean HNR were included in the model and 252 regressed out to examine variance not accounted for by these parameters. Results 253 showed that the large negative correlation in the auditory cortex had disappeared, 254 confirming that it was largely explained by the HNR and distance-to-mean of the 255 voices. However, two bilateral regions of inferior prefrontal cortex, pars triangu-256 laris, survived after removing variance accounted for by acoustics: these regions still 257 showed the negative relation with attractiveness. This region is part of Broca's area 258 (Anwander, Tittgemeyer, von Cramon, Friederici, & Knosche, 2007) and is strongly 259 connected to sensory cortex (Petrides & Pandya, 2009). In addition to its involve-260 ment in language perception, bilateral activity in Broca's area has been linked to 261 auditory working memory in which increased task demands correlate with increased 262 activity (Martinkauppi, Rama, Aronen, Korvenoja, & Carlson, 2000; Arnott, Grady, 263 Hevenor, Graham, & Alain, 2005). Our results thus may suggest that increasingly 264 unattractive voices demand larger processing resources and may point towards the 265 role of the IFG pars triangularis as being involved not only in the processing of 266 language and affective prosody but also in integrating acoustic information received 267 from bilateral TVA into a unified percept of attractiveness. 268

A clear limitation of the above findings is that they were obtained with the use of brief vowels and hence cannot be easily generalized to realistic speaking situations in which a number of additional cues are present, including intonation, speaking rate, etc. Therefore, our results concern only one component that contributes to perceived voice attractiveness in realistic settings. Nonetheless, these findings have important potential implications for voice-based technology, suggesting simple ways

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of enhancing the attractiveness of synthetic voices at a time when automated voice production systems become ubiquitous.

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Abstract	been attributed to fem but they also tend to s affects the subjective a	ed voices tend to be rated as more attractive by female listeners; this tendency has ale sexual selection. Males not only speak with a lower pitch than females, however peak at a faster tempo. Therefore, this study investigates whether speech tempo also attractiveness of male speakers for female listeners. To this end, sentences read by 2 hanged in relative tempo (factors 0.85, 1.00, and 1.15) and in overall pitch (-1.5 , 0,	

male speakers were changed in relative tempo (factors 0.85, 1.00, and 1.15) and in overall pitch (-1+1.5 semitone), and were presented with and without fictitious portraits of the speakers. Ratings of

	speakers' attractiveness by female heterosexual listeners show significant effects of both tempo and pitch, in that voices with increased pitch and with decreased tempo are rated as significantly less attractive. In conclusion, female listeners rate a male speaker as less attractive if his voice pitch is increased (higher) and if his speech tempo is decreased (slower). Therefore, both tempo and pitch may be relevant for speech-based sexual selection of males by females.
Keywords	Sexual selection - Voice pitch - Speech tempo - Speaking rate - Attractiveness - Experiment - Proportional odds model

Chapter 9 Attractiveness of Male Speakers: Effects of Pitch and Tempo



Hugo Quené, Geke Boomsma, and Romée van Erning

Abstract Men with lower pitched voices tend to be rated as more attractive by

- female listeners; this tendency has been attributed to female sexual selection. Males
 not only speak with a lower pitch than females, however, but they also tend to
- ³ not only speak with a lower pitch than females, however, but they also tend to
- speak at a faster tempo. Therefore, this study investigates whether speech tempo also
 affects the subjective attractiveness of male speakers for female listeners. To this end,
- ⁶ sentences read by 24 male speakers were changed in relative tempo (factors 0.85,
- 7 1.00, and 1.15) and in overall pitch (-1.5, 0, +1.5 semitone), and were presented with
- ⁸ and without fictitious portraits of the speakers. Ratings of speakers' attractiveness
- ⁹ by female heterosexual listeners show significant effects of both tempo and pitch, in
- 10 that voices with increased pitch and with decreased tempo are rated as significantly
- less attractive. In conclusion, female listeners rate a male speaker as less attractive if
- his voice pitch is increased (higher) and if his speech tempo is decreased (slower).
- ¹³ Therefore, both tempo and pitch may be relevant for speech-based sexual selection
- 14 of males by females.
- ¹⁵ Keywords Sexual selection · Voice pitch · Speech tempo · Speaking rate ·
- 16 Attractiveness · Experiment · Proportional odds model

17 9.1 Introduction

- ¹⁸ Male and female speakers differ in their average fundamental frequency (F0, per-
- ¹⁹ ceived as pitch), viz., typically about 110 Hz for males and 205 Hz for females (Holm-
- ²⁰ berg, Hillman, & Perkell, 1988; Simpson, 2009, Puts, Apicella, & Cárdenas, 2012).

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This large and significant difference in F0 develops in conjunction with primary and 21 secondary sexual characteristics, during puberty. This suggests that the pitch dif-22 ference may be related to some sexual function. The voice pitch of an adult male 23 speaker is indeed reportedly related to the speaker's level of testosterone (Dabbs 24 & Mallinger, 1999; Puts et al., 2012) and to the speaker's self-reported number of 25 children (Apicella, Feinberg, & Marlowe, 2007) (but see Smith, Olkhov, Puts, & Api-26 cella, 2017 for the mediating effect of hunting reputation). Thus, a male speaker's 27 pitch may indicate his health and physical dominance, by virtue of the intercorrela-28 tions between male speakers' pitch and testosterone level (Dabbs & Mallinger, 1999; 29 Puts et al., 2012), body height (Pisanski et al., 2014), physical strength (Puts et al., 30 2012), and masculinity (Clark & Henderson, 2003; Archer, 2006). Female listen-31 ers may, therefore, use voice pitch to assess the male speaker's physical suitability 32 for producing and protecting offspring, i.e., in sexual selection via female choice 33 of mate (Andersson, 1994). Indeed, ratings of attractiveness by female listeners are 34 (negatively) correlated with the male speaker's F0 (Collins, 2000; Bruckert, Liénard, 35 Lacroix, Kreutzer, & Leboucher, 2006), and experiments have confirmed that manip-36 ulations of F0 influence these attractiveness ratings (Feinberg, Jones, Little, Burt, & 37 Perrett, 2005). In addition, voice pitch may be used to indicate health and dominance 38 among male competitors, i.e., in sexual selection via male-male competition (Puts, 39 Gaulin, & Verdolini, 2006), a mechanism which may be more important than female 40 choice (Hill et al., 2013; Kordsmeyer, Hunt, Puts, Ostner, & Penke, 2018). 41

Males not only speak with a lower F0 than females, however, but they also tend to 42 speak at a faster speech rate or tempo than females (about 5% faster) (Quené, 2008; 43 Jacewicz, Fox, & Wei, 2010). This difference too may be related to male dominance, 44 as the faster tempo presumably indicates the speaker's cognitive abilities and motor 45 skills through his speaking. The faster tempo requires more physical energy (Moon & 46 Lindblom, 2003), even more so because the male speech organs have somewhat more 47 mass than the females', and it also requires more cognitive effort in linguistic planning 48 and motor control. Indeed, faster speakers tend to be rated as more convincing, 49 reliable, empathic, serious, active, and competent (Apple, Streeter, & Krauss, 1979; 50 Smith, Brown, Strong, & Rencher, 1975). Presumably, then, female listeners also 51 use a male speaker's tempo, to assess his motor skills and cognitive suitability as a 52 potential mate. 53

This study aims primarily to replicate previous findings on female preference for 54 male voices with lower *pitch*, and secondly to extend that work by investigating the 55 presumed female preference for male speakers speaking at a faster *tempo*. Thirdly, 56 we are interested in the interaction between the two factors. From a sexual selec-57 tion perspective, a speaker who combines a low pitch with a fast tempo may be 58 most attractive (and vice versa), because this combination would suggest a healthy 59 physique as well as good motor and cognitive capabilities, a combination which is 60 presumably more rare in potential male partners than the separate capabilities and 61 characteristics. 62

The experiment reported below addresses these questions by manipulating Dutch sentences in tempo and pitch, and then asking Dutch female listeners to rate the attractiveness of the speaker. This attractiveness rating is regarded here as a proxy for the female listener's degree of preference for that male speaker in sexual selection, although vocal attractiveness also affects other social attributions (Babel, McGuire, & King, 2014).

In addition, this study also investigates whether these hypothesized effects of pitch 69 and tempo are moderated by the presence of visual cues about the speaker in a portrait 70 photo (see details below). On the one hand, humans have evolved to assess speakers 71 not only by ear but also by eye,¹ so the task of rating a speakers' attractiveness may be 72 more ecologically valid when a portrait is available. On the other hand, the presence 73 of visual cues may well dampen the effects of prosodic cues. The fourth aim of this 74 study was, therefore, to establish whether and how the presence of a portrait photo 75 would affect a listeners' ratings of attractiveness of the speaker. 76

77 9.2 Methods

The experiment consisted of two sessions, in which the same speech stimuli were used. In the first session, speaker's voices were presented without a simultaneous portrait photo. In the second session, which included listeners who participated in the first session as well as new listeners, the same speech stimuli were presented *with* a portrait photo, in order to assess the effects of the portrait on listeners' responses. Listeners' task was to rate the attractiveness of the speaker.

⁸⁴ During each session, a listener rated two different sentences spoken by the same ⁸⁵ speaker. One sentence was unchanged from the original, and the other sentence ⁸⁶ was manipulated orthogonally in pitch and/or in tempo, as described below. (This ⁸⁷ single-interval rating paradigm was chosen, instead of a two-interval forced-choice ⁸⁸ paradigm, because the latter would have highlighted the phonetic manipulations ⁸⁹ in one of the two speech intervals, and thus would have introduced biases in the ⁹⁰ responses subsequent to a listener noticing the manipulations).

The within-listener and within-speaker design allows for testing our primary predictions regarding the hypothesized effects of manipulated pitch and manipulated tempo on the subjective voice attractiveness of male speakers. Listeners' judgements are predicted to be affected by the phonetic manipulations, with higher ratings for lowered pitch and faster tempo, and with lower ratings for higher pitch and slower tempo, as argued above. The effects of phonetic manipulations may interact, and may be moderated by the photo conditions.

¹Although present-day listeners may be used to hear speakers without seeing them, this is presumably not how speech has evolved in humans.

98 9.2.1 Participants

Listeners were 208 students or employees at Utrecht University, from 8 different undergraduate course groups taught in Dutch. In order to conceal the research topic (knowledge of which might have biased responses), targeted participants as well as other persons were tested and subsequently presented with a questionnaire asking about gender, sexual orientation, age, speech/hearing problems, and guess about the purpose of the experiment. Data from 58 persons were excluded for various reasons listed in Table 9.1.

Subsequent analysis was based on data from 150 remaining targeted participants: all female, self-identified other than lesbian, within age range 17–29 (median age 20, median absolute deviation 1.5, at second session; this was done to select participants from approximately the same age range as the speakers, to improve ecological validity), without self-identified speech/hearing problems, and not aware of the purpose of the study. All participants were highly proficient in Dutch, as their native language or as a non-native language attested at an advanced academic level (B2 or higher).

113 9.2.2 Materials

No valid responses

Orientation lesbian

Age < 16 or > 30

Participants remaining

Gender male or unspecified

Stimulus sentences were taken from Dutch spontaneous monologues by 24 male 114 speakers (age M = 18.0, s = 0.7, range 16–19 years), who spoke about an informal 115 topic of their own choice. These monologues had been previously recorded for a 116 different study at 44.1 kHz (for further details, see Quené & Orr, 2014; Quené, Orr, 117 & van Leeuwen, 2017). Two sentences were selected from each speaker's interview. 118 Selected sentences were between 2.5 and 3.5 s in duration, which were spoken fluently 119 and without a long pause, with neutral content, comprehensible without context, and 120 not elliptic (i.e., contained both a subject and an inflected verb). Thus the sentences 121

may apply to a single participant			
Description	Female	Male	Total
All participants tested	≥155	≤53	208
Aborted prematurely	<u>≤</u> 3	≤1	3
Already knew purpose of study	6	3	9
Speech/hearing problems	7	4	11

1

0

0

0

<u>≤</u>35

1

35

3

3

150

0

0

3

3

150

Table 9.1	Numbers of participants,	with reasons for	exclusion from	data analysis.	Multiple reasons
may apply	to a single participant				

should provide listeners with enough speech material to rate voice attractiveness,
without requiring listeners' inference of context or grammar.

For each of the 24×2 selected stimulus sentences, average syllable duration 124 (excluding pauses, Quené, 2008 and average F0 (over voiced portions) were measured 125 using Praat (Boersma & Weenink, 2015). These measurements were then analyzed 126 by means of linear mixed models (Quené & van den Bergh, 2004; 2008; Bates et 127 al., 2015; R Core Team, 2018) with only the intercept as a fixed predictor, and with 128 speakers as random intercepts. The estimated average syllable duration was 0.188 s 129 $(s_u = 0.015, s_e = 0.026, ICC = 0.25, i.e., with most variance between sentences$ 130 within speakers), and the estimated average F0 was 116 Hz ($s_u = 16$, $s_e = 7$, ICC = 131 0.82, i.e., with most variance between speakers). 132

In order to once again conceal the research topic, similar filler stimuli, but spoken by female speakers, were also included in the experiment. These filler sentences were taken from recorded monologues of 24 female speakers (each contributing one sentence) from the same corpus and using the same selection criteria as for male speakers. Neither the filler sentences themselves nor any responses to these fillers were further analyzed.

For the second session, each individual speaker (male or female voice) was matched to an individual portrait photo. These photos were taken from 3 public databases of facial portraits (Hancock, 2008; Nefian, 1999; Spacek, 2008) and did *not* portray the actual speakers. The selected photos of 24 males and 24 females each showed one person in the target age range (18–25 years) with a neutral facial expression. All selected photos were cropped and/or resized to the same size.

145 9.2.3 Speech Manipulations

One of the two sentences of each male speaker was retained as a baseline stimulus 146 with unchanged tempo and unchanged pitch. The other sentence of each male speaker 147 was varied in tempo (factors 0.85, 1.00, 1.15) and in overall pitch (-1.5, 0, +1.5) 148 semitone), yielding 8 manipulated versions of each sentence. The changes are well 149 above the respective just noticeable differences (Quené, 2006; 'THart, Collier, & 150 Cohen, 1990) and they correspond to approximately $\pm 1s_e$ for both manipulations, 151 while the resulting sentences still sound very natural to us. Filler sentences by female 152 speakers were not varied. Tempo and pitch were manipulated by means of sox 153 (Bagwell, 2013). Finally, stimulus and filler sentences were all scaled to -0.5 dB154 relative to the maximum amplitude. 155

156 9.2.4 Procedure

The 8 manipulated versions of each sentence were distributed over 8 experimental lists, counterbalanced over the 24 male speakers. The 24 unchanged male-spoken 159 sentences and 24 female-spoken filler sentences were added to each experimental 160 list. Hence, the unchanged sentences of all speakers were presented to all listen-161 ers, whereas the changed sentences were partitioned over lists so that each listener 162 heard only a single changed version of a particular sentence. This design allowed 163 subsequent within-speaker and within-listener comparisons of baseline and changed 164 versions. The 72 sentences were presented in quasi-random order² (which was how-165 ever the same across the 8 lists).

The experiment was conducted in a classroom setting, with each experimental list presented to a separate undergraduate course group. In the first session, speech stimuli were presented (using PowerPoint) over the classroom sound system. In the second session, typically a few days later, the same speech stimuli were presented with simultaneous portraits visible, using the same sound system and the classroom computer projector. The inter-stimulus interval was 3 s in both sessions, as determined in pilot tests.

Of the remaining 150 participants, 76 participated only in the first session (absent from the second session), 20 only in the second session (absent from the first session), and 54 participated in both sessions, the latter group allowing within-subject comparisons.

Participants were instructed to rate the attractiveness of the speaker on a 7-point Likert scale (1 extremely unattractive, 7 extremely attractive) on a printed response sheet. For the first session, their instruction was as follows (in translation):

... In a moment you will hear 72 sound fragments of people saying something. We'd like to
 ask you to indicate for every sound fragment how attractive you find the speaker. You have
 about 3 s to respond for each person.

¹⁸³ For the second session, participants' instruction was as follows (in translation):

... In a moment you will see 72 photos of people. With every face you will also hear a sound
 fragment. We'd like to ask you to indicate for every person how attractive [Dutch: "hoe
 antrekkelijk"] you find that person. You have about 3 s to respond for each person.

After the rating sessions, participants were invited to answer a brief questionnaire about their gender, age, native language(s), hearing problems, speech problems, dexterity, and sexual orientation as heterosexual or homosexual or bisexual or unknown (including unwilling to answer); see Sect. 9.2.1.

191 9.3 Results

The average ratings by the targeted listeners observed in the listening experiment are summarized in Table 9.2. The lower standard error in the baseline condition is due to the larger number of responses in this condition, because all listeners have judged the unchanged sentences of all speakers (see Sect. 9.2.4).

²Between stimuli involving the same speaker, at least 5 different test or filler sentences were presented.

		Pitch		
		Lower	Unchanged	Higher
Tempo	Slower	2.78 (0.06)	2.94 (0.06)	2.47 (0.05)
	Unchanged	3.28 (0.06)	3.30 (0.02)	2.55 (0.05)
	Faster	3.15 (0.06)	3.39 (0.06)	2.55 (0.06)

Table 9.2 Mean responses (by targeted listeners only) of subjective attractiveness on a 7-point scale, broken down by manipulations of tempo and pitch, with standard errors in parentheses

The separate responses given by each of the 150 remaining listeners to each 196 of the 24 unchanged and 24 manipulated speech stimuli were analyzed by means 197 of a cumulative-link mixed-effects model (CLMM) (Quené & van den Bergh, 2004; 198 Christensen, 2015). This family of models (also known as proportional odds models) 199 regards the dependent variable as ordinal, and coefficients represent the changes in 200 log odds of a response falling in the *i*th category or higher. In other words, a CLMM 201 as used here is somewhat similar to a GLMM (Quené & Van den Bergh, 2008), but 202 with multiple ordered response categories. Fixed predictors in the CLMM were the 8 203 manipulated conditions of tempo and pitch (using dummy coding, with the unchanged 204 condition as baseline), the centered trial number,³ and the absence (baseline code 205 0) or presence (contrast code 1) of a portrait photo. Two-way interactions between 206 photo and manipulation conditions were also included as fixed predictors. Random 207 predictors in the CLMM were listeners (n = 150), speakers (n = 24), and sentences 208 (n = 48) as three crossed random intercepts. The main effect of the photo condition 209 was also included as a random slope at the speaker level, thus allowing for nonuniform 210 effects of the portrait photo across speakers. 211

The fixed regression coefficients, random variances and correlations, and category thresholds estimated by the CLMM described above are listed in Table 9.3.

The **fixed** part of the CLMM shows several interesting effects. In the conditions without a photo (first session), the conditions with slower tempo, as well as the conditions with higher pitch, all yield a significant negative effect: slower tempo is *less* attractive than the unchanged baseline, and so is higher pitch. However, none of the opposite conditions with faster tempo (conditions FU and FL), and none of the conditions with lower pitch, yields a positive effect: faster tempo is equally attractive as the unchanged baseline, and so is lower pitch.

Second, the photo condition yielded a large and significant negative main effect, with considerably lower ratings in the second session (with photo) as compared to the first session (without photo). The interactions suggest that the negative effect of adding a photo is significantly mitigated, in particular, in those phonetic conditions yielding the most negative ratings without a photo. As discussed below, this interaction pattern may suggest a floor effect.

³This centered trial number was scaled by factor 0.1 for computational reasons.

Table 9.3 Estimated coefficients of the CLMM, for intercepts and effects of conditions of tempo (S: slower, U: unchanged, F: faster) and pitch (L: lower, U: unchanged, H: higher), trial number (centered and scaled), and photo condition. Random effects are reported in units of variance of log odds (logit), with standardized correlation among random effects; a significant correlation is marked with an asterisk (p < 0.05 according to bootstrapped 95% confidence interval of the correlation, over 200 bootstrap replications). Fixed effects are reported in log odds (logit) units; significant coefficients are marked with an asterisk (p < 0.05)

Random: listeners	Variance			
(Intercept)	0.9569			
Random: speakers	Variance	Correlation		
(Intercept)	0.8032			
Photo	0.4856	-0.57*		
Random: sentences	Variance			
(Intercept)	0.4076			
Fixed	Estimate	Std. Error	z value	p value
cond.SH	-1.75	0.22	-8.11	< 0.0001*
cond.SU	-0.78	0.21	-3.65	0.0003*
cond.SL	-0.97	0.21	-4.54	< 0.0001*
cond.UH	-1.29	0.21	-6.05	< 0.0001*
cond.UL	-0.10	0.21	-0.49	0.6224
cond.FH	-1.84	0.22	-8.55	< 0.0001*
cond.FU	0.15	0.21	0.71	0.4806
cond.FL	-0.07	0.21	-0.32	0.7457
photo	-1.38	0.16	-8.84	< 0.0001*
cond.SH:photo	0.59	0.16	3.36	0.0008*
cond.SU:photo	0.26	0.17	1.53	0.1257
cond.SL:photo	0.45	0.17	2.63	0.0087*
cond.UH:photo	0.17	0.18	0.98	0.3261
cond.UL:photo	0.12	0.17	0.71	0.4789
cond.FH:photo	1.14	0.17	6.53	< 0.0001*
cond.FU:photo	-0.20	0.17	-1.22	0.2225
cond.FL:photo	-0.01	0.17	-0.04	0.9700
trial	-0.09	0.06	-1.59	0.1120
Category thresholds	Estimate	Std. Error	z value	
112	-3.25	0.24	-13.36	
213	-1.43	0.24	-5.91	
314	-0.04	0.24	-0.17	
415	1.19	0.24	4.94	
516	2.75	0.24	11.28	
617	4.82	0.26	18.55	

Finally, the coefficients in the fixed part of the CLMM did not show an effect of the trial number on listeners' judgements: listeners did not tend to increase or decrease their ratings during a session.

The **random** part of the CLMM shows that speakers' intercepts correlate with speakers' slope of the photo condition (r = -0.57): speakers whose voices were judged as more attractive tended to "lose" less when combined with an alleged portrait, or in other words, the negative main effect of the photo portrait was relatively stronger (more negative) for less-attractive voices.

235 9.4 Discussion

First, the results confirm previously reported effects of **pitch** manipulations on attrac-236 tiveness (Collins, 2000; Feinberg et al., 2005): male voices with increased pitch are 237 rated as less attractive by heterosexual female listeners. While previous studies used 238 only short vowel stimuli, these findings are partially replicated here with sentence-239 length stimuli. This result further corroborates the evidence for the role of male voice 240 pitch in sexual selection through female choice of mate. In spite of this effect in the 241 manipulated stimuli, however, the corresponding effect was not observed for voices 242 with decreased pitch. 243

Second, the results confirm our prediction that manipulations of **tempo** also affect the speaker's attractiveness, with slower speech being less attractive. Slower speakers may be regarded as less attractive because speech tempo may indicate the speaker's (relatively poor) motor skills and cognitive capabilities. Again, the corresponding effect was not observed for voices with increased tempo.

In comparison, the detrimental effect of slower tempo appears to be somewhat 249 smaller than that of higher pitch (cf. Table 9.3). This difference in effect size for pitch 250 and tempo may be explained in three ways. One explanation could be that pitch con-251 stitutes a more salient cue in sexual selection than tempo, because pitch varies more 252 between speakers (and less within speakers) than tempo does (cf. Sect. 9.2.2 for vari-253 ations in our stimuli), so that pitch may be a more reliable indicator of the speaker's 254 individual characteristics than tempo. Another plausible explanation could be that 255 our pitch manipulations were perceptually larger than our tempo manipulations, rel-256 ative to the individual differences between speakers. The prosodic measurements 257 and manipulations described above (Sects. 9.2.2–9.2.3), however, do not support this 258 latter explanation: the pitch manipulations are about $\pm \frac{1}{2}s_u$ whereas the tempo manip-259 ulations are relatively larger, about $\pm 2s_u$ (for comparison, both manipulations were 260 about $\pm 1s_e$ in magnitude). A third explanation was proposed by Babel et al. (2014) 261 who argue that attractive voice properties may not be universal, but dependent on cul-262 tural preferences; the weights of tempo and pitch properties on voice attractiveness 263 may thus be culturally constrained. Further research, with different sizes of phonetic 264 manipulations and with listeners sampled from different cultures, would be required 265 to rule out one or more of these explanations. 266

Third, the results do not support the hypothesized interaction between pitch and tempo cues on speakers' attractiveness. In the first session (without photo), neither lower pitch, nor faster tempo, nor the combination of these two manipulations yielded a positive effect on voice attractiveness. Moreover, lowest ratings were obtained in conditions with increased pitch, irrespective of the tempo manipulations. This suggests that the combined traits of physical and cognitive capabilities are somehow assessed independently, contrary to the expectations outlined in Sect. 9.1.

Finally, the results suggest that the **photo** portraits may have introduced floor 274 effects in this experiment. Coefficients in the fixed part of the CLMM suggest that 275 conditions yielding the lowest ratings without a photo (session 1) also decrease 276 less with a photo (session 2), which may be because the conditions involving less-277 attractive speech cannot "lose" as many points when combined with a photo. In 278 addition, speakers who are rated as more attractive tend to "lose" more when accom-279 panied by a photo (r = -0.57, Table 9.3), which may again be because less-attractive 280 speakers cannot be rated below the floor of the Likert scale. The photos were included 281 in the experimental design in order to investigate the effects of (ecologically valid) 282 visual cues on voice attractiveness ratings. However, the unexpected negative effect 283 of adding a portrait photo may have resulted in ratings that were too low to show 284 the effects of phonetic properties. One possible explanation is that the photos were 285 taken from relatively old sources (portraits were at least 8 years old at the time of 286 testing) and may have contained outdated visual cues regarding style, hairdress, etc., 287 for the target listeners in our study. More speculatively, there may have been some 288 unknown mismatch between (non-Dutch) portraits (Hancock, 2008; Nefian, 1999; 289 Spacek, 2008) and (Dutch) voices, yielding a negative effect on the ratings in the 290 with-portrait condition. For further phonetic research into listeners' attractiveness 201 judgements, we recommend to refrain from randomly matched portraits accompa-292 nying the voice stimuli. 293

294 9.5 Conclusions

Female listeners rate a male speaker as less attractive if his voice pitch is increased 295 and if his speech tempo is decreased, relative to a baseline sentence with unchanged 296 pitch and tempo. These effects suggest that both pitch and tempo play a role in 297 speech-based sexual selection of males by females, although our results suggest that 298 the underlying mechanisms for pitch and tempo may well be different. Voice pitch 299 indicates the speaker's health and physical dominance (Dabbs & Mallinger, 1999; 300 Puts et al., 2012; Collins, 2000; Feinberg et al., 2005), while speech tempo may 301 indicate the speaker's motor skills and cognitive competence (Apple et al., 1979; 302 Smith et al., 1975). The effect of voice pitch on attractiveness is larger than that of 303 speech tempo, perhaps because pitch varies relatively more between speakers than 304 within speakers, in contrast to tempo, so that pitch may constitute a more reliable 305 cue to a speaker's individual characteristics. 306

9 Attractiveness of Male Speakers: Effects of Pitch and Tempo

Acknowledgments Results from a different, related study (using the same audio stimuli, always presented with photos, with different participants) were reported at the Speech Prosody 2016 conference (Boston, U.S.A.). We thank Nivja de Jong, Gerrit Bloothooft, Huub van den Bergh, the audience at Speech Prosody 2016, and three anonymous reviewers, for helpful comments and suggestions.

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Abstract	Speech contains pronounced amplitude modulations in the 1–9 Hz range, correlating with the syllabic rate of speech. Recent models of speech perception propose that this rhythmic nature of speech is central to speech recognition and has beneficial effects on language processing. Here, we investigated the contribution of amplitude modulations to the subjective impression listeners have of public speakers. The speech from presidential candidates Hillary Clinton and Donald Trump in the three TV debates of 2016 was acoustically analyzed by means of modulation spectra. These indicated that Clinton's speech had more pronounced amplitude modulations than Trump's speech, particularly in the 1–9 Hz range. A subsequent perception experiment, with listeners rating the perceived charisma of (low-pass filtered versions of) Clinton's and Trump's speech, showed that more pronounced amplitude modulations (i.e., more 'rhythmic' speech) increased perceived charisma ratings. These outcomes highlight the important contribution of speech rhythm to charisma perception.			
Keywords	Amplitude modulations - Speech rhythm - Modulation spectrum - Charisma perception - Temporal envelope - Political debates			

Chapter 10 The Contribution of Amplitude Modulations in Speech to Perceived Charisma



Hans Rutger Bosker

- Abstract Speech contains pronounced amplitude modulations in the 1–9 Hz range,
- ² correlating with the syllabic rate of speech. Recent models of speech perception
- ³ propose that this rhythmic nature of speech is central to speech recognition and has
- ⁴ beneficial effects on language processing. Here, we investigated the contribution of
- ⁵ amplitude modulations to the subjective impression listeners have of public speakers.
- ⁶ The speech from presidential candidates Hillary Clinton and Donald Trump in the
- three TV debates of 2016 was acoustically analyzed by means of modulation spectra.
 These indicated that Clinton's speech had more pronounced amplitude modulations
- than Trump's speech, particularly in the 1–9 Hz range. A subsequent perception
- ¹⁰ experiment, with listeners rating the perceived charisma of (low-pass filtered ver-
- sions of) Clinton's and Trump's speech, showed that more pronounced amplitude modulations (i.e., more 'rhythmic' speech) increased perceived charisma ratings.
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- 14 perception.

¹⁵ Keywords Amplitude modulations • Speech rhythm • Modulation spectrum •

¹⁶ Charisma perception · Temporal envelope · Political debates

17 10.1 Introduction

Any spoken utterance, regardless of talker, language, or linguistic content, contains fast-changing spectral information (e.g., vowel formants, consonantal frication, etc.) as well as slower changing temporal information. The temporal information in speech is particularly apparent in the temporal envelope of speech, which includes the fluctuations in amplitude from consonants (constricted vocal tract, lower amplitude) to

vowels (unconstricted vocal tract, higher amplitude), from stressed (prominent) to

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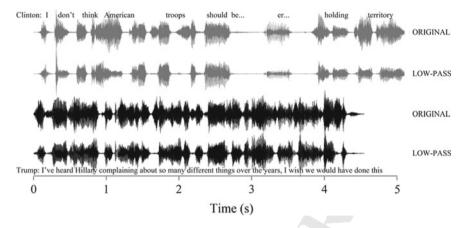


Fig. 10.1 Excerpts of Clinton's speech (in gray) with a notable syllabic rhythm around 3 Hz and Trump's speech (in black) with a notable lack of consistent slow-amplitude modulations. Below each waveform are the low-pass filtered versions of the excerpts, demonstrating that the original slow-amplitude modulations are maintained to a large degree

unstressed syllables (less prominent), etc. For instance, the top example in Fig. 10.1
has pronounced fluctuations in amplitude (also known as amplitude modulations)
occurring at around 3 Hz, related to the syllabic rate of the utterance (i.e., roughly
three syllables per second).

The temporal dynamics of speech (e.g., energy patterns and syllable durations 28 in speech) are semi-regular at multiple (segmental, syllabic, sentential) timescales 29 (Poeppel, 2003; Rosen, 1992). Hence, speech is an intrinsically rhythmic signal, with 30 'rhythmic' referring to the semi-regular recurrence over time of waxing and waning 31 prominence profiles in the amplitude signature of speech (for other conceptualiza-32 tions of speech rhythm, see Kohler, 2009; Nolan & Jeon, 2014). Naturally produced 33 syllable rates typically do not exceed a rate of 9Hz (Ghitza, 2014; Jacewicz, Fox, 34 & Wei, 2010; Pellegrino, Coupé, & Marsico, 2011; Quené, 2008; Varnet, Ortiz-35 Barajas, Erra, Gervain, & Lorenzi, 2004). As such, most of the energy in the ampli-36 tude modulations in the speech signal is found below 9Hz (Ghitza & Greenberg, 37 2009; Greenberg & Arai, 1999, 2004), across a range of typologically distant lan-38 guages (Ding et al., 2017; Varnet, Ortiz-Barajas, Erra, Gervain, & Lorenzi, 2017), 39 with the most prominent modulation frequencies near the average syllable rate of 40 3–4 Hz (Delgutte 1998). 41

In recent models of speech perception (Ghitza 2011; Giraud & Poeppel, 2012;
Peelle & Davis, 2012), this rhythmic nature of speech is said to play a central role in
speech recognition. For instance, speakers who are intrinsically more intelligible than
others show more pronounced low-frequency modulations in the amplitude envelope
(Bradlow, Torretta, & Pisoni, 1996). In fact, when the slow amplitude fluctuations
in speech are degraded or filtered out, intelligibility drops dramatically (Drullman,
Festen, & Plomp, 1994; Ghitza, 2012; Houtgast & Steeneken, 1973), while speech

with only minimal spectral information remains intelligible as long as low-frequency
temporal modulations are preserved (Shannon, Zeng, Kamath, Wygonski, & Ekelid,
1995). Similarly, speech stream segregation (understanding speech in noise; Aikawa
& Ishizuka, 2002), word segmentation (resolving continuous speech into words;
Cutler, 1994; Cutler & Butterfield, 1992; Cutler & Norris, 1988), and phoneme
perception (Bosker, 2017a; Bosker & Ghitza, 2018; Quené, 2005) are all influenced
by regular energy fluctuations in speech.

A powerful demonstration of the contribution of regular amplitude modulations 56 to speech comprehension is the finding that otherwise unintelligible speech can be 57 made intelligible by imposing an artificial rhythm (Bosker & Ghitza, 2018; Doelling, 58 Arnal, Ghitza, & Poeppel, 2014; Ghitza, 2012, 2014). For instance, Bosker and 59 Ghitza (2018) took Dutch recordings of seven-digit telephone numbers (e.g., "215– 60 4653") and compressed these by a factor of 5 (i.e., make the speech five times as 61 fast while preserving spectral properties such as pitch and formants). This heavy 62 compression manipulation made the intelligibility of the telephone numbers drop 63 from the original 99% to about 39% digits correct. However, Bosker and Ghitza then 64 imposed an artificial rhythm onto the heavily compressed speech, by taking 66 ms 65 windows of compressed speech and spacing these apart by 100 ms of silence (i.e., 66 inserting 100-ms silent intervals). This 'repackaged' condition did not contain any 67 additional linguistic or phonetic information compared to the heavily compressed 68 speech; it only differed in having a very pronounced amplitude modulation around 69 6Hz. The authors found that imposing this artificial rhythm onto the compressed 70 speech boosted intelligibility (from 39 to 71%) digits correct, demonstrating that 71 regular amplitude modulations play a central role in speech perception. 72

Rhythmic amplitude modulations in speech not only affect speech intelligibility 73 but they also play a role in spoken communication more generally. For instance, syn-74 tactic processing (Roncaglia-Denissen, Schmidt-Kassow, & Kotz, 2013), semantic 75 processing (Rothermich, Schmidt-Kassow, & Kotz, 2012), and recognition memory 76 (Essens & Povel 1985) are all facilitated by regular meter. Moreover, there are even 77 suggestions in the literature that listeners explicitly prefer listening to speech with a 78 clear rhythmic structure. For instance, Obermeier et al. (2013) took four-verse stan-79 zas from old German poetry and independently manipulated the rhyme and meter of 80 these poetry fragments. Rhyme was manipulated by substituting rhyming sentence-81 final words with non-rhyming words with the same metrical structure (maintaining 82 meter), while meter was manipulated by substituting a sentence-medial word with a 83 word with mismatching metrical structure (e.g., "Nacht" > "Dunkelheit"; maintain-84 ing rhyme in sentence-final words). Native German participants rated the original and 85 manipulated fragments of poetry on liking and perceived intensity. Results indicated 86 that non-rhyming and non-metrical stanzas received lower ratings on both the liking 87 and perceived intensity scales, suggesting that the presence of rhythmical structure 88 induces greater esthetic liking and more intense emotional processing (Obermeier et 89 al., 2013, 2016). 90

Here, we examined the contribution of rhythmic amplitude modulations to the **Q1** perception of charisma in public speakers' voices. Charisma and charismatic lead-93 ership are intensively studied topics, with clear implications for public speakers, 93 politics, religion, and society at large. There seems to be a consensus in the literature 94 that being a charismatic speaker is a necessary precondition for being a charismatic 95 leader. In fact, how one speaks (i.e., performance characteristics, such as pitch, loud-96 ness, prosody, etc.) has been argued to contribute to charisma perception more than 97 what one says (i.e., the linguistically formulated communicative message; Awamleh 98 & Gardner, 1999; Rosenberg & Hirschberg, 2009). Several studies have, therefore, 99 attempted to find acoustic correlates of charisma in public speakers' voices (see 100 also in this volume; Rosenberg & Hirschberg, this volume; Brem & Niebuhr, this 101 volume). For instance, pausing behavior (D'Errico, Signorello, Demolin & Poggi, 102 2013), speech rate (D'Errico, et al. & Poggi, 2013), overall intensity (Niebuhr, Voße & 103 Brem, 2016), number and type of disfluencies (Novák-Tót, Niebuhr, & Chen, 2017), 104 and timbre (Weiss and Burkhardt, 2010) have all been identified as contributing to 105 perceived charisma and personality. However, although there are suggestions in the 106 literature that greater variability in pitch and intensity contours increases perceived 107 charisma (D'Errico et al., 2013; Niebuhr et al., 2016; Rosenberg & Hirschberg, 2009), 108 it is unclear what the role of the rhythm of speech is in charisma perception. There-109 fore, the present research goal was to investigate how political debaters make use of 110 variation in the amplitude envelope in speech production and how this variation, in 111 turn, may affect speech perception. 112

Regarding rhythm in speech production, we report an acoustic comparison of 113 the temporal amplitude modulations in the speech produced by two presidential 114 candidates in the American elections of 2016: Hillary Clinton and Donald Trump. 115 Recordings from three national presidential debates were collected and the speech 116 produced by both candidates was first matched for overall intensity. Thereafter, their 117 speech was analyzed by means of modulation spectra (Bosker & Cooke, 2018; Ding 118 et al., 2017; Krause & Braida, 2004). These modulation spectra quantify the power 119 of individual modulation frequency components present in a given signal (e.g., see 120 Fig. 10.2), with power on the y-axis and modulation frequency on the x-axis. They 121 can be used to assess which modulation frequencies are most prominent in differ-122 ent signals (e.g., speech and music show well-separated peaks around 5 and 2Hz, 123 respectively; Ding et al. 2017) but also to compare the overall power (in differ-124 ent frequency bands) across talkers or speech registers (Krause & Braida, 2004). For 125 instance, Bosker and Ghitza 2018 calculated modulation spectra of spoken sentences 126 produced in quiet (plain speech) and the same sentences produced in noise (Lom-127 bard speech). Results showed greater power in Lombard speech compared to plain 128 speech, particularly in the 1–4 Hz range, demonstrating that talkers produce more 129 pronounced amplitude modulations when talking in noise, presumably to aid speech 130 comprehension. 131

Similarly, the present acoustic analysis compared the power of different modulation frequency bands across the two talkers. Greater power in the modulation spectrum of one speaker over another would reveal a more pronounced temporal

envelope in that particular candidate's speech (i.e., greater amplitude modulations). 135 Specifically, we expect power differences to occur within the frequency range of 136 typical speech rates, namely below 9Hz because (1) this modulation range is most 137 characteristic of spontaneous speech (Ding et al., 2017); and (2) previous research 138 indicates that differences between speech registers (plain vs. Lombard speech) are 139 apparent in the lower modulation range (Bosker and Ghitza 2018). Power differ-140 ences in this 1–9 Hz modulation range would be indicative of a more regular syllabic 141 rhythm. Moreover, the locations of peaks in the modulation spectrum would reveal 142 which modulation frequencies are most pronounced in that speaker's amplitude enve-143 lope, being indicative of a specific rhythm preference. By contrast, differences in the 144 power of modulation frequencies between 9–15 Hz are expected to be smaller (if 145 present at all) since this modulation range is less pronounced in speech and is not 146 straightforwardly related to particular acoustic or perceptual units in speech. 147

When it comes to quantifying rhythm in speech, modulation spectra have several 148 advantages over other rhythm metrics that have been introduced in the literature, 149 such as %V (percentage over which speech is vocalic; Ramus et al. (1999)), ThetaC 150 (standard deviation of consonantal intervals; Ramus et al. (1999)), PVI (pairwise 151 variability index; Grabe and Low (2002)), or normalized metrics such as VarcoV 152 and VarcoC (Dellwo, 2006; White and Mattys, 2007). These metrics assess dura-153 tional variability (Loukina et al., 2011), not necessarily periodicity. That is, both 154 isochronous and anisochronous distributions of vowels and consonants can have the 155 same %V. Moreover, such measures are influenced by between-language differences, 156 whereas modulation spectra are not (Ding et al., 2017). 157

Going beyond merely identifying differences in the use of rhythm between speak-158 ers in speech production, we also tested the contribution of pronounced amplitude 150 modulations to speech perception. Specifically, a rating experiment was carried out 160 with low-pass filtered versions of (a subset of) the speech from both speakers. Fil-161 tering was applied to reduce the contribution of lexical-semantic information to 162 participants' judgments while maintaining the temporal structure of the acoustic sig-163 nal (see Fig. 10.1), forcing listeners to base their judgments primarily on temporal 164 characteristics. In line with the introduced beneficial effects of rhythmic regular-165 ity on speech intelligibility and esthetic liking, we hypothesized that the perceived 166 charisma ratings would correlate with the speech rhythm in the signals. That is, 167 speech fragments with more pronounced amplitude modulations in the 1–9 Hz range 168 would be expected to be rated as more charismatic than speech fragments with less 169 pronounced amplitude modulations. If corroborated, this would indicate that speech 170 rhythm not only contributes to intelligibility and the qualitative appreciation of the 171 linguistic message but also to the subjective impression listeners have of a (public) 172 speaker. 173

174 10.2 Acoustic Analysis

175 10.2.1 Method

176 **10.2.1.1** Materials

Recordings of all three presidential debates between Hillary Clinton and Donald 177 Trump were retrieved from Youtube. The first debate (NBC News 2016) took place 178 at Hofstra University, Hempstead, NY, USA, on September 26, 2016, and had the 179 form of a traditional debate: the two candidates responded to questions posed by a 180 moderator. The second debate (ABC News, 2016a) was broadcasted from Washing-181 ton University in St. Louis, St. Louis, MO, USA, on October 9, 2016. This debate 182 was structured as a 'town hall discussion' with the candidates responding mostly to 183 audience member questions. To illustrate, Fig. 10.1 shows two excerpts of Clinton's 184 and Trump's speech in the second debate. The presence of a 3 Hz syllabic 'beat' is 185 clearly visible in Clinton's waveform, whereas Trump's speech notably lacks slow-186 amplitude modulations. Finally, the third debate (ABC News, 2016b) took place at 187 the University of Nevada, Las Vegas, Las Vegas, NV, USA, on October 19, 2016, 188 and had the form of a traditional debate again. 189

All monologue speech from either candidate was manually annotated. That is, 190 only those speech fragments in which one talker and one talker alone was speaking 191 (uninterrupted monologue including all pauses, corrections, hesitations, etc.) was 192 analyzed. Speech fragments that included crosstalk, laughter, applause, questions 193 posed by the moderator, etc., were excluded from analyses. Monologues longer than 104 approximately 35 s were cut into smaller fragments of <35 s at sentence boundaries. 195 For the first debate, these annotations resulted in 93 speech fragments produced by 196 Clinton (duration: M = 24s; SD = 7 s; range = 5-36 s; total = 2263 s) and 98 197 speech fragments produced by Trump (duration: M = 25 s; SD = 7 s; range = 6-198 35 s; total = 2514 s). For the second debate, these annotations resulted in 77 speech 100 fragments produced by Clinton (duration: M = 29 s; SD = 5 s; range = 8-36 s; 200 total = 2243 s) and 82 speech fragments produced by Trump (duration: M = 27 s; 201 SD = 6 s; range = 7-35 s; total = 2241 s). For the third debate, these annotations 202 resulted in 93 speech fragments produced by Clinton (duration: M = 24 s; SD = 7203 s; range = 5-35 s; total = 2245 s) and 76 speech fragments produced by Trump 204 (duration: M = 23 s; SD = 8 s; range = 5-34 s; total = 1779 s). 205

206 10.2.1.2 Procedure

Before analysis of the speech fragments, the overall power (root mean square; RMS)
in each fragment was normalized (set to an arbitrary fixed value), thus matching
the overall power of the speech from both speakers. Following this normalization
procedure, the speech fragments from each debate were analyzed separately.

First, the modulation spectrum of each individual speech fragment produced by 211 Clinton was calculated, using a method adapted from (Bosker and Cooke 2018). 212 It involved filtering the speech fragment by a band-pass filter spanning the 500– 213 4000 Hz range and deriving the envelope of the filter's bandlimited output (i.e., 214 Hilbert envelope). The envelope signal was zero-padded to the next power of 2 215 higher than the length of the longest fragment of that particular speaker to achieve 216 the same frequency resolution across recordings. This signal was then submitted 217 to a Fast Fourier Transform (FFT), resulting in the modulation spectrum of that 218 particular speech fragment. Finally, the average power in two frequency bands was 219 calculated: average power in the 1-9Hz range and average power in the 9-15Hz 220 range, resulting in two different observations for each of the speech fragments. Note 221 that natural speech rates typically fall below 9 Hz. The same steps were then repeated 222 for Trump's speech fragments. 223

This analysis procedure was followed for each of the three debates and formed the two dependent variables (average power below and above 9 Hz) for statistical analyses reported below. In order to visualize the average rhythmicity in the speech of one speaker in one debate, all individual modulation spectra of one speaker in one debate were downsampled by a factor of 25 and thereafter averaged.

229 10.2.2 Results

Data from the three debates are reported separately to allow for comparison across debates. Note, however, that follow-up analyses did not reveal large qualitative differences between the outcomes of the three debates.

233 10.2.2.1 First Debate

The average modulation spectra of the speech produced by both speakers in each of the three debates is given in Fig. 10.2.

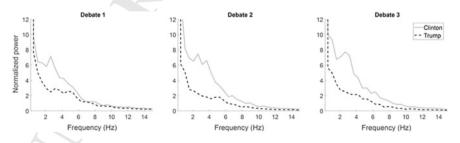


Fig. 10.2 Average modulation spectra of the speech produced by Hillary Clinton (gray solid lines) and Donald Trump (black dashed lines), separately for the three presidential debates

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A simple linear model was built in R (R Development Core Team, 2012) separately 236 for each of the two frequency bands (1-9 and 9-15 Hz), predicting the average power 237 for each of the two speakers. The first model, predicting power in the 1–9Hz range, 238 showed a significant effect of Speaker (b = 1.265, F(1, 189) = 90.91, p < 0.001, 239 $adjusted R^2 = 0.321$), indicating that Clinton's speech contained more power in the 240 lower frequencies compared to Trump's speech. The other model, predicting power 241 in the 9–15 Hz range, also showed a significant difference between the two speakers, 242 only with a much smaller effect size (b = 0.164, F(1, 189) = 42.75, p < 0.001,243 adjusted $R^2 = 0.180$). These findings reveal that, in the first presidential debate, 244 Clinton's speech contained more power in the 1-9 Hz range, and also slightly more 245 power in the frequency range above 9 Hz. 246

247 10.2.2.2 Second Debate

The average modulation spectra of all speech produced by the two speakers in the second debate are given in Fig. 10.2.

Again, simple linear models were built separately for each of the two frequency 250 bands (1–9 Hz and 9–15 Hz). The first model, predicting power in the 1–9 Hz range, 251 showed a significant effect of Speaker (b = 2.322, F(1, 157) = 434.5, p < 0.001, 252 adjusted $R^2 = 0.733$), as did the second model, predicting power in the 9–15 Hz 253 range, only with a considerably smaller effect size (b = 0.263, F(1, 157) = 250.9, 254 p < 0.001, adjusted R2 = 0.613). These findings reveal that, in the second presi-255 dential debate, Clinton's speech contained considerably more power in the 1–9Hz 256 range, and also somewhat more power in the frequency range above 9 Hz. 257

Note that, similar to the first debate, there is a clear peak in the modulation
 spectrum of Clinton around 3 Hz. This peak indicates a pronounced syllabic rhythm
 around 3 Hz in the amplitude envelope of Clinton's speech (cf. Fig. 10.1).

261 10.2.2.3 Third Debate

The average modulation spectra of the speech produced by both speakers in the third debate are given in Fig. 10.2.

Once more, simple linear models were built separately for each of the two fre-264 quency bands (1-9 Hz and 9-15 Hz). The first model, predicting power in the 1-265 9 Hz range, showed a significant effect of Speaker (b = 2.427, F(1, 167) = 207.5,266 p < 0.001, adjusted $R^2 = 0.551$), as did the second model, predicting power in the 267 9–15 Hz range, only with a considerably smaller effect size (b = 0.350, F(1, 167) =268 197.6, p < 0.001, adjusted $R^2 = 0.539$). These findings from the third debate mirror 269 those from the second debate: Clinton's speech contained considerably more power 270 in the 1-9 Hz range, and also slightly more power in the frequency range above 9 Hz. 271

10.3 Perception Experiment

273 10.3.1 Participants

²⁷⁴ Native Dutch participants (N = 20; 17 females, 3 males; $M_{age} = 25$) with normal ²⁷⁵ hearing were recruited from the Max Planck Institute's participant pool. Participants ²⁷⁶ in all experiments reported here gave informed consent as approved by the Ethics ²⁷⁷ Committee of the Social Sciences department of Radboud University (project code: ²⁷⁸ ECSW2014-1003-196).

279 **10.3.2** Material

Only speech fragments from the third debate were included in the perception experiment because (1) it was impossible to include the speech from all debates in a single rating experiment for reasons of length and (2) the third debate showed the largest difference between the two talkers in the power of amplitude modulations in the 1–9 Hz range.

Speech fragments from the third debate were first scaled to 70 dB using Praat 285 (Boersma & Boersma, 2016). We did not want raters to base their judgments on the 286 linguistic content of the speech since this was not controlled across the two speakers. 287 Therefore, all speech was low-pass filtered (450 Hz cutoff, using a Hann window with 288 a roll-off width of 25 Hz as implemented in Praat) to avoid lexical-semantic inter-280 ference, while preserving sufficient ecological validity (being like naturally filtered 290 speech, as if overhearing a person in another room). This manipulation crucially 291 leaves the amplitude fluctuations present in the original speech signals relatively 292 intact (cf. Fig. 10.1). After low-pass filtering, the speech was scaled to 70 dB. 293

²⁹⁴ 10.3.3 Procedure

Participants in the experiment listened to the low-pass filtered speech fragments 295 from either Clinton or Trump (counter-balanced across participants) in random order. 296 Participants were instructed to rate the items for charisma, basing their judgments on 297 the sound of the speech. They were explicitly pointed to the speaker's identity (but 298 remained unaware that ratings of the other speaker were also collected). Nevertheless, 299 they were told not to let any potential political or personal preferences influence their 300 ratings. The use of a between-participants design reduced the contrast between the 301 two speakers, thus further minimizing potential biases due to speaker sex, pitch, 302 political stance, etc. Participants were instructed to rate the items for charisma using 303 an Equal Appearing Interval Scale (Thurstone, 1928), including seven stars with 304 labeled extremes (not charismatic on the left; very charismatic on the right). 305

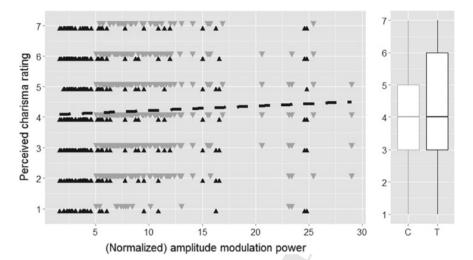


Fig. 10.3 *Left panel*: Individual perceived charisma ratings (on a scale from 1 "not charismatic" to 7 "very charismatic") of each speech fragment as a function of the (normalized) average power of amplitude modulations in the 1–9 Hz range. Gray triangles indicate speech fragments from Clinton and black triangles those from Trump. The black dashed line shows a (simple) linear regression line across all data points. *Right panel:* Boxplots showing the charisma ratings split for the two speakers (C = Clinton; T = Trump)

306 10.3.4 Results

The average perceived charisma rating of the speech of Clinton was 4.1, while Trump received an average rating of 4.3. Speech fragments with outlier values for the average power of amplitude modulations in the 1–9 Hz range (i.e., > 2 * SD; n = 8) were excluded to avoid the heavy weight of these outliers on the correlation analyses reported below. Figure 10.3 shows the individual perceived charisma ratings of speech fragments as a function of the average power of amplitude modulations in the 1–9 Hz range.

The right panel of Fig. 10.3 suggests that, on average, Trump (black) received higher charisma ratings than Clinton (gray). The left panel suggests that the charisma ratings seem to be a function of the average power of amplitude modulations in the 1–9 Hz range, with greater power of the amplitude modulations leading to higher charisma ratings.

Perceived charisma ratings were entered into a simple linear model, including the predictor's Speaker (categorical predictor; deviation coding, with Trump coded as -0.5 and Clinton as +0.5), Modulation Power Below 9 Hz (continuous predictor; z-scored), Modulation Power Above 9 Hz (continuous predictor; z-scored), and interactions between Speaker and the two Modulation Power predictors. This model, first, revealed a significant effect of Modulation Power Below 9 Hz (b = 0.318, F(5, 1664) = 2.245, p = 0.041). This indicates that, across the two talkers, speech with greater power in the 1–9 Hz range led to higher charisma ratings. Second, we found a main effect of Speaker (b = -0.209, F(5, 1664) = 2.245, p = 0.014), suggesting that Trump's speech was rated as more charismatic overall than Clinton's speech. No effect of Modulation Power Above 9 Hz was observed (p = 0.151), nor was their statistical evidence for either interaction term.

331 10.3.5 General Discussion

The present research goal was to investigate the role of temporal amplitude modulations in charisma perception in political debates. An acoustic analysis of the speech from two presidential candidates, Hillary Clinton and Donald Trump, in three different debates was carried out by means of modulation spectra, revealing the spectral content of the amplitude envelopes. Also, a perception experiment investigated whether judgments of perceived charisma would be sensitive to the speech rhythm in the acoustic signal.

Comparison of the amplitude spectra of Hillary Clinton's and Donald Trump's 339 speech revealed considerably greater power in the modulation spectra of Clinton's 340 speech than in those of Trump's speech. This power difference cannot be due to 341 overall intensity differences between the two speakers since all speech was normal-342 ized in overall power prior to analysis, matching the overall intensity of Clinton's 343 and Trump's speech fragments. Also, the power difference cannot be attributed to 344 differences in habitual speech rate since such differences would be expected to lead 345 to peaks at different frequencies in the modulation spectra, rather than differences 346 in overall power. Instead, this finding indicates that there was a more pronounced 347 temporal envelope in Clinton's speech (compared to Trump's speech). 348

Note that this power difference was concentrated (i.e., largest) in the 1–9 Hz range, 349 the range of typical syllable rates (Ding et al., 2017; Ghitza & Greenberg, 2009; 350 Greenberg & Arai, 1999, 2004). This suggests that the power difference between 351 Clinton and Trump is driven by more pronounced syllabic amplitude fluctuations 352 in the speech of Clinton. Moreover, across the three debates, there seems to be a 353 relatively consistent peak around 3 Hz in Clinton's modulation spectra, suggesting 354 a preferred syllabic rate. In contrast, Trump's modulation spectra lack pronounced 355 peaks, indicating particularly flat, that is, unmodulated amplitude envelope contours. 356

Whether or not Clinton used this particular speaking style (with regular ampli-357 tude modulations) purposefully and strategically remains unknown. In this regard, 358 one may note that speakers, in general, tend to produce greater amplitude modulations 359 when instructed to produce clear speech (Krause & Braida, 2004) or when talking 360 in noise (Bosker & Cooke, 2018), presumably for reasons of achieving greater intel-361 ligibility. As such, Clinton's speaking style during the three debates examined here 362 may be the result of her extensive experience with making herself understood during 363 public addresses. We may speculate that the influence of the enhanced modulation 364 signature of Clinton's speech did not influence charisma perception alone. Regular 365 energy fluctuations have been shown to benefit speech recognition (Doelling et al., 366

³⁶⁷ 2014; Ghitza, 2012, 2014), particularly in noisy listening conditions (Aikawa and ³⁶⁸ Ishizuka, 2002), and, as such, may have improved Clinton's intelligibility in the noisy ³⁶⁹ environment of a live debate. This seems particularly relevant considering the large ³⁷⁰ number of interruptions (i.e., overlapping speech) that Clinton encountered during ³⁷¹ the three debates (Trump: N = 106 vs. Clinton : N = 27). Also, rhythmic ampli-³⁷² tude modulations facilitate recognition memory (Essens & Povel 1985), potentially ³⁷³ serving Clinton's political aims at the time.

One may also speculate about the absence of amplitude modulations in Trump's 374 speech. Tian's recent analysis (Tian, 2017) of Trump's disfluency patterns during 375 these presidential debates indicated that Trump was considerably more disfluent 376 than Clinton. Trump was found to use particularly many repetitions, repairs, and 377 abandoned utterances (Tian, 2017); all types of disfluencies that signal less extensive 378 utterance planning and self-monitoring. As such, Tian suggested that Trump used 379 less rehearsed utterances compared to Clinton. This difference in utterance planning 380 can well be thought to underlie the difference in rhythmic structure between the two 381 speakers: putting more effort in cognitive planning would also allow the speaker to 382 better temporally organize the syllabic structure of the utterance, and especially so 383 with increased public-speaking experience. 384

The outcomes of the perception experiment supported two conclusions. First, more pronounced amplitude modulations biased raters toward higher perceived charisma ratings. Across all speech fragments from both talkers, we observed that those items with a higher power of amplitude modulations in the 1–9 Hz range also received higher perceived charisma ratings—independent from the main speaker effect. This suggests that the rhythm of speech contributes to perceived charisma, with implications for public speakers in general.

The second conclusion is that Trump's speech was, on the whole, rated as more 392 charismatic than Clinton's. Although this may seem at odds with the observation 393 that less pronounced amplitude modulations result in lower perceived charisma rat-394 ings, it is important to realize that listeners could base their judgments on a larger 395 set of acoustic characteristics than just rhythm. It is unlikely that participants in the 396 study based their perceived charisma ratings solely on the amplitude modulation 397 signatures of the speech signals. Many other (acoustic) characteristics are likely to 398 have contributed to participants' judgments-even in the case of low-pass filtered 399 speech (i.e., without access to linguistic content). One potential acoustic cue that 400 was available to listeners and that may account for the main effect of Speaker is 401 pitch. The low-pass filter applied to the speech only filtered out spectral informa-402 tion above 450 Hz, leaving fundamental frequencies relatively intact. As such, the 403 low-pass filtered stimuli still contained acoustic cues to talker gender (distinction 404 male vs. female cued by pitch). Indeed, talker gender is known to bias charisma 405 ratings (and the perception of other personality traits), with male talkers generally 406 being perceived as more charismatic than female talkers (Brooks, Huang, Kearney, 407 & Murray, 2014; Niebuhr, Skarnitzl, & Tylecková, 2018; Novák-Tát, 2017). There-408 fore, the main effect of Speaker is likely driven by a range of acoustic and social 409 factors that were not controlled for. Still, it is important to note that the correlation 410 between more pronounced amplitude modulations and higher perceived charisma 411

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ratings held across talkers (no interaction between modulation power and speaker).
This means that, despite an overall difference between the male and female voice,
enhanced amplitude modulations in speech equally affected the ratings of Trump's
and Clinton's speech.

Another possible explanation for the overall effect of Speaker could be related to 416 the concept of 'effectiveness windows' in charisma perception (Niebuhr, Tegtmeier, 417 & Brem, 2017). It has been proposed that public speakers, in attempting to per-418 suade their audiences, should use charisma-relevant acoustic cues within particular 419 functional ranges, avoiding, for instance, exaggerated vocal characteristics. Maybe 420 Clinton's consistent use of regular amplitude modulations was perceived as an "over-421 dose" of charismatic vocal cues, thus at some point hurting, rather than serving, the 422 subjective impression listeners had of her. However, such an interpretation would 423 also predict an inverse U-curve in the relationship between modulation power and 424 charisma perception, such that greater rhythmicity would be beneficial only up to 425 a certain point. However, follow-up statistical analyses (i.e., testing for a quadratic 426 effect of Modulation Power Below 9Hz) and visual inspection of Fig. 10.3 do not 427 support the presence of such a U-shaped relationship, arguing against this particular 428 explanation. 429

The fact that we used low-pass filtered speech may be seen as both a strength as 430 well as a limitation of the current study. It is a strength of the methodology of the 431 experiment because this allowed us to isolate the (temporal) acoustics of the speech 432 from the linguistic content. In this fashion, potential interference from the linguistic 433 message was reduced. At the same time, one may argue that it limits the generaliz-434 ability of the present findings since in most natural communicative situations we hear 435 unfiltered speech. For our current purposes, we valued experimental control higher 436 than ecological validity and future studies may investigate whether the rhythm of 437 speech also influences charisma perception in more natural settings. 438

Another limitation of this study is that we only performed correlational analyses.
Even though we are unaware of possible confounds, we acknowledge that the present
empirical evidence does not necessarily warrant the conclusion that more pronounced
amplitude modulations causally influence perceived charisma. Future investigations
may, for instance, examine this causal relationship by directly manipulating the
modulation depth of speech fragments—while keeping all other (acoustic, linguistic,
social) cues present in the signal constant.

Finally, one further highly relevant issue in the field of charisma research is the 446 role of listener variation in charisma perception. Most empirical studies of charisma 447 perception have used subjective ratings collected from young university students. In 448 fact, some studies, like the present one, recruited non-native speakers of the language 449 under study (e.g., Brem & Niebuhr, this volume). It remains unclear how variation 450 among raters might impact charisma perception and the perceptual weight assigned to 451 various vocal characteristics. Is charisma perception language- or culture-dependent 452 (cf. D'Errico, 2013)? Do non-native speakers of a language weight the acoustic cues 453 to charisma differently from native speakers, possibly through influences from their 454 L1? Do male and female raters differ in how they judge male versus female public 455 speakers (cf. Brem & Niebuhr, this volume)? What is the role of one's own speech 456

production patterns on the perception of others (cf. Bosker, 2017b)? For instance, do
 fast talkers find fast speech more attractive or persuasive than others? These questions
 regarding inter-individual variation in charisma perception are promising avenues for
 future research.

461 **10.4 Conclusion**

The present outcomes shed light on the use and function of speech rhythm in polit-462 ical debates, specifically comparing the speech produced by Hillary Clinton and 463 Donald Trump in three presidential debates in 2016. Clinton's speech was observed 464 to contain more power in the modulation spectra, particularly in the 1-9Hz range, 465 suggesting more pronounced amplitude modulations in her speech (compared to 466 Trump). This may be argued to indicate that Clinton planned her utterances more 467 extensively, allowing more opportunity to temporally organize the syllabic structure 468 of her utterances. At the same time, the lack of rhythmic amplitude modulations in 469 Trump's speech may indicate a level of spontaneity in his speech production, with 470 little attempt to pre-plan certain utterances. 471

Perceptual data revealed a positive correlation between the strength of amplitude
modulations in the syllabic range (1–9 Hz), on the one hand, and perceived charisma
ratings, on the other hand. This suggests that greater rhythm in the speech of a public
speaker positively influences listeners' impressions of the speaker charisma. Thus,
it highlights the important contribution of speech rhythm to charisma perception.

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Abstract	mobile on-demand ma further into the realm combined effects of va A perception experime manipulation steps and experiment and rated of four females, on three visual stimuli consiste photograph. Results cl perceived charisma. T and with gender-specir that it depends on their	natic speech becomes a highly relevant issue in times of globalized markets and ss media that strengthen the influence of individuals. Pushing phonetic research of non-lexical charisma triggers, the present study is the first to investigate the ariation in attire and prosody on the perception of male and female speaker charisma. ent was carried out with Attire and Prosody as independent variables, each with two d embedded in a 2×2 orthogonal design. A total of 53 participants took part in the eight senior business leaders of well-known US American companies, four males and approved charisma-related scales: convincing, passionate, charming. The audio- d of a keynote-speech excerpt of a speaker in combination with a matching early show that both Attire and Prosody are additive, but in gender-specific ways fic effect sizes. A bipartite results pattern among the female speakers further suggests r physical attractiveness whether Attire and Prosody conditions have a charisma- a-reducing effect. The results are discussed in terms of their practical implications for of man and women	

Chapter 11 Dress to Impress? On the Interaction of Attire with Prosody and Gender in the Perception of Speaker Charisma



Alexander Brem and Oliver Niebuhr

Abstract Understanding charismatic speech becomes a highly relevant issue in 1 times of globalized markets and mobile on-demand mass media that strengthen the 2 influence of individuals. Pushing phonetic research further into the realm of non-3 lexical charisma triggers, the present study is the first to investigate the combined Δ effects of variation in attire and prosody on the perception of male and female speaker 5 charisma. A perception experiment was carried out with Attire and Prosody as inde-6 pendent variables, each with two manipulation steps and embedded in a 2 × 2 orthog-7 onal design. A total of 53 participants took part in the experiment and rated eight 8 senior business leaders of well-known US American companies, four males and 9 four females, on three approved charisma-related scales: convincing, passionate, 10 charming. The audio-visual stimuli consisted of a keynote-speech excerpt of a speaker 11 in combination with a matching photograph. Results clearly show that both Attire and 12 Prosody had significant effects on the speakers' perceived charisma. The charisma 13 effects of Attire and Prosody are additive, but in gender-specific ways and with 14 gender-specific effect sizes. A bipartite results pattern among the female speakers 15 further suggests that it depends on their physical attractiveness whether Attire and 16 Prosody conditions have a charisma-supporting or charisma-reducing effect. The 17 results are discussed in terms of their practical implications for the daily business 18 life of men and women. 19

Keywords Charisma · Passion · Charm · Persuasion · Attire · Public speaking ·
 prosody · English speech · Perception · Expressive · Speech

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22 11.1 Introduction

²³ 11.1.1 Charisma and Delivery

We live in times in which individual politicians are increasingly able to determine 24 people's opinion and voting behavior (whether for better or for worse), in which 25 managers become an integral part of a company's brand image (like Steve Jobs 26 was for Apple and Elon Musk is for Tesla), and in which entrepreneurship, i.e., 27 the motivation, passion, and persuasive power of individuals, becomes a mainstay 28 of national prosperity in international competition networks. In these times, it is of 20 high societal and economical importance to understand in detail what good speakers 30 actually do and how, in which way, and to what degree they influence listeners. Good 31 speakers draw us under their spell. We cannot help but listen to them, we believe in 32 what they tell us, and we are willing to adopt their opinions, attitudes, and/or agendas. 33 Attracting attention as well as gaining and persuading followers without having to 34 use force or referring to formal authority is the essence of charisma. In the more 35 speaker- than listener-oriented words of Antonakis, Fenley & Liechti (2016: 304), 36 charisma is defined as "values-based, symbolic, and emotion-laden leader signaling". 37 Charisma leads to more successful brainstorming outputs and salary negotiations 38 (Pentland, 2008), results in better learning outcomes of students and, generally, in 39 more satisfied subordinates (Towler, 2003; Lee, 2014), helps raise more start-up 40 funding (Davis, Hmieleski, Webb, & Coombs, 2017), changes people's opinions and 41 decisions (Brilman, 2015), and makes a product or service appear more credible and 42

likable to customers (Gélinas-Chebat, Chebat, & Vaninsky, 1996). Previous studies
also demonstrated that charisma is not a mysterious talent of a few gifted people, as
was originally claimed by Weber (1947), but a tangible skill that anyone can learn
and improve (Antonakis et al., 2011, 2012).

However, this learning and improving requires that we understand how the mech-47 anisms work that makes a speaker sound charismatic, in particular the mechanisms 48 of the so-called "delivery" that consists of everything a speaker conveys beyond the 49 words themselves. Delivery includes auditory components like the speaker's speech 50 prosody as well as visual components like body language and attire, and cross-51 modal components like age and gender.¹ Results of experimental studies repeatedly 52 suggested that these components of delivery are-alone or in combination-more 53 important than words for a speaker's charismatic impact (Holladay & Coombs, 1994; 54 Awamleh & Gardner, 1999; Chen et al., 2014; Brilman, 2015). 55

¹Note that "gender" is very often used also to refer to the biological concept of "sex", even in the scientific literature and across disciplines (cf. Brooks, Huang, Kearney, & Murray, 2014). Therefore, in order to be easily understandable for a broad, interdisciplinary readership, we decided to use "gender" in the sense of "sex" in the present paper.

56 11.1.2 The Roles of Prosody and Attire

As the transdisciplinary science "whose goal is the description, modeling and expla-57 nation of speech communication in the languages of the world" (Kohler, 2000: 1) and 58 whose areas of instrumental-experimental research range from physiology through 50 acoustics to cognition and perception, phonetics is perhaps in the best position of all 60 scientific disciplines to decipher, objectively quantify, and ultimately understand how 61 and by means of which signal cues charisma is created in the perceiver's brain. In fact, 62 the intensive exploration of charismatic speech in phonetic production and perception 63 experiments has already greatly expanded our knowledge of the acoustic-phonetic 64 indicators of perceived speaker charisma. We know today that acoustic parameters 65 such as the level, range, and dynamics of pitch² and intensity patterns, the durations 66 of pauses and utterances, the number of emphatically emphasized words, the vocal 67 tract's resonance frequencies (lower levels of the first three formants), and the timbre 68 of the voice (e.g., in terms of HNR or the Hammarberg index) are all involved in 69 the signaling of speaker charisma (Touati, 1993; Rosenberg & Hirschberg, 2009; 70 Signorello, D'Errico, Poggi, & Demolin, 2012; Scherer, Layher, Kane, Neumann, & 71 Campbell, 2012; D'Errico, Signorello, Demolin, & Poggi, 2013; Chen et al., 2014; 72 Brilman, 2015; Shim et al., 2015; Hiroyuki & Rathcke, 2016; Bosker, 2007; Niebuhr, 73 Thumm, & Michalsky, 2018a, b). In addition, we know that the general relevance 74 of these parameters for speaker charisma does not differ between politics and busi-75 ness (Niebuhr, Brem, Novák-Tót, & Voße 2016; Novák-Tót, Niebuhr, & Chen 2017); 76 maybe not even across cultures. 77

However, what does differ is which parameter level is appropriate and how 78 strongly each parameter contributes to making a speaker sound charismatic. Not 79 only culture, situation, industry sector, and listener age are relevant factors in this 80 connection (Biadsy, Rosenberg, Carlson, Hirschberg, & Strangert, 2008; Abidi & 81 Gumpert, 2018; Jokisch, Iaroshenko, Maruschke, & Ding, 2018), but also speaker 82 gender. Most prosodic parameters have an identical effect on the charisma of male 83 and female speakers and differ solely in the magnitude of this effect. Two parameters 84 are different, though. These two parameters are pitch level and speaking rate. While 85 men need to raise their pitch levels to sound more charismatic, women need to lower 86 the pitch level (Berger, Niebuhr, & Peters, 2017; Niebuhr et al., 2018b); and while it 87 is beneficial for the charisma effect of male speakers to increase the speaking rate, 88 women must reduce their speaking rate to sound more charismatic (Bachsleitner & 89 Popp, 2018). The gender-specific effect of speaking rate may be due to the fact that 90 women already sound subjectively faster than men at the same objectively measured 91 speaking rate (Weirich & Simpson, 2014). 92

For the visual components of charismatic delivery, and attire in particular, there are far less solid empirical findings from controlled experimental studies. For male

 $^{^{2}}$ Similarly as for "gender", we use the term "pitch" here as it is easily understandable to a broad, interdisciplinary (and non-expert) readership. What we actually mean is the acoustic fundamental frequency (F0), from which pitch is derived in the perception of speech signals, see Terhardt (1974) for further information.

speakers, things seem pretty straightforward, though. Compared to any form of casual 95 or smart-casual attire, formal business attire supports the perception of charisma in 96 terms of charisma-related attributes such as competence, credibility, and assertive-97 ness. In addition, the formal business attire of men is guite clearly and narrowly 98 defined as a dark-colored suit, see Furnham and Petrova (2010), Furnham, Chan, 99 and Wilson (2014). In contrast, for women things are not that straightforward. On 100 the one hand, women "have less freedom to wear more comfortable or casual attire" 101 in the workplace (Franz & Norton, 2001: 88, see also Behling & Williams, 1991; 102 Furnham et al., 2014). That is, wearing casual attire is less harmful for men than for 103 women. On the other hand, the appropriate standard for the formal business attire of 104 women is less clearly defined than for men. While every little detail counts for the 105 perception of male charisma (up to the pattern of the tie and the garment of the suit, 106 cf. Howlett, Pine, Orakçıoğlu, & Fletcher, 2013), even somewhat salient differences 107 in female attire like that between a skirt suit and a pantsuit seem to play a lesser role 108 in the perception of charisma-related attributes of women (Morris, Gorham, Cohen, 109 & Huffman, 1996), perhaps because female attire is subject to much greater and 110 faster fashion variation than male attire (Auty & Elliot, 1998; Molloy, 1996). 111

Furthermore, contradicting the traditional dress-code instructions for women in 112 brochures and guidebooks (cf. Molloy, 1977; McEwan & Agno, 2011; Hoover, 2013), 113 recent papers advise female leaders to "think color" (Karabell, 2016). More specif-114 ically, concerning the color range of a proper female business attire, these papers 115 recommend wearing "all shades of red" (Karabell, 2016), i.e., all colors from blue-116 red to pink, as they are supposed to represent signals of power and charismatic qual-117 ities like "confidence and leadership" (Silverberg, 2017). The experimental study of 118 Radeloff (1990) showed that red can compete with traditional business colors like 110 (dark) blue and black when it comes to proper female business attire. Molloy's (1996) 120 more practical research agrees with Radeloff's experimental data. Additionally, he 121 points out that things have changed since the 1980s and that today "using color 122 correctly can give businesswomen an advantage over men" (p. 157). In this context, 123 Radeloff (1990) especially highlights the value of red for businesswomen, whereas 124 for businessmen, the range of wearable colors is typically restricted to black or dark 125 blue and, beyond that, hardly addressed in the literature; or, as in the case of grey and 126 earth tones, associated in brochures and guidebooks with very different statements 127 and recommendations that clearly reflect the lack of a solid empirical basis. 128

So, while everything from red to pink seems to be more effective than dark blue or black for female speakers' charisma, this color range certainly is a charisma killer for male speakers (e.g., the Financial Post³ regards red as one of the three worst colors for men to wear in the office). In the opposite direction, while male leaders can at least dare to speak to an audience in jeans, T-shirt or hoody, this kind of casual business attire seems to be an absolute no-go for female leaders.

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³https://business.financialpost.com/business-insider/the-best-and-worst-colours-to-wear-to-the-office.

135 11.1.3 Aims and Assumptions

In summary, with respect to the key charisma factor of delivery, intensive phonetic 136 research provided us with a fairly detailed empirical picture of the charisma-relevant 137 parameters of speech prosody and their context-specific phonetic variation. However, 138 this does not apply to the same degree to the visual communication signals of 139 speaker charisma, especially not to the factor attire. Moreover, we still know practi-140 cally nothing about the interplay of attire and prosody in the perception of speaker 141 charisma, which is interesting not only because both factors make a major contribu-142 tion to speaker charisma, but also because of the gender-specific differences in each 143 factor. 144

Therefore, our goal is to expand the empirical knowledge of the non-verbal ingre-145 dients of speaker charisma beyond prosody into the visual components of delivery. 146 Continuing our previous studies (see Niebuhr et al., 2017), the focus of this line of 147 research is not on political leaders but on business leaders. The first step presented 148 here addresses the attire of speakers and their interaction with prosody. We report 149 the results of a perception experiment with special emphasis on the gender-specific 150 aspects of prosody and attire. The factor prosody was represented by a two-step 151 manipulation of speaking rate and pitch level in male and female speech stimuli. 152 The factor of attire was also represented by a two-step variation. However, unlike for 153 prosody, this variation was not carried out analogously for male and female speakers, 154 but took into account the fact that for men it is the style of attire that is most relevant 155 in everyday business life, while for women it is primarily the color of attire. 156

¹⁵⁷ Our study is able to test three basic assumptions. The present experiment:

- (1) replicates the known gender-specific effects of pitch level and speaking rate on
 perceived speaker charisma;
- (2) finds an additional gender-specific effect of attire on perceived speaker charisma,
- with male and female speakers being supported by a dark-colored suit or a red attire, respectively;
- (3) finds the gender-specific effects of attire and prosody to be additive in the
 perception of speaker charisma.

165 11.2 Method

166 11.2.1 Speakers

Instead of using specifically designed and staged laboratory data, we opted for an approach with genuine, ecologically valid field data. This was for two reasons. First, for complex concepts like charisma whose multi-faceted perceptual nature is still too poorly understood to replicate it properly and consistently in the laboratory, the practical relevance of research findings critically relies on the authenticity of the analyzed data. We wanted our results to have as much practical value as possible,

and one obvious way to enhance the relevance of our findings *for* practitioners was to
 take real data *from* practitioners. Second, both pilot tests and our own experience from
 previous studies indicated that subjects in perception experiments take the assessment
 of speaker charisma the more seriously (i.e., they make more reflective, elaborate

¹⁷⁶ of speaker charisma the more seriously (i.e., they make more reflective, elaborate ¹⁷⁷ judgments) the more well-known and influential the speakers are (cf. also Pearce

¹⁷⁸ & Brommel, 1972). This can only be credibly achieved with data of real speakers.

All our speakers (or the companies they represent) can be considered similarly well
known and influential. A high degree of popularity and influence also had the positive
side effect that enough speech and image material of our speakers was available on

182 the internet.

Since we worked with publicly available materials (i.e., field data), we had to
 choose our speakers such as to minimize the influence of potentially confounding
 between-speaker variables. On this basis, we chose the following eight speakers, four
 females (F1–F4) and four males (M1–M4):

(F1) Margret Whitman, born August 4, 1956, in Cold Spring Harbor, New York,

USA; CEO and President of Hewlett Packard Enterprise (until January 31, 2018).

- (F2) Virgina Marie Rometty, born July 29, 1957, in Chicago, Illinois, USA; CEO
 and President of IBM.
- (F3) Sara Blakely, born February 27, 1971, in Clearwater, Florida, USA; Founder
 and CEO of Spanx Inc.
- (F4) Sheryl Kara Sandberg, born August 28, 1969, in Washington D.C., USA;
 COO of Facebook Inc.
- (M1) Reid Hoffman, born August 5, 1967, in Stanford, California, USA; Co Founder of LinkedIn, former manager of PayPal.
- (M2) Satya Nadella, born August 19, 1967, in Hyderabad, India; CEO of
 Microsoft.
- (M3) Sundar Pichai, born 1972, in Madurai, India; CEO of Google LLC.
- (M4) Mark Zuckerberg, born May 14, 1984, in White Plains, New York, USA;
 CEO of Facebook Inc.

All selected speakers are leading senior managers (CEOs or COOs) of well-known 202 US American companies and were either born in the US or came from other English-203 speaking countries and then lived in the US for decades. Accordingly, all selected 204 managers were native speakers of English and fluent speakers of American English, 205 albeit with different regional and dialectal characteristics. However, these charac-206 teristics can be considered irrelevant to the questions of the present study, not least 207 because—as became apparent from the metadata and participant feedback collected 208 after the perception experiment-our participants were unable to either detect these 209 characteristics or to associate them consistently with a specific geographical origin. 210 Thus, it is unlikely that dialectal or regional stereotypes, their related socio-economic 211 associations, or similar socio-phonetic effects were able to bias the participants' judg-212 ments of speaker charisma in a systematic and consistent way, cf. Ladegaard (1998), 213 Bayard, Weatherall, Gallois, and Pittam (2001), Bailey (2003), and Andersson (2009) 214 for the relationships between varieties of English and the judgment of their speakers. 215

All speakers are from the educated upper social class of the USA; and all were 216 between 30 and 60 years old when they gave those speeches whose excerpts we used 217 to create our stimuli. In this middle biological age range, we can assume all speakers 218 to have the same basic physiological prerequisites with regard to the production of 219 speech prosody (e.g., Schötz, 2006), except for some gender-specific differences, 220 of course (Xu & Sun, 2002; Pépiot, 2013). Similarly, our speakers' age range was 221 chosen small enough to prevent any potential age-related charisma differences from 222 masking the actually investigated main effects of Attire and Prosody. Results of 223 empirical studies suggest that perceived age has a separate influence on speaker 224 charisma (e.g., Jokisch et al., 2018). Speaker charisma increases with age, but not 225 linearly. 226

All speakers are leading IT executives. This restriction was added because initial 227 results from another study (Abidi & Gumpert, 2018) suggest that speaker charisma 228 is produced and assessed in an industry-specific fashion. For example, it seems that 229 different ideas of charismatic presentations exist in the automotive sector as compared 230 to the IT sector, which, in turn, seems to have different expectations concerning 231 charismatic speeches than the financial sector. Although these results are still very 232 preliminary, we nevertheless wanted to control this factor by keeping our dataset 233 homogenous by focussing on the IT sector. A further advantage of this decision is 234 that the IT sector is the same sector from which also the participants of the perception 235 experiment were recruited. This had the advantage that our participants had already 236 dealt with the eight selected speakers in one way or another, for example, by reading 237 or writing about them in their course of studies or in related journals or newspapers. 238 That is, all participants were similarly familiar with the speakers and well aware of 239 their top positions in market-leading companies (see Rosenberg & Hirschberg, 2009 240 for the charisma-increasing effect of speaker familiarity and Pearce & Brommel, 241 1972 for the charisma-increasing effect of a higher social status). 242

243 11.2.2 Image Material and the Independent Variable Attire

The independent variable Attire is represented in the experiment by presenting the eight male and female speakers on different photographs. Two photographs were selected for each speaker. One shows the speaker in a more formal or conservative attire. The other one shows the speaker in a more casual or expressive attire. The full set of photographs can be made available to interested persons upon individual request.

Like in the selection of speakers (2.1), a maximum of comparability and control of potentially confounding factors was a major criterion for choosing suitable photographs. This was true within and across each speaker's pair of photographs. For example, all selected photographs showed the eight speakers from a similar angle (frontal view), in a similar posture (standing upright), and against the similar background of a large exhibition hall. Furthermore, all photographs showed the eight

speakers with open and slightly rounded lip positions, which indicated that the photo-256 graph was taken while giving a speech. Head postures and hand and arm gestures on 257 each photograph additionally characterized their speech as animated and passionate. 258 In addition, we made sure that the two points in time at which the photographs of a 259 speaker had been taken were less than 24 months apart (so as to prevent differences 260 in a speaker's visual age across attire conditions, cf. Grd, 2013) and that the two 261 photographs showed the speaker similarly large, i.e., up to the hips with the legs not 262 being visible. The latter was important as the size of a person on a photograph (or 263 screen) influences the subjective spatial distance of this person to the viewer. This 264 distance, in turn, determines the level of social and emotional connection that the 265 viewer feels for the person on the photograph (Reeves & Nass, 1996). As this connec-266 tion is obviously related to concepts like perceived charisma, we had to control for 267 this factor in the experiment. 268

Figure 11.1 shows, as an example, pairs of photographs for one female speaker (Sheryl Sandberg) and for one male speaker (Mark Zuckerberg) similar to those used in the actual experiment. As can be seen in Fig. 11.1, and as was mentioned Sect. 11.1.2, the biggest difference between the pairs of photographs was that, in the case of the male speakers, the independent variable Attire was operationalized

Mark Zuckerberg - CEO of Facebook





Sheryl Sandberg - COO of Facebook





Fig. 11.1 Examples of photographs showing female and male speakers giving a keynote speech in conservative (left) and expressive (right) business attire. Top left photo taken by Pete Souza (2015), top right photo taken by Anthony Quintano (2018), bottom left photo taken by Moritz Hager (2012, photo edited by 1st author), bottom right photo taken by Remy Steinegger (2016). All photo are under CC-BY license

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as the difference between a dark-colored business suit and a light-blue T-shirt. In 274 the case of the female speakers, it was operationalized as the difference between a 275 dark-colored and a red or pink pantsuit. Thus, in the case of the male speakers, attire 276 concerns the *style* of clothing, whereas, in the case of female speakers, it concerns 277 the *color* of clothing. For lack of better generic terms that equally apply to both 278 types of attire variation (formal vs. casual is considered inappropriate), we refer the 270 attire variation in both gender conditions as *conservative* versus *expressive*. Note 280 that, based on the literature summarized in the introduction, it is the *conservative* 281 Attire condition that is assumed to support the charisma perception of *male* speakers, 282 whereas the *expressive* Attire condition is assumed to make *female* speakers more 283 charismatic. 284

Mixing up style and color in the Attire variable follows the charisma-related 285 statements in the literature on gender and attire. However, we also had no other 286 option. It was no problem to find photographs of the male speakers wearing a T-287 shirt, even for similar public-speaking situations as in the business-suit condition. 288 The same was not possible for the female speakers, though. In fact, for none of our 289 female speakers, we were able to find one single photograph on which the speaker 290 does not wear a formal dress or pantsuit. That is, photographs showing our female 291 executive leaders in a T-shirt, sweater, hoody, jeans, or a similar casual clothing do 292 not exist on the internet, no matter which occasion or which monologue or dialogue 203 situation. We think that this fact resonates well with the literature in Sect. 11.1.2, 294 in that it tells a lot about the different socio-cultural demands on male and female 295 business attire, and about the leeway that male and female executive leaders have 296 for choosing their attire in the workplace (or for public speeches as in the present 297 experiment). Thus, although the two expressive Attire conditions of men and women 208 obviously differ at the surface level (style vs. color), the variable Attire is nevertheless 299 appropriately and homogeneously implemented in the experiment, because the two 300 variable levels conservative and expressive equally cover for both genders the real full 301 range of possible attire variation in the workplace. Yet, an obvious task of subsequent 302 studies is, of course, to repeat the present experiment with staged photographs of fake 303 executive leaders in order to implement the variable Attire in a consistent way across 304 both genders, i.e., as the difference between business suit and T-shirt. 305

11.2.3 Speech Material and the Independent Variable Prosody

We chose one YouTube clip per speaker from one of his/her major public keynotes held in front of a large audience. Since the durations of speech stimuli are known to correlate positively with the perception of speaker charisma (i.e., the longer the stimulus the higher the speaker charisma, see Biadsy et al., 2008; Rosenberg & Hischberg, 2009), a similarly long speech section of 19–20 s was extracted from all eight YouTube clips. The onsets and offsets of these speech excerpts coincided in all cases with major intonational phrase boundaries (see AE-ToBI, Beckman,
Hirschberg, & Shattuck-Hufnagel, 2005) at the beginnings and ends of syntactically
complete utterance. Furthermore, all eight speech excerpts were free from disfluencies like hesitational lengthening, hesitation particles, overlong silent pauses (for
turn-internal standards, Ten Bosch, Oostdijk, & de Ruiter, 2004), etc. The speech
excerpts also contained no applause, music inserts, and other background noises.

Studies by Antonakis et al. (2011, 2012) showed on an experimental basis that, in 320 addition to prosody, traditional morphosyntactic and lexical instruments of rhetoric 321 have an influence on the perceived charisma of a speaker as well (an effect that 322 manifests itself in both speaker ratings and participant behavior). Antonakis et al. 323 summarized these effective rhetorical instruments under the umbrella term "Charis-324 matic Leadership Tactics" (CLTs). These CLTs include, for example, metaphors, 325 analogies, contrasts, rhetorical questions, and three-part lists (marked either explic-326 itly/verbally or implicitly/prosodically). Also, the use of the 1st person (instead of 327 the 3rd person) singular or plural contributes to perceived speaker charisma (Biadsy 328 et al., 2008). 329

We controlled our speech excerpts such that they all contained a similar total 330 number of CLT items and were dominated by verbs of the 1st person singular or plural. 331 There were 3-4 CLT items within the 19-20 s excerpt of each speaker. The range of 332 CLT items ranged from rhetorical questions ("How do you communicate authenti-333 cally?", Sheryl Sandberg) through metaphors and analogies ("... we will unlock new 334 platforms", Mark Zuckerberg; "We could not think of our users as wallets", Margret 335 Whitman) or syntagmatic contrast constructions ("We have talked about machine 336 learning [...], but it also important to think about ...", Sundar Pichai) to three-part 337 lists ("it's black, it's invisible, it's not understood-sight, sound, music ...", Virgina 338 Marie Rometty; "It's the same amount of blood, sweat, and tears when you start a 339 company", Reid Hoffman). In addition, all eight speech excerpts are similar in that 340 they outline an inspiring new idea in the context of a visionary future perspective 341 ("You actually do not know inside of it, what it is—and that's what's changing in this 342 new era", Virgina Marie Rometty; "Aiming for something large is really important", 343 Reid Hoffman; "but it's also important to think about how to do this technology can 344 have an immediate impact on people's lives", Sundar Pichai). 345

Using an online script, the selected waveform signal was extracted from each YouTube clip and stored as an uncompressed audio file (.wav) in mono with a sound quality of 48 kHz and 24-bit. Each speech excerpt was characterized by a moderate speaking rate of on average about (5 syllables per second (syll/s) and a moderate pitch level of on average about 140 Hz (male speakers) or 205 Hz (female speakers). These moderate levels are suitable for performing a parameter manipulation without creating audible artifacts or extreme values of speaking rate and pitch.

The manipulation was done by means of the PSOLA resynthesis algorithm implemented in PRAAT (Mouliner & Charpentier, 1990; Boersma, 2001). For each speech excerpt, two combined PSOLA manipulations were performed and presented to the participants in the perception experiment instead of the original speech excerpt. That is, the perception experiment included only resynthesized audio stimuli. In this way, we ensured that all audio stimuli had the same sound quality.

The first stimulus condition of the independent variable Prosody was created by 359 decreasing the speaking rate by 10% and the pitch level by 2 semitones (st) for each 360 speaker. The pitch level was manipulated in st (i.e., along a logarithmic scale) so 361 that the changes in acoustic F0 were perceptually equal for men and women. The 362 size of the manipulation (2 st) was above the Just Noticeable Difference (JND) and 363 hence audible for participants (Jongman, Qin, Zhang, & Sereno, 2017), but still small 364 enough not to affect the naturalness of the speech. The speaking-rate manipulation 365 was performed linearly across consonants and vowels. This is a simplification. In 366 actual speech, vowel durations would change more as a function of speaking rate 367 than consonant durations (van Santen, 1994); rate changes would also be paralleled 368 by changes in speech reduction that cannot be imitated in resynthesized speech (see 369 Ernestus & Smith, 2018). However, the resulting PSOLA output still sounded natural; 370 also because 10% was, like for pitch, above the JND for speaking-rate changes at 371 the utterance level (Quené, 2004), but small enough for the simplification and other 372 manipulation artifacts to not become salient. 373

The second stimulus condition of the independent variable Prosody was created exactly inversely to the first one. That is, the speaking rate was increased by 10%, and the pitch level by 2 st compared to the original parameter values.

Note that we manipulated speaking rate and pitch level in combination rather than 377 independently of each other because our focus was not on the interplay of the two 378 prosodic parameters in charisma perception. Both parameters are well investigated 379 in this respect already (Berger et al., 2017). Our aim was to create a strong and 380 reliable variation in prosody-induced charisma and determine its interplay with a 381 variation in attire-induced charisma. To that end, it was an advantage to co-vary two 382 prosodic parameters, especially those whose effects on charisma are consistent and 383 well investigated, also with respect to speaker gender. 384

At the end of the manipulation procedure, we had two versions of the same 385 19–20 s speech excerpt for each speaker: one with higher parameter values (+10%)386 speaking rate, +2 st pitch level) and one with lower parameter values (-10% speaking 387 rate, -2 st pitch level). In connection with the independent variable Prosody, the 388 former version is henceforth called the *high* condition; the latter version is referred 389 to as the *low* condition. Note that, like for Attire, the two variable levels have a 390 gender-specific implication for charisma perception. Based on previous findings, 391 male speakers should sound more charismatic in the high Prosody condition, whereas 392 female speakers should sound more charismatic in the low Prosody condition. 393

394 11.2.4 Experiment Design

The more and less charismatic speech excerpts (audio stimuli) of a speaker were combined with the conservatively and expressively dressed photographs (visual stimuli) of that speaker. Thus, all stimuli of the perception experiment were multimodal. Per speaker, there were $2 \times 2 = 4$ different audio-visual stimulus conditions:

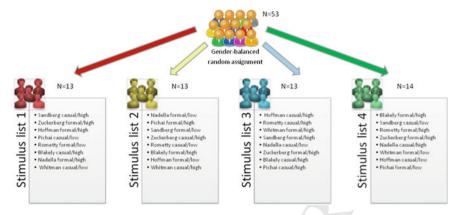


Fig. 11.2 Assignment of the 53 participants to four stimulus lists. Note that the order of the stimuli in each list is an example. Stimulus orders were individually randomized in the experiment

conservative/high, conservative/low, expressive/high, and expressive/low. For eight speakers, this gave a total of 32 stimuli.

In order to keep the experiment short and interesting, the 32 stimuli were not all 401 presented to each participant. Rather, four different stimulus lists were compiled. 402 The four audio-visual stimulus conditions of each speaker were distributed across 403 these four lists such that each participant saw, heard, and rated each speaker only 404 once, see Fig. 11.2. This made it impossible for individual participants to uncover the 405 independent variables and their manipulations and infer from them the actual goal of 406 the experiment. Participants only received eight differently dressed and differently 407 speaking leading managers of US American companies, men and women, whose 408 speaker charisma was to be assessed by them. Note that due to distributing the four 409 audio-visual stimulus conditions across the four lists, both Attire and Prosody became 410 between-subject factors in the experiment design. 411

Charisma is a complex, multi-faceted concept. Accordingly, our experience from 412 pilot testing suggests in agreement with previous studies that participants respond 413 insecurely and/or heterogeneously when being asked to rate the charisma of a speaker 414 directly on a scale. For this reason, we decomposed charisma into three attributes 415 that participants could rate separately for each audio-visual stimulus: "The speaker is 416 ..." (1) convincing (German: überzeugend); (2) passionate (German: enthusiastisch); 417 (3) charming (German: ansprechend). This decomposition creates a clear frame of 418 reference and provides participants with a concrete idea of what they are supposed to 419 rate. In this way, the ratings become simpler and more consistent. The three attributes 420 were chosen, because they are known from previous studies to be highly correlated 421 with perceived speaker charisma (Rosenberg & Hirschberg, 2009), and because they 422 are equally applicable to both attire and speech prosody. 423

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424 11.2.5 Participant Sample and Experimental Procedure

The experiment was conducted as an online experiment (based on SoSci Survey). 425 A total of 53 participants took part in the experiment; 23 men and 30 women who 426 were between 21 and 48 years old. The average age of the participant sample was 427 24.7 years. All participants were native speakers of German and undergraduate or 428 graduate students of social-science disciplines ("Innovation and Business" or "Inno-429 vation and Technology Management"). All had a very good command of English, 430 i.e., either level B2 or C1 according to university-internal student entry tests. Never-431 theless, their skills as non-native speakers were not sufficient to consistently identify 432 regional or dialectal differences between speakers and associate them with positive 433 or negative stereotypes or speaker attributes (Bailey, 2003). The 53 participants were 434 distributed almost equally over the four stimulus lists. The 13 or 14 participants per 435 list included about equal numbers of men and women. Except for controlling these 436 basic factors, the participant-to-list assignment was entirely random. 437

Each online session of SoSci Survey started with the information that the exper-438 iment would be about the assessment of perceived speaker charisma. The compo-439 sitional concept of charisma was briefly outlined to the participants with reference 440 to Antonakis et al. (2016) who defined charisma as "values-based, symbolic, and 441 emotion-laden leader signaling" (p. 304). In addition, the participants were given 442 some names of particularly charismatic speakers for further illustration. These names 443 included, for example, Steve Jobs, Barak Obama, and Martin Luther King Jr. In order 444 to increase the spontaneity and impartiality of assessments, it was emphasized to the 445 participants that assessments of perceived speaker charisma are inevitably subjective 446 and that there is no right or wrong in subjective assessments. 447

Subsequently, participants were told that they would successively see and hear 448 eight fairly popular and influential male and female managers (CEOs or COOs) of 449 leading US companies. Each audio-visual stimulus would consist of a photograph 450 of one of these eight managers at an important keynote speech and an approxi-451 mately 20-second audio clip from that keynote speech. On this basis, their task 452 would simply be to listen to each of the eight audio-visual stimuli separately, i.e., 453 without drawing comparisons between the speakers, and each time as if being part 454 of the speaker's keynote audience. Then, ratings were to be made about how the 455 speaker was experienced in terms of perceived charisma on three scales 456

- 457 Convincing,
- ⁴⁵⁸ Passionate,
- 459 Charming.

Participants received the 6-level system of German school grades from "1" (=very good) to "6" (=not good at all) for their assessments, as this is a system that all participants were well familiar with. Judgments were made by clicking, for each charisma attribute, the respective button of a 6-point Likert scale whose endpoints, "very good" and "not good at all", were displayed above the three scales. An example of one judgment trial of the experiment is shown in Fig. 11.3.

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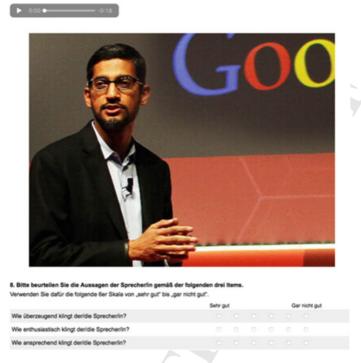


Fig. 11.3 Screenshot of one judgment trial of the male speaker Sundar Pichai in the experiment. Photo of Sundar Pichai taken by Maurizio Pesce (2015, edited under CC-BY license by 1st author)

Following the initial instructions, the participants were presented with the eight audio-visual stimuli of their respective stimulus list. The experiment was performed in a self-paced fashion. Each participant received the eight audio-visual stimuli of his/her list in an individually randomized order.

After the experiment was over, a few metadata of the participants were queried. 470 These included age, gender, level of English, familiarity with the eight managers, and 471 further speaker-oriented judgments on estimated age, perceived physical attractive-472 ness, and estimated leadership experience. Furthermore, the participants were asked 473 to specify their foreign or second language skills (besides English) and to give some 474 feedback on the difficulty and the assumed purpose of the experiment as well as on 475 the applicability of the rating scales. Together with this final metadata questionnaire, 476 the entire experiment took about 10-12 min. 477

478 11.3 Results

The statistical processing of the data was performed separately for the two quadruplets of male and female speakers, taking into account that we expect the Attire

and Prosody manipulations to affect speaker charisma in diametrically opposed 481 ways depending on speaker gender. The gender-specific results are presented in 482 Sects. 11.3.1 and 11.3.2. One of the three charisma-related scales, charming, did 483 not yield conclusive results, and in the feedback questionnaire after the experiment 484 participants also reported problems with applying this scale to the stimuli (we will 485 address these problems in more detail in the discussion). For this reason, only the other 486 two scales—convincing and passionate—were taken into account in the analysis and 487 presentation of the results. 488

In accord with the use of convincingness and passion scales in previous studies, 489 we found that the two scales are good representatives of charisma and suitable for 490 asking participants to assess perceived speaker charisma. First, the participants rated 491 the application of the scales to the stimuli and the general concept of charisma as 492 simple and intuitive. Second, matching with the participants' report, we found no 493 contradicting ratings in our results data, i.e., no cases in which the convincingness 494 and passion ratings of a single stimulus go in opposite directions. On the contrary, 495 the convincingness and passion ratings are correlated with each other in an order of 496 magnitude that matches with how strongly they correlated with charisma itself in 497 previous studies (r[200] = 0.55, p < 0.001 for the male speakers' stimuli and r[200]498 = 0.69, p < 0.001 for the female speakers' stimuli). That is, convincingness and 499 passion both represent perceived speaker charisma equally well, but are nevertheless 500 related to different facets of the phenomenon. Reflecting this fact, the results section 501 presents the convincingness and passion ratings separately, but at the same time 502 interprets them coherently in terms of perceived speaker charisma. 503

For the statistical analysis, a three-way General Linear Model (GLM) was used, 504 with the two independent variables Attire and Prosody being fixed factors. As the 505 third fixed factor, Speaker was additionally included in the model (four levels for the 506 four male or female speakers). For supplementary t-tests and multiple comparisons 507 between factor levels (e.g., of the fixed factor Speaker), alpha-error levels were 508 adjusted using the Sidak method. Dependent variable was the rating score 1-6 on the 509 respective grading scale per participant. The participant him/herself was taken into 510 account as a random factor in the GLM. Participant as a random factor was appropriate 511 here for two reasons. First, the participants were randomly selected, and, secondly, 512 we were not interested in identifying possible differences between participants as a 513 previous inspection of the data already indicated no separate systematic effects of 514 participant age, gender, and international/linguistic background. In contrast, in the 515 case of Speaker, we were interested in possible differences among the male or female 516 speakers. For this reason, we made Speaker a fixed factor. However, note that we 517 would arrive at the same conclusions with (male or female) Speaker being a second 518 random factor. Further aspects of the generalization of the findings are addressed in 519 Sect. 11.4.5. 520

Separate statistical analyses (GLMs) were conducted for the two assessment scales
 convincing and passionate. Each of these analyses was based on 212 participant
 ratings, 106 for the variable Attire, and 106 for the variable Prosody. All individual
 t-tests comparisons were conducted with 52–56 participant ratings in each sample.

We use bar plots below for illustrating the statistical patterns and summarizing the results descriptively. As it would be confusing for many readers that higher rising bars mean worse and lower rising bars better ratings of speaker charisma (as 6 =best and 1 = worst), we plotted the bars upside down. So, the lower a bar reaches the more negative is the charisma-related rating.

530 11.3.1 Male Speakers

The bar plot in Fig. 11.4 shows the effects of the variable Attire on the rating of the 531 four male speakers. The individual bars display, in a different color for each speaker, 532 the cumulative mean value of the difference between the two Prosody conditions 533 low and high across all 53 participants. So, for example, if the mean rating of a 534 speaker on the convincingness scale were 3.4 in the Prosody condition low and 2.4 535 in the Prosody condition *high*, then Fig. 11.4 would show a value of +1 for this 536 speaker (recall that higher numbers in the German school grading system mean a 537 worse performance). 538

The results shown in Fig. 11.4 can be summarized as follows. In terms of the two attributes convincing and passionate, speaker charisma is perceived to be higher for the *conservative* Attire condition than for the *expressive* Attire condition. In other words, wearing a conservative attire supports the speakers to the extent that it doubles their perceived charisma The scale values halved accordingly: For perceived convincingness, we can see a decrease in the overall assessment across the four

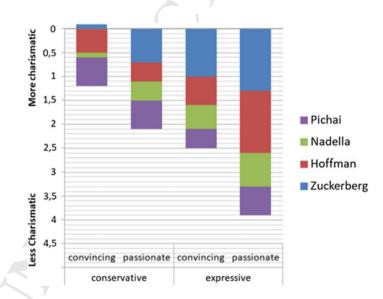


Fig. 11.4 Results of the Attire conditions conservative and expressive on the male-speaker assessments

speakers from 2.5 in the *expressive* Attire condition to about 1.2 in the *conservative*Attire condition. For perceived passion, the cumulative mean value of just under 4.0
in the *expressive* condition is halved to only 2.1 in the *conservative* condition.

With respect to Prosody, Fig. 11.4 shows further that, with one exception, all the mean differences between the two Prosody conditions *low* and *high* give a positive value. This means that each speaker was judged to be more convincing and passionate—i.e., overall more charismatic—for the higher than for the lower parameter values of speaking rate and pitch level.

In the corresponding GLMs the results of Fig. 11.4 manifest themselves in signif-553 icant main effects of Attire (convincing: F[1,196] = 440.70, p < 0.001, $\eta_p^2 = 0.69$; 554 passionate: F[1,196] = 687.20, p < 0.001, $\eta_p^2 = 0.78$) as well as in similar, but 555 in terms of partial Eta-squared slightly weaker significant main effects of Prosody 556 (convincing: F[1,196] = 219.68, p < 0.001, $\eta_p^2 = 0.53$; passionate: F[1,196] = 350.75, 557 p < 0.001, $\eta_p^2 = 0.64$). The fixed factor Speaker had significant main effects as well 558 (convincing: F[3,196] = 307.48, p<0.001, $\eta_p^2 = 0.83$; passionate: F[3,196] = 629.17, 550 p < 0.001, $\eta_p^2 = 0.91$). Moreover, there were, for both assessment scales, significant 560 interactions between Speaker and Attire (convincing: F[3,196] = 33.52, p < 0.001, 561 $\eta_p^2 = 0.34$; passionate: F[3,196] = 11.85, p < 0.001, $\eta_p^2 = 0.15$). The three-way 562 interaction was not significant. 563

Figure 11.5 shows in more detail how the speaker rating changes as a result of the Prosody variable, pooled across the two scales convincing and passionate. There is a significant interaction of the variable Prosody with the variable Attire (convincing: F[1,196] = 6.79, p < 0.01, $\eta_p^2 = 0.11$; passionate: F[1,196] = 41.72, p < 0.001,

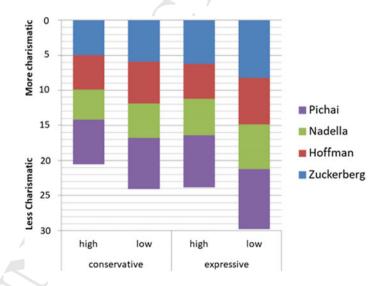


Fig. 11.5 Results of the Prosody conditions *high* and *low* in each Attire condition on the malespeaker assessments

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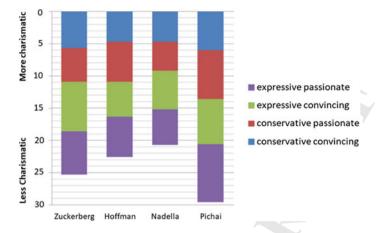


Fig. 11.6 Total assessment of the male speakers on the two charisma scales convincing and passionate

 $\eta_p^2 = 0.18$). For a *conservative* attire, the charisma-supporting or reducing effect of 568 Prosody is smaller than for an *expressive* attire. This means that, for a participant's 569 rating of a speaker's charisma, the factor Prosody counts more if the speaker wears 570 an expressive attire. In other words, those who wear a expressive attire (as a man) 571 have to focus more on producing a charismatic speech prosody than those who wear 572 a conservative attire. In fact, the two Attire-Prosody combinations conservative/low 573 and *expressive/high* came out as statistically equivalent (p > 0.05) in separate t-tests 574 for all 4 male speakers. 575

Figure 11.5 also shows that some speakers consistently contributed more than 576 others to the cumulative mean values of each bar. That is, some speakers were consis-577 tently rated worse than others. Figure 11.6 illustrates this finding more clearly. Across 578 the Attire and Prosody conditions and the two scales convincing and passionate, 579 Zuckerberg and Pichai yielded the highest sums of mean ratings and hence the overall 580 worst charisma ratings, with Pichai being slightly worse than Zuckerberg. Nadella 581 performed best. Reid Hoffman's performance was, in the overall assessment of the 53 582 participants, somewhere in between Pichai and Nadella. Multiple t-test comparisons 583 between the four speakers showed accordingly that all speakers differed from each 584 other at p < 0.001, except for Zuckerberg and Pichai on the convincingness scale (p 585 > 0.05) and Nadella and Hoffman on the same scale (p > 0.05). 586

587 11.3.2 Female Speakers

The results of the four female speakers are different. Unlike for the male speakers, the main effects of Attire and Prosody are not significant. Figure 11.7a, i.e., the counterpart of the male speakers' Fig. 11.5, shows very clearly that the cumulative

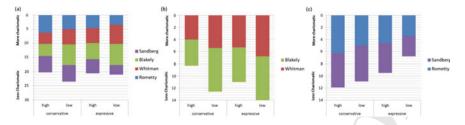


Fig. 11.7 Results of the Prosody conditions *high* and *low* in each Attire condition **a** for all four female speakers, and separately for **b** the Blakely–Whitman speaker pair and **c** the Sandberg–Rometty speaker pair

charisma ratings of the 53 participants are roughly the same for all independent vari-591 able conditions. The reason for this becomes obvious in Figs. 11.7b-c and 11.8 (the 592 counterpart of the male speakers' Fig. 11.4): The female speaker sample contains 593 two pairs of speakers whose Attire and Prosody conditions were rated in a diamet-594 rically opposed fashion by the 53 participants. This manifests itself in the GLMs 595 in a significant main effect of Speaker (convincing: F[3,196] = 221.01, p < 0.001, 596 $\eta_{p}^{2} = 0.77$; passionate: F[3,196] = 100.50, p < 0.001, $\eta_{p}^{2} = 0.61$) and in significant 597 interactions of Speaker and Attire (convincing: F[3,196] = 199.78, p < 0.001, η_p^2 598 = 0.75; passionate: F[3,196] = 169.39, p < 0.001, $\eta_p^2 = 0.72$) and of Speaker and 599 Prosody (convincing: F[3,196] = 148.63, p < 0.001, $\eta_p^2 = 0.70$; passionate: F[3,196] 600 = 276.08, p < 0.001, $\eta_p^2 = 0.81$), each with high Eta-squared effect sizes. The three-601 way interaction is significant as well (convincing: F[3,196] = 21.49, p < 0.001, η_p^2 602

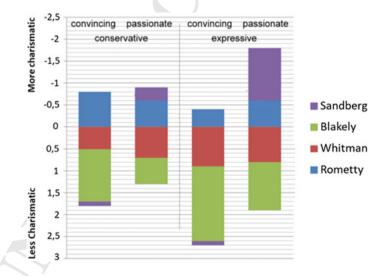


Fig. 11.8 Results of the Attire conditions *conservative* and *expressive* on the female speaker assessments

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= 0.25; passionate: F[3,196] = 27.12, p < 0.001, η_p^2 = 0.29). Multiple-comparisons tests within the factor Speaker showed further that the participants' ratings of Blakely and Whitman differ on neither of the two scales. The same negative result was found for Sandberg and Rometty. At the same time, the latter two speakers differ significantly from the former two speakers on both scales at p < 0.001. These test statistics support that Blakely and Whitman on the one hand and Sandberg and Rometty on the other really formed two different pairs of speakers.

In order to look at the two speaker pairs in more detail, we ran separate additional GLMs for the Blakely–Whitman pair and for the Sandberg–Rometty pair.

The results of the two female speakers Blakely and Whitman largely agree with 612 those of the male speakers. That is, the *conservative* Attire condition (dark-colored 613 pantsuits) supports the two speakers' perceived charisma relative to the expressive 614 Attire condition (red or pink pantsuits). The corresponding main effects are signif-615 icant (convincing: F[1,102] = 59.23, p < 0.001, $\eta_p^2 = 0.45$; passionate: F[1,102] = 616 39.86, p < 0.001, $\eta_p^2 = 0.23$). Likewise, the Prosody condition *high*—characterized 617 by increases in speaking rate and pitch level-supports the charisma perception of 618 the two speakers relative to the Prosody condition low. The corresponding main 619 effects are significant as well (convincing: F[1,102] = 61.71, p < 0.001, $\eta_p^2 = 0.51$; 620 passionate: F[1,102] = 363.44, p < 0.001, $\eta_p^2 = 0.66$). 621

In contrast, for the two female speakers Sandberg and Rometty, the effects of 622 Attire are exactly inverse and hence also run counter to those of the four male speakers 623 (convincing: F[1,102] = 121.26, p < 0.001, $\eta_p^2 = 0.80$; passionate: F[1,102] = 411.41, 624 p < 0.001, $\eta_p^2 = 0.94$). The same applies to Prosody (convincing: F[1,102] = 50.58, p < 0.001, $\eta_p^2 = 0.37$; passionate: F[1,102] = 123.77, p < 0.001, $\eta_p^2 = 0.82$). Unlike 625 626 for Blakely and Whitman and the four male speakers, it is the Prosody condition 627 *low* rather than *high* in which Sandberg and Rometty sound more charismatic in the 628 ears of the 53 participants. Moreover, it is the *expressive* rather than the *conservative* 629 attire condition that makes Sandberg and Rometty look more charismatic in the eyes 630 of the 53 participants. 631

What all four female speakers have in common is that the overall effect of Attire is 632 smaller than for the male speakers. While the choice between a conservative and an 633 expressive attire was able to increase male speaker charisma by about 50%, female 634 speaker charisma could only be increased by about 20%. A t-test based on abso-635 lute difference values between the Attire conditions in the male and female speaker 636 samples shows that this gender-specific effect size of Attire is significant (p < 0.01). 637 For the effect of Prosody, it were the female speakers for whom the difference between 638 the two conditions *low* and *high* had an overall larger effect on perceived charisma 639 than for the male speakers. Going from low to high (for Blakely and Whitman) 640 or from high to low (for Sandberg and Rometty) enhanced the female speakers' 641 charisma level by up 50%, independently of the Attire condition. In contrast, for the 642 male speakers, the ability of Prosody to increase speaker charisma was between 10 643 and 20% and depended on the Attire condition. A t-test based on absolute differ-644 ence values between the Prosody conditions in the male and female speaker samples 645 shows that this gender-specific effect size of Prosody is also significant (p < 0.001). 646

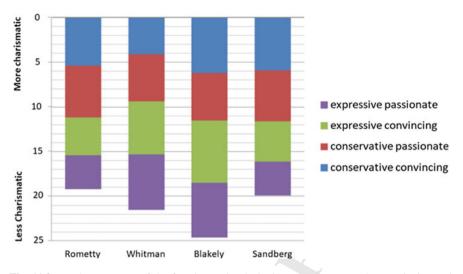


Fig. 11.9 Total assessment of the female speakers' charisma on the two scales convincing and passionate

Regarding the reason why the female speaker sample included two differently 647 rated pairs of speakers, we discovered a parallel between the rating of participants 648 and the speakers' perceived physical attractiveness. These attractiveness ratings (on 649 a scale of 0-10) were made by participants in the feedback questionnaire after the 650 experiment. An analysis of these judgments revealed that Rometty and Sandberg 651 obtained physical-attractiveness values that were, according to within-subjects t-652 tests, statistically equivalent (p > 0.05), but clearly and significantly lower than those 653 obtained by Blakely and Whitman ($\phi 4.1 \text{ vs. } 6.6, t[105] = -12.76, p < 0.01$), whose 654 physical-attractiveness judgments were again statistically equivalent (p > 0.05). 655 Further questionnaire analyses and even additional acoustic-prosodic measurements 656 and analyses of the keynote-speech excerpts (for the charisma-relevant parameters 657 specified in Niebuhr et al. (2017) showed that attractiveness was the only factor whose 658 statistical results pattern runs exactly parallel to that of the two differently rated 659 female speaker pairs. The total charisma scores shown in Fig. 11.9 yielded a similar, 660 but not exactly parallel results picture as there is a significant difference between 661 Blakely and Whitman (p < 0.05) on the one hand, but no significant differences 662 different Whitman and Sandberg and Rometty on the other hand. 663

664 11.4 Discussion

The present study investigated the interaction effects of variation in attire and prosody on the perception of male and female speaker charisma. A total of 53 participants

took part in the experiment and rated, in individually randomized orders, audio-667 visual stimuli of eight senior business leaders, four males and four females, on three 868 charisma-related scales that were successfully tried and tested in many previous 669 studies. In the debriefing questionnaire, the participants described the experiment as 670 pleasant and easy, and judged the charisma ratings on the two scales of convincingness 671 and passion as intuitive and applicable (the problematic scale "charming" is discussed 672 in Sect. 11.4.4). Therefore, we view the significant effects of our results as (internally 673 and externally) valid and reliable. This view is also corroborated by the fact that Mark 674 Zuckerberg turned out to be a fairly uncharismatic speaker, which is consistent with 675 previous studies (Niebuhr et al., 2016b). The following discussion is based on this 676 validity and reliability. 677

678 11.4.1 Assumptions

We tested three assumptions with our experiment. The first one was whether or 679 not the experiment replicates the known gender-specific effects of pitch level and 680 speaking rate on perceived speaker charisma. This assumption is partially supported 681 by the results of the experiment. The male speakers were rated more charismatic if 682 they spoke with increased pitch and speaking-rate levels (compared to the original 683 prosodic setting of the corresponding speaker). Changes toward lower pitch and 684 speaking-rate levels significantly negatively impacted the charisma of male speakers. 685 For two of the female speakers, Sandberg and Rometty, this influence of prosody 686 on the perceived charisma was exactly inverse. That is, it was the lower pitched, 687 slower way of speaking that was more charismatic, not the higher pitched, faster 688 way of speaking. This gender-specific difference meets the first assumption and is 689 consistent with the results of Berger et al. (2017) and Bachsleitner and Popp (2018). 690 For the other two female speakers, Blakely and Whitman, however, the results were 691 diametrically opposed (i.e., in line with those the male speakers again). Thus, they 692 run counter to what we expected from our assumption (1) for female speakers. In 693 Sect. 11.4.2, we offer an explanation for why the bipartition of our female speakers' 694 results have occurred and why the deviating results for Blakely and Whitman are 695 probably only in apparent contradiction to assumption (1) and the findings of Berger 696 et al. (2017), Bachsleitner and Popp (2018). 697

Our second assumption was that the experiment would find a gender-specific 698 effect of attire on perceived speaker charisma. This assumption is clearly supported 699 by the findings. Male speaker charisma was enhanced by the conservative style of 700 a dark-colored suit rather than by the expressive style of t-shirt, jeans, and similar 701 casual clothes. The attire effect on female speaker charisma differed from that of 702 the male speakers and was overall more complex. For two female speakers, the 703 assumption was met that an expressive red, as opposed to a conservative dark color, 704 had a charisma-supporting effect. For the other two speakers, it was the other way 705 around. 706

The third assumption was that the experiment would find the gender-specific 707 effects of attire and prosody to be additive in the perception of speaker charisma. 708 Additive means that an unfavorable attire condition and an unfavorable prosody 709 condition together reduce the perceived speaker charisma more than each unfavorable 710 condition alone. In the opposite direction, a favorable attire condition and a favorable 711 prosody condition together should enhance perceived speaker charisma more than 712 each favorable condition alone. Combinations of favorable and unfavorable attire 713 and prosody conditions should neutralize each other or result in minimally positive 714 or negative charisma effects only. Exactly this overall pattern was found in the exper-715 iment for all our eight male and female speakers. For example, it is clearly visible 716 for the male speakers in Fig. 11.5 that *conservative/low* was less charismatic than 717 conservative/high, and that expressive/low was less charismatic than expressive/high. 718 The two extreme pairs of conditions, i.e., the maximally favorable *conservative/high* 719 combination and the maximum unfavorable *expressive/low* combination, yielded the 720 largest overall difference in perceived speaker charisma. The two cross-over combi-721 nations conservative/low and expressive/high neutralized each other statistically. The 722 third assumption was thus clearly met by the data. 723

724 11.4.2 The Bipartition of the Female Speaker Group

As was reported in the results section, the bipartition of the female speaker group 725 in terms of charisma ratings runs parallel to the attractiveness ratings of the female 726 speakers. The speaker pair Sandberg/Rometty was perceived most charismatic in 727 the expressive/low stimuli and received at the same time relatively low physical-728 attractiveness ratings (ø 4.1, between-speaker difference <0.5, n.s.). The speaker 729 pair Blakely/Whitman received significantly higher physical-attractiveness ratings (ø 730 6.6, between-speaker difference < 0.5, n.s.) and was perceived most charismatic in the 731 conservative/high stimuli. No other differences in speaker judgments, metadata, or 732 personal characteristics (like hair color, age, size, or estimated leadership experience), 733 and no uncontrolled acoustic-prosodic parameter differences matched equally well 734 with the bipartition of the female speaker group as the attractiveness rating. Although 735 it is "a myth that you have to be attractive to be charismatic" (Fox Cabane, 2012: 736 102), charisma and physical attractiveness are still to some degree related perceptual 737 concepts (Grabo, Spisak, & van Vugt, 2017). Furthermore, it is known that charisma 738 can also be exaggerated and, thus, reversed by an overdose of acoustic or visual 739 triggers. For this reason, Niebuhr et al. (2017) determined so-called "effectiveness 740 windows" that charisma-relevant parameters should neither fall below nor exceed. 741 Against this background we suggest the following explanation for why the bipartition 742 of the female speaker group occurred. 743

If physically more attractive female speakers already start from an inherently higher perceived charisma level than physically less attractive female speakers, then adding further charisma-enhancing stimuli like a red attire and a slow, low-pitched prosody can result in an overdose and hence in a reversed effect of attire and prosody on perceived charisma. This could have happened for the speaker pair Blakely and Whitman. In contrast, if physically less attractive female speakers start from an inherently lower perceived charisma level, then they can still benefit from adding further charisma-enhancing stimuli like a red attire and a slow, low-pitched prosody to the overall charisma they convey. This could be true of the speaker pair Sandberg and Rometty.

The advantage of this explanation is that it would be consistent with both the 754 assumed charisma-enhancing effect of a red attire and the previously found gender-755 specific prosodic effects of pitch level and speaking rate in the studies of Berger et al. 756 (2017), Bachsleitner and Popp (2018). Moreover, the provided explanation would 757 also mean that the Attire and Prosody conditions did actually have the same effect on 758 all females speakers. It would only be due to the interaction with attractiveness that 759 this uniform effect surfaces differently for the two speaker pairs Blakely/Whitman 760 and Sandberg/Rometty. On this basis, assumption (1) would be fully supported by 761 the present results. It is further in accord with the provided explanation that no 762 attractiveness differences showed up for the four male speakers (all received average 763 ratings between 5.5 and 6.5 on the 10-point scale). Thus, Attire and Prosody were 764 able to influence charisma ratings in a uniform way for the male speakers. In fact, it 765 seems that men are generally rated less critically in terms of physical attractiveness 766 than women, especially in the context of business, leadership, and perceived charisma 767 (Friedman, Riggio, & Casella, 1988). Note in this context that rater gender did not 768 play a significant role in the physical attractiveness ratings of our speakers. Female 769 raters behaved in the same way as male raters. 770

An alternative but related explanation refers to the experiment of Pearce and 771 Brommel (1972). They found that non-lexical charisma triggers only have a positive 779 effect on attributes of perceived speaker charisma if the audience assesses the speaker 773 as credible and competent. If the same charisma signals are conveyed by a less 774 credible and competent speaker, then they have no effect or even a negative effect 775 on the speaker's charisma. In the light of these findings, the bipartition of the female 776 speaker group in the present experiment could also mean that the 53 participants (i.e., 777 both males and females) assessed the physically more attractive female speakers 778 Blakely and Whitman to be less credible and competent than the less attractive 779 speakers Sandberg and Rometty. 780

Subsequent studies must continue to investigate which of the two explanations (or 781 maybe a third one) underlies the bipartition of the female speaker group in the present 782 experiment. However, regardless of the explanation, the present findings already have 783 an important practical implication: Female speakers need to pay more attention than 784 men to how many and strong audio-visual charisma triggers they convey, and it is 785 likely that physical attractiveness is an important factor to take into account in this 786 context. More physically attractive women should perhaps rather try to downgrade 787 their remaining charisma triggers, for example, by using a conservative dark-colored 788 outfit and clearly also a less charismatic prosody, whereas for physically less attractive 789 women the opposite can be recommended, i.e., using a more expressively colored 790 outfit and definitely a more charismatic prosody. Why we stress prosody in this 791 connection is stated in 11.4.3, together with further practical implications. 792

ditor Proof

793 11.4.3 Further Practical Implications

Our results show that the charisma rating of male speakers can be increased or 794 decreased by about 50% through the attire choice alone. The effect of prosody on 795 the charisma rating was smaller and depended on the attire (at least for the two 796 parameters pitch level and speaking rate manipulated here). For women, the effect 797 of prosody was larger than the effect of attire. Like for men, there was an interaction 798 with the choice of attire. However, as we discussed in detail in Sect. 11.4.2, this 700 interaction did not affect the size of the prosody effect, but its direction. The size of 800 the prosody effect was independent of the choice of attire. 801

Two practical implications can be derived from these findings. First, women 802 benefit more from using the right prosody, while men benefit more from choosing 803 the right attire. Second, in a charisma-supporting conservative attire style (dark suit), 804 men may well afford smaller weaknesses in prosodic charisma performance. In an 805 expressive, casual attire style, on the other hand, men have to take care to deliver a 806 very charismatic prosodic performance if they still want to make a strong charismatic 807 impression. So, anyone who (as a man) has confidence in his excellent delivery can 808 basically also perform in an expressive, casual style of clothing in front of his audi-809 ence (although a conservative attire would still be better). For those who are insecure 810 and unskilled in their speech performance, a conservative dress style should be a 811 must. 812

813 11.4.4 The Scale "Charming"

The inconclusive results of the scale charming and the application problems reported 814 by the participants in the debriefing questionnaire came unexpected. The scale 815 charming was selected, as Rosenberg and Hirschberg (2009) showed that this attribute 816 is even higher correlated with charisma than convincing and passionate and can also 817 be applied more consistently to charisma than convincing and passionate. However, 818 the key difference between our study and that of Rosenberg and Hirschberg is that we 819 presented not just audio stimuli, but multi-modal audio-visual stimuli. It is obvious 820 that charming-unlike convincing and passionate-has both an auditory and a visual 821 rating dimension (to a limited degree, this is also true of passionate, but all passion-822 related signals of body language were carefully controlled and kept homogeneous in 823 the photographs). In accord with the participants' comments in the debriefing ques-824 tionnaire, we assume that it was this modality-based ambiguity of the term charming 825 that caused the inconclusive results of the corresponding scale. For example, it turned 826 out that some participants interpreted charming in the sense of a purely visual physical 827 attractiveness and then used it automatically in the sense of sex appeal/attractiveness 828 rather than in the intended sense of speaker charisma. 829

In summary, the correlated, consistent use of the scales convincing and passionate on the one hand shows that, with the multi-dimensional scaling method, we have a

valid and sensitive instrument for the evaluation of speaker charisma. Pilot studies 832 show that charisma is a too complex concept to be directly rated by participants in a 833 consistent way, see Sect. 11.2.4. By breaking down the concept into scales that are 834 highly correlated with each other and with charisma, we can make the rating task 835 easier and more consistent-and still measure the same "thing". However, on the 836 other hand, the inconclusive, inconsistent use of the scale charming also reveals and 837 stresses the current limitations of this instrument. We have not fully understood as 838 yet which facets of charisma are covered by each scale and how complementary and 839 exhaustive this coverage is. Moreover, we have not enough knowledge today to put 840 together a set of scales that are specifically tailored to measuring perceived speaker 841 charisma for different types and modalities of stimuli. Also note in this context that 842 the male speakers were generally rated worse on the passionate scale than on the 843 convincing scale in the present study. For women it was the other way around. That 844 is, independently of the set of scales and the stimuli, special care should be taken 845 when comparing absolute scale levels between experimental conditions. 946

847 11.4.5 Generalization

As for all other experiments, our results apply primarily to the conditions under which 848 they were obtained. The simpler and more controlled these conditions are, the lower 849 is the potential generalization of the findings. As we said in the beginning, we selected 850 photos and speech materials from the "field" and, moreover, used multiple speakers 851 per gender to maximize generalizability within the experimental setup. Therefore, we 852 think that our findings are sufficiently generalizable to have a practical use and to give 853 male and female speakers guidance in public-speaking and presentation scenarios. 854 We show with regard to perceived speaker charisma that prosody has an effect, that 855 attire has an effect, that the effect of attire can also be negative (like that of prosody), 856 and that the effects compensate, cancel out, or enhance each other and, in the latter 857 case, can probably also cause overdoses. These facts will be valid in the real world 858 regardless of the current experimental setting. 859

But, of course, there are many other auditory and visual sources of perceived 860 speaker charisma that play a role, but are not considered or varied here. That is, we 861 expect the strength of the present effects to be shaped by a number of other variables, 862 which themselves may have favorable or unfavorable charisma effects. On the part of 863 the recipients (i.e., the raters), these are, for example, variables from which norms and 864 stereotypes emerge, such as educational attainment, age, cultural background (Power 865 & Galvin, 1997), and the zeitgeist (50 or 100 years ago, a different way of speaking 866 may have been considered more charismatic, cf. Madill, 2015 and the term "vocal 867 zeitgeist" in McCabe & Altman, 2017; also business fashion changes constantly, 868 especially for women, see Sect. 11.1.1). On the part of the speakers, relevant further 869 variables are those that determine competency and prestige attributions, such as race, 870 age, gender, attractiveness, occupation, and social status. Additionally, on the part of 871 both recipient and speaker, there are the linguistic (including dialectal) background 872

and the communication medium, which in our opinion represent secondary variables.
These variables do not interact directly with speaker charisma, but indirectly through
an influence on primary variables such as competence, stereotypes, etc.

With the exception of some indications on attractiveness, our study cannot make 876 any new conclusions about these additional variables. However, as our male speakers 877 were all rated consistently—despite showing a greater racial diversity than our female 878 speakers—it appears that the factor race plays a subordinate role in speaker charisma, 879 at least among educated raters (like students) and for speakers with a high status 880 and prestige (like business leaders). Age and gender have an effect on charisma. In 881 tendency, those speakers are considered more charismatic who have a similar age as 882 the audience; and men tend to be inherently more charismatic than women (Jokisch 883 et al., 2018; Brooks et al., 2014), in both women's and men's ratings (recall that we, 884 too, have found no gender-specific rating differences). Our own data from a different 885 study (Abidi & Gumpert, 2018) further suggest that the factor second language (L2) 886 does not have to have a negative effect on charisma. Direction and strength of the 887 L2 effect seem to depend less on the comprehensibility of the foreign accent or the 888 command of the foreign language than on the prestige of foreign and native language. 889 Regarding the communication channel, Gallardo and Weiß (2017) found a positive 890 correlation between the signal-compression rate in (mobile) phone communication 891 and listener ratings of charisma-related features. Despite initial emergent answers, 802 there is still a plethora of open questions for all of the factors mentioned above. These 893 open questions must be answered step by step, successively involving more factors. 894 On this basis, we offer a brief outlook. 895

896 11.5 Conclusion and Outlook

The present experiment further supports the results of earlier research by identi-897 fying attire and prosody as relevant factors in the perception of speaker charisma. In 898 addition, given the considerable effects of the two factors, our findings also support 899 the conclusion of earlier studies that non-lexical factors such as attire and prosody 900 are particularly influential for the perception of speaker charisma; probably more 901 important than the words of a speaker. The paper started with a question: Dress to 902 impress? The answer must clearly be "yes", especially in the case of men. Unlike 903 women, it seems that men are less able to compensate for a charismatically unfavor-904 able attire with prosodic means. Women, in turn, should probably be more careful in 905 combining attire and prosody with other factors such as their own physical attractive-906 ness. Regardless of the gender-specific interactions of attire and prosody, the effects 907 of the two factors in the perception of charismatic speakers are largely additive, both 908 in the positive and in the negative direction. 909

Based on these new findings, the task of follow-up studies must be to further refine and differentiate the very roughly varied attire and prosody conditions of the present study, and to homogenize the attire variable, for which we had to mix-up style and color in order to be able to use authentic field data of real senior leaders. Using

(staged) lab data or field data of less popular speakers (entrepreneurs) could be ways 914 to achieve a greater control of the independent variable conditions. Follow-up studies 915 could also work with A/V videos instead of combinations of photographs and speech, 916 especially if more and richer body-language factors are to be addressed. Two findings 917 are conceivable with using A/V videos. Either the richer body language of videos 918 distracts the raters from the factor attire so much that the latter becomes less relevant 919 than with the photos in this study; or, through the attribution of speaker competence 920 (Pearce & Brommel, 1972), attire functions as a limiting factor, so that any charisma-921 supporting effects of a richer body language cannot unfold without a favorable attire. 922 In this context, it is also essential to check the charisma attributes used in multi-923 dimensional rating tasks for their multi-modal suitability. In fact, we believe that the 924 exploration and development of methods for the assessment of speaker charisma 925 or similar socio-communicative concepts is a field of research in its own right. 926 Methods need a solid empirical foundation and have to meet certain standards in 927 terms of their internal validity, exhaustiveness, contextual vulnerability, and sensi-928 tivity. Regarding the contributions in this volume as well as the recent developments 929 in human-machine interaction and the growing intercultural and digital commu-930 nication, it is obvious that the experimental investigation of charisma and similar 931 socio-communicative concepts becomes a topic of growing relevance and urgency. 932

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Abstract	Dating conversations are especially influenced by the interlocutors' perceived attractiveness. As visual attractiveness determines the course and nature of the interaction, the perceived overall quality of the conversation may also be influenced by the perceived attractiveness and simultaneously also affect the further development of the conversation. Accordingly, perceived attractiveness and conversational quality constantly interact in dating conversations. Studies focusing on the effects of both impressions on a speaker's vocal behavior in terms of prosodic entrainment, i.e., the adaptation of a speaker's prosodic features relative to his/her interlocutor, suggest that higher visual attractiveness leads to a greater divergence in f0 in mixed-sex pairs, while greater conversational quality results in larger degrees of f0 entrainment. In this paper, we further investigate the effects of both perceived attractiveness and conversational quality on prosodic entrainment of f0 in dating conversations with a special focus on their interaction. We conducted a dating experiment with 20 young heterosexual singles who engaged in 100 short spontaneous mixed-sex dating conversational quality. Prosodic entrainment decreased with higher ratings of perceived attractiveness and increased with higher ratings of perceived conversational quality. Additionally, the results indicate that f0 entrainment not only depends on the impressions of attractiveness and conversational quality but also affects them. Furthermore, seemingly conflicting effects may be resolved by emphasizing one effect over the other, e.g., quality over attractiveness. This emphasis seems to depend on speaker sex and may also change during the course of the	

complex interaction, their interdependence, the importance of speaker sex, as well as possible implications are discussed.

 Keywords
 Attractiveness - Conversational quality - Likability - Dating - Entrainment - Accommodation - Adaptation

 - F0

Chapter 12 Birds of a Feather Flock Together But Opposites Attract! On the Interaction of F0 Entrainment, Perceived Attractiveness, and Conversational Quality in Dating Conversations



Jan Michalsky and Heike Schoormann

Abstract Dating conversations are especially influenced by the interlocutors' per-1 ceived attractiveness. As visual attractiveness determines the course and nature of the 2 interaction, the perceived overall quality of the conversation may also be influenced 3 by the perceived attractiveness and simultaneously also affect the further develop-Δ ment of the conversation. Accordingly, perceived attractiveness and conversational 5 quality constantly interact in dating conversations. Studies focusing on the effects of 6 both impressions on a speaker's vocal behavior in terms of prosodic entrainment, i.e., 7 the adaptation of a speaker's prosodic features relative to his/her interlocutor, sug-8 gest that higher visual attractiveness leads to a greater divergence in f0 in mixed-sex 9 pairs, while greater conversational quality results in larger degrees of f0 entrain-10 ment. In this paper, we further investigate the effects of both perceived attractiveness 11 and conversational quality on prosodic entrainment of f0 in dating conversations 12 with a special focus on their interaction. We conducted a dating experiment with 13 20 young heterosexual singles who engaged in 100 short spontaneous mixed-sex 14 dating conversations. The results suggest that f0 entrainment correlates with both 15 perceived attractiveness and conversational quality. Prosodic entrainment decreased 16 with higher ratings of perceived attractiveness and increased with higher ratings 17 of perceived conversational quality. Additionally, the results indicate that f0 entrain-18 ment not only depends on the impressions of attractiveness and conversational quality 19 but also affects them. Furthermore, seemingly conflicting effects may be resolved by 20 emphasizing one effect over the other, e.g., quality over attractiveness. This emphasis 21 seems to depend on speaker sex and may also change during the course of the conver-22 sation. The details of this complex interaction, their interdependence, the importance 23 of speaker sex, as well as possible implications are discussed. 24

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27 12.1 Introduction

28 12.1.1 Prosodic Entrainment and Its Role in Interaction

Most if not all prosodic features bear a high functional load on several commu-29 nicative levels. Pitch, intensity, or speaking rate, for example, can convey linguistic 30 functions such as focus (cf. Ladd 2008), paralinguistic meanings such as a speaker's 31 emotions or attitudes (cf. Scherer, Ladd, & Silverman, 1984; Ladd, Silverman, Tolk-32 mitt, Bergmann, & Schere, 1985), while simultaneously providing extra-linguistic 33 information such as the sex or age of a speaker (cf. Linville, 1996) within the same 34 stretch of speech. A change in prosodic features, such as increasing the speaking rate, 35 reducing intensity, or raising the f0 mean, can reflect the social relationship of two 36 speakers, e.g., in terms of social status (cf. Gregory, 1996) or dominance (cf. Puts, 37 Gaulin, & Verdolini, 2006), while signaling attitudes and emotions that in turn affect 38 and influence the interpersonal relationship. However, a phenomenon that has been 39 linked to signaling and influencing interpersonal relationships has not been observed 40 in the way prosodic features vary by themselves, i.e., in absolute terms, but in the 41 way they change relative to the correspondent prosodic features of the interlocutor. 42 Entrainment, also often referred to as accommodation, convergence, or adapta-43

tion among others, describes this observed interdependence, i.e., speakers adjusting 44 their linguistic features to those of the interlocutor particularly by becoming more 45 similar (cf. Levitan, 2014). Entrainment can occur on all linguistic levels and may 46 lead to an adaptation of the lexical choice (Brennan & Clark, 1996) and the syntac-47 tic structure (Reitter & Moore, 2007) but it can also influence prosodic features by 48 matching speaking rate (Schweitzer, Lewandowski & Duran, 2017), intensity (cf. 49 Levitan, 2014), or aspects of the fundamental frequency (cf. Levitan, 2014). Edlund, 50 Heldner, and Hirschberg (2009) as well as Levitan (2014; see also Sect. 11.2.3) distin-51 guish three types of prosodic entrainment which need to be differentiated. Proximity 52 describes two interlocutors becoming similar with respect to a prosodic feature dur-53 ing a conversation, convergence describes two interlocutors becoming increasingly 54 more similar during the course of a conversation, and synchrony describes a relative 55 adaptation to the dynamics of an interlocutor's prosodic feature without necessarily 56 becoming more similar in absolute terms. 57

There are two explanatory approaches to the occurrence of entrainment in human communication. Although they are often considered to be competing and mutually exclusive, we suggest that both approaches complement each other. According to the *communication model* (Natale, 1975) as well as the *perception behavior link* (Chartrand & Bargh, 1999), entrainment can be regarded as a device to enhance intelligibility by matching speaking styles and thus facilitating the identification of

phonological categories by reducing phonetic variability. Accordingly, entrainment 64 is a more or less automatic human behavior. This approach is supported by the fact 65 that we also find entrainment in non-social interaction with synthetic voices used by 66 machine applications (cf. Gessinger et al., 2018). The communication accommoda-67 tion theory (Giles, Coupland, & Coupland, 1991) among others, however, assumes 68 an iconic relationship between entrainment and social distance with smaller linguis-60 tic differences signaling closeness on a social level. This approach thus suggests that 70 entrainment is not a mere automatism in interaction but it is dependent on the social 71 relationship. 72

The focus of this paper lies on the role of f0 in signaling the relationship between 73 interlocutors and a speaker's perceived attitude toward an interlocutor, respectively. 74 Specifically, we study the connection between f0 entrainment and social distance 75 in the situational setting of dating conversations. One factor that has a stronger 76 influence in the current setting compared to other communicative situations is the 77 perceived visual attractiveness of the interlocutor as dating conversations involves 78 mating intention. Although especially important in mating contexts, the perceived 79 attractiveness affects most if not every kind of conversation from everyday small talk 80 to business communication (cf. Cialdini, 2009; Brooks, Huang, Kearney, & Murray, 81 2014). As of yet, it is largely unknown how perceived attractiveness interacts with 82 prosodic entrainment and the perceived pleasantness of a conversation, henceforth 83 referred to as conversational quality. The connection between the perceived visual 84 attractiveness of the interlocutor, the perceived conversational quality, and a speaker's 85 change in fundamental frequency constitutes the objective of the study at hand. 86

12.1.2 Prosodic Entrainment and Perceived Conversational Quality

Assuming a link between prosodic entrainment and social distance, the question 89 arises how social distance was measured in previous studies. Rather than measured 90 directly, social distance was approached as a construct derived from a wide variety **Q1** of social features associated with closeness such as mutual liking (Levitan et al., 92 2012), support (Street, 1984; Levitan et al., 2012), giving encouragement (Nenkova, 93 Gravano, & Hirschberg, 2008), or higher degrees of collaboration and cooperation 94 (Lubold & Pon-Barry, 2014). We can assume that social closeness is reflected in the 95 perceived quality of the conversation and will thus regard conversational quality as 96 a predictor for social distance in the framework of this study. As we assess conver-97 sational quality through the subjective evaluation of the interlocutors, any further 98 mention of conversational quality refers to the perceived conversational quality. 99

First evidence for the connection between entrainment and conversational quality stems from it signaling a closer connection between interlocutors and resulting in higher degrees of communicative success. Entrainment as an indicator for task success has been described for several different tasks. Thomason, Nguyen, and Litman (2013) report that student engineering groups that showed higher degrees of entrain-

ment also showed better task results. Similar observations also hold for map task 105 experiments (Reitter & Moore, 2007) as well as student tutoring programs (Fried-106 berg, Litman, & Paletz, 2012). According to the theory of alignment (Pickering & 107 Garrod, 2006), entrainment is a crucial contributor to communicative success in 108 general. Lubold and Pon-Barry (2014) suggest that entrainment is connected to col-109 laboration and rapport in learning tasks which also positively affects communicative 110 success and thereby task success. Similarly, Taylor (2009) and Beňuš (2014) pro-111 pose that task success greatly depends on the establishment of a common situational 112 model, a process which is facilitated by the coordination of behavior. Accordingly, 113 becoming closer with respect to verbal and non-verbal behavior might facilitate the 114 construction of a common situational model. 115

How does task success relate to conversational quality? In other words, what 116 is the goal of a non-task-oriented conversation? Although this is a rather difficult 117 question to answer extensively, we can regard the establishment of a social bond 118 as a major goal of verbal communication (cf. Dunbar, 2020). This is even more 119 apparent in dating conversations where the establishment of a social bond serves as 120 the basis for a romantic relationship that can be regarded as an explicit rather than an 121 implicit goal (Hewstone, Stroebe, & Jonas, 2012: 870ff).¹ We can assume that the 122 quality of a conversation greatly affects a conversations' ability to establish and/or 123 improve the social relationship of two interlocutors. Accordingly, conversational 124 quality can be regarded as the non-task-oriented equivalent of collaboration, affecting 125 communicative success by affecting the social relationship. 126

Although previous studies on entrainment have for the most part been linked 127 to either a speaker's perception of his/her interlocutor or the previously mentioned 128 task success, there are some studies on meanings more closely related to conversa-120 tional quality. Gonzales, Hancock, and Pennebaker (2009) found entrainment to be 130 correlated to overall dialogue quality. Ireland et al. (2011) report that entrainment 131 predicts the probability of initiating romantic relationships as well as the stability 132 of existing relationships. In marriage counseling dialogues, Lee et al. (2010) found 133 higher degrees of entrainment when couples were talking about positive rather than 134 negative topics. Furthermore, entrainment was reported to result in smoother conver-135 sation with respect to turn latencies and fewer interruptions which can be regarded as 136 attributes of high quality in conversations (Nenkova et al., 2008). Lastly, Michalsky 137 et al. (2018) also found conversational quality and entrainment to be connected in 138 dating conversations with smaller differences in f0 occurring in conversations that 139 were perceived as more pleasant. 140

In conclusion, although conversational quality has rarely been assessed explicitly within the respective studies, we expect conversations that are perceived as better or more pleasant to show a higher degree of prosodic entrainment. This expectation applies to conversations in general and specifically to dating conversations.

¹However, this is only true if we restrict our investigation to dating conversations which aim at finding a potential partner, which of course is not true for every kind of dating conversation.

145 12.1.3 Prosodic Entrainment and Perceived Attractiveness

The topic of vocal attractiveness received a lot of attention not only from a pho-146 netic or even linguistic perspective but also from a sociological and psychological 147 perspective. Furthermore, the immediate connection between attraction and aspects 148 of evolutionary biology has generated assumptions that lead to specific linguistic 149 hypotheses. Although this paper focuses on how speakers react prosodically to per-150 ceived attractiveness, i.e., the attracted voice, the underlying assumption is that we 151 react to attractiveness by trying to sound more attractive (cf. Hughes, Farley, & 152 Rhodes, 2010; Fraccaro et al., 2011). Accordingly, speakers would try to imitate 153 features of attractive voices when perceiving their interlocutor as more attractive. 154 To this end, a short overview on the prosodic features of attractive voices will be 155 provided. 156

What prosodic features contribute to the impression of vocal attractiveness is a 157 complex topic and cannot be solely and maybe not even primarily attributed to voice 158 pitch. However, fundamental frequency as the acoustic correlate of voice pitch is 159 the commonly studied feature of vocal attractiveness. The main reason for this can 160 be found in the frequency code (Ohala, 1983, 1984) which assumes an evolutionary 161 connection between pitch and attractiveness. In animal mating behavior, female indi-162 viduals show the general tendency to select bigger and stronger male individuals to 163 ensure protection as well as survival of their offspring. Accordingly, size is a biologi-164 cal factor in natural selection. While many species developed strategies to project size 165 visually, others employ strategies to signal largeness through vocal features. Since 166 due to physiological reasons larger individuals generally have a lower fundamental 167 frequency, certain species such as wolves use lower pitch to suggest largeness. As 168 largeness plays a role in selecting a partner for female individuals rather than males, 169 it is associated with masculinity while smallness and high pitch are associated with 170 femininity. 171

In general, studies confirmed these findings for human communication. Female 172 listeners were found to evaluate male voices as significantly more attractive when 173 they were realized with a lower f0 mean (Collins, 2000; Feinberg, Debruine, Jones, 174 & Perrett, 2005; Hodges-Simeon, Gaulin, & Puts, 2010; Jones Feinberg, Debruine, 175 Little, & Vukovic, 2010; Xu, Lee, Wu, Liu, & Birkholz, 2013) while male listeners 176 judged female voices with a higher f0 mean as more attractive (Collins & Missing, 177 2003; Feinberg et al., 2008; Jones et al., 2010; Xu et al., 2013). However, the results 178 for male listeners and thus female voices were not consistent. Oguchi and Kikuchi 179 (1997) as well as Leaderbrand et al. (2008) suggest that female voices are perceived 180 as more attractive when realized with a lower f0 mean. One explanation for this con-181 tradiction is provided by Karpf (2006) who proposed two different types of female 182 attractiveness. Following Karpf's (2006) distinction, lower pitch is associated with 183 the concept of sexiness and seductiveness while high pitch is associated with femi-184 ninity. However, both are perceived as attractive female voices in general. Another 185 explanation may be found in the communicative setting and thus the communicative 186 intent. There are several goals such as intimacy goals, identity goals, or status goals 187

sought in a relationship (cf. Zimmer-Gembeck, Hughes, Kelly, & Connoly, 2011)
that can affect whether individuals are looking for anything from short-term flings to
long-term relationships as well as different qualities sought in a partner associated
with different goals which may lead to different concepts of attractiveness. However, this assumption has never been incorporated into experimental studies on vocal
attractiveness.

In addition to the general features of male and female vocal attractiveness, the 194 following findings are of relevance to the study at hand. Firstly, Vukovic et al. (2010) 195 report that the perception of pitch as a cue to attractiveness not only depends on 196 the speaker's absolute pitch but also on the listener's own average pitch. Further-197 more, Borokowska and Pawlowski (2011) found a threshold at which an increase or 198 decrease in mean fundamental frequency, respectively, does not increase perceived 199 attractiveness any further. Lastly, Fraccaro et al. (2011) point toward the importance 200 of naturalness and context when investigating perceived attractiveness as this feature 201 seems to be especially susceptible to artificiality. 202

Most studies on vocal attractiveness commonly avoid defining the concept of 203 attractiveness altogether. As evident from the inconsistent findings for female voices, 204 listeners may employ a variety of different concepts of attractiveness when judging 205 vocal attractiveness. However, we propose that investigating the prosodic effects 206 of perceived visual attractiveness allow us to dispense with this problem and the 207 need for defining the concept. Although listeners may still have a variety of rea-208 sons to perceive another person as more or less attractive, the result of the perceived 209 attractiveness should always be attractive which can be connected to a physiologi-210 cal reaction and should therefore be more or less consistent across individuals (cf. 211 Fraccaro et al., 2011). Although speakers may still employ different vocal strategies 212 to express attraction, those differences are most likely not caused by differences in 213 the concept of attractiveness that caused said attraction. Accordingly, the concept 214 of attractiveness should be largely independent of the effects found for perceived 215 attractiveness. 216

The effects of perceived attractiveness of an interlocutor on a speaker's f0 seem to 217 confirm the assumption that speakers react to perceived attractiveness by mimicking 218 the features of attractive voices and thereby trying to sound more attractive them-219 selves. Male speakers who interacted with more attractive female interlocutors were 220 found to lower their f0 mean (Hughes et al., 2010). For female speakers, however, we 221 again find contradicting results. Female speakers were found to lower their f0 mean 222 (Hughes et al., 2011) when talking to a more attractive male interlocutor as well as to 223 raise their f0 mean under the same conditions (Fraccaro et al., 2011). According to 224 Fraccaro et al. (2011) this may be explained through different experimental settings 225 with varying degrees of contextual naturalness. In addition, the differences could 226 again be related to the two different concepts of female attractiveness suggested by 227 Karpf (2006). However, this assumption not only implies that male listeners have two 228 different concepts of attractiveness associated with female voices but also that female 229 speakers readily employ these two different concepts when signaling attraction. 230

How the prosodic effects of perceived visual attractiveness relate to prosodic entrainment has not been studied prior to Michalsky and Schoormann (2017) but there

are some conclusions to be drawn from the research described above. Studies suggest 233 that male speakers lower their f0 while female speakers, at least in some cases, raise 234 their f0 when interacting with a more attractive interlocutor. Since male speakers 235 on average have a lower f0 mean than female speakers for physiological reasons, 236 both effects result in the speakers increasing the distance in f0 and thus showing 237 what is called *prosodic disentrainment*. Michalsky and Schoormann (2017, 2018) 238 suggest that this connection of prosodic disentrainment and perceived attractiveness 239 can indeed be found in spontaneous dating conversations. A recent study by Beňuš 240 et al. (2018) suggests that disentrainment can lead to the impression of dominance, 241 which, according to the frequency code (Ohala, 1983, 1984), can be associated with 242 masculinity. Yet, these results obtained from human-machine interaction would only 243 support the hypothesis for the female listeners and not for the male listeners. A study 244 by Schweitzer et al. (2017) suggest that there might also be effects of entrainment 245 related to attractiveness. However, their findings are restricted to speaking rate and 246 not f0 and furthermore focused on the concept of social attractiveness in same-sex 247 dialogues. 248

In conclusion, we expect perceived attractiveness to result in prosodic disentrainment, directly contradicting the effects we expect for conversational quality.

12.1.4 The Dilemma: Good Conversations with Attractive Interlocutors

Regarding the effects of conversational quality and perceived attractiveness on 253 prosodic entrainment we arrive at the preliminary expectation that higher conversa-254 tional quality would result in social closeness and thus smaller differences in prosodic 255 features, i.e., prosodic entrainment, while perceived attractiveness results in larger 256 prosodic differences and hence prosodic disentrainment. This contradiction poses a 257 challenge since conversational quality and perceived attractiveness not only operate 258 on the same prosodic feature (f0 mean) while pointing in opposite directions but also 259 because we expect both social parameters to highly influence dating conversations 260 and thus to frequently co-occur and even interact. As such, we need to ask what hap-261 pens with a speaker's f0 in conversations with high conversational quality and high 262 perceived attractiveness, i.e., in conversations in which we would expect prosodic 263 entrainment as well as prosodic disentrainment? 264

One hypothesis is that one effect overrules the other, i.e., signaling either conversational quality or perceived attractiveness is more important in dating conversations and thus only one of the contradicting effects is observable in this conversational setting.

A second hypothesis would be that the effects of perceived attractiveness are sensitive to the naturalness and context of the interaction. Higher perceived attractiveness may result in disentrainment only when investigated specifically in a mating context with scripted messages as done by Fraccaro et al. (2011) while possibly enhancing

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the effects of conversational quality by strengthening the social bond and thereby
leading to more entrainment in spontaneous dating scenarios. However, this would
contradict our previous finding on perceived attractiveness in dating conversations
(Michalsky & Schoormann 2017, 2018).

Thirdly, the effects of perceived attractiveness and conversational quality may cancel each other out. This assumption would, however, entail a very uneconomic use of social signals. Accordingly, where f0 fails to signal conversational quality and perceived attractiveness simultaneously, other prosodic parameters may assume this function. Unfortunately, the scope of this paper is limited to f0.

Lastly, although effects of perceived attractiveness and conversational quality 282 may co-occur within the same conversation, they need not occur simultaneously. 283 One possibility is that perceived attractiveness is based on a first impression and the 284 signaling of attraction hence decisive for the initiation of a conversation. Accordingly, 285 the effects may be restricted to the first part of a conversation. Conversational quality 286 on the other hand, develops over time and peaks during the course of the conversation. 287 The effects of conversational quality may, therefore, be the strongest in the later 288 parts of the conversation when the effects of perceived attractiveness have declined. 289 Another distribution might regard different topics or even different intentions during 290 the conversation. There may be phases where interlocutors are predominantly flirting, 291 showing stronger effects of perceived attractiveness, and others where interlocutors 202 are bonding, showing stronger effects of conversational quality. While we investigate 293 only the former question by looking at different time points of the conversation, the 294 latter remains for future research. 295

The study at hand was designed to improve on three shortcomings encountered 296 in the previous research. Firstly, most studies investigate either perceived attractive-207 ness or conversational quality. We suggest that if not explicitly asked to separate the 298 two, speakers are inclined to let the two notions influence each other. Accordingly, 299 we expect the judgement on perceived attractiveness to be influenced by the over-300 all conversational quality and in return the impression of conversational quality to 301 be compromised by the attractiveness of the interlocutor. Although this interdepen-302 dence can never be totally excluded, explicitly instructing participants to judge both 303 impressions on different scales is a first approach to telling them apart by raising 304 awareness of the potential conflict. 305

Secondly, perception ratings are often taken from external observers rather than from the subjects participating in the study. Since the perception of attractiveness as well as conversational quality can and will greatly vary between participants actually partaking in the respective conversations and external observers, all judgements in this study are taken directly from the interlocutors.

Lastly, there are two possible perspectives regarding the connection of prosodic entrainment and social variables with respect to causality that are frequently separated and rarely both investigated within the same studies. On the one hand, the social relationship of two interlocutors can manifest itself in prosodic entrainment which thus serves as an indicator for the social relationship. On the other hand, prosodic entrainment may in return affect the social relationship and even facilitate the establishment of social bonds. Accordingly, we can either ask how the relationship affects prosodic entrainment but also how prosodic entrainment affects a social relationship. In this study, we incorporate both views to shed some light on the question of correlation and causality, although a definite answer to that question is categorically impossible.

This study is based on the same corpus as some of our previous work on the topic 322 (cf. Michalsky, 2017; Michalsky & Schoormann, 2016, 2017, 2018; Michalsky et al., 323 2018, 2018). We would like to inform the reader about the possibility of conflicting 324 information. Our previous research on the topic constitutes work in progress on a 325 growing corpus with changing normalization methods and shifting focus regarding 326 the f0 parameters in question. Since the results presented in this paper constitute the 327 final state of the analysis, the information presented in this paper explicitly replaces 328 older information. 329

330 Perceived visual attractiveness

- Does the perception of visual attractiveness in an opposite-sex interlocutor systematically correlate with a speaker's f0 entrainment in accordance with previous findings?
- Do changes in a speaker's f0 entrainment correlate with an interlocutor's perception of the speaker in terms of visual attractiveness?
- 336 3. Are these two effects connected in a systematic way?
- 337 Perceived conversational quality
- Does the perceived conversational quality systematically correlate with a speaker's
 f0 entrainment in accordance with previous findings?
- Do changes in a speaker's f0 entrainment correlate with an interlocutor's perception of the conversational quality?
- 342 3. Are these two effects connected in a systematic way?
- 343 Perceived visual attractiveness and conversational quality
- Do the effects of perceived attractiveness and conversational quality interact in their influence on f0 entrainment?
- 2. Does f0 entrainment show contradicting or complementing effects on the percep-
- tion of attractiveness and conversational quality?

348 12.2 Method

349 12.2.1 Subjects

The study was conducted with 20 participants, 10 female, and 10 male, all paid volunteers and at the time of the experiment students at the University of Oldenburg. All subjects were aged between 19 and 28 and monolingual speakers of High German who spent the majority of their lives in Lower Saxony. Furthermore, all subjects reported to be heterosexual as well as single during the whole course of the study.
 With the exception of two speakers, whose conversation was excluded from the
 experiment, all subjects were previously unacquainted. All subjects were informed
 about the nature of the experiment as a dating situation.

358 12.2.2 Procedure

All participants were informed about the dating setting of the experiment prior to 359 their recordings. Female and male participants waited in separated rooms and were 360 led to the recording rooms via separate staircases to avoid any interaction prior to 361 their actual conversations. Each participant was paired with every other participant of 362 the opposite sex resulting in a total of 100 opposite-sex conversations, all recorded 363 in two parallel recording sessions in two quiet separate university office rooms. 364 All recordings were done within two weeks during spring break. The use of the 365 phonetic laboratory was explicitly avoided to ensure a more natural setting based on 366 the importance of naturalness in evaluating attractiveness by Fraccaro et al. (2011). 367 The participants were encouraged to engage in spontaneous conversations of 15– 368 20 min without any restrictions or guidelines regarding the choice of conversational 360 topics. However, example topics were provided in case conversations were stalling 370 and subjects needed inspiration. 371

Immediately before each conversation all participants judged their respective 372 interlocutor on a 10-point Likert scale with respect to their perceived visual attractive-373 ness and general likability. The participants were separated by a screen that allowed 374 them to see each other's faces but concealed the questionnaire so that the evaluations 375 were not revealed to the interlocutor. The screen was removed at the beginning of 376 the conversation. Directly after each conversation, the participants received another 377 questionnaire and repeated the covert evaluation of perceived visual attractiveness 378 and general likability. Furthermore, a third scale was added to this second question-379 naire to evaluate how pleasant the subjects perceived the conversation as a whole to 380 assess conversational quality. 381

Recordings were made in stereo using head-mounted microphones (DPA 4065 FR) to ensure an optimal balance between recording quality and naturalness. We used a portable digital recorder (Tascam HD P2) at a sampling rate of 48 kHz and 24-bit resolution.

386 12.2.3 Types and Measurements of Entrainment

According to Edlund et al. (2009) and Levitan (2014) we can distinguish three different types of entrainment: *proximity, convergence,* and *synchrony*.

Proximity covers what is usually referred to as entrainment, accommodation, or 380 adaptation and describes two speakers being more similar with respect to a linguistic 300 feature when talking to each other than when not talking to each other. Accordingly, 391 proximity needs some sort of reference value by either operating on a local level and 392 comparing the differences of prosodic features at adjacent turns with non-adjacent 393 turns (Levitan, 2014) or globally by comparing the differences during a conversation 304 with differences to other speakers or conversations. In this study we combine the two 395 by comparing the general differences at adjacent turns in correlation with perceived 396 attractiveness as well as conversational quality across conversations. 397

Convergence describes increasing proximity over time during the course of a single
 conversation. Accordingly, we again measure the difference in a linguistic feature at
 adjacent turns but with respect to their changes during the conversation. Convergence
 can either be assessed locally by tracking changes from turn to turn or globally, e.g.
 by comparing the first and second half of a conversation.

Synchrony constitutes a categorically different type of entrainment that is either not 403 considered at all or assumed as the primary type of entrainment. Synchrony describes 404 the relative adaptation of a speaker's linguistic features to the respective feature of 405 his/her interlocutor by adjusting their values relative to each other without necessarily 406 becoming more similar. For example, a speaker may react to a raised f0 mean of 407 his/her interlocutor by raising his/her own f0 mean by the same amount, thus imitating 408 his/her interlocutor's prosodic behavior without a decrease in the differences between 409 the two as it is the case for proximity or convergence. To measure synchrony, we 410 check for correlations between the prosodic feature of the turn-taking speaker and 411 the turn-passing speaker in adjacent turns of a speaker change inducing turn break. A 412 positive correlation generally points toward synchrony while a negative correlation 413 is often linked to an effect of increased or decreased proximity. 414

415 12.2.4 Acoustic Analysis

For the acoustic analysis we used Praat (Boersma & Weenink, 2016). Since the 416 recordings were made in stereo, we separated the audio tracks for each speaker. 417 The audio tracks were manually annotated for interpausal units (IPU, cf. Levitan, 418 2014). We analyzed all IPUs adjacent to a turn break inducing speaker change. 419 IPUs were defined mechanically by stretches of speech preceded or followed by a 420 pause with a pause defined as an interruption of speech by silence or non-speech 421 noise of at least 500 ms. Accordingly, we made no difference between pauses at 422 phrase boundaries and hesitation pauses in favor of interlabeler reliability. The corpus 423 consists of 14.687 IPUs from 98 conversations. One conversation had to be excluded 424 due to prior acquaintance of the participants another one was lost to a recording 425 error. We extracted the f0 mean from the interpausal units as we suggest that the 426 f0 mean captures the register better than the median (cf. Michalsky & Schoormann, 427 2016; Michalsky et al., 2018). Furthermore, range features at phrase final boundaries 428

are heavily distorted by pragmatic functions and therefore unreliable in capturing 420 entrainment in this specific data set (cf. Michalsky, 2014, 2015). For synchrony, we 430 measured the f0 mean of the IPU of the turn-passing and the turn-taking speaker and 431 converted it to semitones to a reference value of 50 Hz. We z-transformed the data by 432 speaker by subtracting the IPUs' f0 mean values from the average f0 mean value of all 433 IPUs of each speaker across all conversations and dividing it by the standard deviation 434 of the same set. For proximity and convergence, we calculated the absolute difference 435 between the f0 mean of IPUs adjacent to turn breaks in semitones. Furthermore, we 436 tagged the IPUs occurring in the first five minutes as well as the last five minutes of 437 the conversations. 438

439 12.2.5 Statistical Analysis

For the statistical analysis, we conducted linear mixed effects models using R (R Core Team 2017) with the *lme4*-package (Bates, Maechler, Bolker & Walker, 2015) and the *lmerTest*-package (Kuznetsova, Brockhoff, & Christensen, 2016). Model fit was determined by maximum likelihood ratio tests. P-values were calculated using the Satterthwaite approximation. We calculated different models for the effects of prosodic entrainment on the investigated social variables and the effects of these social variables on prosodic entrainment.

For the effects of perceived ATTRACTIVENESS and CONVERSATIONAL 447 OUALITY on prosodic entrainment we used different dependent variables with 448 respect to the type of prosodic entrainment. For synchrony, we calculated Pear-110 son correlation coefficients (fo correlation) between the f0 mean of the turn-passing 450 speaker and the turn-taking speaker, which resembles the degree of synchrony (cf. 451 Edlund et al., 2009; Levitan, 2014), and used it as the dependent variable. As fixed 452 factors, we used perceived visual attractiveness (ATTRACTIVENESS), perceived 453 conversational quality (QUALITY), speaker sex (SEX) and all interactions. In both 454 the proximity model and the convergence model, we used the difference between the 455 f0 means of the IPUs adjacent to turn breaks (f0 difference) as dependent variables. 456 For the proximity model, fixed factors were identical to the synchrony model. For 457 the convergence model, we added the TIME (in seconds) of the respective turn break 458 as a fixed factor. 459

For the effects of prosodic entrainment on perceived attractiveness and conver-460 sational quality, we calculated two different models for each of the three types of 461 entrainment with either perceived attractiveness (attractiveness) or perceived conver-462 sational quality (conversational quality) as dependent variables with the respective 463 counterpart serving as fixed factor (ATTRACTIVENESS or QUALITY). In the syn-464 chrony model, we used the correlation coefficients (F0 CORRELATION) described 465 above as a fixed factor as well as SEX and all interactions. In the proximity model 466 we used the difference between the IPUs adjacent to turn breaks (F0 DIFFERENCE) 467 as well as SEX and their interaction as fixed factors. For the convergence model, we 468

again expanded the proximity model by the fixed factor TIME and the additionalpossible interactions.

Since we suggest that the effects of perceived attractiveness and conversational 471 quality may affect different parts of the conversation to different degrees, we con-472 ducted post hoc tests for every model described above separated by conversational 473 part. The variable conversational part splits the data set into turns occurring within 474 the first five minutes of each conversation and turns occurring within the last five 475 minutes of each conversation to see whether the effects are restricted to certain con-476 versational parts. Note that this leads to a substantial reduction of the data set and 477 may result in statistically insignificant effects due to insufficient data points. How-478 ever, this was only done for proximity as effects for convergence were already absent 479 from the entire conversation and the Pearson correlation coefficients calculated for 480 synchrony were not robust enough for splitting the data set into thirds. 481

482 12.3 Results

483 12.3.1 Effects of Perceived Attractiveness and Conversational 484 Quality on Prosodic Entrainment

485 12.3.1.1 Proximity

Table 12.1 presents the results for the effects of perceived ATTRACTIVENESS and 486 conversational QUALITY on proximity. We find significant interactions between 487 the two factors as well as a three-way-interaction with SPEAKER SEX illustrated 488 in Fig. 12.1. Accordingly, we conducted post hoc tests separated by SPEAKER SEX 489 to investigate the nature of this three-way-interaction. Tables 12.2 and 12.3 present 490 the post hoc results for the female and the male speakers, respectively. Table 12.2 401 shows that the male speakers show significant effects for both perceived ATTRAC-492 TIVENESS and QUALITY without interactions although marginal effects are sug-493 gested by Fig. 12.1. Male speakers decrease their f0 differences between turns with 494 increasing conversational OUALITY and increase these differences with increasing 495 visual ATTRACTIVENESS of the interlocutor. For the female speakers we find a 496 significant interaction between ATTRACTIVENESS and conversational QUALITY 497 (s. Table 12.3). Female speakers also decrease their f0 differences with increasing 498 CONVERSATIONAL QUALITY and increase f0 differences with visual ATTRAC-499 TIVENESS. However, as shown in Fig. 12.1, the effects for ATTRACTIVENESS 500 become smaller with increasing conversational QUALITY. This means that female 501 speakers do react less to the perceived ATTRACTIVENESS of their interlocutor 502 when the conversation is perceived as highly positive. In conversations with below 503 average QUALITY, however, ATTRACTIVENESS significantly correlates with the 504 degree of proximity. 505

 Table 12.1
 Significant main effects and interactions of perceived ATTRACTIVENESS and CON-VERSATIONAL QUALITY on *proximity*

Fixed factors	b	SE	df	t	р
ATTRACTIVENESS	0.74	0.09	14560.00	8.32	< 0.001
SEX	3.11	0.99	129.90	3.16	< 0.01
ATTRACTIVENESS * QUALITY	-0.07	0.01	14570.00	-5.27	< 0.001
ATTRACTIVENESS * SEX	-0.84	0.15	14570.00	-5.72	< 0.001
QUALITY * SEX	-0.34	0.12	14570.00	-2.79	< 0.01
ATTRACTIVENESS * QUALITY * SEX	0.10	0.02	14570.00	4.83	< 0.001

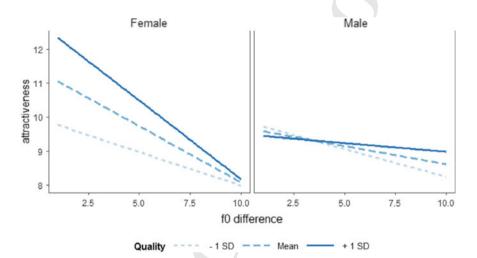


Fig. 12.1 Interaction of the effects of perceived ATTRACTIVENESS, QUALITY, and SEX on *f0 difference*

 Table 12.2
 Post hoc significant main effects and interactions of perceived ATTRACTIVENESS and CONVERSATIONAL QUALITY on *proximity* for the male speakers

Fixed factors	b	SE	df	t	p
ATTRACTIVENESS	0.11	0.04	7375.06	2.86	< 0.01
QUALITY	-0.10	0.04	7372.77	-2.65	< 0.01

 Table 12.3
 Post hoc significant main effects and interactions of perceived ATTRACTIVENESS

 and CONVERSATIONAL QUALITY on *proximity* for the female speakers

Fixed factors	b	SE	df	t	р
ATTRACTIVENESS	0.74	0.09	7100.57	8.10	< 0.001
ATTRACTIVENESS * QUALITY	-0.07	0.01	7179.94	-5.17	< 0.001

 Table 12.4
 Post hoc significant main effects and interactions of perceived ATTRACTIVENESS

 and CONVERSATIONAL QUALITY on *proximity* for the male speakers for the first five minutes of a conversation

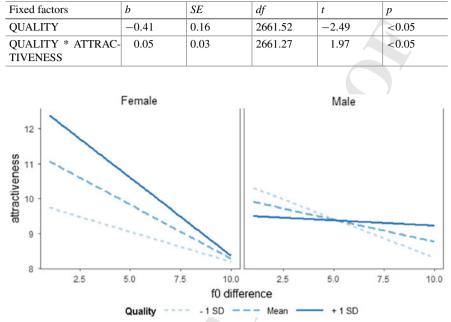


Fig. 12.2 Interaction of the effects of perceived ATTRACTIVENESS, QUALITY, and SEX on *f0 difference* in the first five minutes

The post hoc investigation of the conversational parts reveals that female speakers 506 behave consistently throughout the entire conversation and show the same effects as 507 reported above for the first as well as the last five minutes. For the male speakers, how-508 ever, the effects change over the course of the conversation. While the effects for the 509 last five minutes are identical to the effects we found for the whole conversation, we 510 find a deviation in the first five minutes. As shown in Table 12.4, male speakers show 511 a significant interaction between ATTRACTIVENESS and conversational OUAL-512 ITY in the first five minutes. Although this interaction also seems to be present in the 513 whole conversation when comparing Figs. 12.1 and 12.2, it only reaches significance 514 for the first five minutes. This interaction is different to the one found for the female 515 speakers. Figure 12.2 shows that the effects of conversational QUALITY become 516 smaller with increasing perceived ATTRACTIVENESS. Accordingly, while for the 517 female speakers conversational QUALITY overruled ATTRACTIVENESS through-518 out the whole conversation, for the male speakers, ATTRACTIVENESS overrules 519 conversational QUALITY. In other words, male speakers do entrain less in pleasant 520 conversations with attractive women. However, this effect is restricted to the first five 521 minutes and is found for neither the last 5 min nor the conversational as a whole. 522

Table 12.5	Significant m	ain effects for con	wergence	
			10	

Fixed factors	b	SE	df	t	p
TIME	-0.0005	0.0001	14550.0000	-4.2530	< 0.001

523 **12.3.1.2** Convergence

Table 12.5 shows that there is a significant effect for TIME on the *f0 differences* at turn breaks. Accordingly, we find a general effect for *convergence* with speakers becoming more similar to each other over time. However, this effect shows no interaction with either perceived ATTRACTIVENESS or conversational QUALITY. Hence, while we find effects of conversational QUALITY and perceived ATTRACTIVENESS on entrainment, the observed general convergence is not enhanced by the social variables investigated.

531 12.3.1.3 Synchrony

Table 12.6 reports the effects of perceived ATTRACTIVENESS and conversational 532 QUALITY on synchrony. In contrast to proximity, we find no significant effects for 533 SPEAKER SEX or any interaction with SEX. Accordingly, we find main effects for 534 ATTRACTIVENESS and conversational QUALITY as well as their interaction for 535 both sexes. Figure 12.3 illustrates the interaction between ATTRACTIVENESS and 536 conversational QUALITY. We find that increasing ATTRACTIVENESS is correlated 537 with greater synchrony if conversational QUALITY is low but correlates with less 538 synchrony if conversational QUALITY is high. The same is true for the opposite per-539 spective. Increasing conversational QUALITY is correlated with stronger synchrony 540 if the perceived ATTRACTIVENESS is low but is correlated with lower synchrony 541 if the perceived ATTRACTIVENESS is high. 542

Fixed factors	b	SE	df	t	p
ATTRACTIVENESS	0.05	0.02	174.50	2.90	< 0.01
QUALITY	0.05	0.01	190.18	3.44	< 0.001
ATTRACTIVENESS * QUALITY	-0.01	0.00	187.27	-3.04	< 0.01

 Table 12.6
 Significant main effects and interactions of perceived ATTRACTIVENESS and CON-VERSATIONAL QUALITY on synchrony

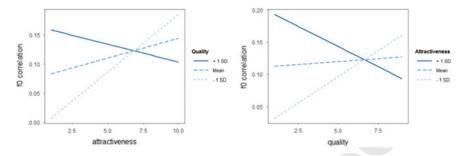


Fig. 12.3 Interaction of the effects of perceived ATTRACTIVENESS and QUALITY on *f0 correlation*

12.3.2 Effects of Prosodic Entrainment on Perceived Attractiveness and Conversational Quality

545 12.3.2.1 Proximity

Table 12.7 presents the effects of PROXIMITY on perceived attractiveness. We find 546 significant effects for the three-way-interaction between F0 DIFFERENCE. OUAL-547 ITY, and SEX. Figure 12.4 illustrates this three-way-interaction while Tables 12.8 548 and 12.9 report the post hoc results separated by SEX. For both sexes, we find a 549 significant interaction between F0 DIFFERENCE and QUALITY. In general, both 550 female and male speakers show a tendency to judge speakers as more attractive if 551 they show greater F0 DIFFERENCES and hence a greater degree of disentrainment. 552 However, female speakers show strong effects of F0 DIFFERENCE for attractive-553 ness if OUALITY is low or average but close to no effects if OUALITY is high. 554 Male speakers on the other hand show noticeable effects for F0 DIFFERENCE if 555 QUALITY is high and less pronounced effects if QUALITY is average or low. 556

Table 12.10 presents the effects of PROXIMITY on perceived *quality*. Comparable to *attractiveness*, we find significant effects for the three-way-interaction between F0 DIFFERENCE, ATTRACTIVENESS, and SEX. Figure 12.5 illustrates this three-

Fixed factors	b	SE	df	t	р
F0 DIFFERENCE	0.10	0.01	14570.00	9.39	< 0.001
QUALITY	0.58	0.02	14580.00	34.78	< 0.001
SEX	1.03	0.32	38.96	3.19	< 0.01
F0 DIFFERENCE * QUALITY	-0.01	0.00	14570.00	-6.98	< 0.001
F0 DIFFERENCE * SEX	-0.12	0.02	14570.00	-7.06	< 0.001
F0 DIFFERENCE * QUALITY * SEX	0.02	0.00	14570.00	6.58	< 0.001

Table 12.7 Significant main effects and interactions of PROXIMITY on perceived attractiveness

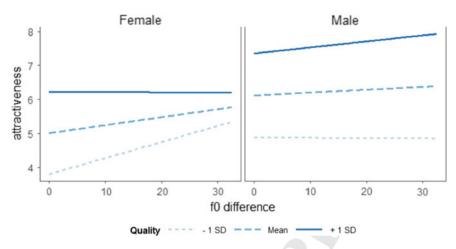


Fig. 12.4 Interaction plot for the effects of F0 DIFFERENCE, QUALITY, and SEX on perceived *attractiveness*

 Table 12.8
 Post hoc significant main effects and interactions of PROXIMITY on perceived attractiveness for the female speakers

Fixed factors	b	SE	df	t	p
F0 DIFFERENCE	0.10	0.01	7272.00	9.63	< 0.001
QUALITY	0.58	0.02	7274.00	35.64	< 0.001
F0 DIFFERENCE * QUALITY	-0.01	0.00	7271.00	-7.15	< 0.001

 Table 12.9
 Post hoc significant main effects and interactions of PROXIMITY on perceived attractiveness for the male speakers

Fixed factors	b	SE	df	t	p
QUALITY	0.59	0.02	7306.00	32.14	< 0.001
F0 DIFFERENCE * QUALITY	0.00	0.00	7302.00	2.43	< 0.05

 Table 12.10
 Significant main effects and interactions of PROXIMITY on perceived conversational quality

Fixed factors	b	SE	df	t	р
ATTRACTIVENESS	0.93	0.02	14580.00	40.55	< 0.001
SEX	1.14	0.38	38.24	3.01	< 0.01
F0 DIFFERENCE * ATTRACTIVENESS	-0.01	0.00	14570.00	-4.48	<.001
ATTRACTIVENESS * SEX	-0.27	0.03	14580.00	-8.20	< 0.001
F0 DIFFERENCE * ATTRACTIVENESS	0.01	0.00	14570.00	3.19	< 0.01
* SEX					

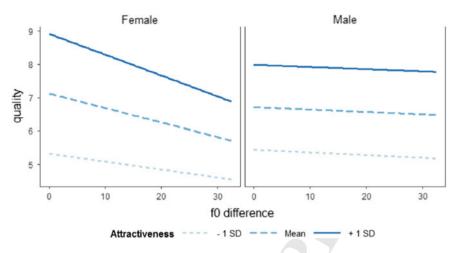


Fig. 12.5 Interaction plot for the effects of F0 DIFFERENCE, ATTRACTIVENESS, and SEX on perceived *quality*

 Table 12.11
 Post hoc significant main effects and interactions of PROXIMITY on perceived conversational quality for the female speakers

Fixed factors	b	SE	df	t	р
ATTRACTIVENESS	0.93	0.03	7279.00	36.81	< 0.001
F0 DIFFERENCE * ATTRACTIVENESS	-0.01	0.00	7273.00	-4.07	< 0.001

 Table 12.12
 Post hoc significant main effects and interactions of PROXIMITY on perceived conversational quality for the male speakers

Fixed factors	b	SE	df	t	p
ATTRACTIVENESS	0.66	0.01	7304.00	72.57	< 0.001

way-interaction while Tables 12.11 and 12.12 report the post hoc results separated 560 by SEX. Again, we see a common general tendency for both sexes but in contrast 561 to perceived attractiveness, both sexes judge the conversation as better if the inter-562 locutor shows smaller F0 DIFFERENCE and hence greater degrees of entrainment. 563 Again, these effects interact with the other social variable, in this case perceived 564 ATTRACTIVENESS. For the female speakers, Fig. 12.5 shows that the effects of 565 F0 DIFFERENCE on *quality* increase with perceived ATTRACTIVENESS, which 566 is statistically significant in the post hoc test reported in Table 12.11. Male speakers 567 show the same tendency but as shown in Fig. 12.5, the effects are much smaller and 568 do not reach statistical significance in the post hoc test (s. Table 12.12). 569

The post hoc investigation of the conversational parts shows that female speakers show the same effects for *attractiveness* as for the conversations as a whole within both the first and the last five minutes of the conversation. For the male speakers,

 Table 12.13
 Post hoc significant main effects and interactions of PROXIMITY and ATTRAC-TIVENESS on perceived *conversational quality* for the male speakers for the last five minutes of a conversation

Fixed factors	b	SE	df	t	р
F0 DIFFERENCE	-0.02	0.01	2615.00	-2.81	< 0.01
ATTRACTIVENESS	0.65	0.02	2615.00	43.00	< 0.001

⁵⁷³ however, we only find significant effects for the conversation as a whole but not for ⁵⁷⁴ the conversational parts. With respect to Fig. 12.4, we suspect that the effects for the ⁵⁷⁵ conversation as a whole are already too small and are hence lost when splitting the ⁵⁷⁶ data set.

Comparable to perceived *attractiveness*, the effects for *quality* are robust for the 577 female speakers within the conversational parts. Female speakers show the same 578 positive effects of entrainment on *quality* for both the start and the end of the con-579 versation. The male speakers, however, show deviating effects from the conversation 580 as a whole, which also point in the opposite direction. While we find effects on 581 attractiveness for the whole conversation but not for the parts, we find the opposite 582 for quality. While entrainment does not significantly correlate with quality in the 583 conversation as whole, we find a significant effect of F0 DIFFERENCE on *quality* 584 in the part subsets (s. Table 12.13). Furthermore, these effects only occur in the last 585 five minutes of the conversation but not in the first five minutes. Lastly, F0 DIFFER-586 ENCE does not interact with perceived ATTRACTIVENESS in contrast to any other 587 entrainment effects reported in this chapter. 588

589 12.3.3 Convergence and Synchrony

⁵⁹⁰ Comparable to the effects of perceived attractiveness and conversational quality on ⁵⁹¹ *convergence* (s. chapter 12.3.1.2) we find no significant effects for convergence on ⁵⁹² either variable. However, in contrast to the effects found for perceived attractive-⁵⁹³ ness and conversational quality on *synchrony* (s. chapter 12.3.1.3) we also find no ⁵⁹⁴ significant effects for synchrony on either variable.

595 12.4 Discussion

The results show that there is a strong connection between prosodic entrainment and both perceived visual attractiveness and conversational quality. We find that prosodic entrainment reflects the social relationship by showing effects for the perceived visual attractiveness of an interlocutor as well as effects for the perceived quality of the conversation. Furthermore, the degree of prosodic entrainment correlates with how

pleasant a speaker perceives a conversation as well as how visually attractive s/he 601 perceives his/her interlocutor. However, while there are core effects that suggest 602 a direct interpretation and are in accordance with previous studies as well as the 603 expectations given in chapter one, there are several findings that pose a challenge for 604 future research. Especially the synchrony effects, the reciprocity of the connection 605 between entrainment and social variables, as well as the interaction of perceived 808 attractiveness and conversational quality leave many open questions as discussed in 607 the following. 608

12.4.1 Effects of Perceived Attractiveness and Conversational Quality on Prosodic Entrainment

Perceived attractiveness and conversational quality both significantly correlate with 611 the degree to which a speaker entrains to his/her interlocutor. However, both variables 612 correlate with entrainment differently and with notable differences depending on 613 speaker sex. In general, both female and male speakers show greater degrees of 614 entrainment in terms of proximity if they perceive the conversation as better. This 615 is compatible with our expectations from the link between prosodic entrainment 616 and conversational quality as well as social distance in general (cf. Nenkova et al., 617 2008; Gonzales et al., 2009; Levitan et al., 2012). In contrast, both sexes show greater 618 degrees of disentrainment in conversations with more visually attractive interlocutors. 619 This is also in accordance with our expectations from previous research on the effects 620 of visual attractiveness on prosody in general (cf. Hughes et al., 2010; Fraccaro et al., 621 2011). However, this also means that the effects are indeed diametrically opposing 622 each other. 623

For the female speakers, this results in a significant interaction between attrac-624 tiveness and conversational quality with respect to entrainment. The effects of attrac-625 tiveness decrease with higher degrees of conversational quality and are even absent 626 in conversations that are perceived as very pleasant. Accordingly, female speakers 627 emphasize conversational quality over attractiveness in terms of entrainment. This is 628 consistent across the entire conversation. The opposite is true for the male speakers. 629 Here we also find a significant interaction but male speakers show decreasing effects 630 of conversational quality as attractiveness increases. Accordingly, male speakers 631 emphasize visual attractiveness over conversational quality. However, this is only 632 true for the first five minutes of the conversation and neither for the last five minutes 633 nor the conversation as a whole. Hence, male speakers emphasize visual attractive-634 ness when first engaging in a conversation but show more balanced prosodic effects 635 for both variables as the conversation emerges. 636

The picture is less clear for the other types of prosodic entrainment. Perceived visual attractiveness and conversational quality both correlate with synchrony. However, the effects are difficult to interpret. Both variables show a positive correlation with the degree of synchrony if the respective other variable is low, negatively if the other variable is high, and marginally or not at all if the other one is average. We suggest that synchrony as measured in this study reflects the complex relationship between attractiveness and conversational quality and cannot be interpreted in its own right. Furthermore, we find a general convergence effect, i.e., a general trend for speakers to become more similar over time. However, this trend is independent from either social variable.

⁶⁴⁷ 12.4.2 Effects of Prosodic Entrainment on Perceived ⁶⁴⁸ Attractiveness and Conversational Quality

The effects of prosodic entrainment on perceived attractiveness and conversational 649 quality show a nearly reciprocal relationship with the effects reported above. Both 650 sexes judge conversations as better where the interlocutor shows a greater degree 651 of prosodic entrainment in the form of proximity. Although the literature on the 652 effects of entrainment on perception is scarce, these effects are in line with our 653 expectations (cf. Nenkova et al., 2008; Gonzales et al., 2009; Levitan et al., 2012). 654 Furthermore, both male and female speakers perceive interlocutors who show greater 655 degrees of disentrainment as more visually attractive. This is also in line with our 656 expectations since disentrainment generally leads male speakers to lower their voices 657 and female speakers to raise their voices, which was found to increase perceived 658 attractiveness (cf. Collins, 2000; Collins and Missing, 2003; Feinberg et al., 2005, 659 2008; Hodges-Simeon et al., 2010; Jones et al. 2010; Xu et al., 2013). However, it is 660 not the mere distinction between low and high which is connected to attractiveness 661 but specifically the distance caused by disentrainment. An interlocutor's pitch is thus 662 evaluated within his/her own natural register and not in absolute terms as comparable 663 across speakers. Again, the effects of perceived attractiveness and conversational 664 quality are contradicting. 665

For the female speakers, the effects of perceived attractiveness and conversational 666 quality interact significantly. The effects of entrainment on conversational quality 667 become stronger with an increased perceived visual attractiveness of the interlocutor. 668 Simultaneously, the effects of attractiveness become weaker the better the conversa-669 tion. Both interactions are consistent across the entire conversation. Accordingly, we 670 find the same dominance of conversational quality over visual attractiveness reported 671 above. Again, the picture is vastly different for the male speakers. While the effects of 672 entrainment on perceived attractiveness are statistically independent from conversa-673 tional quality, the effects of entrainment on conversational quality become weaker the 674 more attractive the interlocutor. Accordingly, the male speakers again show a dom-675 inance of attractiveness over conversational quality. Furthermore, we find another 676 effect compatible with the results reported above. While the dominance of visual 677 attractiveness over conversational quality on entrainment disappears after the first 5 678 min of the conversation, the effects of entrainment on conversational quality only 679 appear after the first 5 min. Hence, although the male speakers show a general domi-680

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nance of visual attractiveness over conversational quality, these effects shift over time
 with attractiveness being emphasized when first engaging in a conversation while
 the perception of conversational quality manifests its effects in the later parts of the
 conversation.

In contrast to the effects of the social variables on entrainment, we find no effects 685 of synchrony on either visual attractiveness or conversational quality. Again, we 686 suggest that this may be related to the complex interaction between the two social 687 factors. Furthermore, the data set may be too small for the reliable application of 688 Pearson correlation coefficients as measurements for synchrony (cf. Edlund et al., 689 2009; Levitan, 2014), since we found effects of synchrony using other although 600 cruder measurements. The size of the data set could also explain the absence of 691 convergence effects. 692

12.4.3 The Dilemma: Good Conversations with Attractive Interlocutors

This chapter has shown that high degrees of conversational quality and visual attrac-695 tiveness within the same conversation do indeed lead to contradicting effects as 696 expected from the introduction. However, with respect to our initial expectations, we 697 do not find one factor completely canceling out the other. Instead, the results suggest 698 a weighting of the two variables. While female speakers emphasize conversational 699 quality, male speakers generally emphasize perceived attractiveness. Accordingly, if 700 both perceived attractiveness and conversational quality are high, female speakers 701 tend to show stronger entrainment while male speakers show stronger disentrain-702 ment. This observation is complemented by the finding that male speakers also show 703 a shift in weighting. While female speakers consistently emphasized conversational 704 quality over attractiveness, male speakers show a tendency to emphasize perceived 705 attractiveness when first engaging in a conversation and then shifting the focus to 706 conversational quality as the conversation progresses. Accordingly, with respect to 707 our initial expectation we find both one factor overruling the other as well as differ-708 ences in distribution across a conversation. However, we did not find an association 709 of different types of entrainment with different social variables. 710

A factor not considered within this study concerns differences in the weighting of 711 these social variables not only in their distribution by time but also by topic. Accord-712 ingly, there may be conversational topics that are thematically closer to mating and 713 hence show a higher demand for signaling attractiveness versus topics closer related 714 to forming stronger bonds and hence related to signaling conversational quality com-715 parable to the effects found for positive versus negative topics by Lee et al. (2010). 716 Such a topic related shift in signaling social variables would also mirror and thus add 717 to the interpretation of the effects observed for the male speakers as a higher density 718 of mating related topics in the first half of the conversation compared to the more 719 bonding related topics in the last half seems likely. 720

Lastly, the weighting of perceived attractiveness may also be related to personality. Emphasizing perceived conversational quality over perceived visual attractiveness could be related to factors such as emotional empathy or agreeableness. Consequently, the differences we find for speaker sex may actually not be related to speaker sex itself but to gender-related personality attributes.

726 12.4.4 Additional Thoughts and Further Implications

Before discussing some further implications of the results, we would like to address 727 two observations regarding the experiment itself to clarify the possible generaliz-728 ability of our results. Prior to the experiment, we assessed personal data from all 729 participants including their intent to participate in the study. As reported above, all 730 participants were informed that the experiment was designed as a dating study. How-731 ever, only three participants stated that they were actually interested in dating and 732 eventually finding a partner. Furthermore, all of these three participants were male. 733 The remaining participants all declared to be merely interested in having good conver-734 sations and meeting new people. Accordingly, the majority of the participants did not 735 intent to date prior to the conversations or at least did not admit it. Inspecting the con-736 versations with respect to content leads to a mixed result. While most conversations 737 confirm the assessment by a lack of flirting, several conversations suggest a strong 738 intent for dating. One pair even requested to exchange contact information although 739 both participants did not declare to be interested in finding a partner. Accordingly, 740 engaging in a dating conversation is not necessarily something that happens inten-741 tionally. Furthermore, participants may just not be willing to admit their intent when 742 participating in a scientific study. The fact, that we do find strong effects for perceived 743 attractiveness may support this conclusion. However, as pointed out above, perceived 744 attractiveness may play a strong role even in non-dating conversations which shifts 745 the focus of the generalizability of this study. 746

The second observation regards the naturalness of the conversations. Although 747 initially most participants were irritated by the setting and often commented on the 748 recording situation, this issue quickly dissipated in most conversations. Overall, we 749 perceive the majority of the conversations as resembling natural interactions. The 750 participants engaged freely in spontaneous dialogues, choosing a wide variety of 751 different topics and transitioning fluently between them. There are also several cases 752 of participants talking about the researchers, other university staff, or even sharing 753 personal information which they were explicitly instructed not to reveal, suggesting 754 that participants quickly forgot about being recorded. 755

With respect to the ongoing debate about the function of entrainment, our study supports both categories of assumptions. The effects of perceived conversational quality strongly support the *communication accommodation theory* (Giles et al., 1991) and related models which link social closeness to greater entrainment. Greater conversational quality can be related to a stronger social bond between the interlocutors and hence a greater degree of social closeness. However, we also find an effect

of categorical convergence, which is not affected by either conversational quality or 762 attractiveness. Accordingly, speakers become categorically closer with respect to f0 763 over time. These effects support the assumption of entrainment as an automatism, for 764 example, to enhance intelligibility by matching speaking styles as suggested by the 765 communication model (Natale 1975) or the perception behavior link (Chartrand & 766 Bargh, 1999) among others. Lastly, the effects of perceived attractiveness allow for 767 two possible interpretations. On the one hand, perceived attractiveness may primarily 768 affect f0 lowering or raising with disentrainment just being a logical consequence 769 and not a feature in itself. On the other hand, the effect of social distance, which is 770 linked to disentrainment (cf. Giles et al., 1991), may actually be the primary effect. 771 Accordingly, there may be sociological/psychological reasons why a higher degree 772 of social distance is linked to greater perceived attractiveness. 773

We suggest that our findings should be generalizable to non-dating conversations 774 to some degree. As described above, the participants mostly stated that they did 775 not intend to flirt or date. Accordingly, we can characterize the conversations as a 776 hybrid of natural conversations in a dating setting leading to real dating conversa-777 tions in some cases. Hence, we expect the effects of perceived attractiveness and 778 conversational quality to be slightly less pronounced in real non-dating mixed-sex 779 conversations and more pronounced in real intended dating conversations but present 780 in both. 781

Another follow-up question concerns the generalizability to same-sex dating con-782 versations. The particular question regards the two possible interpretations of the 783 findings on perceived attractiveness as primarily leading to a raising or lowering in 784 f0 or to an effect of disentrainment with respect to the interlocutor. Accordingly, 785 for same-sex dating conversations we would either expect both female speakers to 786 raise and both male speakers to lower their f0 or both speakers to move away from 787 the interlocutor's f0. In the latter case, we would expect the speaker with the higher 788 register to raise his/her f0 and the other speaker to lower his/her f0. The fact that 789 female speakers consistently raised their f0, although both lowered and raised f0 is 790 perceived as attractive by male listeners (cf. Karpf, 2006), supports the assumption 791 that indeed disentrainment and not primarily f0 movement is linked to perceived 792 attractiveness. 793

With respect to other prosodic cues, the effects observed for f0 are not easily 794 generalizable. The effects found for f0 entrainment and conversational quality are in 795 line with studies on other prosodic parameters. For example, Schweitzer et al. (2017) 796 observe a link between social attractiveness and speaking rate. However, there are no 797 studies on the effects of visual attractiveness or any observations of disentrainment 798 regarding anything but f0. If the disentrainment in f0 is a secondary effect of raising or 799 lowering f0, then those effects are linked to the natural sex differences expected from 800 the frequency code (Ohala, 1983, 1984) and should not transfer to anything other 801 than f0. However, if disentrainment and hence signaling social distance is the primary 802 cue, we could expect other prosodic features to show similar effects. Accordingly, 803 taking other prosodic features into consideration could also further our understanding 804 concerning what to expect in same-sex conversations for reasons explained above. 805

806 12.5 Conclusion

This paper shows that the perceived quality of a conversation and the perceived 807 visual attractiveness of an interlocutor are linked to f0 entrainment. This relationship 808 is largely reciprocal with f0 entrainment both apparently affecting and reflecting 809 the social variables. Regarding the different types of entrainment (cf. Edlund et al., 810 2009; Levitan, 2014), the effects are mainly restricted to f0 proximity with no system-811 atic effects for synchrony or convergence. As expected from the literature, we find 812 contradicting effects with conversational quality being linked to more entrainment 813 and attractiveness being linked to more disentrainment. Additionally, both variables 814 depend on as well as affect each other and the respective effects on and of entrain-815 ment. This contradiction is primarily resolved by emphasizing one over the other 816 with female speakers emphasizing conversational quality over attractiveness and 817 male speakers doing the opposite. However, male speakers also show a shift from 818 emphasizing attractiveness to conversational quality over the course of the conversa-819 tion. Future research needs to investigate how the connection of f0 entrainment and 820 perceived attractiveness and conversational quality relates to conversational topics as 821 well as personality profiles, as well as take other prosodic features such as speaking 822 rate, intensity variation, or voice quality into consideration. Furthermore, the role of 823 synchrony leaves several open questions for further investigation. 824

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	were excluded. These ratings. Six promising regression, and regress	stimuli were recorded in high quality and were subjected to third-party listeners' acoustic parameters from related work are tested applying methods of correlation, sion trees. These parameters are average fundamental frequency, articulation rate, both and of intensity, as well as spectral center of gravity. The amount of variance

explained remains below 50%. Results confirm variability of the fundamental frequency as dominating correlate of likable voices in male and female speakers. It is concluded that the promising acoustic parameters are not robust to stimulus duration and scenario. Therefore, it is argued to explore the applicability of locally defined and linguistically motivated parameters.

Keywords

Voice - Acoustic parameters - Likability - Rating test - Database - Analysis - Modelling

Chapter 13 Acoustic Correlates of Likable Speakers in the NSC Database



Benjamin Weiss, Jürgen Trouvain, and Felix Burkhardt

Abstract Speech stimuli from scenario-based conversations were analyzed regard-

- ² ing acoustic correlates of likability. Utterances from the pizza ordering scenario of the
- ³ NSC corpus were selected, and the confederate's turns were excluded. These stimuli
- ⁴ were recorded in high quality and were subjected to third-party listeners' ratings.
- ⁵ Six promising acoustic parameters from related work are tested applying methods
- of correlation, regression, and regression trees. These parameters are average fun damental frequency, articulation rate, standard deviation of both and of intensity, as
- damental frequency, articulation rate, standard deviation of both and of intensity, as
 well as spectral center of gravity. The amount of variance explained remains below
- 50%. Results confirm variability of the fundamental frequency as dominating corre-
- ¹⁰ late of likable voices in male and female speakers. It is concluded that the promising
- acoustic parameters are not robust to stimulus duration and scenario. Therefore, it
- ¹² is argued to explore the applicability of locally defined and linguistically motivated
- ¹³ parameters.

¹⁴ Keywords Voice · Acoustic parameters · Likability · Rating test · Database ·

15 Analysis · Modelling

16 13.1 Introduction: Likability of Speakers

¹⁷ The aim of this chapter is twofold: First, acoustic correlates of likability ratings for

¹⁸ the common stimulus length of a single utterance are presented as brief literature

¹⁹ survey with a focus on re-occurring results. The second aim is to check whether such

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confirmed correlates can be applied for longer stimuli provided with a database for
 studying attributions and preference of speakers. The domain hereby is limited to
 evaluations of unacquainted speakers in order to maximize the impact of the first
 impression obtained from voice and speaking style of speakers.

The question of whether a person likes another person or not represents one of the 24 most crucial social attitudes in humans, as it lays the basis for own social behavior 25 (Chap. 1). In the most extremes of cases, liking somebody or not can determine 26 not only the kind of social interaction, but whether there is avoidance or approach 27 in the first place. In the research topic of first impressions, studies investigated the 28 potential impact of surface signals, like clothing and facial expressions, but also 29 voice and speaking style, on the formation of likability (Ambady & Skowronski, 30 2008). While people might not be inclined to immediately judge whether they truly 31 like a person from a few seconds of interaction of recorded voice samples, listeners 32 can express their gradual preference of the voice of a speaker, and thus his or her 33 likability. 34

Such explicit ratings already show significant consistency between raters. For 35 example, a standard measure of consistency between multiple raters is the intra-36 class correlation (ICC) with values between 0 and 1. It ranges for likability ratings 37 from ICC = 0.76 (Burkhardt, Schuller, Weiss, & Weninger, 2011) to ICC = 0.9338 (Weiss & Burkhardt, 2010). This strong consistency documents that not only visual, 30 but also acoustic information has a systematic relationship with a first impression. 40 As the first impression is persistent over time and has predictive power (Ambady, 41 Bernieri, & Richeson, 2000, 2006; Peterson, Cannito, & Brown, 1995; Hecht & 42 LaFrance, 1995), it also potentially affects relationship building. As such acoustic 43 or visual data in first encounters are sparse and superficial, attributions and even 11 stereotypes play an important role in the formation of likability judgments. Salient 45 attributions of regional or social background of speakers or disfluencies are relevant 46 for likability (Scherer & Giles, (Scherer and Giles, 1979); Giles, 1980, Weiss & 47 Burkhardt, 2012; McCroskey & Mehrley, 1969). 48

When studying acoustic correlates of likable voices, the effect of such attribu-49 tions should therefore be minimized by providing homogeneous groups of speakers 50 in terms of social and regional background, age, speech pathology, physical attrac-51 tiveness, or gender (Murry, Singh, & Sargent, 1977; Murry & Singh, 1980; Linville, 52 2001; Brückl, 2011; Kreiman & Gerratt, 1996). Ideally, homogeneous groups of 53 raters/listeners should be selected as well, or a diverse group that is balanced for these 54 influencing factors can be recruited (Deal & Oyer, 1991). Of course, this statement 55 holds not for the case of explicitly aiming to test for the effects of those attribu-56 tions. Physical attractiveness that is inferred from voice and speaking style is such an 57 example. Attractiveness is, like aesthetics for many other domains, a well-known and 58 important factor for preference and liking, regardless of the sexual preference. The 59 aim of this chapter is to present work that identifies which acoustic characteristics 60 affect likability of unacquainted speakers, apart from the aforementioned attributions 61 of age, gender, regional, and social background or speech-related pathologies. 62

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63 13.2 A Review on Acoustic Correlates

In search for acoustic correlates of likability ratings, the dominant perspective is a global one, spanning the entire stimulus: The chosen stimuli are acoustically analyzed as a whole, and parameter values are aggregated, for example, to obtain the average fundamental frequency (F_0) for a complete utterance. As a consequence, vowel formants are typically only analyzed if the stimulus consists only of a single vowel (e.g., Bruckert et al., 2006).

Early research has brought a body of results on the so-called suprasegmentals, 70 which are F_0 , intensity, and duration (Lehiste, 1970). For these suprasegmentals, 71 analysis and re-synthesis studies have been conducted to identify acoustic parameters 72 and test their impact on listeners' ratings. As outlined in Chap. 1, likability can be 73 used as a synonym for social attractiveness. It can be related to unacquainted speakers 74 to the attribution of warmth or benevolence—although there are social situations, in 75 which competence might play a bigger role. Therefore, some of the results mentioned 76 here stem not directly from ratings of likability but were elicited by questionnaires 77 with related items or scales that also contribute to social attractiveness. Examples 78 are friendliness, sympathy, or pleasantness (Weiss & Möller, 2011). If available in 79 the studies, results for competence are also mentioned. 80

At least for male speakers and sometimes for females as well, the fundamental 81 **frequency** (F_0) correlates negatively with ratings of benevolence, trust, likability, 82 or pleasantness (Brown, Strong, & Rencher 1974; Apple, Streeter, & Krauss, 1979; 83 Bruckert et al., 2006; Gravano et al., 2011; Weirich, 2010; Chattopadhyay, Dahl, 84 Ritchie, & Shahin, 2003; Weiss & Burkhardt, 2012; Weiss, 2013). Noteworthy, how-85 ever, are contradicting results of a positive correlation reported for German male 86 speakers (Scherer, 1979). A similar opposing effect was found for the brief greeting 87 "hello" in Scottish English (McAleer, 2014). Both results can be interpreted in a dif-88 ferent communicative context, in which a raised average pitch is more appropriate, 89 maybe to signal arousal. 90

The observed general tendency of a lower F_0 being evaluated more positively 91 concurs with a positive association of perceived "darkness" for male speakers and 92 the attribution of "being relaxed" for voices of the two genders considered (Weiss 93 et al., 2018b). Variability or range of F_0 shows a positive effect on likability-related 94 concepts of benevolence or warmth (Brown et al., 1973, 1974; Ray, 1986) but also 95 on competence (Ray, 1986). There is also evidence for a positive effect of a rising F_0 96 contour (Bruckert et al., 2006; Weiss & Burkhardt, 2012, McAleer, 2014). However, 97 this seems to be a more problematic acoustic correlate due to its dependency on the 98 linguistic material. 99

Intensity as the second aspect reveals a negative correlation with benevolence but a positive one with competence (Ray, 1986), although this relationship might be more complex (Scherer, 1979). Effects caused by speech manipulation also have shown to add up or cancel each other out, dependent on the sign of correlation, which means that they can be considered as being independent of each other (Ray, 1986).

With respect to articulation rate, an ideal-point relation was found for likability-105 related concepts, especially for benevolence. This relation can be visualized as an 106 inverted U-shaped line. This separates its effect from the more linear positive corre-107 lation with competence (Brown et al., 1974, 1975; Smith, Brown, Strong, & Rencher, 108 1975; Apple et al., 1979; Street, Brady, & Putnam, 1983). For articulation rate, an 109 additional effect could be found. Apparently, the raters' own intrinsic rates affect the 110 evaluation of speakers' rates (Street et al., 1983; Feldstein, Dohm, & Crown, 2001). 111 One interpretation is that listeners perceive articulation rate according to their own 112 reference as high or low. A second interpretation would be that there is an effect of 113 similarity preference, which may interfere with a linear relation between rate and lik-114 ability. In all cases, the result shows a positive correlation with moderate or slightly 115 increased rates, confirming the rough inverted U shape of relationship, and thus a 116 saturation for very fast conditions (Street & Brady, 1982). This is why Table 13.1 117 gives results on both, positive correlations and an ideal-point relation with moderate 118 or similar rates. 119

All these suprasegmentals are relatively easy to manipulate, e.g., Trouvain et al. 120 (2006) could convincingly model personality dimensions such as sincerity, compe-121 tence, and excitement with speech synthesis. These suprasegmentals are also easy to 122 measure automatically (maybe apart from articulation rate). This may be the reason 123 that they have been studied extensively. More recently, spectral measures have been 124 moved into focus with the aim to study voice quality, but also other, yet understud-125 ied, anatomical and articulatory sources of spectral aspects of speech. For example, 126 shimmer, i.e., the local variability in amplitude, correlates positively with likability 127 (Gravano et al., 2011), while measures of energy distribution, such as spectral tilt 128 or center of gravity, show positive evaluation with less energy in higher frequencies 120 (Weiss et al., 2017; Weiss, 2015). One reason could be a co-variation with the aver-130 age F_0 , i.e., the perception of "dark" or "relaxed" voices (Weiss et al., 2016; Weiss, 131 2018b). However, a summary of many studies on this topic reveals non-significant 132 results for spectral parameters (cf. Table 13.1). 133

There is some kind of tendency to be found in this summary. First of all, there are studies showing no effects, which are mostly analysis studies and thus might represent a non-sufficient variability in parameter values to show an effect. But also, F_0 mean, F_0 variability, and articulation rate seem to form a kind of majority vote to have a systematic effect, despite some contradicting results. For other parameters, such as variability in intensity or articulation rate, but also for spectral measures, such a systematic pattern is not obvious.

A particular issue is the status of the stimuli used in listening-and-rating experi-141 ments that are typically applied in this line of research. For example, the very short 142 stimulus "hello" was rated and acoustically analyzed (McAleer, 2014). In this study, 143 step-wise regression models of likability for male voices include average F_0 and, 144 negatively, the harmonic-to-noise ratio (HNR). For female voices, a similar model 145 is made up of HNR (negative sign), a rising F_0 contour, and the F_0 range. The pos-146 itive, and thus contradicting, result for pitch might have not appeared in the case of 147 presenting the full utterances the "hello" was cut out from. While other studies used 148 even shorter stimuli, i.e., vowels that have been excluded in this chapter, likability 149

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Table 13.1 Summary of results from literature on acoustic correlates of likability and similar concepts. Positive, negative, and non-significant relations are depicted by +, -, and \circ , respectively. Gender of the speakers is indicated by m, f, respectively, as is language, and if the stimuli were re-synthesized. Reports on non-significant results may be incomplete

Reference	Gender	Language	Re-	F_0	F_0	F_0	Intensity Intensity		Arti-	Ideal	Arti-	Harmonic-	Harmonic-Shimmer Jitter		Voiced-	Formant	Formant Spectral		Spectral Spectral	Spectral
		(synthesized		variation raise	raise	mean	variation	culation	articula-	culation	to-noise			unvoiced frequen-		disper-	tilt		skew-
									rate mean	rate	rate variation	rauo				cles	sion		gravity	ness
Brown et al. (1973)	u	en	В		+					+										
Brown et al. (1974)	в	en	R	1	+					+										
Bruckert et al. (2006)	н	fr*				+										0	0			
Duran (2017)	mf	de		0	+							0	0	0						
Feldstein et al. (2001)	mf	en								+										
Fernández Gallardo and Weiss (2016)	n	de		0	0		•	0	I			0						+	I	
	f	de		0	0		0	+	0			0						0	0	
Gravano et al. (2011)	mf	en		I	I	0	+		0			0	1	0	0					
McAleer (2014)	в	en		+	0	0						I	0	0			0	0		
	f	en		0	+	+)		ζ		1	0	0			0	0		
Ray (1986)	m	en	R		+		1	7												
Smith et al. (1975)	ш	en	R							+										
Street and Brady (1982)	m	en	R							+										
Street et al. (1983)	m	en							+	+										
Weiss (2015)	ш	de		0	0				0										0	0
	f	de		0	0				+			5							0	+
Weiss & Burkhardt (2010)	н	de		I					+										I	0
	f	de		0					+				/						I	+
Weiss et al. (2010)	m	de											1							
	f	de											0							
Weiss (2013)	н	de		I	0	0		1	0		0							2		
	f	de		I	0	0		0	+		I							01		
Weiss and Burkhardt mf (2012)	t mf	de		I	0	+		0	+			0		+			Y	0	0	
Weiss et al. (2017)	f	de	R															+		

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*vowels only, female raters only

¹⁵⁰ is a concept that emerges in social situations. It should therefore be studied not only ¹⁵¹ concerning the voice quality but also the speaking style. In order to use more realistic ¹⁵² data and to identify or verify correlates that emerge only with longer stimuli, such as ¹⁵³ variability of F_0 , the Nautilus Speaker Characteristics (NSC) database was recorded ¹⁵⁴ and used. It is described in the next section.

155 13.3 Material

The aim of this new analysis is to extend the insight into acoustic correlates of 156 likable voices by avoiding several limitations of earlier research. First of all, the 157 number of speakers analyzed has often been very small, about 20–30, for example. 158 Secondly, the social situation has been unclear. Examples are the aforementioned 159 utterance "hello" or reading aloud single sentences. And thirdly, the stimuli have 160 been very short. Therefore, the Nautilus¹ database was created. It features 300 Ger-161 man speakers (aged 18-35, of which are 126 males) and was recorded with the 162 aim to study speaker characteristics (Fernández Gallardo & Weiss, 2018). During 163 recruitment, the speakers were subjectively checked for neither exhibiting a strong 164 regional or social accent, nor displaying signs of a voice-related sickness or speech 165 disorder. Although all speakers display Standard German, some speakers do exhibit 166 some regional features and suprasegmental non-modal voice qualities. Hearing issues 167 were not reported during collecting speakers' details, which is important for properly 168 conducting the interactive scenarios and understanding the instructions of the exper-169 imenter. The database and documentation of the Nautilus Speaker Characteristics 170 (NSC) have been compiled by Fernández Gallardo (2018). NSC includes recordings 171 from simulated telephone conversations, read passages, and read sentences in high 172 signal quality.² From this database, telephone scenarios were chosen as appropriate 173 material, as it contained a typical and well-defined social situation of unacquainted 174 dyads that can be judged by third-party listeners. The scenario used for analysis here 175 is ordering something to eat from a pizza service with a phone call. It stems from a 176 list of pre-defined scenarios used for evaluating audio network transmission quality 177 (Rec & P.805, 2007). The invited and recorded speakers all took over the role of 178 the caller, while a student confederate played the pizza service. The caller obtained 179 the following task information: a fake surname, address, and phone number. The 180 instruction was to order a single pizza for two people, preferably a vegetarian option. 181 During the conversation, the caller is asked to note down the exact final toppings, 182 price, and duration until delivery. Such a conversation typically took about 60s to 183 complete. 184

¹Nautilus is the recording booth name used in the laboratory.

²The ISLRN of this corpus is 157-037-166-491-1. Is has been made available at the CLARIN repository: hdl.handle.net/11022/1009-0000-0007-C05F-6 under the CLARIN ACA+BY+NC+NORED license (freely available for scientific research).

In preparation of the stimuli for the listening-and-rating test on likability, all parts 185 of the confederate in the pizza scenario were removed from the recordings. The 186 resulting stimuli have an average duration of 23 s (SD = 3.3 s). Based on a question-187 naire with 34 items that was developed to assess voice-based personality attributions 188 (Weiss & Möller, 2011; Fernández Gallardo & Weiss, 2017b), a final version was 189 created with only minimal changes (Fernández Gallardo & Weiss, 2018).³ For the 190 evaluation, each stimulus was rated by 15.1 listeners on average (sd = 1.17, due 191 to splitting the students into groups). Altogether, 114 students, in the frame of a 192 lecture's exercise, took part in this test (44 females, 70 males, aged on average 24.5 193 years with an SD of 3.4). 93 of these were native German speakers, and the remaining 194 participants were fluent in German. Each listener rated male and female stimuli in 195 separate blocks with sliders on continuous scales. On average, each rater listened to 196 about 16.9 males (sd = 0.49) and 23.2 females (sd = 2.33, due to splitting the data 197 into sets). A single session took about 50 min. 198

The questionnaire itself includes items to cover major concepts of personal-199 ity attributions. It is based on existing instruments for the personality circumflex 200 (Wiggins, Trapnell, & Phillips, 1988) for the first impression of warmth and agency, 201 the OCEAN personality taxonomy (Rammstedt & John, 2007), the three-dimensional 202 model of emotional states with valence, activity, and potency (Osgood, Suci, & Tan-203 nenbaum, 1957), and estimation of physical attractiveness that is affecting person-204 ality attributions and frequent attributions observed empirically for unacquainted 205 voices (Weiss et al., 2018b). The questionnaire also includes the item of likability. 206 A screenshot shows all scales with sliders on one page Fig. 13.1. 207

208 13.4 Analysis

Data analysis is presented in four sections. First, the comprehensive questionnaire responses are reduced in dimensionality to obtain values for the concept of likability. The subsequent correlation analysis aims at testing promising acoustic parameters from Sect. 13.2 on the new stimuli. Two simple modeling approaches are presented with different aims, mainly to find out how much variance the acoustic correlates of likability can explain. In order to inspect potentially non-linear relationships, a regression tree is applied.

³likable/non-likable, insecure/secure, unattractive/attractive, sympathetic/unsympathetic, decided/ indecisive, obtrusive/unobtrusive, close/distant, interested/bored, unemotional/emotional, irritated/not irritated, passive/active, unpleasant/pleasant, characterful/characterless, reserved/sociable, nervous/relaxed, distant/affectionate, conformable/dominant, affected/unaffected, cold/hearty, young/old, factual/not factual, excited/calm, competent/incompetent, beautiful/ugly, unfriendly/ friendly, feminine/masculine, offensive/submissive, committed/indifferent, boring/interesting, compliant/cynical, genuine/artificial, stupid/intelligent, adult/childish, bold/modest.

unaffektiert	affektiert	unsympathisch	sympathisch
herzlich	gefühlskalt	sicher	unsicher
alt	jung	attraktiv	unattraktiv
unsachlich	sachlich	verständnislos	verständnisvoll
ruhig	aufgeregt	unentschieden	entschieden
inkompetent	kompetent	unaufdringlich	aufdringlich
hässlich	schön	distanziert	nah
freundlich	unfreundlich	gelangweilt	interessiert
männlich	weiblich	emotional	emotionslos
gehorsam	provokativ	nicht genervt	genervt
gleichgültig	engagiert	aktiv	passiv
interessant	langweilig	angenehm	unangenehm
zynisch	folgsam	charakterlos	charaktervoll
aufgesetzt	unaufgesetzt	gesellig	reserviert
intelligent	dumm	entspannt	nervös
kindlich	erwachsen	mitfühlend	distanziert
bescheiden	frech	dominant	unterwürfig

Inwieweit treffen die folgenden Attribute auf den Sprecher zu?

Fig. 13.1 Screenshot of the first page of the rating interface. After pressing "Start" a new playback and continue button appears, while the scales remain

216 13.4.1 Factor Analysis

A factor analysis of the personality questionnaire was conducted to identify the most 217 relevant basic dimension that explains the ratings. With this method, co-variabilities 218 are represented by a smaller number of underlying factors each representing multiple 219 questionnaire items for subsequent analysis. As human social evaluation concepts 220 can be expected to be correlated to some degree, a non-orthogonal method was 221 applied. The result of the factor analysis reveals five factors. These are named after 222 inspecting the items that contribute to each one as warmth, attractiveness, confidence, 223 compliance, and maturity (Fernández Gallardo & Weiss, 2017a, 2018). The first 224 two show a strong correlation with each other (r = 0.77). Not only because of this 225 correlation, but also due to the single questionnaire item "likability" correlating with 226 these two dimensions (with warmth: r = 0.87, with attractiveness: r = 0.83), these 227

two dimensions are apparently related to the attitude toward speakers. Considering the small number and inconsistent groups of raters, the first principal component of warmth and attractiveness is used to represent the concept of likability more robust than the single item "likability". This principal component is used as target for identifying acoustic correlates and represents likability on values from -3 to +3.

233 13.4.2 Correlation Analysis

For the first analysis, we tested the most important and promising acoustic param-234 eters that can be derived from Table 13.1.⁴ The chosen candidates are F_0 mean, 235 F_0 SD, intensity SD, articulation rate mean, articulation rate SD, and Center of 236 Gravity (CoG). Although variability in intensity and rate are not very promising can-237 didates according to Table 13.1, they were chosen nevertheless. This was done to test 238 whether the claim of Ketrow (1990) can be supported that variability in supraseg-239 mentals generally is signaling benevolence and positively affects likability. Except 240 articulation rate, all acoustic parameters were measured with Praat (Boersma, 2001). 241 Average articulation rate and its SD were estimated by an acoustic model (Weiss 242 et al., 2018a) that was trained on the perceptually motivated "perceived local speak-243 ing rate" (PLSR) (Pfitzinger, 1990). The reason for applying this method is that 244 stimulus duration would not be appropriate because of the varying linguistic mate-245 rial of the spontaneous utterances and that other established methods (De Jong & 246 Wempe, 2009) sometimes have issues with the detection of silence and of unstressed 247 syllables. 248

The results of linear bivariate correlations are presented in Table 13.2, separately 249 for females and males. This separation reflects different value ranges of acoustic 250 parameters but also the potentially different references and relations in likability 251 formation. Gender of the raters was not analyzed due to the small number of listeners 252 for each stimulus. False discovery rate approach is used to adjust for multiple testing 253 (Benjamini & Hochberg, 1995). It is not as conservative as Bonferroni correction. 254 The false discover rate sorts all p-values from lowest (i = 1) to highest (i = max(i))255 and adjusts the *alpha*-level by $i/max(i) \cdot \alpha$. There are only two significant results for 256 male and female speakers, respectively (see Sect. 13.5), indicated by bold p-values. 257 Using the divergence from a global mean in articulation rate in order to represent an 258 ideal-point relation is not significant in either gender. Before discussing these results, 259 simple modeling of the data is conducted. 260

⁴While articulation rate is not an acoustic parameter in a narrow sense, the estimates used here are a prediction result based on spectral data, and it is also called acoustic parameter for convenience.

Parameter	Female speaker	rs	Male speakers	ers	
	Pearson's r	p-value	Pearson's r	p-value	
F ₀ mean	0.25	0.0008	0.16	0.0688	
F ₀ SD	0.44	<0.0001	0.52	<0.0001	
Intensity SD	-0.04	0.5975	-0.07	0.4427	
Artic. Rate mean	0.05	0.4937	0.30	0.0006	
Artic. Rate SD	0.02	0.7845	0.15	0.0913	
CoG	0.05	0.5521	0.18	0.0445	

 Table 13.2
 Pearson's correlation between selected acoustic parameters and likability

Table 13.3 Linear models for Likability: Females (p < 0.0001, $R^2 = 0.206$); males (p < 0.0001, $R^2 = 0.345$). Parameters not included into a model are represented by "—". (significance levels of $< .05^*$, $< .01^*$, and $< .001^{***}$ are applied)

Parameters	Females	Males
Intercept	-0.56**	-0.15
F ₀ mean	0.38	-0.67*
F ₀ SD	0.49***	0.83***
Artic. rate mean	-	0.22**
Artic. rate SD	-	-
Intensity SD	-	-
CoG	-	-

261 13.4.3 Linear Regression Analysis

As a second step, describing likability ratings with these selected acoustic parame-262 ters can shed a light on the amount of variance explained. Due to the relatively large 263 number of stimuli, acoustic modeling can furthermore help to identify additional 264 candidates of acoustic correlates that have non-linear relationships or meaningful 265 interaction effects with other parameters, as attempted in the next subsection. As 266 linear baseline, linear regression with step-wise inclusion of parameters was per-267 formed.⁵ Overall, the resulting models are significant but explain only about 1/5 of 268 the variance for female and about 1/3 for male speakers (Table 13.3). While, for males, 269 articulation rate mean is included in addition to the two pitch-related parameters, F_0 270 mean does contribute significantly to the model with F_0 SD, most likely due to a 271 cross-correlation between them ($r = 0.34^{***}$). The resulting estimates are depicted 272 in Fig. 13.2. 273

⁵Based on AIC, and single inclusion and exclusion of variables; only main effects.

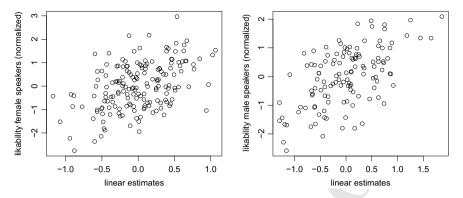


Fig. 13.2 Results of the two linear models for likability of female (left) and male (right) speakers. Average likability values versus model estimates from acoustics

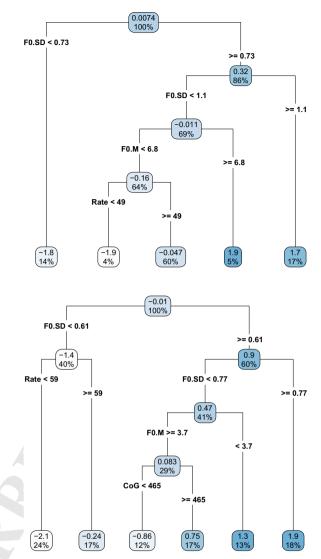
274 13.4.4 Non-linear Modeling

A second simple approach to modeling is using regression trees to better take non-275 linearities into account. The main aim is not a better fit, but a better view for identify-276 ing acoustic correlates of likability in voices. Such trees, pruned on cross-correlation 277 errors to avoid overfitting, improve the amount of variance a little, but without suc-278 ceeding 50% of variance. Figure 13.3 shows the two regression trees, with the target 279 likability value and the percentage of data points given in the boxes, while the joints 280 are labeled with the conditional value of the acoustic parameter used for splitting the 281 data. 282

283 13.5 Discussion

The positive correlation of likability with F_0 SD for both speaker sets and articulation 284 rate for males is in line with results of other studies presented in the literature survey in 285 Sect. 13.2. However, other promising parameters are not significantly correlated for 286 the stimuli from our pizza order scenario, in particular, CoG and, for males, F_0 mean. 287 Actually, average F_0 is even correlated negatively for female speakers, which is in 288 contrast to the state of the art. One reason for these results may be the small number 289 and inconsistently selected raters (Fernández Gallardo & Weiss, 2018). However, a 290 more probable cause can be suspected in the much longer stimulus durations and 291 the different genres compared to other experiments. In particular, the strong effect 292 of variability in the fundamental frequency (F_0 SD) may mask smaller effects, for 293 example, CoG as timbre-related parameter. The two modeling approaches indicated 294 that F_0 mean is relevant for male speakers. 295

The unexpected positive correlation with average F_0 for females is still surprising, as other work with shorter German stimuli repeatedly showed an opposite effect. This **Fig. 13.3** Results of the two regression trees for likability of female (top; $R^2 = 0.312$) and male (bottom; $R^2 = 0.437$) speakers. **F0.M** refers to F_0 mean in ERB (as normalization attempt from Hz); values of **Rate** are in the units of PLSR (Perceived Local Speaking Rate, usually between 50 and 150) instead of syllables/s



Editor Proof

even holds in combination with a positive impact of higher F_0 SD, which seems to 298 exclude the possibility of articulatory grounding of raising F_0 mean by increasing F_0 299 variability. This contradicting result may indicate a situational difference between 300 reading single utterances in a rather factual tone, where low articulatory tension or 301 even larger vocal folds in males may be rewarded, whereas in a truly conversational 302 situation a social signal of interest (a raised voice due to higher tension), benevolence, 303 or even a biological signal of female attractiveness might be positively perceived. 304 This kind of speculation has of course to be tested, for example, with re-synthesis 305

experiments for both kinds of situations. At least, for the non-significant correlation in males, the two models solve this issue by including F_0 both times with a negative relationship.

The attempt to describe likability ratings with simple models reveals only low 309 performing results. Not even half of the variance is explained, despite applying 310 approaches that use all data for training. More interesting are the systematics incor-311 porated in the models. First of all, parameters, which are non-significant in the corre-312 lation analysis, are included in order to explain more variance, i.e., male F_0 mean in 313 males for the linear and the tree model, and CoG in the regression tree. For females, 314 rate is included in the regression tree. For one split in the female data, the positive 315 impact of higher F_0 mean is confirmed. For male speakers, a lower F_0 has a posi-316 tive impact, just as expected from literature. Additionally, still very simple regression 317 trees perform better than the linear baseline, indicating non-linearities observed else-318 where (Weiss & Burkhardt, 2012). 319

320 13.6 Conclusion

Despite some agreement in English and German studies, the attempt to confirm a 321 set of potential acoustic correlates of likable voices was not overall successful. The 322 analysis of the Nautilus data confirms only F_0 variation and articulation rate as rele-323 vant parameters. Especially, F_0 variation seems to be a very salient parameter in this 324 conversational data. The role of F_0 , or pitch level in general, has to be re-examined. 325 Currently, a stereotype of low-pitched male voices and high-pitched female ones 326 seem to be too simple for German. In light of other studies, there seems to be a pool 327 of potential correlates that not necessarily show a relation in each analysis. However, 328 generalization seems not to be possible from the given results. 329

This reveals a more general issue with the material. Most data referred to as 330 related work are single short sentences, which are sometimes difficult to discern as 331 read or not, but for which simple aggregated values are intuitive parameter choices. 332 With longer durations, as in the Nautilus database, not only more material, including 333 several sentences and utterances, are available, but also a specific social situation 334 is evident. Apart from obvious differences due to this kind of styles, aggregating 335 simple acoustic parameter values over time could result in unreliable correlates. As 336 almost all parameters are globally defined, they seem to be fragile for changes in 337 material. In order to better compare acoustics between for example brief greetings 338 ("hello") (McAleer, 2014) to longer utterances or even short conversations, the value 339 of locally defined or dynamic parameters has to be tested. 340

In order to define more robust parameters and even more automatic measurement, segment-based and articulatorily defined candidates should be defined to better represent perceptually salient aspects that are relevant for likability, especially when studying timbre. One example is the so-called speakers' or actors' formant to assess a potentially positive effect of trained voices. It manifests as a peak in the acoustic spectrum: 3–4 kHz for males (Nawka, Anders, Cebulla, & Zurakowski,1997), and

4–5 kHz for females (Tayal, Stone, & Bisrkholz, 2017). This resonance seems to be 347 caused by an epi-laryngeal narrow and pharyngeal wide configuration that is evident 348 in professional speakers, and it is considered as pleasant also for non-trained speak-349 ers (Leino, Laukkanen, & Radolf, 2011). The issue is to properly re-synthesize this 350 phenomenon in a valid and salient way. A recent analysis shows a relation for males 351 voices (Weiss, 2015) that is even stronger than the typical average F_0 . However, this 352 effect was not confirmed by a first attempt of overall spectral manipulation (Karnop 353 & Weiss, 2016), maybe due to missing representation in other acoustic features that 354 are perceptually relevant for stimulating the acoustic effect of this configuration. 355 Other, more phonetically or phonologically defined parameters such as vowel for-356 mant dispersion as a measure of articulatory precision or aspects of intonation, have 357 not yet been studied in depths for likability, simply because they require manual or 358 automatic phonetic analysis for segmental selection. 359

There are further factors in the research of likability of voices that remain under-360 explored or simply ignored. Among them is the question of how audible smiling 361 in voices has an influence on whether somebody likes a formerly unknown person. 362 Certain types of smiling are perceived as displays of happiness (Krys, 2016). For 363 instance, in a Brazilian study smiling faces were considered as happier and even as 364 more attractive than a neutral expression (Otta, Abrosio, & Hoshino, 1996). How-365 ever, there is evidence that in some cultures visually transmitted smiling faces of 366 unknown persons may have a *negative* image on side of the viewers (Krys, 2016). 367 Thus, it could be that similar patterns could occur for audibly transmitted smiling. 368

As mentioned in the introduction, the level of speech fluency can also have an effect 369 on the perceived attractiveness of voices and thus might affect social attractiveness 370 as well. For instance, Zuta (2007) showed that in retold narratives male voices were 371 considered least attractive by female listeners when comparatively many disfluencies 372 occurred, along with less varied F0 and a high degree of nasality. Also, the number 373 and the duration of pauses is a strong marker of fluency but also of the valence of 374 speech (Tisljár-Szabó and Pléh, 2014). Too long pauses seem to have a tendency 375 toward a negative and less likable image of the speaker, also in dialogs. 376

With regard to intonation contours, the impression of politeness and pleasantness obviously depend on the sentence mode. For instance, Uldall (1960) found that declarative sentences were perceived with a high degree of pleasantness when produced with either a falling or rising pitch at the end; however, questions and commands tend to be felt pleasantly only when they showed a final rise.

Audible smiling, fluency, pauses, sentence accents, and phrase tones can be considered as local phenomena of spoken sentences and longer stretches of speech. In contrast, a regional or a foreign accent is always a global phenomenon. Regarding accents, people sometimes have more or less strong attitudes which can heavily influence the likability of the speakers in a negative and likewise in a positive way. Lastly, acoustic correlates of sexual preference and physical attractiveness have been mostly neglected in this line of research. While there are some crosscorrelations found for likability as social attractiveness and subjective estimates of physical attractiveness from voice or ratings of vocal attractiveness directly (McAleer, 2014), well-founded correlates, such as formant dispersion in males (Fitch & Giedd, 1999; Bruckert et al., 2006) might increase insight into the cause of a likable first impression in speech.

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Abstract	Speech quality and likability is a multi-faceted phenomenon consisting of a combination of perceptory features that cannot easily be computed nor weighed automatically. Yet, it is often easy to decide which of two voices one likes better, even though it would be hard to describe why, or to name the underlying basic perceptory features. Although likability is inherently subjective and individual preferences differ, generalizations are useful and there is often a broad intersubjective consensus about whether one speaker is more likeable than another. We present a methodology to efficiently create a likability ranking for many speakers from crowdsourced pairwise likability ratings which focuses manual rating effort on pairs of similar quality using an active sampling technique. Using this methodology, we collected pairwise likability ratings for many speakers (>220) from many raters (>160). We analyze listener preferences by correlating the resulting ranking with various acoustic and prosodic features. We also present a neural network that is able to model the complexity of listener preferences and the underlying temporal evolution of features. The recurrent neural network achieves remarkably high performance in estimating the pairwise decisions and an ablation study points toward the criticality of modeling temporal aspects in speech quality assessment.			
Keywords	Ranking - Speech qual	lity - Likability ratings - Found data - Crowdsourcing - Sequence modelling		

Chapter 14 Ranking and Comparing Speakers Based on Crowdsourced Pairwise Listener Ratings



Timo Baumann

Abstract Speech quality and likability is a multi-faceted phenomenon consisting 1 of a combination of perceptory features that cannot easily be computed nor weighed 2 automatically. Yet, it is often easy to decide which of two voices one likes better, even 3 though it would be hard to describe why, or to name the underlying basic percep-Δ tory features. Although likability is inherently subjective and individual preferences 5 differ, generalizations are useful and there is often a broad intersubjective consensus 6 about whether one speaker is more likeable than another. We present a methodology 7 to efficiently create a likability ranking for many speakers from crowdsourced pair-8 wise likability ratings which focuses manual rating effort on pairs of similar quality 9 using an active sampling technique. Using this methodology, we collected pairwise 10 likability ratings for many speakers (>220) from many raters (>160). We analyze 11 listener preferences by correlating the resulting ranking with various acoustic and 12 prosodic features. We also present a neural network that is able to model the com-13 plexity of listener preferences and the underlying temporal evolution of features. The 14 recurrent neural network achieves remarkably high performance in estimating the 15 pairwise decisions and an ablation study points toward the criticality of modeling 16 temporal aspects in speech quality assessment. 17 Keywords Ranking · Speech quality · Likability ratings · Found data 18

¹⁹ Crowdsourcing · Sequence modelling

20 14.1 Introduction

Speaker traits (such as age or gender), emotional coloring (such as anger or distress), socio-cultural aspects (such as accent or dialects), conscious or subconscious coloring toward the addressee (such as friendliness or positivity), and other paralinguistic aspects (such as clarity and comprehensibility) are expressed through various prosodic, suprasegmental, segmental, and non-segmental aspects of one's speech

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and voice, where the combination of features and their temporal evolution are far
from trivial. Intermittent deficiencies (e.g., a lisp) or deviations limited to a few features (e.g., nasalisation) can already have strong influences on the perceived quality.
Together, they form the 'quality' of speech. It is important to note that no one 'best'
combination of all features exists that would constitute 'ideal' speech.

Voice is a highly personal and subjective matter such that a multitude of combina-31 tions of these features result in a 'good' voice. This often makes likability compar-32 isons hard and inherently subjective. Despite subjective preferences, intersubjective 33 agreement on the preferences can often be found by-and-large, making generaliza-34 tions useful. Generalizations are also necessary, for example, to cast news speakers, 35 readers, or other speaking roles that need to approximate an intersubjective consen-36 sus. Such castings are typically performed by small expert jurys (potentially limiting 37 the universality of decisions) and for small numbers of speaker candidates (for prac-38 tical reasons). 39

In our work, we use rankings to analyze the influencing factors of speaker likability for broad speaker populations, or to eventually 'score' a voice sample along a range of speakers. Hence, we are interested in full rankings rather than in who is the best speaker for a task. Our aim is to create rankings for large speaker populations, by large and diverse jurys, and while keeping the effort as low as possible.

To simplify the human effort involved in creating the ranking, we have partici-45 pants take many pairwise decisions on which of two stimuli is better. We then create 46 a ranking from the pairwise comparisons (see below). The number of possible pairs 47 grows quadratically with the number of the stimuli compared. Thus, while full com-48 parisons for each rater are possible for small speaker groups (10 speakers \rightarrow 45 49 rating pairs), these are infeasible for large speaker groups (225 speakers \rightarrow 25200 50 rating pairs), in particular when relying on volunteer raters. Thus, our method must 51 be able to build rankings from incomplete comparisons. Note, however, that many of 52 the ratings will have predictable outcomes if one known-strong and one known-weak 53 speaker are paired. It will be helpful to not waste too much human effort on such 54 pairs; in contrast, human input on speakers of similar (or unknown) quality is most 55 informative. 56

The main idea is to start from an initial ranking (based on some initial ratings) which is iteratively revised as more evidence becomes available with more ratings. Once the initial ranking is available, rating outcomes can be predicted and human effort can be directed away from comparisons with clear outcomes and toward the most informative pairs; this will be described in detail in Sect. 14.2.

Section 14.3 describes the corpus developed via crowdsourcing and based on the iterative method, both in terms of the stimuli used, as well as the resultant preference ratings. Section 14.4 examines the overall preference ranking derived from all pairwise ratings and finds some explaining factors in terms of high-level properties of the speech stimuli (and their speakers) via linear correlations.

As outlined above, however, prosody is a highly non-linear phenomenon and we hence build a recurrent neural network-based model that successfully identifies listener preferences using non-linear (but opaque) aggregation functions. Via an ablation study we find that the tunes in to phone-specific prosodic aspects given ⁷¹ phonetic identity as additional features. Section 14.5 describes model for estimating

⁷² the preferences of raters and analyzes the importance of features for modeling speaker

⁷³ preference. We conclude that modeling the *temporal aspects* of speech is critical for

74 preference estimation.

75 14.2 Rankings from Pairwise Comparisons

Rankings have a long history in competitive sports, where individuals or teams play 76 against each other in order to determine who's best. Two common forms, elimination 77 and round-robin tournaments, both require a high degree of control over who plays 78 who, which is not always possible. In addition, they may lead to only partial rank-79 ings. In chess, Elo's system (Elo, 1978) was designed to overcome these issues: a 80 player's skill is estimated based on prior match outcomes, and skills are updated after 81 each match. Skill changes correspond to the surprisal of the system by the match 82 outcome. A ranking can be derived by ordering players by their skill. Microsoft 83 TrueSkillTM (Herbrich, 2007) uses a Bayesian estimation of rankings from pairwise 84 comparisons originally developed for ranking players of online games (based on 85 their win/loss performance). TrueSkill models skill as a normal distribution, i.e., it 86 makes the system's uncertainty about skill explicit, which enables smoother updates 87 and more robust results when few match outcomes are available. 88

Most work in speech quality estimation has used direct scalar ratings of individual 89 stimuli (Burkhardt, Schuller, Weiss, & Weninger, 2011) or required each subject to 90 assign a complete ranking for all stimuli. Gallardo (2016) feeds paired comparisons 91 into a Bradley–Terry–Luce model (Bradley & Terry, 1952) and finds similar results 92 to direct scaling. Both of these methods have been limited to few raters and/or 93 few stimuli. We extend the methodology introduced by Sakaguchi, Post, and Van 94 Durme (2014) who created rankings for machine translation systems from pairwise 95 comparisons using Microsoft TrueSkill™. In our metaphor, we view each rating as 96 a 'match' in which the preferred stimulus wins against the dispreferred stimulus. 97 We then compute the 'skill' of stimuli and their ranking. TrueSkill also provides 98 match making capabilities that, given one player, select an opponent that has the most 99 similar skill and where uncertainty of the skill difference is low (technically, TrueSkill 100 estimates the probability of a draw and prefers matches with high draw probability). 101 This is meant to lead to interesting matches with similarly skillful opponents. We use 102 match making to select stimulus pairs for human rating in an iterative fashion which 103 uses the ratings collected so far to steer our *active sampling* approach to select among 104 the possible stimulus pairs to be compared. We actively select stimulus pairs that are 105 expected to be informative for the full ranking based on a preliminary ranking of all 106 ratings performed so far. 107

In our application, we found the abovementioned strategy for match making to be flawed: as scores tend to get more certain with more data, stimuli are preferred that already participated in many comparisons. As a result, the number of comparisons

is not balanced on all stimuli but accumulates on few, well-known anchor points.¹ 111 We use an approach that better balances the number of ratings per stimulus: We 112 (1) pick a first stimulus based on the system's uncertainty about its ranking and (2) 113 compute the match quality for all opponents and pick the opponent based on the 114 predicted match quality with a dampening factor for the number of comparisons 115 that the opponent has played so far. As a result, we (a) favor little-tested stimuli 116 over well-tested ones and (b) select informative games over predictable ones. We 117 randomly select pairs weighted by the criteria mentioned above which enables us to 118 sample multiple 'interesting' pairs at once. 119

In comparison to Sakaguchi et al. (2014), which ranked 13 translation systems for which complete evaluation data had already been collected, we rank a total of 223 speakers, thus well over an order of magnitude more, in a live setting without external reference ranking.

124 14.3 Stimuli and Rating Collection via Crowdsourcing

We limit our likability judgements to one specific reading genre: the reading of 125 encyclopaedic entries in Wikipedia. We use recordings from the Spoken Wikipedia.² 126 as a broad sample of read speech in the wild The Spoken Wikipedia project unites 127 volunteer readers who devote significant amounts of time and effort into producing 128 read versions of Wikipedia articles as an alternate form of access to encyclopaedic 129 content. It can thus be considered a valid source of speech produced by ambitious 130 but not always perfect readers. The data has been prepared as a corpus (Baumann, 131 Köhn, & Hennig, 2018) and the German subset of the corpus, which we use here, 132 contains \sim 300 h of speech read by \sim 300 speakers. 133

To avoid rating preferences based on what is spoken rather than how, we choose 134 as stimuli the opening that is read for every article in the Spoken Wikipedia, which 135 is (supposed to be) identical for all articles except for the article lemma.³ We extract 136 that stimulus for every speaker in the German subset of the Spoken Wikipedia Corpus 137 using the alignment information given in Baumann et al. (2018). As some alignment 138 information was missing or clearly wrong, our stimulus pool is reduced to 227 speak-139 ers. We then masked the article lemma with noise in a length that matches the average 140 reading speed of the stimulus. The mean/median duration per stimulus is 4.7/4.57 s 141 with 5/95% quantiles at 3.74/6.03 s. 142

For every rating pair, participants were asked to rate which of the two voices they would prefer for having a Wikipedia article read out to them. We realized a webbased rating experiment on the basis of BeaqleJS Kraft and Zölzer (2014) which we

¹This may not be a problem when using TrueSkill for match assignment, as participation in games is limited by the players' availability.

²https://en.wikipedia.org/wiki/Wikipedia:WikiProject_Spoken_Wikipedia.

³Expected reading: 'Sie hören den Artikel *article lemma* aus Wikipedia, der freien Enzyklopädie.' (You are listening to the article *article lemma* from Wikipedia, the free encyclopedia.).

extended to allow for an open number of pairwise ratings for each participant. The
experiment operated with a mini-batch cache of 1000 rating pairs from which clients
sampled randomly. The cache was updated manually whenever more than 200 ratings
had been submitted by re-creating a new best ranking and selecting stimulus pairs
as outlined above. We opted against an active backend with immediate update and
selection of the next most relevant rating pair to ensure availability in times of high
system usage (e.g., during the minutes after a mailing list advertised our experiment).

We solicited participants to our experiment via the German Wikipedia 'off-topic bulletin board' and various open mailing lists of student organizations (particularly CS students), as well as the Chaos Computer Club in Germany, Austria, and Switzerland in order to reach a wide variety of dialect and age groups. We deliberately did not explicitly invite the Spoken Wikipedia community to participate, as they could have been particularly biased.

Statistics of the participants' self-reported meta data are shown in Table 14.1. As
can be seen, Northern Germans, males, and 20–30 years olds are over-represented in
our data (presumably computer science students at Universität Hamburg). However,
almost all other demographic groups are included as well, at least to some extent.
In total, we collected 5440 ratings from 168 participants. Participation was strictily
voluntary and without compensation and hence the resulting ratings are unlikely to
be prone to vandalistic behavior.

Although participants could perform as many ratings as they liked, they were instructed that 10 ratings are sufficient, 30–50 preferable, and that they should take a break after 100 ratings (and possibly return the next day). We excluded participants who submitted a single rating only. The median ratings per participant were 26 with half the participants between 11 and 43 ratings and 5/95% quantiles at 4 and 101 ratings, respectively.

Participants were asked to always state a preference, even if unsure, and did not 172 explicitly have the option to state that they could not decide. It is more informative for 173 our setup to get contradicting preferences than to explicitly invite the participants to 174 omit a decision. As our method steers toward 'difficult' comparisons, many omitted 175 decisions could otherwise have been expected. Our software, however, did allow to 176 skip ahead without making a decision and sometimes participants did not provide 177 a decision (accidentally or on purpose). These instances were ignored in further 178 processing, as no rating has been recorded. 179

We also measured the time taken for each rating. The median time per rating is 14.3 s with half the ratings between 11.3 and 21.3 s and 5/95% quantiles at 6.3 and 39.7 s, respectively. 6.3 seconds can still be considered a reasonable lower bound for listening to both stimuli and then taking the decision quickly. In total, participants spent \sim 26 h on rating stimulus pairs.⁴

 $^{^{4}}$ We substitute the median for the slowest 2.5% of ratings, as participants were obviously side-tracked who spent more than 55 s for a single rating.

	Total	Participants	Ratings	
		168	5440	
Gender	Female	41	1665	
	Male	109	3221	
	Unreported	18	554	
Age	<20	18	358	
	20-30	78	2593	
	30-40	34	1030	
	40-60	24	886	
	>60	6	418	
	Unreported	8	155	
Dialectal origin	Northern Germany	83	2656	
	Berlin/Brandenburg	8	128	
	Northrhine-Westphalia	11	464	
	Middle Germany	9	443	
	Rhine-/Saarland	3	82	
	Baden-Wurttemberg	15	432	
	Bavaria	8	405	
	Austria	5	179	
	Switzerland	0	0	
	Unsure/other	26	651	

Table 14.1 Breakdown of self-reported meta information of participants and their rating counts

The stimulus ordering was randomized. Participants have a slight tendency for stimulus B over A (2784 versus 2656, n.s.: sign test, p = .09), which could be interpreted as a recency effect.

We measure the degree of disagreement by constructing a directed acyclic graph 188 of the preference relation expressed through all ratings (i.e., the stimuli are nodes 189 and one edge is introduced per rating). If ratings were consistent, there would not 190 be any rating circles (a < b, b < c but c < a) and the proportion of feedback arcs 191 can be taken as a measure of consistency. We heuristically compute the minimum 192 feedback arc set of all ratings (Eades, Lin, & Smyth, 1993) and find the proportion 193 to be 29%. In a preliminary experiment using only 10 stimuli and all 45 possible 194 comparisons, only one rater was 'perfect' in not producing any circles. Hence, we 195 know that both within-rater and across-rater inconsistencies occur. In addition, our 196 stimulus selection process is tailored towards choosing pairs that are expected to be 197 hard to rate (and the disagreeing proportion grew over the runtime of the experiment). 198

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199 14.4 Ranking Analyses

We feed all pairwise ratings into TrueSkillTM to derive rankings. In TrueSkill, more recent ratings are more influential for the final ranking due to the iterative update mechanism.⁵ As proposed by Sakaguchi et al. (2014), we use the fact that rankings depend on the rating order to validate our method: we permute the ratings and create many rankings for the same set of ratings (below: N = 300). We then take the median ranking as the final decision. Thus, we are also able to report ranking confidence levels.⁶

Rankings can be compared using correlation coefficients like Kendall's Tau 207 (Langville & Meyer, 2012, Chap. 16). We find that pairwise correlations of the 300 208 rankings result in $\tau > 0.92$ and that each ranking against the median ranking gives 209 $\tau > 0.95$. Thus, we conclude that TrueSkill leads to consistent rankings (within 210 bounds) and that the median ranking is a meaningful middle ground for all rankings. 211 The final median ranking with quartile and 5/95% confidence ranks is shown in 212 Fig. 14.1. As can be seen in the figure, there is no one clear ranking of all speakers. 213 While there is a best and worst stimulus shared among all rankings, variability is 214 larger in the middle. Overall, the average rank variability is 6.7 ranks within the 215 25-75% confidence interval and 16.4 ranks within the 90% confidence interval. 216 Interestingly, some clusters of similarly 'good' stimuli emerge, e.g., as highlighted 217 in the green circled area where 11 stimuli share similar ranks with a high variability 218 that are delimited with high confidence to higher ranks (upper right of circled area) 219 and slightly less to lower ranks. 220

Finally, we use rankings to predict the outcome of ratings as another way of testing 221 the ranking validity. We assume that a rating will be 'won' by the better ranked 222 stimulus (although similarly ranked stimuli could easily have any outcome). We use 223 100-fold cross-validation and find that on average, the prediction performance is 224 68%. Given that 29% of ratings can be expected to be mis-predicted due to the rating 225 inconsistencies, the rankings have a high level of predictive value. As described 226 above, TrueSkill can compute match quality, effectively describing how likely a 227 rating will lead to disagreement among raters. We find that prediction performance 228 highly correlates with that score (Kendall's $\tau = -0.81$, p < .001). 229

We investigate which stimulus pairs have been selected for comparison to find out whether the method proposed in Sect. 14.2 works effectively. The rated pairs are presented in Fig. 14.2. We find that pairs along the diagonal (i.e., with similar ranks) have been tested more densely than pairs further apart. Furthermore, the plot shows that 'better' stimuli (as per the ranking) win more often against inferior stimuli (green/blue division of the plot) and multiple controversial ratings (red) mostly occur along the diagonal. Overall, our 5440 ratings spread over 4000 different pairs, that is,

⁵This is a feature when ranking human players, as their true performance may change over time – but this is not the case in our experiment.

⁶The confidence is about TrueSkill producing a preference ordering given another permutation of ratings. We cannot make any guarantee with respect to some 'gold' ranking, which does not exist for our data.

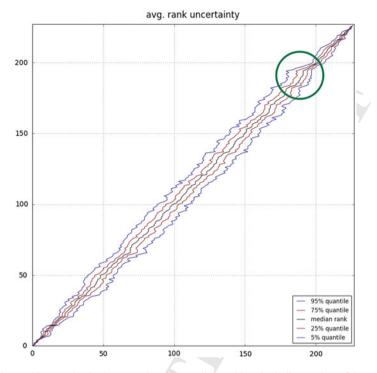


Fig. 14.1 Ranking results (both axes ordered by median ranking) including rank confidence on the x-axis. The circled area is further discussed in the text

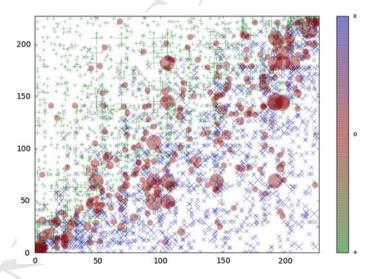


Fig. 14.2 Scatter plot of pairs compared (axes ordered by median ranking, color-coding indicates the avg. outcome of comparisons). The plot is more dense along the diagonal, as stimuli are compared more often when they are of comparable rank

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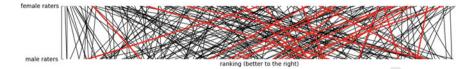


Fig. 14.3 Line graph comparison of median rankings for female (top) and male (bottom) raters. Stimuli spoken by females are shown in red

7,7% of all possible comparisons. 3057 pairs have been tested once, 666 pairs twice,
and the remaining pairs up to 9 times (which seem to be artefacts of older versions of
pair selection). Overall, the average stimulus has been rated 46 times with the 5/95%
quantiles at 39 and 56 ratings. Thus, our rating pair selection strategy successfully
balances stimulus selection and opponent assignment.

14.4.1 The Influence of Rater Population on Ranking Outcome

Finally, we analyze the rankings wrt. to gender. We produce one median ranking 244 each for ratings from female and male listeners (randomly subsampling the male 245 ratings to the number of female ratings; see Table 14.1). We find only a moderate 246 correlation ($\tau = 0.44$, $p \ll .001$) between female and male listener rankings, which 247 indicates different preferences between these listener groups. We further analyze the 248 ranking wrt. to speaker gender of the stimuli.⁷ The rank assigned to a female speaker 249 is on average 12.7 ranks better for female than for male listeners (half of the stimuli 250 between -32 and +60 ranks), indicating that one major difference between female 251 and male listeners is their preference toward female voices. 252

Figure 14.3 compares the gender-dependent rankings (each line corresponds to 253 a stimulus, female stimuli in red). The less inclined a line, the more similar the 254 rank for female/male listeners. As can be seen, preferences differ both in ranking 255 female speakers as for male speakers. It is interesting to note that Dykema, Diloreto, 256 Price, White, and Schaeffer (2012) find that male speakers respond more truthfully 257 to questions posed by female voices, yet they seem to disprefer them in our data. The 258 results highlight the importance of gender-appropriate voice selection for reading 259 encyclopaedic, and possibly other factual information. 260

We also divide our data by age (<30 versus >30) and dialect (Northern German versus all other dialects as there is insufficient data to further differentiate among dialects). In both cases, correlation between the groups is stronger (age: $\tau = 0.50$, dialect: $\tau = 0.54$) than in the gender partition. No age or dialect information is available for the speakers, hence we cannot compare within/across-group effects (e.g., we would expect matched dialects of speaker and listener being preferred).

⁷Unfortunately, just 20 of 227 stimuli (9%) were spoken by females.

²⁶⁷ 14.4.2 Acoustic Correlates of Ranking Quality

We finally experiment with acoustic factors that could explain the speaker likability 268 expressed by the median ranking shown in Fig. 14.1. First, we compute the percep-269 tual quality of audio stimuli as standardized by ITU-T P.563 (Malfait, Berger, & 270 Kastner, 2006). We find a low (but significant) correlation ($\tau = 0.14, p < .002$) of 271 achieved median ranking and estimated MOS for the audio transmission quality.⁸ 272 We conclude that carefully arranged recording conditions could coincide with better 273 speech quality, or that listener judgements are influenced by encoding quality-in 274 contrast to Burkhardt et al. (2011) where no such influence was found in a similar 275 task. 276

We estimate the liveliness of the speaker's prosody as it might be a relevant factor 277 of likability. We compute the pitch range in semi-tones and take the 50% (25-75%) 278 and 90% (5-95%) ranges of the measured pitch. On average, the 50/90% ranges 279 are 4.3/12.8 semi-tones for all speakers. We find very slight but non-significant 280 correlations between either liveliness measure and the ranking. As this could be 281 due to very little data from each short stimulus, we also extract pitch from the full 282 articles. This allows us to estimate each speaker's liveliness in general, not just in 283 the opening of the article. Here we find that the inter-quartile (50%) pitch range 284 correlates somewhat ($\tau = 0.10, p < .03$) with the ranking. 285

14.5 Listener Preference Classification

In previous work (Eyben, Wöllmer, & Schuller, (Burkhardt et al., 2011)), speaker 287 likability has been modeled using OpenSmile (Eyben et al., 2010) features based on 288 linear and non-linear aggregation functions (such as means and medians) to aggregate 289 over the duration of the stimulus. Features were used to train classifiers such as SVMs 290 which resulted in moderately high (better than chance) performance in classifying 291 speakers as being above or below median likability (Burkhardt et al., 2011). Like 292 the analyses in Sect. 14.4.2, the abovementioned aggregation functions cannot take 293 into account the context of feature characteristics in the stimulus, and are unlikely 294 to accurately express more fine-grained details relevant for speech quality (such as 295 where and how a pitch accent is realized, beyond mean pitch). In this section, we 296 experiment with neural sequence-learning methods (RNNs) to encode the complex 297 temporal evolution of features of speech quality into a latent feature space and use 298 the difference in these for pairs of speech stimuli to train our classifier. 299

⁸We must mention that all speech in the Spoken Wikipedia is distributed as OGG/Vorbis, with varying bit rates and under diverse recording conditions.

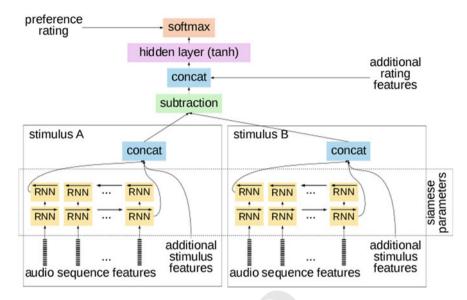


Fig. 14.4 Diagram of the neural architecture for speech likability preference. The task is symmetric (whether a stimulus is A or B is irrelevant) and hence the parameters for the RNNs can be shared (siamese network). Additional features about stimuli and the rating can be concatenated in

300 14.5.1 Model Architecture

The task of preference ranking is *asymmetric* in the sense that if the two stimuli to be compared are swapped, then the comparison result is the opposite. This has two consequences: (a) parameters for sequence analysis of both stimuli can be shared which is called a *siamese model* (Bromley et al., 1994) and reduces the degrees of freedom of the model, making learning more efficient, and (b) the outputs from sequence analysis of each stimulus can simply be subtracted and the difference be subjected to a final decision layer.

In our model and as shown in Fig. 14.4, we use two layers of bidirectional RNN (LSTMs Hochreiter & Schmidhuber, 1997 or GRUs (Cho et al., 2014)) to model the feature sequence of each stimulus and concatenate the outputs of the forward and backward pass. We can also concatenate additional stimulus-level features into the representation at this time, e.g., measures of signal quality such as ITU-T P.563 (Malfait et al., 2006) (cmp. Sect. 14.4.2), or meta information about the speaker or the audio recording (such as gender or bitrate, cmp. Sect. 14.4.1).

Given that our final decision is based on the quality *difference* alone, not the overall quality, we subtract both stimuli's vectors.⁹ We then pass the difference to one hidden layer and a final binary softmax layer that models the preference decision. We can

⁹We found, in initial experimentation, that this performs much better than concatenating the outputs of each speaker.

also optionally include additional meta features of the rating (such as identity, age, or
dialectal region of the rater). These can easily be concatenated in before the hidden
layer, in order to model the relative preferences of individual raters or rater groups.
As we found that preferences differ, this could be useful information.

322 14.5.2 Data and Evaluation

The original purpose of the rating collection reported in Sect. 14.3 was to create a ranking and effort was put into maximizing the efficiency of human annotation by focusing the human effort on 'difficult' pairs using *active sampling* of stimulus pairs that focus human annotation effort on 'similarly good' speakers. As a result, the stimulus pairs that were rated by participants are much more similar in their quality than randomly selected stimulus pairs would be.

In addition, inconsistency in the data set is high, as are pairs of stimuli that have 329 been rated multiple times. Above, we have computed the minimum feedback arc set, 330 i.e., the subset of ratings that lead to a fully consistent ranking (Eades et al., 1993). 331 We found the proportion of conflicting arcs to be 29%. This can act as an indicator of 332 the proportion of ratings that are inconsistent (where potentially different raters have 333 different preferences, or simply cannot reliably tell the difference). In addition, we 334 here compute an oracle correctness for all pairs that have been rated more than once. 335 by checking for each rating, if it is the majority rating for this pair (deciding randomly 336 to resolve draws). We find that such an *oracle classifier* reaches a correctness of only 337 65% for those pairs that have been rated more than once. Pairs that were rated just 338 once *potentially* are easier to classify, which makes it possible to beat this oracle. 339

For evaluations, we report multiple settings below. The settings are meant to counterbalance the difficulties introduced by the data elicitation technique and to test different aspects of listener preference classification:

naïve we sample randomly among the evaluation instances from the corpus of human-rated pairs; as the corpus focuses on difficult pairs, we cannot expect a spectacular performance;

easy
 based on the median ranking derived in Sect. 14.4, we sample instances with
 'large' ranking differences (distance on the ranking scale >0.25 or >0.5), in
 order to test if our classifiers fare better with stronger preference differences
 (and hence easier to identify differences in speech quality).

Given that stimuli were presented in random order, the data set is balanced in terms of which stimulus outperforms the other. Thus, we focus on accuracy as the only evaluation metric.

14.5.3 Features and Conditions

Using a sliding window, we derive a multitude of local features from the audio stream 354 that might capture aspects of speech quality. All features use a frame shift of 10 ms. In 355 particular, we measure Mel-frequency cepstral coefficients (MFCCs, 12 + 1 energy) 356 to capture voice and recording characteristics, f_0 (measured using Snack's esps 357 implementation) as a first measure of speech melody, and fundamental frequency 358 variation (FFV) features (Laskowski, Heldner, & Edlund, 2008) as these are more 350 robust (and might contain more valuable information) than single f_0 . Using Praat 360 (Boersma, 2002), we compute jitter (PPQ5), shimmer (APQ5), and harmonics-to-361 noise ratio (Boersma, 1993). We do not perform z-scale normalization on the feature 362 streams. 363

The Spoken Wikipedia Corpus also contains phonetic alignments that were computed using the MAUS tool (Schiel, 2004). The alignments allow us to assign phone annotations to every frame. With this information, the model is informed explicitly that different phones have different phonetic characteristics (as expressed in the MFCCs) and can condition its learning of speech quality on these characteristics. In other words: the model can learn to focus on a phone's quality aspects (e.g., nasalization) without needing to learn to differentiate phones.

One frame of features for every 10 ms may overwhelm the model with very large amounts of parameters, reducing training efficiency as well as effectiveness. In order to keep training tractable, we subsample the feature frames with various values (see *seq. step size* in Table 14.2). When we do so, we use mean aggregation for numeric values (ignoring missing values for pitch and HNR).

376 14.5.4 Experiments and Results

We separate out about 1/10th of the 5440 ratings as the test data: the **naïve** test set contains 400 ratings, and we sample among ratings with 'large' differences 100 ratings each for the >0.25 and >0.5 **easy** test sets.

We implemented our network in dynet (Neubig, 2017). In the experiments reported below, we train for 50 epochs using AdamTrainer and no dropout. We concatenate the various audio features that are computed for every frame. We use embeddings to characterize the phonetic labels.

384 14.5.4.1 Meta Parameter Optimization

As originally reported in Baumann (2018), we have performed an optimization to find good sizes for various meta parameters of the model:

• To reduce the length of the sequence that need to be learned by the LSTMs (and to avoid the problem of vanishing gradients through long sequences), we subsample

Meta parameter	Values
Sequence step size	5, 10, 15
Phone embed size	8, 16, 24
Sequence state size	24, 32, 48 , 64
Hidden layer size	2, 3 , $4 \times$ sequence state size

 Table 14.2
 Meta parameters considered in grid search. Best values are shown in boldface

- the audio features by mean-aggregating values over a number of frames (5, 10, or 15).
- To represent the discrete phonetic labels, we use embeddings of varying sizes (8, 16, or 24), in order to allow the model to cluster similar phones.
- The sequential LSTM state size determines how many dimensions can be considered during the sequence analysis and we experiment with various sizes (24, 32, 48, or 64).
- The output from concatenation of both forward and backward LSTMs doubles the size of the next layer's input. For the hidden layer size, we hence consider scaling factors (2, 3, or 4) over the size of the sequential state size.
- We performed a grid search over the possible meta parameter values as summa-300 rized in Table 14.2 and focusing on the naïve data set. We found an optimum for 400 sequence step size of 5 (i.e., one feature frame for every 50 ms of speech), phone 401 embedding with 16 dimensions, sequence state size of 48, and hidden layer size of 402 $3 \times 48 = 144$ (sequence state size of 32 and $4 \times 32 = 128$ was a close contender). 403 At these settings, our model yields an accuracy of 67.25% on the naïve test set, 404 93% on the easy-0.25 test set and 97% on the easy-0.5 test set. The accuracy on the 405 naïve test set is close to what we estimated as the upper limit for the harder part of 406
- 407 our training data.

408 14.5.4.2 Ablation Study on Phonemic Alignments

We hypothesized above that our performance gain over previous work may be largely 409 due to the model being able to perform prosodically meaningful aggregations and 410 could, for example, relate prosodic parameters to the phones spoken. To test this 411 hypothesis, we perform an ablation study and remove the phoneme embeddings 412 from the input features. We perform this experiment with the other meta parameters 413 set to their optima as found in the previous subsection. As shown in Table 14.3, we 414 find performance to drop substantially when the phone identity feature is removed. 415 We believe this is because the model is unable to make maximum sense of features 416 such as MFCCs given speech quality is obviously just a secondary feature, far behind 417 phone identities. If the model is not informed about the phonetic identities, it needs to 418 resolve whether input has good quality, whereas the full model only needs to resolve 419 the quality of a feature given the particular speech sound. 420

Setting	Accuracy	uracy		
	naïve	easy-0.25	easy-0.5	
Full mode	67.25	93	97	
Without phone alignment	58.75	73	80	

Table 14.3 Accuracy (in percent) of full and reduced feature set (without phone alignment)

421 14.6 Conclusions and Future Work

We have presented a method for creating crowdsourced speaker likability rankings from pairwise comparisons. The material that we base our ratings on is freely available and we likewise publish the ratings and the software to derive rankings from those ratings under the same terms. Unlike Gallardo (2016) which uses Bradley– Terry–Luce models, our method does not require a complete comparison of all pairs, and works on a small subset (in our case: 7% of possible comparisons) jointly provided by many participants.

One advantage of the Spoken Wikipedia corpus is the availability of much more 429 data from each speaker beyond the short stimuli that are used in the ranking exper-430 iment. Thus, more complex characteristics of a speaker, such as accentuation and 431 other prosodic idiosyncrasies (which listeners presumably would be able to judge in 432 one sentence), can be derived from up to an hour of (closely transcribed and aligned) 433 speech. In fact, we found in Sect. 14.4.2 that extracting the 50% pitch range as an 434 estimate of liveliness significantly correlates with likability, at least if liveliness is 435 extracted from the full speech, rather than just the one sentence used in human rat-436 ings, potentially because this circumvents effects from faulty fundamental frequency 437 extraction. 438

We have also presented a neural architecture for determining which of two speech stimuli is rated as the better of the two in noisy human annotations. Our model yields good performance most likely because the RNN provides for complex aggregations of the (conventional) feature sequences. Our model's aggregations are able account for sequential information, in particular it is able to relate acoustic features to the phones spoken, unlike more coarse-grained aggregation functions as have been used before.

In Burkhardt et al. (2011), the authors train classifiers to differentiate whether a stimulus is better/worse than average and reach a classification accuracy of 67.6%. Their setup is comparable to our decisions for stimuli that are relatively far apart on the rating scale, in which case the neural aggregation and classification yields a classification accuracy of 93–97%. We believe this to be caused by the better temporal modeling of our approach and the use of phonetic identities during aggregation.

⁴⁵² Despite the relatively good results, our method is still basic in terms of the neural
⁴⁵³ architecture employed. In particular, our method does not yet employ an attention
⁴⁵⁴ mechanism that could help to better weigh the speech quality encoding. Given that
⁴⁵⁵ all speakers in our corpus speak (more or less) the same content, we envision that

our model would profit greatly if the comparison between both stimuli could attend 456 to particular differences rather than only the comparison of the final BiLSTM output 457 vectors. An attention model would also help the analysis of why a speaker is rated as 458 better than another, as it would indicate the relative importance of parts of the stimuli 459 in the comparison. Another venue, at least for comparisons on shared text would be 460 connectionist temporal classification to temporally relate the feature streams before 461 comparison for a better notion of timing differences between the stimuli. Finally, it 462 might be worthwhile to pre-train the intermediate representations of the model. 463

In the end, our model could weigh slight mis-pronunciations against voice quality or prosodic phrasing, and we intend to use analysis techniques to ultimately understand the relative weights of these aspects in comparisons.

We have limited our study to one identical stimulus sentence in order to exclude contextual differences, and to one stimulus per speaker. We plan to extend the study to other stimulus pairs where the sentences (or sentence fragments) are spoken by different speakers across the Spoken Wikipedia. In this way, we hope to get a better judgement of the speakers, based on more than (on average) 4.7 s of their speech.

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Abstract	In this chapter, a new framework of listener-dependent quantification of voice attractiveness is introduced. The probabilistic model of paired comparison results is extended to the multidimensional merit space, in which the intrinsic attractiveness of voices and the preference of listeners are both expressed as vectors. The attractiveness for a specific listener is then obtained by calculating the inner product of two vectors. The mapping from the paired comparison results to the multidimensional merit space is formulated as the maximization problem of the likelihood function. After the optimal mapping is obtained, we also discuss the possibility of predicting the attractiveness from the acoustic features. Machine learning approach is introduced to analyze the real data of Japanese greeting phrase "irasshaimase," and the effectiveness is confirmed by the higher prediction accuracy.		
Keywords	Paired comparison - Mapping - Optimization - Listener's preference - Multidimensional - Acoustic feature - Machine learning		

Chapter 15 Multidimensional Mapping of Voice Attractiveness and Listener's Preference: Optimization and Estimation from Audio Signal



Yasunari Obuchi

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- ² voice attractiveness is introduced. The probabilistic model of paired comparison
- ³ results is extended to the multidimensional merit space, in which the intrinsic attrac-
- ⁴ tiveness of voices and the preference of listeners are both expressed as vectors. The
- ⁵ attractiveness for a specific listener is then obtained by calculating the inner product
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- is introduced to analyze the real data of Japanese greeting phrase "irasshaimase,"
- and the effectiveness is confirmed by the higher prediction accuracy.
- 12 Keywords Paired comparison · Mapping · Optimization · Listener's preference
- ¹³ Multidimensional · Acoustic feature · Machine learning
- 14 15.1 Introduction

Most people believe that there are attractive voices and unattractive voices. However,
they also believe that there are voices that are attractive and unattractive depending
on who is listening. This chapter deals with such objectivity and subjectivity of voice
attractiveness. We start the discussion by establishing a framework of voice attractiveness quantification based on the probabilistic analysis of experimental results.
Once the quantification framework is given, we then try to predict the attractiveness
of a new voice from its acoustic characteristics.

In this chapter, we focus on the social attractiveness, especially in a commercial context. For example, if you make a commercial video for your product with some narration, its attractiveness has strong influence on your business. In the pre-Internet

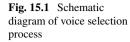
Y. Obuchi (🖂)

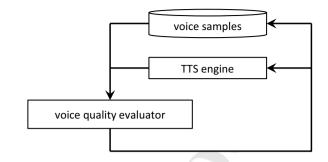
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era, voice attractiveness was evaluated as a scalar, typically the average of evalu-

ation by a mass audience. However, in the Internet era, in which the contents can

²⁷ be customized on delivery, it is important to evaluate voice attractiveness for each
²⁸ customer.

The voice selection process in commercial applications is illustrated in Fig. 15.1. If the system uses recorded voice samples, the quality of each sample is evaluated, and the sample with the highest score is selected. If the system uses text-to-speech (TTS) software, the evaluation score is fed back to the TTS engine, and the system parameters are adjusted. In both cases, the voice quality evaluator plays the central role.

Voice quality evaluation can be realized by collecting a mass of human judg-35 ments. Typical evaluation methods include the mean opinion score (MOS) test and 36 preference test. The MOS test is designed to give an absolute score for each voice 37 sample, whereas the preference test focuses on relative quality of two or more voice 38 samples. Both tests are based on subjective judgment of human listeners, and it 39 requires days or weeks of evaluation process in the development cycle. If we can 40 replace the human-based evaluator with the computer-based automatic evaluator, the 41 development cycle would be accelerated dramatically. 42

Although we have limited insight into the physical features representing voice attractiveness, an automatic evaluator can be developed using the machine learning framework. If we have plenty of data with correct attractiveness label, machine learning algorithms such as support vector machine can provide a model which connects voice signals and their attractiveness.

Figure 15.2 shows the way to train the model from a large database. Before starting 48 the training process by a machine learning tool, we have to prepare appropriate 49 labels of voice attractiveness. We know from our daily experiences that the definition 50 of attractiveness is ambiguous, and the evaluation results of human listeners are 51 often inconsistent. Therefore, the first important problem is how to prepare correct 52 attractiveness labels. For this problem, we start with the paired comparison test (Shah 53 et al., 2014). Since it is difficult to give a concrete definition of the attractiveness 54 scale, it is easier for a typical listener to answer the question "which voice is more 55 attractive, A or B?" than the question "how attractive is this voice in the scale of one 56 to five?". 57

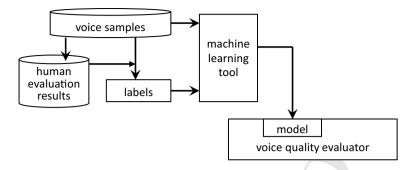


Fig. 15.2 Schematic diagram of voice quality evaluator training

The drawback of paired comparison test is that it includes more inconsistency than the absolute evaluation such as MOS test. In addition to the inconsistency between listeners, sometimes a listener gives inconsistent evaluation results within his/her own comparisons. A typical example is that A is better than B, B is better than C, and C is better than A. Such kind of discussion leads us to the probabilistic model of paired comparison test, in which the intrinsic attractiveness of voices works as the parameter of winning probability.

In this chapter, a new probabilistic model of voice attractiveness is introduced, in which the intrinsic attractiveness of voices and the intrinsic preference of listeners are handled in a unified form. In this model, the voice attractiveness is represented as a multidimensional vector in the "merit space." The preference of listener is described as a direction in the merit space, and the evaluation of a voice by a listener is expressed as the inner product of those vectors. The process to obtain the optimal mapping from the paired comparison results will also be discussed.

After the optimal mapping is obtained, we move on to the discussion of merit vector estimation from the acoustic features of a new voice. If the estimation scheme is established, we can predict the comparison results for the new voice, and the effectiveness of the whole framework can be confirmed by the correctness of prediction.

76 15.2 Analysis of Paired Comparison

In this section, we discuss how to model the paired comparison test of voice attrac-77 tiveness. In the development process of text-to-speech (TTS) systems, voice quality 78 assessment by MOS (Ribeiro, Florêncio, Zhang, & Seltzer, 2011) and paired compar-79 ison (Zen, Tokuda, Masuko, Kobayashi, & Kitamura, 2004; Junichi, Onishi, Masuko, 80 & Kobayashi, 2005) test are both used. Although the MOS test has the advantage 81 that the results can be used directly as the absolute attractiveness value, it imposes a 82 heavy burden on listeners and the results are often unreliable. That is the reason why 83 we decided to use the paired comparison test. Below we introduce various models 84 of paired comparison result interpretation. 85

⁸⁶ 15.2.1 Universal Attractiveness Model

A straightforward interpretation of paired comparison test is that each voice has own
attractiveness and the listener compares two attractiveness values to make a decision.
In this paper, such interpretation is referred to as the *universal attractiveness model*because each voice sample is assumed to have one attractiveness value which is
applicable to everyone.

The easiest case is that all comparison results are completely consistent. If so, we can obtain at least the order of the voices. Any mapping rule can be acceptable if it satisfies the order. However, such results are rarely obtained, and we need a mapping rule to handle inconsistent results that are unavoidable. From that viewpoint, various analysis methods were applied in various fields, including an example in sports competition (Cattelan, Varin, & Firth, 2013).

A typical approach of probabilistic modeling is based on minimization of the log likelihood function. Assuming that the probability of the voice *i*'s winning against the voice *j* only depends on the difference of their attractiveness values, the total log likelihood function *L* can be written as follows.

$$L = \sum_{i} \sum_{j} w_{ij} \log f(d_{ij})$$
(15.1)

$$d_{ij} = a_i - a_j \tag{15.2}$$

where a_i and a_j are the attractiveness of the voice *i* and *j*, $f(d_{ij})$ is the probability that the voice *i* wins against the voice *j*, and w_{ij} is the number of voice *i*'s winning against the voice *j*.

6

¹⁰⁷ Historically, there have been two major models of $f(d_{ij})$. In the Bradley–Terry ¹⁰⁸ model (Bradley & Terry, 1952), two voices behave as though competing for the ¹⁰⁹ shared resource and the probability represents the ratio of one's resource over the ¹¹⁰ other.

111

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$$f(d_{ij}) = \frac{e^{a_i}}{e^{a_i} + e^{a_j}} = \frac{1}{1 + e^{-d_{ij}}}$$
(15.3)

In the Thurstone-Mosteller Case V model (Mosteller, 1951), the observation probability of each voice is assumed to be a Gaussian whose mean corresponds to its own attractiveness. The probability that the voice *i* wins against the voice *j* is equal to the probability that the observation of voice *i* is larger than the observation of voice *j*, which is calculated by

$$f(d_{ij}) = \frac{1}{2}(1 + \operatorname{erf}(d_{ij}))$$
(15.4)

where erf represents the error function.

In both cases, a scaling factor can be multiplied to d_{ij} . A larger scaling factor induces less frequent "upset," in which a less attractive voice wins against a more

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ditor Proof

attractive voice. However, it was omitted in the definition of $f(d_{ij})$ because the attractiveness a_i itself has the freedom of scale.

If the definition of $f(d_{ij})$ is fixed, it is easy to obtain the optimal set of $\{a_i\}$ for a given result of paired comparison. We start with randomly selected initial values of $\{a_i\}$, and update them on the direction of gradient ascent of *L*.

126

$$\frac{\partial L}{\partial a_i} = \sum_{j \neq i} f'(d_{ij}) \left(\frac{w_{ij}}{f(d_{ij})} - \frac{w_{ji}}{1 - f(d_{ij})} \right)$$
(15.5)

127 15.2.2 Personalized Attractiveness Model

In paired comparison test, two listeners may have opposing opinions for a given pair. 128 In the universal attractiveness model, such event is interpreted simply as an occur-129 rence of less likely event. However, in our social experience, we would react to such 130 situations by saying "tastes differ." However, we also feel that there are some voices 131 which many people tend to like. These two aspects of voice attractiveness—listener's 132 preference and voice likability-can be modeled by defining voice attractiveness as 133 a function of voice-originated character and listener-originated character. Such rela-134 tionship can be visualized by mapping voices onto a multidimensional merit space. 135 in which the voices are given as points and the preferences are given as directions. 136

There have been some studies proposing multidimensional extension of Bradley-137 Terry model. Fujimoto, Hino, and Murata (2009) proposed a mixture model and 138 applied it as a visualization method to the movie rating task. The idea of calculating 139 the inner product between the voice-originated vector and listener-originated vec-140 tor is an extension of Fujimoto's model. Another example if the work of Causeur 141 and Husson (2005), in which a two-dimensional model representing ranking and 142 relevance axes is proposed and applied to the consumer's preference of cornflakes. 143 In the proposed personalized attractiveness model, the likelihood function has 144

the same form as the universal attractiveness model, but an additional parameter of listener's index k is introduced.

$$L = \sum_{i} \sum_{j} \sum_{k} w_{ijk} \log f(d_{ijk})$$
(15.6)

where w_{ijk} is the number of times the listener k prefers the voice *i* to the voice *j*. The fact that d_{ijk} includes the listener index k means that the attractiveness a_{ik} depends on the lister k. A simple model to define the listener-dependent attractiveness is

$$d_{ijk} = a_{ik} - a_{jk} \tag{15.7}$$

$$a_{ik} = \mathbf{p}_k \cdot \mathbf{m}_i \tag{15.8}$$

151 152 where $\mathbf{p}_k(|\mathbf{p}_k|=1)$ is the preference vector for the listener *k* and \mathbf{m}_i is the merit vector intrinsic for the voice *i*.

The process to obtain the optimal set of preference vectors and merit vectors is similar to the case of universal attractiveness model. We start with randomly selected initial values of $\{\mathbf{p}_k\}$ and $\{\mathbf{m}_i\}$, and update them on the direction of gradient ascent of *L*.

In the 2-dimensional case, we can describe the preference and merit vectors as $\mathbf{p}_k = (\cos \theta_k, \sin \theta_k)^T$ and $\mathbf{m}_i = (\xi_i, \eta_i)^T$, where θ_k, ξ_i , and η_i are the parameters to be adjusted. The parameter θ represents the preference angle. Two parameters ξ an η are interchangeable, and represent the elements of merit vector. The differentiation of *L* in terms of those parameters are calculated as follows.

$$\frac{\partial L}{\partial \xi_i} = \sum_{j \neq i} \sum_k f'(d_{ijk}) \left(\frac{w_{ijk}}{f(d_{ijk})} - \frac{w_{jik}}{1 - f(d_{ijk})}\right) \cos \theta_k \tag{15.9}$$

$$\frac{\partial L}{\partial \eta_i} = \sum_{j \neq i} \sum_k f'(d_{ijk}) \left(\frac{w_{ijk}}{f(d_{ijk})} - \frac{w_{jik}}{1 - f(d_{ijk})} \right) \sin \theta_k$$
(15.10)

$$\frac{\partial L}{\partial \theta_k} = \sum_i \sum_{j \neq i} f'(d_{ijk}) \left(\frac{w_{ijk}}{f(d_{ijk})} - \frac{w_{jik}}{1 - f(d_{ijk})} \right) r_{ijk}$$
(15.11)

$$d_{ijk} = (\xi_i - \xi_j) \cos \theta_k + (\eta_i - \eta_j) \sin \theta_k$$
(15.12)

$$r_{ijk} = (\eta_i - \eta_j) \cos \theta_k - (\xi_i - \xi_j) \sin \theta_k$$
(15.13)

Additional restriction is applied to constrain the vectors in the unit square.

$$0 \le \xi_i \le 1 \tag{15.14}$$

$$\leq \eta_i \leq 1 \tag{15.15}$$

$$0 \le \theta_k \le \pi/2 \tag{15.16}$$

Using above equations, the optimization procedure can be described by the pseudocode shown in Fig. 15.3. Since the quality of solution strongly depends on the initial values, the procedure is repeated using various initial values, and the best combination is selected as the final solution.

The process described above can be extended to the higher dimensional cases easily. In the N-dimensional space, we assume

179	$\mathbf{m}_i = [\xi_{1i}, \xi_{2i}, \dots, \xi_{Ni}]$	(15.17)
180	$\mathbf{p}_k = [\sin \theta_{1k} \sin \theta_{2k} \cdots \sin \theta_{N-1,k}]$	$\cos heta_{Nk},$
181	$\sin\theta_{1k}\sin\theta_{2k}\cdots\sin\theta_{Nk},$	
182	$\sin\theta_{1k}\sin\theta_{2k}\cdots\sin\theta_{N-2,k}\cos\theta_{N-2,k}$	os $\theta_{N-1,k}$,
183		
184	$\sin\theta_{1k}\cos\theta_{2k},$	

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170 171 172 **Fig. 15.3** Pseudocode for log likelihood maximization in the two-dimensional merit space

1: set small step value of s 2: repeat 3: initialize $\{\xi_i\}, \{\eta_i\}, \{\theta_k\}$ randomly 4: repeat 5: for all i, k do calculate $\frac{\partial L}{\partial \mathcal{E}_i}$, $\frac{\partial L}{\partial \mathcal{E}_i}$, $\frac{\partial L}{\partial \mathcal{E}_i}$ using (15.9),(15.10),(15.11) 6: 7: end for for all i, k do 8: $\xi_i \leftarrow \xi_i + \frac{\partial L}{\partial \xi_i} s$ 9: 10: $\xi_i \leftarrow \max(\min(\xi_i, 1), 0)$ $\eta_i \leftarrow \eta_i + \frac{\partial L}{\partial n_i} s$ 11: 12: $\eta_i \leftarrow \max(\min(\eta_i, 1), 0)$ $\theta_k \leftarrow \theta_k + \frac{\partial L}{\partial \theta_k} s$ 13: 14: $\theta_k \leftarrow \max(\min(\theta_k, \frac{\pi}{2}), 0)$ 15: end for 16. until converge 17: calculate L using (15.6) and store $\{\xi_i\}, \{\eta_i\}, \{\theta_k\}, L$ 18: **until** N times 19: return $\{\xi_i\}, \{\eta_i\}, \{\theta_k\}$ that yielded the largest L

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and obtain the update rule, which is a straightforward extension of Eqs. (15.9)–(15.13).

Finally, we selected the Thurstone-Mosteller Case V model (15.4) for f, and the derivative is given by

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ditor Proof

$$f'(d_{ijk}) = \frac{1}{\sqrt{\pi}} e^{-d_{ijk}^2}$$
(15.19)

In fact, the factor $1/\sqrt{\pi}$ can be omitted because the step *s* has the freedom of arbitrary scale.

193 15.3 Estimating Merits from Acoustic Features

 $\cos \theta_{1k}$]

There have been many studies that tried to connect the subjective nature of voices and 194 their physical characteristics. The largest field is emotion recognition from speech. 195 Various acoustic features and machine learning techniques were applied to predict 196 the emotional state of speaking person, and the achievements were compared in 197 challenges (Ringeval et al., 2017; Schuller et al., 2017). Early researches focused on 198 the prosodic features such as F0 and loudness (Tato, Santos, Kompe, & Pardo, 2002), 199 but the cepstral features were also found to be effective (Sato & Obuchi, 2007). In 200 recent years, it is common to prepare many features and apply machine learning 201 algorithms to find the best feature set. The success of those studies encouraged us to 202 connect the voice attractiveness in the multidimensional merit space and the acoustic 203 features using the machine learning framework. 204

(15.18)

We start the analysis by preparing a redundant set of acoustic features. Those features are extracted using **OpenSMILE** (Eyben, Weninger, Groß, & Schuller, 2013) and **Julius** (Lee & Kawahara, 2009).

OpenSMILE is a multi-purpose feature extractor from audio signal. It divides the 208 input voice into 25 ms overlapping frames with 10 ms frame interval, and extract 209 various low-level descriptors (LLDs) including energy, pitch, and spectral centroid. 210 Those LLDs are accumulated from all frames, and then various interframe features 211 (functionals) are extracted from each type of LLD. As shown in Tables 15.1, we 212 prepared 14 LLDs related to energy, pitch, and spectral features, and 23 functionals 213 related to extremes, regression, and segment. The total number of features extracted 214 by OpenSMILE is 322. 215

Julius is an open-source speech recognition engine. We assume that the transcrip-216 tion of voice is given, and Julius is used as the forced-alignment tool. The features 217 provided by Julius include the acoustic model score, total utterance length, and the 218 length of the final phoneme (mostly vowels in Japanese). The first feature indi-219 cates how typically the utterance was pronounced, because it represents the distance 220 between the utterance and the standard acoustic model. The second feature indicates 221 how fast the utterance was pronounced. The third feature represents the hesitation, 222 which is frequently observed in Japanese conversation. 223

Starting with 325 baseline features (322 from OpenSMILE and 3 from Julius), we try to reduce the number of features using the backward stepwise selection (BSS) framework. For any set of features, candidate subsets are made by removing single feature, and each subset is evaluated by cross validation. After evaluating all subsets, the subset with the highest score survives as the set for next step. The same procedure is repeated until only one feature remains. We also tried forward stepwise selection (FSS) in which a null set is prepared as the baseline, and candidate features are added

LLDs		Functionals		
Energy/Pitch	Spectral	Extremes	Regression	Segment
RMS energy	Max position	Max	Linreg slope	Number of seg
Log energy	Min position	Min	Linreg offset	Seglen mean
F0	Centroid	Range	Linreg linear error	Seglen max
Voicing prob.	Entropy	Max position	Linreg quadratic error	Seglen min
	Variance	Min position	Qreg coef 1	Seglen std. dev.
	Skewness	Mean	Qreg coef 2	
	Kurtosis	Max-mean	Qreg coef 3	
	Slope	Mean-min	Qreg linear error	
	Harmonicity		Qreg quadratic error	
X	Sharpness		Qreg contour centroid	

 Table 15.1
 List of LLDs and functionals. Linreg stands for linear regression, qreg for quadratic regression, and seglen for segment length

step by step. However, FSS achieves much worse results than BSS, so the detailed
 investigation was done with BSS only.

Prediction of the multidimensional merit values are realized by the regression
algorithm called SMOreg (Shevade, Keerthi, Bhattacharyya, & Murthy, 2000, which
is an extension of support vector machine algorithm. We use WEKA (Hall et al.,
2009), which provides various machine learning algorithms including SMOreg.

237 15.4 Experimental Results

In this section, two important issues are examined by the experiments using a real database. The first issue is how efficient mappings of voices can be obtained by the optimization process of personalized attractiveness model. The second issue is how accurately those mappings can be reproduced from the unknown voice using acoustic features.

243 15.4.1 Recordings and Comparisons

For the experiments, we recorded voices of Japanese greeting "irasshaimase (wel-244 come)" uttered by 115 university students. They were recorded using Panasonic 245 RR-XS355 digital voice recorders with 44.1 kHz sampling rate, stereo recording and 246 16-bit quantization condition. Since "irasshaimase" is the phrase given by the shop 247 clerk every time a customer comes in, it is uttered very frequently in commercial 248 situations and its impression is very important for the business. The recording was 249 done in a typical classroom situation, in which voluntary students with no payment 250 were asked to say "irasshaimase" one by one. No instruction was given as for the 251 speaking style. Silence was not kept during the recording and the recorded voices 252 include some environmental noises. 253

In the feature extraction process, OpenSMILE version 2.3.0 rc1 and Julius version 4.2 grammar kit were used. OpenSMILE used the recorded data as their original format, and Julius used the converted version to 16 kHz monaural sampling. The original Japanese acoustic model delivered with the Julius main program was used.

Eighteen listeners participated in comparison experiments. Since we used a 258 browser-based comparison system equipped with anonymous login function, gender 259 and age distribution of the listeners are not available. However, we assume that the 260 majority are in their twenties and there are more male listeners than female listeners. 261 Each listener was given 38 or 39 sets of triplet voices, and asked to choose the most 262 attractive one. The sets were made randomly. We used triplet comparison instead 263 of paired comparison simply because we can obtain more comparison results with 264 smaller number of trials, although we understand that it is controversial whether 265 triplet comparison provides as reliable results as paired comparison. A single triplet 266 comparison result was interpreted as two paired comparison results. If voice A was 267

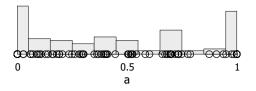


Fig. 15.4 Optimal mapping of 1-dimensional merit space. The variable a is the 1-dimensional merit value. Since there are many circles that are completely overlapped, bars were added to show the histogram. There are 26 voice mapped to a = 0 and 22 voices mapped to a = 1

chosen from the triplet {A, B, C}, it was interpreted that A won in the comparisons
{A, B} and {A, C}. Finally, we collected 1,388 paired comparison results (76 or
78 randomly chosen comparisons for each listener) over 115 voice samples.

271 15.4.2 Mapping to Multidimensional Merit Space

First, we confirmed the effectiveness of mapping to 1-dimensional merit space, which corresponds to the universal attractiveness model. The likelihood function *L* of Eq. (15.1) was minimized in terms of 115 scaler values $\{a_1, a_2, ..., a_{115}\}$ using Eq. (15.5).

Figure 15.4 shows the obtained mapping. Using the attractiveness values shown in Fig. 15.4, we can calculate which voice deserves a win for each comparison. Accordingly, the human judgments are categorized into anticipated or surprising. The mapping efficiency is defined by the ratio of anticipated judgments.¹

A common metric for such efficiency is called "Kendall rank correlation coefficient," or "Kendall's τ " in short. To deal with the incomplete comparison with ties, we modify "Kendall's τ_b " as

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ditor Proof

$$\tau_b = \frac{N_C - N_D}{\sqrt{N_C + N_D + N_T}\sqrt{N_C + N_D}}$$
(15.20)

where N_C is the number of concordant (anticipated) pairs, N_D is the number of discordant (surprising) pairs, and N_T is the number of tied pairs in which two voices have the same attractiveness. τ_b becomes 1 if all comparisons are concordant and -1if all comparisons are discordant. In the case of Fig. 15.4, τ_b was 0.622.

Next, the same procedure was applied to the higher dimensional cases. The procedure in 2-d was described in Fig. 15.3. In the cases with higher dimension, it was
 extended in a natural manner. In each case, we repeated the update 80 times with
 random initialization, but they converged to several mappings only.

¹It is similar to the athletes' ranking. If the high-ranked player always wins, the ranking is efficient. If there are many upsets in which the low-ranked player wins, the ranking is not efficient.

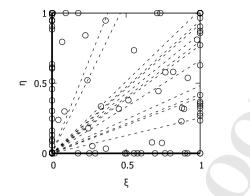


Fig. 15.5 Optimal mapping of 2-dimensional merit space. The voices are represented by circles. The listeners are represented by dashed lines. There are two listeners with $\theta_k = 0$ (x-axis) and three listeners with $\theta_k = \pi/2$ (y-axis)

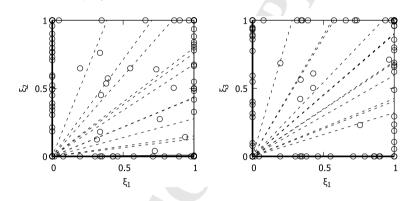


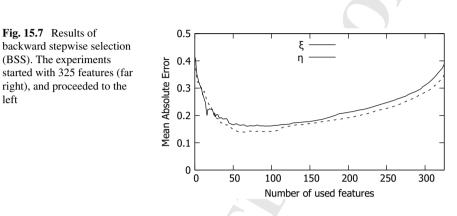
Fig. 15.6 Optimal mapping of 3-dimensional merit space. The left plot shows the first and second dimension, and the right plot shows the first and third dimension. There is one listener with $\theta_{1k} = 0$, three listeners with $\theta_{1k} = \pi/2$, four listeners with $\theta_{2k} = 0$, and two listeners with $\theta_{2k} = \pi/2$

Figures 15.5 and 15.6 are the optimal mapping in 2-d and 3-d cases. It can be seen that many voices have either 0 or 1 as an element of **m**, meaning that the goodness or badness in terms of specific viewpoint is judged unanimously. The voices located on the right-top corner are perfectly attractive voices for everyone. The voices on the left-bottom are perfectly unattractive for everyone. There are 16 perfectly attractive and 15 perfectly unattractive voices in 2-d mapping, and 8 perfectly attractive and 7 unattractive voices in 3-d mapping.

Table 15.2 shows τ_b values in the mapping in various dimensions up to eight. Since the larger number of free parameters have more power to solve inconsistency of comparison results, it is natural that τ_b increases as the larger dimension is introduced. However, it can be noticed that τ_b seems to saturate at around D = 5.

Dim	1	2	3	4	5	6	7	8
N _C	1068	1143	1200	1237	1306	1262	1309	1310
ND	232	186	159	132	79	121	71	76
N_T	88	59	29	19	3	5	8	2
$ au_b$	0.622	0.705	0.758	0.802	0.885	0.824	0.895	0.890

Table 15.2 Values of τ_b calculated from the optimal map



15.4.3 Merit Estimation from Acoustic Features 303

After confirming the effectiveness of multidimensional mapping, our concern shifted 304 to the relationship between the merit space and the acoustic features. In particular, 305 the most interesting question would be whether we can predict \mathbf{m}_i from the voice 306 itself. If \mathbf{m}_i is predictable, we can predict the voice attractiveness at least for the 307 known listeners whose preference vector \mathbf{p}_k is given. 308

Since the size of our database is not large enough for two-stage (optimal mapping 309 and merit estimation) fully open condition experiments, we conducted evaluation 310 experiments under a semi-open condition. The optimal mapping in multidimensional 311 merit space was obtained using all data. However, after the merit values for all voices 312 are fixed, the predictability of those merit values from the acoustic features was 313 evaluated using WEKA version 3.6.13 under an open condition using tenfold cross 314 validation. As mentioned before, we started the experiments using all of the 325 315 features. SMOreg estimator with the second-order polynomial kernel was used. BSS 316 was carried out using the criteria of mean absolute error between real and predicted 317 values. 318

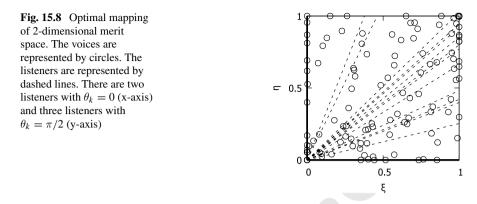
Figure 15.7 shows how BSS reduced the mean square error when the number of 319 used features changed in the 2-dimensional case. In the case of ξ , the error drops 320 from 0.39 with all features to 0.16 with 68 carefully selected features. The error of η 321 drops from 0.35 with all features to 0.14 with 66 features. Using the predicted values 322 of ξ and η in cross-validation for all 115 voices, we obtained the estimation map 323 shown in Fig. 15.8. 324

left

Fig. 15.7 Results of

(BSS). The experiments

right), and proceeded to the



Dim	1	2	3	4	5	6	7	8
N_C	1057	1127	1175	1206	1221	1194	1243	1252
N _D	320	260	211	182	167	194	144	136
N_T	11	1	2	0	0	0	1	0
$ au_b$	0.533	0.625	0.695	0.738	0.759	0.720	0.792	0.804

Table 15.3 Values of τ_b calculated from the estimated mapping

It is straightforward to predict paired comparison results from the mapping of Fig. 15.8. The efficiency of prediction is quantified by τ_b . Among 1,388 comparisons, we obtained 1,127 concordant pairs, 260 discordant pairs, and 1 tie prediction. The value of τ_b was calculated as 0.625, which is slightly better than τ_b obtained with 1-dimensional optimal mapping.

After all, we carried out experiments in various dimensions, and obtained τ_b values of estimated attractiveness as shown in Table 15.3. Since the mapping itself becomes more powerful as the dimension increases, the value of τ_b also increases as the higer dimension is introduced. The tendency that the efficiency saturates at around D = 5does not change.

335 15.5 Conclusions

In this chapter, a multidimensional mapping scheme of voice attractiveness was proposed. Intrinsic attractiveness of voice samples are represented as vectors in the merit space, and listener-dependent preferences are represented as directions in the same space. The attractiveness of a voice for a listener is calculated as the inner product of these two vectors. This mapping scheme provides a better-fit model for the comparison results to which the universal attractiveness model assigned small likelihood values. The effectiveness of the proposed model was confirmed by the experiments using real voices and their attractiveness judgments. The multidimensional mapping scheme achieves the higher likelihood for the Thurstone-Mosteller model, and better prediction of comparisons.

We also tried to predict the merit values of a new voice sample from its acoustic features. If we can do so, we can predict the comparison result at least for the known listener. A set of machine learning-based experiments confirmed the feasibility of such prediction. If we use four or higher dimension merit space, more than 1,200 of 1,388 paired comparisons can be predicted correctly.

The proposed scheme can be applied to select attractive voice samples for commercial applications. Moreover, it can also be applied to the development process of TTS systems. Since it is easier to synthesize various voices than to prepare a large set of recorded voices, a TTS-based system can speak with the tailor-made voice for the customer.

Although the results presented in this chapter are promising, there are three important problems to solve. First, the experiments presented in this chapter are not fully open. In a sense, the optimization process of multidimensional mapping and feature selection are optimized using the evaluation data. If such optimization tends to overfit the training data, we would have less accurate results with completely new data, especially in the higher dimension cases. To avoid that problem, we need more data and more experiments under the fully open condition.

The second problem is that the paired comparison data were collected with only small number of listeners. Due to the limited data size, it remains an open question whether the model trained in a certain listener group is transferable to another listener group. In addition to the data size problem, anonymousness of the listeners made it impossible to analyze the age and gender dependency of the preference.

The third problem is that all results in this chapter were obtained for just one phrase "irasshaimase." Although it is a very important phrase in the commercial context, we may have something different if we use different phrases. However, the methodology to deal with the merit space and acoustic features is applicable to any phrase, and that is the most important achievement of the work described in this chapter.

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Part V Technological Applications

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Abstract	Trust is fundamental for successful human interactions. As robots become increasingly active in human society, it is essential to determine what characteristics of robots influence trust in human–robot interaction, in order to design robots with which people feel comfortable interacting. Many interactions are vocal by nature, yet the vocal correlates of trust behaviours have received relatively little attention to date. Here we examine the existing evidence about dimensions of vocal variation that influence trust: voice naturalness, gender, accent, prosody and interaction context. Furthermore, we argue that robot voices should be designed with specific robot appearance, function and task performance in mind, to avoid inducing unrealistic expectations of robot performance in human users.		
Keywords	Speech - Robots - Voice design - Human-robot interaction - Trustworthiness - Speech prosody		

Chapter 16 Trust in Vocal Human–Robot Interaction: Implications for Robot Voice Design



Ilaria Torre and Laurence White

Abstract Trust is fundamental for successful human interactions. As robots become

increasingly active in human society, it is essential to determine what characteristics

³ of robots influence trust in human-robot interaction, in order to design robots with

⁴ which people feel comfortable interacting. Many interactions are vocal by nature,

⁵ yet the vocal correlates of trust behaviours have received relatively little attention to

date. Here we examine the existing evidence about dimensions of vocal variation that
 influence trust: voice naturalness, gender, accent, prosody and interaction context.

⁷ influence trust: voice naturalness, gender, accent, prosody and interaction context.
 ⁸ Furthermore, we argue that robot voices should be designed with specific robot

⁹ appearance, function and task performance in mind, to avoid inducing unrealistic

¹⁰ expectations of robot performance in human users.

11 Keywords Speech · Robots · Voice design · Human-robot interaction ·

¹² Trustworthiness • Speech prosody

13 16.1 Introduction

Trust is an essential foundation for human societies. Numerous approaches have been 14 taken towards understanding the means by which it is negotiated. For background, the 15 reader is referred to texts in biology (Bateson, 2000), evolutionary theory (Harcourt, 16 1991), sociology (Luhmann, 1979), economics (Berg, Dickhaut, & McCabe, 1995) 17 and neuroscience (Bzdok et al., 2011). Here, it will suffice to say that trust relates 18 both to attribution—when someone makes a decision to trust someone else—and to 19 states and traits, when someone acts, in the short term or over the long term, in a 20 trustworthy manner. 21

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Human social evolution has made us very sensitive to cues that may provide 22 information about state or trait trustworthiness in others (e.g. Jones & George, 1998), 23 to the point that a short extract of someone's speech (McAleer, Todorov, & Belin, 24 2014), or a short exposure to someone's face (Willis, 2006) are enough to make us 25 form a consistent impression of that person's trustworthiness. As robots increasingly 26 become part of our daily lives, it is important to understand what makes people trust 27 robots and, conversely, how we can design robots to appear trustworthy, in order 28 to facilitate human-robot interaction (HRI) and collaboration. While much effort 29 is put into designing robots to look trustworthy and appropriate for their task (e.g. 30 Saldien, Goris, Yilmazyildiz, Werner, & Lefeber, 2008; DiSalvo, Gemperle, Forlizzi, 31 & Kiesler, 2002; Lütkebohle et al., 2010; Oh et al., 2006), less consideration is given to 32 designing voices for these robots (e.g. Sandygulova & O'Hare, 2015). As we argue in 33 this chapter, voice is a very powerful cue used in judgements of trustworthiness, and it 34 should be carefully considered-in conjunction with the robot's appearance/function 35 and with the users' expectations-when designing a robot. 36

With regard to vocal attractiveness more generally, this chapter considers how 37 characteristics of a robot's voice that contribute to an impression of trustworthiness 38 reinforce, and are reinforced by, features of vocal attractiveness. Dion, Berscheid, 39 & Walster (1972) used the phrase 'what is beautiful is good' to refer to the fact that 40 attractiveness is strongly perceived as related to other positive traits, including that 41 of trustworthiness. Indeed, attractiveness and trustworthiness loaded on the same 42 factor in McAleer et al. (2014)'s study of vocal features. Additional evidence of 43 the close link between attractiveness and trustworthiness comes from neuroscience 11 (Bzdok et al., 2011) and neurobiology Theodoridou, Rowe, Penton-Voak and Rogers 45 (2009), Bzdok et al. (2011), for example, concluded that specific brain regions, such 46 as the amygdala, might selectively reinforce sensory information with high social 47 importance, such as information concerning potential relationships (e.g.: 'Is this 48 person attractive? I might date them in the future.'; 'Is this person trustworthy? I 49 might collaborate with them in the future'.). Here, we examine what characteristics 50 of a robot's voice, by analogy with human voices, contribute to an impression of 51 trustworthiness as a socially relevant cue for human-robot interaction. 52

53 16.2 Trust in Voices

Most human communication is predicated on some degree of mutual trust between
interlocutors. When we ask a stranger for directions, we trust that they will give us the
correct information, to the best of their knowledge (cf, Cooperative Principle, Grice,
1975). Moreover, like the fabled 'boy who cried wolf', untrustworthy communicators
tend to be downgraded as interlocutors once their deceiffulness has been exposed.

As the spoken channel is typically our main mode of communication, we have naturally developed vocal means to signal our trustworthiness and to detect it in others. Indeed, the natural tendency to trust speech is mediated by heuristics that give us indicators about when the speaker might not be trustworthy. Not being able to determine a speaker's background can contribute to this impression, as can vocal
identifiers of social affiliations disfavoured by the perceiver, or prosodic indicators
of aggression or dominance. Conversely, positive evidence for trustworthiness can
be inferred from many vocal features, such as accent (e.g. LevspsAri & Keysar,
2010), prosodic cues (e.g. Miller, Maruyama, Beaber, & Valone, 1976), or emotional
expressions (e.g. Schug et al., 2010).

Regarding accents, the literature suggests that foreign accents tend to be trusted 69 less than native accents (LevspsAri & Keysar, 2010), and that, within a language, 70 'prestigious' and 'standard' accents are trusted more than regional accents (Giles, 71 1970). For example, in the context of the UK, Standard Southern British English 72 (SSBE) is generally evaluated as more trustworthy than, for example, typical London 73 or Birmingham accents (Bishop, Coupland, & Garrett, 2005. Furthermore, experi-74 mental evidence suggests that such first impressions of trustworthiness might persist 75 over time, despite being mediated by experience of a speaker's actual behaviour 76 (Torre, White, & Gosli, 2016). 77

Results are less conclusive, indeed sometimes contradictory, regarding the direc-78 tion of influence of various prosodic features on trust attributions. For example, 79 OConnor and Barclay (2017) found that people had greater trust in higher pitched 80 male and female voices (based on average fundamental frequency, f0). By contrast, 81 Villar, Arciuli, and Paterson (2013), amongst other studies, have found that partic-82 ipants raise their vocal pitch when lying, and Apple (1979) showed that speakers 83 with a high f0 and slow speech rate were rated as 'less truthful'. A fast speaking 84 rate was found to be a feature of charismatic and persuasive speakers (Jiang & Pell, 85 2017; Chaiken, 1979), but has also been found to detract from charisma in speech 86 (Niebuhr, Brem, Novák-Tót, & Voße, 2016). Finally, higher pitch and slower speech 87 rate predicted greater trusting behaviour in an economic game (Torre et al., 2016). 88 Such variable results might be due to the fact that the studies employed different 89 methods, such as questionnaires or behavioural measures, and looked at different 90 aspects of trust, such as deception, economic trust, voting behaviour, charisma, and 91 so on. They might also reflect quantitative variation in the prosodic features examined 92 in the different studies: it is unlikely that the relationships between trust attributions 93 and, for example, speech rate or pitch range are strictly linear. Additionally, rather 94 than individual vocal characteristics, it is more likely to be a combination of features 95 that determine the perceiver's assessment of trustworthiness, along with how vocal 96 features interact with physical appearance, interaction context and the perceiver's 97 emotional state. 98

⁹⁹ Voice is a powerful medium through which a diversity of speaker-specific index ¹⁰⁰ ical information is transmitted and interpreted, and robot voices are likely to be
 ¹⁰¹ subjected to similar appraisals. Thus, the design of robot voices should be influenced
 ¹⁰² by the nature of the attributions appropriate to the purposes of particular human-robot
 ¹⁰³ interactions.

104 16.3 Trust in Robot Voices

People tend to attribute personality traits to computers and robots as if they were 105 human agents (Nass & Lee, 2001; Nass, Moon, Fogg, Reeves, & Dryer, 1995; Walters, 106 Syrdal, Dautenhahn, Te Boekhorst, & Koay, 2008), and to respond to robots as if 107 they had a personality (Lee, Peng, Jin, & Yan, 2006). Given also that people attribute 108 traits to human speakers based on subtle speech characteristics (e.g. Torre et al., 109 2016; McAleer et al., 2014), there is reason to assume that voice information will 110 be used to attribute traits—e.g. of trustworthiness—to robots as well. Thus, voice 111 selection should be an integral part of the overall robot's design. Issues to take 112 into consideration are numerous and diverse, the following being just a selection. 113 Should large robots have lower pitched voices than small robots, congruent with 114 anthropomorphic expectations about larger larynxes? Should human-like robots have 115 natural human voices? Should robot voices have regional accents? If so, should these 116 be chosen to reflect the accent of the person with whom they are interacting or, for 117 example, to reflect a stereotyped association between particular voice styles and the 118 specific functions that the robot will perform? The latter approach risks reinforcing 119 stereotypes, but ignoring any considerations of voice-function congruency could be 120 problematic for the naturalness of the interaction. 121

It seems, however, that relatively little attention is currently paid to how the selec-122 tion of robot voices in HRI research might affect our interaction with robots. For 123 example, McGinn and Torre (2019) conducted an informal survey of researchers 124 whose paper at the Human-Robot Interaction 2018 conference featured a speaking 125 robot. Specifically, they asked if they chose the voice of their robot and, if so, why. 126 Of the 18 responses received, six had used the Nao robot built-in voice, seven had 127 used a voice generated with a Text-To-Speech system, either because it was freely 128 available or because it was the voice that the robot came with, three pre-recorded 129 the voice using actors, and two simply described what the voice sounded like (e.g. 130 'androgynous, child-like voice'). In addition, six of these authors specified that they 131 had adjusted the robot voice in terms of pitch or speech rate to increase intelligibility 132 or to elicit the perception of a particular voice age. Only one author mentioned the 133 accent that the voice had, and only one author mentioned looking for a voice that 134 would specifically suit the task that the robot had to carry out in the experiment. About 135 the reasons for their choice, two authors specified that 'it was the only good one' and 136 'because it was open source'. While 11 mentioned the gender of the robot's voice, 137 only a minority considered other voice characteristics such as prosody or accent, or 138 the context in which the interaction would take place. However, as we show in this 139 chapter, all of these features influence human perception of robots, and should not 140 be neglected. 141

Studies experimentally manipulating a robot voice in order to measure its effect on users' perceptions and behaviours are relatively scarce, but here we review work in which a robot's voice was manipulated, or where vocal characteristics were considered in the analyses. As trust is related to other positive traits—a typical 'halo effect' Dion et al. (1972)—and as studies examining the effect of robot voices on

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trust are limited, we evaluate voice-based research in human–robot interaction in
 general, considering the implications for trustworthiness in particular.

149 16.3.1 Voice Naturalness

One key aspect of voice that is often taken into account when designing robots is 150 naturalness. While current efforts in the speech technology community are dedicated 151 to creating the most natural-sounding artificial voices, it might not be the case that 152 people actually prefer interacting with a robot or other artificial agent with a perfect 153 natural-sounding voice (Hinds, 2004). For example, Sims et al. (2009) showed that 154 being able to speak with either a synthetic or a natural voice was enough for a robot 155 to be treated as a competent agent: people gave more commands to a robot that 156 had a voice, whether synthetic or natural, and fewer to a robot that communicated 157 with beeps. They hypothesised that people assumed that speechless robots would 158 not understand language, and thus they did not speak either. Within the speaking 159 robot condition, however, participants gave more commands to the synthetic-voiced 160 robot than the natural one: (Sims et al., 2009) suggested that participants might have 161 thought that a robot with a human voice was more competent and therefore needed 162 fewer commands. Taking a different perspective, Mitchell et al. (2011) argued that 163 incongruence in the human likeness of a character's face and voice can elicit feel-164 ings of eeriness. In contrast, Tamagawa, Watson, Kuo, MacDonald, and Broadbent 165 (2011) argued that, for the sake of clarity and familiarity, people would prefer such 166 an 'incongruent' robot. In Eyssel, Kuchenbrandt, Hegel, and de Ruite (2012), par-167 ticipants were shown a video of a Flobi robot saying: 'it's quarter past three' and 168 were asked to rate the robot in terms of anthropomorphism, likeability, psycholog-169 ical closeness and intentions. The robot had either a natural or a synthetic voice. 170 Interestingly, voice had an effect only on participants' ratings of likeability, with 171 people rating the natural voice higher. On the other hand, in Theodoridou et al. 172 (2009), people implicitly trusted robots with synthetic voices more than those with 173 natural voices when they were behaving trustworthily, but found the opposite effect 174 when the robots were behaving untrustworthily. This also points to the importance 175 of interaction context for robot voice design (Sect. 16.3.5). 176

More generally, Hegel (2012) did not find strong evidence that the human like-177 ness of a robot's appearance influenced the perception of its social capabilities. If the 178 same were true for the human likeness of robot *voices*, this would argue that voice 179 naturalness might not be critical for creating feelings of trust. However, another 180 factor to take into account when considering naturalness is listening effort: thus, 181 listening to synthetic voices can increase cognitive load relative to natural voices 182 (Simantiraki, Cooke, & King, 2018; Francis & Nusbaum, 2009). In turn, high cogni-183 tive load hinders strategic thinking and can lead to trust misplacement, for example, 184 to trusting untrustworthy individuals (Duffy & Smith, 2014; Samson & Kostyszyn, 185 2015). This suggests that—especially if the robot is meant to sustain an extended 186

vocal communication with a person—it should be given a natural—or high-quality
 synthetic,—voice, notwithstanding any contradictions with the robot's mechanical
 looks.

¹⁹⁰ *16.3.2 Voice Gender*

Talking specifically about trust, research on human-human interaction has not found 191 consistent differences in trust judgments towards men or women (e.g. Nass & Brave, 192 2005; Chaudhuri, 2007; Boenin & Serra, 2009; Slonim & Guillen, 2010). Given that 193 people's mental models of humanoid social robots are generally similar to human 194 models (Lee et al., 2005; Kiesler & Goetz, 2002), it would be reasonable to expect a 195 lack of overall difference, when it comes to trusting a 'female' or 'male' robot. Indeed, 196 Crowell, Scheutz, Schermerhorn, and Villano (2009) failed to find any difference 197 in how people reacted to a mechanical robot that had either a female or a male 198 voice. Thus, in terms of voice design, the straightforward expectation would be that 199 robots that are designed to look more feminine or masculine should have a voice 200 corresponding to their apparent gender. 201

The problem of voice gender selection may be further simplified by the fact that 202 many robots are not perceived as having a clearly defined gender. For example, in a 203 recent study (partially described in Theodoridou et al. (2009)), we used a Nao robot 204 with two different natural female voices, with participants interacting with both. At 205 the end of the experiment, a random sample of the 120 participants was asked what 206 gender they thought the robots had. Of the 66 randomly sampled participants, 23 said 207 they thought the robot was always female, 17 always male, 20 did not associate any 208 gender, and 6 associated a different gender to the two robots they played with. This 209 suggests that even a natural female voice does not consistently convey information 210 about the gender of the robot with that voice. Similarly, the majority of participants 211 in Walters et al. (2008) who interacted with a robot that had either a pre-recorded 212 male voice, a pre-recorded female voice, or a synthesised voice, gave either a male 213 or a neutral name to the robot, even when the robot had a female voice. 214

Thus, it seems that the gender of a robot voice does not necessarily influence whether people will perceive the robot to have the same gender. However, describing a study involving 9–11-year-old children, Sandygulova and O'Hare (2015) suggested that children assigned a gender to a Nao robot on the basis of the voice alone. This was a synthetic male or female voice. However, participants heard all the possible voices in succession with the same robot, and so a contrast effect may have contributed to the gender attribution being based on voice in this case.

While there is no evidence that voice gender influences a positive human–robot interaction, it is possible that it could interact with presumed gender-specific knowledge (e.g. Powers et al., 2005). As discussed later (Sect. 16.3.5), the context in which the interaction takes place might be more important for trustworthy voice design than voice gender as an isolated feature.

227 16.3.3 Voice Accent

Everyone has an accent. The term 'accent' refers to systematic patterns of realisation 228 of the sounds of a language-phonetic and phonological-that people belonging 229 to certain geographically or socially defined groups tend to have in common (Lip-230 pispsGreen, 1997). Accents thus provide immediate information about whether or 231 not two interlocutors belong to similar social and/or regional groups, information 232 that we tend to implicitly use in judgements of trustworthiness (e.g. Kinzler et al., 233 2009). Specifically, in-group membership elicits favourable first impressions, includ-234 ing with robots (Kuchenbrandt, Eyssel, Bobinger, & Neufeld, 2013). Given that every 235 speaker has an accent, and that these accents affect the way we interpret interpresonal 236 communication, should speaking machines have purpose-specific human accents? 237

There is, unsurprisingly, evidence of straightforward accent preferences in inter-238 actions with robots. For example, children based in Ireland showed a preference 239 towards male and female UK English over US English in a Nao robot (Sandygulova 240 & O'Hare, 2015). We can also contribute some survey data regarding overall pref-241 erences for robot accents. All the participants of various UK-based studies run over 242 3 years were asked what accent they would like a robot to have. The question was 243 open-ended, so we re-coded the answers to fit in broad categories (e.g. 'West Coun-244 try' and 'South West' would both be coded as 'South West'; labels such as 'English', 245 'British', 'RP' would be coded as 'SSBE'). Figure 16.1 shows these standardised 246 answers from all 503 participants who answered this question. As the figure shows, 247 the majority of respondents answered with 'SSBE', followed by 'Neutral' accent 248 (which in the UK is also likely to mean the non-regional SSBE), followed by 'Irish'. 249 All of the respondents were native British English speakers, with the following self-250 reported regional identities: southwest England (58%), southeast England (22%), 251 Midlands (8%), Wales (5%), East Anglia (3%), with participants from northeast 252 England, northwest England and Scotland comprising almost all of the remaining 253 3-4%. As shown in Fig. 16.1, very few people reported a preference for a robot to 254 have a machine-like voice. There were also relatively few preferences for a regional 255 accent reflecting one's own origins: 58% of respondents were from the southwest but 256 only about 5% of all respondents said they would like the robot to have a southwest-257 ern accent (which here we use to encompass Bristol, Cornwall, Devon, Plymouth or 258 general South-West). 259

Preferences for robot accents may well also be influenced by the nature of the inter-260 action, however. For example, research from Andrist (2015) on the Arabic language 261 showed an interaction between accent and behaviour in human-robot interaction 262 (see Sect. 16.3.5): participants believed that robots with the same regional accent as 263 theirs were more credible-when the robots were knowledgeable-than those with 264 a standard accent, whereas robots with standard accents were perceived to be the 265 more credible when the robots had little knowledge. Similar interactions between 266 accents and behaviour are, of course, likely with other languages. For example, Tam-267 agawa et al. (2011) ran two experiments comparing synthesised British, American, 268 and New Zealand English accents. In the first experiment, participants from New 269

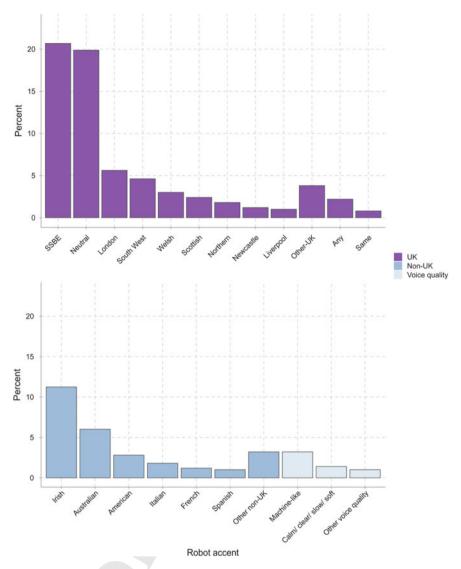


Fig. 16.1 Preference for a robot's accent from a survey of 503 native British English speakers. The question allowed a free response and the bars indicate the overall proportion of all responses that fitted within each accent category (see text for how accent responses were categorised). 'Any' means 'any accent'; 'Same' means 'the same accent as me'

Zealand explicitly rated the disembodied UK accent more positively than the US
one, while their own New Zealand accent was not rated significantly differently
to either of the other accents. In the second experiment, participants were told by
a healthcare robot, in one of the three accents, how to take blood pressure mea-

surements on themselves. After the interaction, they completed a questionnaire, and reported more positive emotions towards the New Zealand-accented robot than the US-accented robot, and thought that the New Zealand robot performed better (no other pairwise comparison was statistically significant). These results also point to the differential effect that accents might have in different interaction contexts (e.g. disembodied voice versus speaking robot).

280 16.3.4 Voice Prosody

Pitch gives information about a speaker's size, being inversely proportional to the 281 body mass (Ohala, 1983). Thus, it might be straightforward to think that bigger 282 robots should have lower pitched voices than smaller robots. However, as we saw 283 in the discussion on voice gender (Sect. 16.3.2), intuitive assumptions regarding 284 appropriate voices do not necessarily apply in practice, and experimental work is 285 required. In Niculescu, van Dijk, Nijholt, and See (2011), after interacting with a robot 286 with either a high-pitched or a low-pitched female voice, participants' questionnaire 287 responses indicated an overall preference for the higher pitched voice. In another 288 study, Yilmazyildiz et al. (2012) asked participants which of two voices, with lower 280 or higher pitch, was more suitable for a NAO-a child-like humanoid robot-or a 290 Probo—a green furry elephant-like robot: participants preferred the higher pitched 291 voice for NAO and the lower pitched voice for Probo. 292

Vocal prosody is also a feature that often manifests convergence. Linguistic 293 convergence-sometimes also called adaptation, entrainment or synchrony, although 204 we prefer the specificity of 'convergence'-is a phenomenon by which two speak-295 ers tend to unconsciously imitate each other's speech characteristics as interac-296 tions proceed (Benuš, 2014). According to Communication Accommodation Theory 297 (Giles, Coupland, & Coupland, 1991), convergence is a signal of openness and 298 positive attitude-including trust-towards the interlocutor. For example, Manson, 299 Bryant, Gervais, and Kline (2013) showed that people who converged in terms of 300 their speech rate trusted each other more in a Prisoner's Dilemma task. Looking at 301 linguistic convergence more generally, Scissors, Gill, Geraghty, and Gergle (2009) 302 found that some types of linguistic similarity positively correlate with behavioural 303 trust in text-based interaction, while others negatively correlate with it: for exam-304 ple, trusting individuals exhibited convergence in the use of words linked to positive 305 emotions, while deceiving individuals exhibited convergence in the use of negative 306 emotions words. 307

The well-documented occurrence of convergence phenomenon in human-human interaction led researchers to examine it in human-agent interaction as well. In a computer game where participants followed the advice of an owl-shaped avatar that was either converging or diverging from the participants' own prosody, Benušet al. (2018) found that female participants followed the advice of the diverging avatar more often than the converging one, while there was no effect for male participants. Also contrary to some expectations, Strupka, Niebuhr, and Fischer (2016) found that

participants tended to diverge prosodically from Keepon robots whose prosody was 315 manipulated. On the other hand, Sadoughi et al. (2017) found that children who 316 played a game with a converging social robot had higher levels of engagement at the 317 end of the interactions than children who played the game with a non-converging 318 robot. The apparent differences in convergence behaviour might be due to several 319 factors, notably whether one is concerned with factors promoting convergence by 320 human speakers towards the vocal features of agents or with the impact of conver-321 gence by agents on human behaviours and attitudes. Additionally, there may be an 322 influence of age differences in participants, adults in Benušet al. (2018) and Strupka 323 et al. (2016), compared with children in Sadoughi et al. (2017): potentially, for exam-324 ple, children may have fewer implicit socio-cognitive biases towards artificial agents. 325 More generally, discrepancies between studies may arise because of intrinsic differ-326 ences in the artificial voices used. Human speech has been shown to converge with 327 artificial voices in terms of phonetics and prosody when the artificial voice is of high 328 quality, but less so when it is of low quality (Gessinger, Raveh, Le Maguer, Möbius, 329 & Steiner, 2017; Gessinger et al., 2018). Differences could also be due to appearance 330 contrasts between artificial agents: for example, in the studies reported above, there 331 was an owl-shaped avatar in Benušet al. (2018), a small, rudimentarily humanoid 332 robot in Strupka et al. (2016) and a life-size humanoid robot in Sadoughi et al. (2017). 333 Interactions between robot appearance and convergence behaviours cannot be ruled 334 out. 335

Prosody conveys important information on the emotional state of the speaker (e.g. 336 Bänziger, & Scherer, 2005; Auberge & Cathiard, 2003). In this regard, it is known that 337 displaying a positive emotion generally leads to attributions of other positive traits— 338 including trustworthiness-a typical 'halo' effect (Lau, 1982; Penton-Voak, Pound, 330 Little, & Perrett, 2006; Schug et al., 2010). Indeed, voice-based Embodied Conver-340 sational Agents that were smiling were trusted more than those with a neutral facial 341 expression (Elkins, 2013). Smiling in the face also led to trusting avatars and robots 342 more (Krumhuber et al., 2007; Mathur & Reichling, 2016). Thus, a robot express-343 ing positive affect in its prosody could similarly increase the human user's feeling 344 that it can be trusted. The situation-congruent expression of affect might increase 345 trust even when it is not displaying a positive emotion. For example, portraying 346 stress and urgency through the voice increased performance in a joint human-robot 347 collaborative task (Scheutz et al., 2006). 348

Apart from signalling a speaker's mood or emotional state, prosodic cues also con-349 tribute to an individual's vocal profile, that is, what makes a voice unique. Arguably, 350 distinct-looking robots should have different-sounding voices, in order to: (a) con-351 tribute to the impression that they are individual agents; (b) be congruent with their 352 physical appearance; (c) elicit personality attributions congruent with the primary 353 functions. In a recent study (partially described in Theodoridou, Rowe, Penton-Voak, 354 and Rogers, (2009), people played a trust game with robots having different voices. 355 We obtained a natural recording of two female SSBE speakers, which we then resyn-356 thesised to sound robotic, thus generating four voices altogether: Speaker 1 natural, 357 Speaker 1 synthetic, Speaker 2 natural, Speaker 2 synthetic. As mentioned earlier 358 (Sect. 16.3.1), much of the variance in trust was explained by the voice naturalness 359

variable: specifically, people trusted robots with synthetic voices more than those 360 with natural voices when they were behaving trustworthily, but the opposite when 361 the robots were behaving untrustworthily (Theodoridou et al., 2009). However, peo-362 ple also demonstrated greater implicit trust to one of the two speaker voices over the 363 other, both in natural-natural and synthetic-synthetic comparisons. This is consis-364 tent with previous studies showing that very fine speech characteristics, which are 365 independent from higher level features such as accent, affect impression formation 366 (e.g. Gobl & Chasaide, 2003; Trouvain, 2006). It also suggests that people's prefer-367 ence for certain individual voices might apply when these voices are embodied in a 368 robot. Thus, idiolectal characteristics, such as those conveyed by prosody, seem to 369 contribute to trusting behaviours as well. 370

Overall, it seems simplistic to relate trustworthiness judgments purely to isolated vocal features—such as gender, naturalness or pitch—and a holistic view of voice might be better suited for promoting positive interactions, rather than only considering specific individual vocal features.

375 16.3.5 Voice Context and Expectations

As discussed earlier, some studies have shown that people perceive robots differ-376 ently depending on the context in which the interaction takes place (Sims et al., 377 2009; Andrist, 2015). Thus, the nature of the specific human-robot interaction may 378 affect the optimal characteristics of the robot (see also Theodoridou et al., 2009). For 379 example, Wang, Arndt, Singh, Biernat, and Liu (2013) found that, in a favourable 380 context, such as a satisfactory customer/employee call centre interaction, customers 381 with an American English background tended to suppress their negative prejudices 382 towards employees with an Indian English accent. On the other hand, when the 383 interaction was not satisfactory, customers tended not to suppress their accent preju-384 dice (Wang et al., 2013). Similarly, Bresnahan, Ohashi, Nebashi, Liu, and Shearman 385 (2002) examined accent perception as a function of the message that the accented 386 speaker was delivering. They recorded two non-native speakers of American English, 387 one very intelligible and one not very intelligible, and one native speaker, reading 388 passages in a 'friend' and 'teaching assistant' condition. Participants were under-389 graduate students of various ethnic origins, but mostly white Americans. They found 390 that the 'friend' context was judged as more attractive and dynamic than the 'teach-391 ing assistant' context, in all accent conditions. Also, participants with and a strong 392 ethnic identity regarded the native accent as higher in status, dynamism and attrac-393 tiveness, while the opposite was found for participants with a weak ethnic identity, 394 who attributed higher status and attractiveness to the not very intelligible foreign 395 accent, as compared to the native one. Thus, not only the interaction context, but also 396 the specific background context of the human interlocutor is likely to influence the 397 interaction success. 398

In HRI, Salem, Ziadee, and Sakr (2013) found that participants' perception—in terms of politeness, competency, extraversion, perceived warmth and shared reality—

of a receptionist robot differed according to the context of the interaction, which was 401 either goal-oriented or open-ended. By contrast, the variation in the robot's politeness 402 level did not influence participants' perception. Additionally, in the aforementioned 403 study by Sims et al. (2009), participants watched videos of a robot in different sce-404 narios (robot damaged, robot in danger, robot requiring more information, robot has 405 located target, robot has completed task). They found that, for example, participants 406 gave more commands to the robot in the videos where the robot needed assistance, 407 and concluded that a robot's voice should be chosen based on task context. In par-408 ticular, this would allow for the transmission of pragmatic information which may 409 increase the operation success. For example, in a search and rescue operation, a syn-410 thetic voice for a robot might be the appropriate choice, because—while it conveys 411 to the person being rescued that the robot is able to help and may be capable of under-412 standing human speech—the fact that the robot voice is not fully human-like could 413 suggest to its human teammates that their input in the operation is still necessary. 414

As reviewed above, a robot's voice, along with its appearance, will have an influ-415 ence on the first impressions of that robot's trustworthiness. Given the role of inter-416 action context, however, these first impressions should be validated over long-term 417 interactions with that robot. In fact, several experiments on trusting behaviour in 418 human-machine interaction showed that incongruency between first impressions of 419 trustworthiness and experience of a speaker's actual trustworthiness can drastically 420 reduce trust (Theodoridou et al., 2009). Thus, if a robot's voice gives the impression 421 that the robot will function well, people might have more negative reactions in the 422 case that the robot's performance does not live up to expectations. If it is expected 423 that a robot will operate with some degree of error, perhaps its design (appearance, 424 voice) should reflect the fact that its performance will not always be flawless, so as 425 not to set the users' expectations too high from the beginning (Van den Brule, Dotsch, 426 Bijlstra, Wigboldus, & Haselager, 2014). For example, Hegel (2012) found that peo-427 ple attributed higher social capabilities, including honesty, to robots that looked more 428 sophisticated. Whether robots can deliver on their promise of sophisticated perfor-429 mance is a different matter, however, and over-reliance on a robot according to posi-430 tive first impressions could have major negative consequences (Robinette, Li, Allen, 431 Howard, & Wagner, 2016; Hancock et al., 2011; Salem, Lakatos, Amirabdollahian, 432 & Dautenhahn, 2015). 433

Emotional expression might also elicit different trusting behaviours depending on 434 the interaction context. Van Kleef, De Dreu, and Manstead, (2010), in the 'Emotions 435 as Social Information' (EASI) model, suggest that emotions are used to make sense 436 of ambiguous situations, and that their effect depends on the situation in which the 437 interaction takes place, being specifically mediated by its cooperative or competitive 438 nature. Thus, displaying a positive emotion, such as happiness, in a cooperative con-439 text will reinforce the parties' belief that everyone is gaining, and will elicit more 440 cooperative behaviours. By contrast, displaying a negative emotion, such as anger, 441 in a cooperative context will hinder future cooperative behaviours. Accordingly, 442 Antos (2011) found that, in a negotiation game, participants tended to select as part-443 ners those computer agents which displayed emotions congruent with their actions. 444

Those agents were also perceived as more trustworthy than agents whose emotional

expression and action strategy did not match, even though the strategy itself was
the same. In summary, emotional expression is helpful only if it is congruent with
behaviour.

448 16.4 Conclusion

This chapter offers an overview of some of the aspects to consider when designing a trustworthy voice to be used in human–robot interaction. Given that many studies in
HRI employing a speaking robot have not carefully considered their robot's voice, the present work aims to be a starting point for subsequent research involving speaking robots.

In particular, we summarised work on the effect that voice naturalness, gender, 454 accent, and prosody can have on trust attributions in human-robot interactions, along 455 with the interactions of such vocal features with the characteristics and demands of 456 the specific human-robot encounter. Naturalness, accent, and prosody seem to be 457 the features with the highest likelihood of shaping trusting behaviour, while voice 458 gender appears secondary. Moreover, carefully controlling for context might be more 459 important than, for example, manipulations of naturalness in the voice: specifically, 460 successful interactions over time may be hindered by inaccurate user expectations 461 arising from mismatches between robot's voice features and robot's competence and 462 performance. 463

It is possible that voice has been a secondary concern in human-robot interaction 464 research so far because vocal interactions have often been scripted, or generated by 465 an imperfect dialogue system, meaning that other aspects of the interaction, such 466 as the robot's movements or attention, might have been prioritised. However, recent 467 advances in the field of natural language and speech processing (such as WaveNet) 468 mean that fluent autonomous human-robot conversations are getting closer to being 469 commonplace. It is time to consider more carefully what the robot's input into these 470 conversations should actually sound like. 471

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Abstract	Interactions with speech interfaces are growing, helped by the advent of intelligent personal assistants like Amazon Alexa and Google Assistant. This software is utilised in hardware such as smart home devices (e.g. Amazon Echo and Google Home), smartphones and vehicles. Given the unprecedented level of spoken interactions with machines, it is important we understand what is considered appropriate, desirable and attractive computer speech. Previous research has suggested that the overuse of humanlike voices in limited-communication devices can induce uncanny valley effects—a perceptual tension arising from mismatched stimuli causing incongruence between users' expectations of a system and its actual capabilities. This chapter explores the possibility of verbal uncanny valley effects in computer speech by utilising the interpersonal linguistic strategies of politeness, relational work and vague language. This work highlights that using these strategies can create perceptual tension and negative experiences due to the conflicting stimuli of computer speech and 'humanlike' language. This tension can be somewhat moderated with more humanlike than robotic voices, though not alleviated completely. Considerations for the design of computer speech and subsequent future research directions are discussed.
Keywords	Speech interface - Voice interface - Intelligent personal assistant - Uncanny valley - Humanlike - Politeness - Vague language

Chapter 17 Exploring Verbal Uncanny Valley Effects with Vague Language in Computer Speech



L. Clark, A. Ofemile, and B. R. Cowan

Abstract Interactions with speech interfaces are growing, helped by the advent 1 of intelligent personal assistants like Amazon Alexa and Google Assistant. This 2 software is utilised in hardware such as smart home devices (e.g. Amazon Echo 3 and Google Home), smartphones and vehicles. Given the unprecedented level of Δ spoken interactions with machines, it is important we understand what is consid-5 ered appropriate, desirable and attractive computer speech. Previous research has 6 suggested that the overuse of humanlike voices in limited-communication devices 7 can induce uncanny valley effects-a perceptual tension arising from mismatched 8 stimuli causing incongruence between users' expectations of a system and its actual 9 capabilities. This chapter explores the possibility of verbal uncanny valley effects in 10 computer speech by utilising the interpersonal linguistic strategies of politeness, rela-11 tional work and vague language. This work highlights that using these strategies can 12 create perceptual tension and negative experiences due to the conflicting stimuli of 13 computer speech and 'humanlike' language. This tension can be somewhat moder-14 ated with more humanlike than robotic voices, though not alleviated completely. 15 Considerations for the design of computer speech and subsequent future research 16 directions are discussed. 17

18 Keywords Speech interface · Voice interface · Intelligent personal assistant ·

¹⁹ Uncanny valley · Humanlike · Politeness · Vague language

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20 17.1 Introduction

As a mode of interaction, speech can affect peoples' perceptions of others in terms 21 of identity, personality, power and attractiveness (Cameron, 2001; Coulthard, 2013; 22 Goffman, 2005; Zuckerman & Driver, 1988). Speech can impact these perceptions 23 in both the language used and the voice quality used to produce it; the latter defined 24 here as 'those characteristics which are present more or less all the time that a person 25 is talking' (Abercrombie, 1967, p. 91 in Laver, 1980, p. 1). As with human-human 26 interaction (HHI), this impact on perceptions can be seen in human-computer interaction (HCI), where speech has become a more prominent mode of interaction. This prominence has been accelerated with the advent of intelligent personal assistants (IPAs) such as Amazon Alexa and Google Assistant featuring in home-based smart speakers like Amazon Echo and Google Home, as well as in mobile devices and vehicles. These are in addition to longer standing speech-based technologies like interactive voice response (IVR) and navigation systems. Although we are beginning to understand more about how people use and communicate with these types of devices (Cowan et al., 2017; Luger & Sellen, 2016; Porcheron, Fischer, Reeves, & Sharples, 2018; Porcheron, Fischer, & Sharples, 2017), less is known about the psychological and behavioural effects of speech interface design choices on users (Clark, Cabral, & Cowan, 2018).

While we are aware that design choices in speech-based HCI can affect user experience (UX) and interaction behaviour, we are still lacking theoretical understandings and subsequent design considerations supporting them (Clark et al., 2019b). Consequently, it is not always clear what linguistic or voice styles may be appropriate, desirable or even attractive to users in HCI. Mimicking aspects of humanness in 43 speech interfaces, for example, may not always be an appropriate design objective 11 and can result in systems being perceived as creepy or even deceitful (Aylett, Cowan, 45 & Clark, 2019). Recent research (Moore, 2017a) has argued that humanlike voices 46 are not always appropriate for non-human artefacts, as they may heighten peoples' 47 expectations of what artefacts are capable of, in contrast to more robotic voices. This 48 heightened perception of humanness can result in a gap between users' perceptions 49 of a system's abilities or *partner models* and the reality of its limitations observed 50 through interaction (Cowan et al., 2017). As well as the quality of a system's voice, 51 there are also less explored questions as to what are considered appropriate styles 52 of language for computer speech, and how humanlike or 'machinelike' they are 53 expected to be Clark (2018), Clark et al., (2019a). 54

This chapter explores the concepts of three interpersonal linguistic strategies politeness, relational work and vague language (VL)—as a lens to examine the possibility of *verbal uncanny valley effects* that exist in users' perceptions towards both voice and language in computer speech. This may underpin some of the user behaviour and perceptions of appropriateness, desirability and attractiveness directed towards speech interfaces in previous research, as well as peoples' expectations and partner models of their computer interlocutors. It is hoped that these discussions may drive theoretical understandings of our interactions with speech interfaces, which may in turn encourage design considerations in the field.

64 17.2 Uncanny Valley

The uncanny valley hypothesis suggests that non-human artefacts approaching close 65 to human likeness, but retaining obvious differences from human norms, can induce 66 negative responses from people due to one or more obvious differences from expected 67 human appearance or behaviour (Mori, 1970; Mori, MacDorman, & Kageki, 2012). 68 These responses may be referred to as concepts like eeriness, revulsion, or a sense of 69 unease, signifying perceptions of undesirable or unattractive characteristics. Disflu-70 encies between appearance and motion, for instance, may be more disliked than 71 entities displaying more congruent features—contrasting an android that is human-72 like in appearance yet displaying robotic movements with an all human and all robot 73 alternative (Carr, Hofree, Sheldon, Saygin, & Winkielman, 2017). 74

While empirical evidence for the uncanny valley is somewhat scarce, a review of 75 uncanny valley research papers highlighted support for two perceptual mismatch 76 hypotheses (Kätsyri, Förger, Mäkäräinen, & Takala, 2015). The first of these 77 hypotheses suggests that uncanny valley effects arise due to mismatches between 78 the human likeness of different sensory cues (e.g. obviously non-human eyes on a 79 fully humanlike face). The second hypothesis posits that the effects occur because of 80 a higher sensitivity towards exaggerated features on more humanlike characters that 81 differ from expected humanlike norms (e.g. 'grossly enlarged eyes, Kätsyri et al., 82 2015, p. 7). Similar explanations for uncanny valley effects are discussed by Moore 83 (2012). In developing a Bayesian explanation for the uncanny valley effect, Moore 84 points to conflicting cues creating a perceptual distortion and subsequent perceptual 85 tension at category boundaries. These categories refer to stimuli that are discrim-86 inately perceived as being different from one another. Stimuli perceived to be at 87 the boundaries of these categories may incur more perceptual distortion than those 88 stimuli perceived to be prototypical examples of those categories. 89

Whereas most uncanny valley research has focused on the visual, there are an 90 increasing number of works that include audio as an additional modality of interest 91 in exploring perceptual mismatches. Grimshaw (2009) discusses the concept of an 92 audio uncanny valley, with the view that further theoretical understandings may be 93 useful for sound design in horror-based computer games in creating perceptions of 94 fear and apprehension. The author provides examples of features that may induce 95 uncanny valley effects, including uncertainty about the location of sound sources 96 and exaggerated articulation of the mouth whilst speaking. Mitchell et al. (2011) 97 and Meah and Moore (2014) explored the concepts of misaligned voice and face 98 cues (or mismatched stimuli) in robots and humans. Both experiments showed that 99 mismatches in voice and face (e.g. robotic voice and human face or human voice and 100 robotic face) result in higher ratings of perceived eeriness than matched stimuli. 101

These experiments give credence to the uncanny valley existing in audio as well 102 as visual stimuli, although the focus in the above work is on multimodal cues and 103 the audio is primarily centred on the voice quality. With the increasing number of 104 speech interfaces, users are exposed to unprecedented levels of primarily speech-105 based interactions with machines. However, there remain important design consider-106 ations on what is considered appropriate speech output by speech interfaces. Moore 107 (2017a), for example, highlights the proliferation of humanlike rather than more 108 robotic sounding voices in computer speech is not always an appropriate design 109 choice. Using humanlike voices can create mismatches between users' expectations 110 of a machine's capabilities and the reality of what it can achieve through speech. This 111 may result in unsuccessful engagement with speech-based, non-human artefacts. 112 Less is understood as to what may be considered appropriate language in spoken 113 interactions with machines—perceptual mismatches may also occur on a linguistic 114 as well as a voice level, potentially resulting in unwanted negative effects to UX 115 (Clark, 2018). The subsequent sections of this chapter reflect on recent research into 116 the use of interpersonal linguistic strategies in spoken computer instructions and 117 discuss the possible boundaries of appropriate language use (as opposed to solely 118 the appropriate humanlike synthesis choices) in light of uncanny valley theories and 119 mismatched stimuli (Clark, Bachour, Ofemile, Adolphs, & Rodden, 2014; Clark, 120 Ofemile, Adolphs, & Rodden, 2016). 121

17.3 Politeness and Relational Work

The concept of politeness is often discussed in terms of Brown and Levinson's (1987) work that associates politeness with the concept of *face*—the social self-image that we present to others during interaction (Goffman, 1955). This self-image is dependent on sociocultural and contextual factors and dynamically progresses between and within interactions. Face theory discusses it being in speakers' own interests to avoid damaging the face of oneself or the face of others during interaction. Conducting this is known as *facework*.

In Brown and Levinson's (1987) research, facework can be accomplished using 130 politeness strategies. *Positive face* refers to desires of being liked and approved. 131 Positive politeness strategies include showing group membership between partners, 132 paying attention to the wants and desires of others, and presenting approval. Negative 133 face refers mainly to the desire not to be imposed upon by others. Negative politeness 134 strategies often focus on minimising this potential imposition. This can be accom-135 plished by being indirect rather than direct, for example, when issuing instructions 136 or making requests that may create an imbalance of power. 137

Relational work seeks to expand Brown and Levinson's (1987) politeness theory
 to include the whole polite–impolite spectrum (Locher, 2004, 2006; Locher & Watts,
 2005, 2008). This includes all work by individuals for the 'construction, maintenance,
 reproduction and transformation of interpersonal relationships among those engaged
 in social practice' (Locher & Watts, 2008, p. 96). As with facework and politeness

described above, relational work is similarly discursive and on-going (Locher &
Watts, 2005, 2008; Watts, 2003).

145 17.3.1 Politeness in Machines

While there are disagreements in politeness and relational work, the politeness strate-146 gies discussed in this chapter focus on the polite end of the relational work spectrum 147 and discuss a combination of positive and negative politeness strategies discussed in 148 Brown and Levinson's (1987) theory. In some previous research, politeness strategies 149 have been explored in both the HCI and human-robot interaction (HRI) communi-150 ties, although the visual modality and/or the use of embodiment was as prominent 151 as speech. For example, Wang et al. (2008) employed politeness strategies in a 152 Wizard-of-Oz experiment providing tutorial feedback to students. The tutorial inter-153 face contained visual features-in the form of text and an animated robotic char-154 acter that produces gestures—and text-to-speech (TTS) synthesis that would appear 155 to come from the robotic character. In comparing polite and direct feedback, the 156 authors note that students receiving the polite tutorial feedback learned better than 157 those receiving the direct feedback. Furthermore, politeness appeared to be espe-158 cially effective for students who displayed a preference for indirect help or were 159 judged to have less ability to complete the task. 160

In an HRI-based experiment, positive attitudinal results were observed. Torrey, 161 Fussell and Kiesler (2013) conducted a study in which participants observed videos 162 of human and robot helpers giving advice to a person learning to make cupcakes. 163 In creating the communication conditions, the authors used combinations of hedges 164 and discourse markers. Hedges (e.g. sort of, I guess) are described by the authors as a 165 negative politeness strategy mitigating the force of messages and reducing threats to a 166 listener's autonomy. The authors acknowledge that descriptions of discourse markers 167 (e.g. *like*, *you know*) have no standard definition,¹ though for the purposes of their 168 study they are described in similar terms hedges in being used to 'soften commands' 169 (Torrey et al., 2013, p. 277). Four communication conditions were created: direct (no 170 hedges/discourse markers), hedges with discourse markers, hedges without discourse 171 markers and discourse markers without hedges. Results of the experiment showed 172 that hedges and discourse markers as individual strategies improved perceptions 173 towards helpers in terms of considerateness, likeability and the helper being control-174 ling compared to the direct condition. However, the combination of the two strategies 175 did not show significant differences compared to the individual strategies. While 176 positive improvements in perceptions towards both human and robot helpers were 177

¹Discourse markers may also be referred to, amongst other terms, as *discourse particles, pragmatic particles* and *pragmatic expressions*. Their purposes can include switching topics, marking boundaries between segments of talk, helping to conduct linguistic repair and being used as hedging devices (Jucker & Ziv, 1998).

observed, participants only observed videos of interactions with helpers, rather than
 interact with any themselves.

In a similar study, Strait, Canning and Scheutz (2014) analysed both observations 180 and actual interactions with robots providing advice in a drawing task. The authors 181 created an experiment comparing three different interaction modalities: remote third-182 person (observations of interactions), remote first person (one-to-one with a robot 183 via a laptop) and co-located first person (one-to-one with robot in the same room). 184 As with the experiment by Torrey, Fussell, and Kiesler (2013), two communication 185 conditions were presented. The indirect condition used a combination of positive 186 politeness strategies (e.g. giving praise, being inclusive) and negative politeness 187 strategies (e.g. being indirect, using discourse markers), whereas the direct condition 188 referred to the absence of these strategies in the robot helper's speech. A further 189 condition was included in the robot's appearance, which compared one robot with 190 a more humanlike appearance and another with a more typical robotic appearance. 191 The results of the experiment showed politeness strategies in the indirect speech 192 condition improve ratings of likeability and reduced ratings of perceived aggression 193 when compared to the direct speech condition. Improved ratings for considerateness 194 were also observed in indirect speech, but only in the remote third-person interaction 195 modality. The findings showed that previous results from observations of interaction 196 of robots do not necessarily transfer to actual interaction. 107

198 17.3.2 Politeness in Non-embodied Computer Speech

The above studies highlight the mixed user responses towards different types of machines and interaction modalities using politeness strategies, focusing in particular on interactions with partners who are embodied or are represented visually. Many modern speech interface technologies like Google Assistant can include a minimal amount of visual output, depending on the device being used but do not necessarily include embodied features.

With this in mind, two further studies explored the use of politeness strategies in 205 HCI, in which participants were tasked with constructing models under the instruction 206 of a speech interface (Clark et al., 2014, 2016). In both studies, VL was used to create 207 indirectness as a form of overall negative politeness strategy.² VL refers to language 208 that is deliberately imprecise and can achieve a wide range of functional and inter-209 personal goals (Channell, 1994). For example, lexical hedges like just and partly can 210 be used as a tension-management device to play down the perceived significance of 211 research during academic conferences (Trappes-Lomax, 2007). Furthermore, vague 212 nouns such as *thing* and *whatsit* can be used to replace a typical noun if speakers 213

²These were adaptors, e.g. *more or less, somewhat* (reduce assertiveness, minimise imposition); discourse markers, e.g. *so, now* (structure talk, mitigate assertive impact of utterance); minimisers, e.g. *just, basically* (structure talk, reduce perceived difficulty, mitigate utterance impact) and vague nouns, e.g. *thing, bit* (improve language efficiency) (Clark et al., 2016).

and listeners have both established what the vague nouns are referring to (Channel,
1994). While not all VL has functions in being polite, this is the primary purpose
of which it used in the speech interface studies—the indirectness and imprecision
of VL can contribute to lessening the perception of speakers being too authoritative
(McCarthy & Carter, 2006) and help create an informal and less direct atmosphere
during interaction.

In the first speech interface study using VL, two communication conditions were 220 developed—a vague condition containing politeness strategies and a non-vague 221 condition excluding these politeness strategies (Clark et al., 2014). Participants were 222 tasked with building Lego models under the verbal instructions of a computer inter-223 face, the speech of which was produced by the TTS voice Cepstral Lawrence.³ During 224 this study, participants interacted with an interface on a MacBook Pro 10.2. This was 225 a minimalistic interface using an HTML file linked to a library of pre-recorded speech 226 files. The interface allowed participants to proceed to the next instruction or repeat 227 a current instruction, with the pace being dictated by the participants. Results of 228 this study showed that the non-vague interface was rated as significantly more direct 229 and authoritative than the vague interface. However, post-task interviews revealed 230 participants perceived the vague interface to be inappropriate in terms of its language 231 choice. This was partly a result of the quality of the voice. People's expectations of 232 a relatively robotic voice were matched more with the non-vague interface than the 233 vague interface, with the latter discussed as being insincere and its language more 234 appropriately suited to a more natural (i.e. humanlike) sounding voice. 235

A follow-up experiment explored vague communication conditions across three 236 different voices (Clark et al., 2016). Two of these were TTS-synthesised voices-237 Cepstral Lawrence as per the previous experiment-and CereProc Giles.⁴ The third 238 voice was provided by a professional voice actor who was deemed to sound similar in 239 age and accent to the two synthesised voices. Participants followed verbal instructions 240 to build models using two of the three voices in two separate tasks. These tasks 241 used the same style of interface as the first experiment. Results showed that the 242 voice actor was perceived as significantly more likeable, more humanlike and less 243 annoying than the two synthesised voices. Furthermore, it was perceived as more 244 coherent than Giles, and both the voice actor and Lawrence were rated as allowing 245 more task completion than Giles. Analysis of post-task interview data also revealed 246 that VL in both synthesised voices was perceived negatively. Participants cited it as 247 inappropriate and often commented on the jarring nature between the quality of the 248 voice and the language being used. However, while the voice actor was seen as a 240 more appropriate fit for VL, results were not wholly convincing. Despite the increased 250 naturalness and humanlikeness, participants still highlighted the disparity between 251 the more machinelike nature of the voice and the humanlike nature of the language. 252 Even with a human voice, there were comments discussing it as 'just a machine' 253 that is not capable of executing VL or politeness strategies, unlike other people, due 254 to their inherent interpersonal and social linguistics purposes. This suggests that the 255

³https://www.cepstral.com.

⁴https://www.cereproc.com.

medium of speech delivery, in this case a machine, can also impact on perceptions
 of appropriateness and attractiveness.

17.4 Implications for Verbal Uncanny Valley Effects

In terms of what may be considered appropriate computer and human speech, the 259 experiments discussed above raise the possibility of category boundaries existing on 260 a linguistic level-verbal uncanny valley effects. While participants could not always 261 explicitly identify individual lexical items that caused negative reactions towards the 262 interfaces, they were able to identify a general disparity between the language being 263 used and the interface that provided the language. Although this was not the case for 264 all participants, there was a general trend towards describing the vague conditions 265 in both experiments as humanlike language, whereas in Clark et al. (2014), the 266 non-vague condition was cited as being appropriately machinelike. 267

In the sense of the latter, the use of direct and non-vague language was seen to 268 match people's expectations of appropriate language use with a robotic synthesised 269 voice. This is an example of matched speech-based stimuli, whereby categories of 270 preconceived 'machine likeness' are aligned. Subsequently, there is little discussion 271 about feelings of the uncanny arising, which are focused more on misaligned stimuli 272 (Mitchell et al., 2011; Moore, 2012a). This also draws similarities with Moore's 273 (2012a) discussion of appropriate voices in non-human artefacts. With non-vague and 274 direct instructions provided by a robotic voice, appropriateness is seemingly deter-275 mined as it matches people's expectations of what their interaction partner is capable 276 of. These expectations and beliefs of what a communicative partner can produce may 277 be referred to as peoples' partner models (e.g. Cowan, Branigan, Obregón, Bugis, 278 & Beale, 2015). Previous research with infrequent users of IPAs has suggested that 279 speech qualities such as regional accents can signal the communicative attributions 280 people make towards artificial assistants (Cowan et al., 2017). Similarly, this may 281 operate with the quality of a system's voice, the language it uses, and how these 282 two relate to one another. A robotic voice may relate more to signals of using direct 283 than indirect language that is absent in relational work, vague language or politeness 284 strategies. In terms of users' expectations, these linguistic concepts may not be seen 285 as residing in the category of appropriate computer speech. 286

This can be observed in the vague conditions of the two experiments (Clark 287 et al., 2014, 2016). In the synthesised voices, in particular, the combination of a 288 robotic sounding voice with language that is used to undertake social goals creates a 289 mismatch in stimuli. Subsequently, uncanny valley effects can be observed, especially 290 in participants' descriptions of their interactions with the interfaces. In the second 291 experiment (Clark et al., 2016), however, using a pre-recorded human voice appeared 292 to cause less perceived stimuli mismatch in the vague conditions than the synthesised 293 voices. This may indicate that perceived categories of appropriate computer and 294 human speech can be blurred somewhat with the introduction of more humanlike 295 voices—a human voice can signal a perceptual cue of being capable of producing 296

more humanlike language, even in a computer interface. However, the mismatch is not
alleviated completely. Other cues, such as the medium and/or context of interaction
(laptop interface providing task-based instructions), may alter what is perceived as
appropriate speech even with a human voice.

³⁰¹ 17.4.1 Identifying Appropriateness in Computer Speech

Indeed, the combination of socially driven linguistic cues and computer speech output may create a *habitability gap* (Moore, 2017b), whereby there is a gap between a users' model of a system and the reality of the actual system (Hone & Graham, 2000). Users' models of computer speech may not include the use of interpersonal linguistic strategies and subsequently the presentation of actual computer speech that includes these creates feelings of unease or *perceptual tension* (Moore, 2012).

The mismatching of cues and accompanying perceptual tension in spoken inter-308 actions with computers and other machines appears strongly linked to perceptions of 309 what is considered appropriate communication. In addition to a possible habitability 310 gap, it may also be the case that perceived inappropriateness of politeness, rela-311 tional work or vague language in computer speech is aligned with the socially driven 312 nature of these concepts. Relational work and politeness strategies, for example, are 313 primarily focused on establishing and maintaining interpersonal relationships with 314 other people (Locher & Watts, 2008; Brown & Levinson, 1987). It is debatable as 315 to what extent this can be accomplished in HCI, how achievable this is as a design 316 goal, and how much users would desire this feature in a speech-based device. The 317 social rules that underpin much HHI do not automatically transfer to HCI and the 318 latter may be markedly diminished in comparison. Moore (2017b, p. 8) highlights 319 a similar possible phenomenon—that there may be a 'fundamental limit' to the 320 linguistic interactions between humans and machines due to them being 'unequal 321 partners'. The very nature of humans and machines means there are inherent differ-322 ences in capabilities, and this is likely present in the partner models users create 323 in speech-based HCI. When these partner models clash with experiences, this may 324 lead to negative user experiences and perceptions of inappropriate, undesirable or 325 unattractive speech interface partners. 326

The social rules underpinning HCI and HHI also do not automatically align. 327 Relational work and politeness strategies are primarily focused on interpersonal 328 relationships. Brown and Levinson's (1987) theory on politeness in particular is 329 strongly associated with the process of facework during interaction. However, the 330 maintenance of face during interaction with machines is different than with other 331 people—machines do not have a face as such to protect and, in turn, users do not 332 have another self-image they have to consider during interaction. There may be 333 elements of corporate rather than individual self-images present during interaction, 334 and users can still be imposed upon by machines. However, this remains markedly 335 different from interaction with other people. Indeed, recent research observed that, 336 while descriptions of conversations with people often discuss social and interpersonal 337

wants and needs, interactions with machines are described in very functional and
tool-like terms (Clark et al., 2019a). This may be due to a lack of familiarity and
experience from which to draw upon. However, spoken interactions with machines
lack many of the conversational complexities seen in human communication and are
often limited to isolated question–answer pairs (Porcheron et al., 2018).

I7.5 Future Work and Considerations for Computer Speech

This chapter has presented the possible existence of verbal uncanny valley effects— 345 that perceptual tension and negative user experiences and attitudes can emerge in 346 spoken interactions with computers when using linguistic strategies that are inher-347 ently social and interpersonal. This effect appears to be intensified with more robotic 348 voices and lessened, though not entirely, with more humanlike voices. This differs 349 from previous discussions of an auditory uncanny valley (e.g. Grimshaw, 2009; Meah 350 & Moore, 2014) in that it focuses on both language and voice quality, and the rela-351 tionship between them. Verbal uncanny valley effects suggest there may be category 352 memberships that exist with styles of language that focus on relational work-i.e. 353 that other people are members of this category, whereas computers do not become 354 automatic members by virtue of employing the same strategies. Doing so may create 355 an impression of machines encroaching upon the verbal space of people. This is 356 similar to Moore's (2017b) discussion of there being a fundamental limit to spoken 357 interaction between humans and machines. Moore (2015) mentions that endowing 358 machines with features like humanlike voices can create the mismatched stimuli that 359 lead to perceptual tension, and this may also hold true for certain linguistic styles. 360 With similar considerations, it appears that reducing perceptual tension with verbal 361 uncanny valley effects may depend partly on the relationship between voice and 362 language. If using a very robotic voice, interpersonal linguistic strategies may not 363 be appropriate and may be subsequently undesirable and unattractive. Conversely, if 364 wanting to employ these strategies, a more humanlike voice would be more appro-365 priate. However, there remains the possibility that no matter what voice is used, 366 certain interpersonal language may be evaluated negatively regardless due to funda-367 mental and embedded differences in user expectation between humans and computers 368 as interlocutors. 369

It is likely that this is not always the case-this argument stops short of saying all 370 types of interpersonal linguistic strategies are off-limits. However, there are design 371 choices around voice and language to consider for computers using speech. There 372 are also other choices to consider. The discussions of politeness strategies and VL 373 in this chapter tend to focus on task-based scenarios in HCI. While this is arguably 374 where most speech-based HCI still currently remains at a linguistic level, it may be 375 the case that instruction-giving or advice-giving computers in task-based scenarios 376 are not appropriate vessels for interpersonal language. If the aim of an interaction 377

between speaking computers and humans is fundamentally an interpersonal one (e.g. 378 social talk Gilmartin, Cowan, Vogel, & Campbell, 2017) or in healthcare dialogues 370 (Bickmore et al., 2018), then these linguistic styles may be more appropriate. Simi-380 larly, the role in which both computer and human play in any given interaction may 381 also influence evaluations of speech—an instruction-giver may be treated differently 382 to a machine that operates more on a peer-level or as a caregiver, due to varying levels 383 of power and exactly what linguistic possibilities these roles may afford. Similarly, 384 human-controlled speech synthesis output, such as the use of a vocal synthesiser to 385 create the ability to speak, may be evaluated differently to speech synthesis output 386 that is controlled by a machine. Furthermore, the direction of interaction may have 387 an effect. Previous experiments often focus on speech output only from a system, 388 whereas two-way dialogue may induce different evaluations. Previous research has 389 shown that politeness can be reciprocated back and forth in an interaction with an 390 in-car help system (Large, Clark, Quandt, Burnett, & Skrypchuk, 2017), though the 391 work does not provide insight into people's actual evaluations of the system. 392

However, while these ideas are rooted in evidence from previous research, there 393 is still the need to test them further. As noted in Sect. 17.2, the evidence for the 394 uncanny valley alone is scarce, with Moore's (2012) Bayesian approach offering a 395 rare quantitative verification of its existence. Future research endeavours can explore 396 the concept of a verbal uncanny valley and its effects further in both quantitative 307 and qualitative means, although any notions of a valley in terms of the shape are 398 arguably less important than the effects caused by underlying concepts of funda-399 mental communicative limits. Comparisons with actual human stimuli as well as 400 computers may also prove beneficial. Indeed, quantifying what constitutes 'human-401 like' or 'machinelike' communication is a complex process. Given the increasing 402 prevalence of computer speech, what is perceived as 'machinelike' may well change 403 over the years as familiarity with these devices increases. Longitudinal studies may 404 also uncover further evidence on the effects of prolonged interaction with devices 405 and the extent to which this may affect any verbal uncanny valley effects. 406

407 17.6 Summary and Conclusion

Determining what is considered appropriate speech in HCI remains a challenge. 408 Moore (2017a) offers examples of how to determine appropriateness in the voices of 409 non-human artefacts and avoid uncanny valley effects-robotic rather than human-410 like in less sophisticated systems may be better at matching users' expectations of a 411 system with reality. Language use, however, is arguably a more complex affair. This 412 chapter discusses three concepts of interpersonal linguistic strategies (politeness, 413 relational work and VL) to explore what may be considered appropriate language 414 use in speech-based HCI. In linking previous experiments on these strategies with 415 research on the uncanny valley, we find that the social rules that underpin human 416 interaction do not automatically transfer to HCI. The concept of face-the social 417 self-image presented to others—is mostly non-existent on the part of the system 418

during interaction. The need to conduct facework, i.e. protecting this self-image, 410 is then diminished. While users can still be imposed upon by an interface, using 420 strategies like politeness and VL may not always be appropriate and may be unde-421 sirable. The combination of computer speech and interpersonal language gives rise 422 to perceptual mismatch at the category boundaries between human and computer 423 speech, creating potential for negative user evaluations of systems. Consequently, 424 this raises the potential of verbal uncanny valley effects, whereby the use of very 425 'humanlike' language creates feelings of perceptual tension in HCI. While a human-426 like voice can act as a moderator for these effects, it does not alleviate perceptual 427 tension completely. Future research should explore the empirical testing of the verbal 428 uncanny valley and its effects, identify what linguistic concepts are seen to reside 429 in the category of appropriate and inappropriate computer speech, and understand 430 what further phenomena (like voice) may influence its evaluation by users. 431

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Instruction to printer	Textual mark	Marginal mark
Leave unchanged	••• under matter to remain	\bigcirc
Insert in text the matter	K	New matter followed by
indicated in the margin		λ or λ∞
Delete	/ through single character, rule or underline or	of or σ_{α}
	⊢ through all characters to be deleted	1 1
Substitute character or	/ through letter or	new character / or
substitute part of one or more word(s)	⊢ through characters	new characters /
Change to italics	— under matter to be changed	
Change to capitals	under matter to be changed	=
Change to small capitals	= under matter to be changed	=
Change to bold type	\sim under matter to be changed	\sim
Change to bold italic	$\overline{\mathbf{x}}$ under matter to be changed	
Change to lower case	Encircle matter to be changed	
Change italic to upright type	(As above)	4
Change bold to non-bold type	(As above)	
		Y or X
Insert 'superior' character	/ through character or	under character
	\boldsymbol{k} where required	e.g. Ý or X
Insert 'inferior' character	(As above)	over character
		e.g. k_{2}
Insert full stop	(As above)	O
Insert comma	(As above)	,
		∮ or ∜ and/or
Insert single quotation marks	(As above)	ý or X
Insert double quotation marks	(As above)	Ϋ́or Ϋ́ and/or
insert double quotation marks		Ϋ́ or Ϋ́
Insert hyphen	(As above)	н
Start new paragraph		_ _
No new paragraph	تے	
Transpose		
Close up	linking characters	\bigcirc
Insert or substitute space	/ through character or	
between characters or words	k where required	Ϋ́
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characters or words	words affected	