H2020 Project K-PLEX: WP4 Report on Data, Knowledge Organisation and Epistemics

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Abstract: This report on Data, Knowledge Organisation, and Epistemic Impact covers the findings of WP 4 of the K-PLEX project. It focuses on data collection, production, and analysis in a broad range of scientific disciplines, on epistemologies and methodologies, and research organisation. The cross-disciplinary research topic "emotions" has been chosen to ensure comparability across disciplines and to investigate different epistemic cultures. Findings are based on a survey with 123 responses and 15 expert interviews.

Results show the heterogeneity of research approaches and epistemic dissonances resulting from a broad variety of epistemic cultures in emotion research. Datafication – the rendering of real-world phenomena into data – inevitably leads to a reduction of complexity of the research object "emotions". This simplification results from the limitations imposed by the epistemologies and the biases inherent to methodological decisions. The dissection into various disciplines and epistemic cultures and the challenges of interdisciplinarity further the marginalisation of complexity.

Interdisciplinarity in emotion research was deemed as both beneficial and demanding. While interdisciplinary research projects were seen to be fruitful on a theoretical and conceptual level, the development of research methodologies that enable data structures which can be aggregated into larger data sets proved to be challenging. Data structures are designed according to methodological requirements and not to ensure reusability. Structural factors like the difficulties of research organisation in large-scale interdisciplinary research units, or the lack of high-ranked journals publishing interdisciplinary results further impede such research endeavours.

Data cannot be seen independently from the context in which they were constructed and collected. The narrower context of the research setting and of the researcher as well as the wider contexts of the historical, political, social, cultural and linguistic circumstances of data collection have thus to be considered. The omission of contexts and the lack of comprehensive theoretical frameworks form considerable barriers to data aggregation and have consequences for data storage, sharing and reuse. A multiplicity of epistemologies and methodologies leads to a plurality of data and metadata formats and to a reduced acceptance of standard formats like the W3C standard EmotionML. In the case of data on emotions, further barriers are formed by legal restrictions or ethical issues in data sharing.

Research participants showed cautiousness with respect to Big Data opening up new research possibilities. Big Data are not collected according to a specific research question or methodology and are thus antecedent to the epistemological process. This can be seen as a major difference between Big Data and research data. Moreover, Big Data are investigated in an exploratory process dominated by serendipitous findings, an approach that runs counter to scientists' conception of a steered navigation of the research process. Concise recommendations on how these conflicting epistemologies could be combined in terms of integrative datafication standards, infrastructure and methodologies are outlined.

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1. WP Objectives

WP 4 investigated the third of the four key themes problematising the concept of data, namely 'knowledge organisation and epistemics'.

The activities of the WP were broken down into the following tasks.

T 4.1 Survey of the current state of knowledge regarding the creation of data by researchers (M 4-6)

The project team built upon the knowledge base already available in Freie Universität Berlin and Trinity College Dublin and extended the state of knowledge about epistemic processes and the nature of research data, in particular in disciplines that have largely resisted quantitative methods, e.g. the humanities and discursive social sciences. In particular, WP4 sought to uncover new sources regarding the impact of personal or rhetorical factors on data aggregability, i.e. through the inclusion of new disciplinary approaches from interdisciplinary emotion research, the anthropology of emotion, neuroanthropology, and cultural psychology.

T 4.2 Development of survey and interview questions (M 7-8)

After the conclusion of this first phase (and in conjunction with the consortium's midterm face-to-face meeting) WP4 developed both an online survey and a set of detailed questions to underpin one-on-one interviews with humanities researchers about their data, the process of datafication, the organisational framework in which they operate, and the potential barriers to its broad aggregation. Both of these instruments were designed to tease a more detailed picture of both the resource barriers to greater sharing, but also the philosophical and ethical ones, such as the fear of ideas being taken and used by someone else, lack of ownership over sources, or a sense that the data is 'too personal' to be of broader use. The survey was used to establish a broad overview of some of the higher level issues, while the interviews went into greater depth about the cultural and ethical questions underlying resistance to data sharing by researchers in these fields. Our targets for each of these were in excess of 100 responses for the survey and in excess of 12 1-hour interviews.

T 4.3 Delivery and initial data preparation/analysis of the survey and interview results (M 9-11)

The online survey was disseminated through local and research community channels; interviewees were recruited from these initial participants as well as from the partner networks (in particular the Freie Universität Berlin project networks, which include over 80 active researchers)

T 4.4 Analysis of data, write up and editing of reports (M 12-14)

Although data analysis and interview transcription were continuous throughout the phase of Task 4.3, this task considered the final data set and determined the overall conclusions and recommendations that became a part of the final WP reports.

T 4.5 Integration of final WP results with overall project (M 15)

The final month of the project was dedicated to the alignment and harmonisation of final results among the WPs, which were pushed forward by the final project plenary meeting at the start of M 15.

All of the tasks were led by WP4 leader (Freie Universität Berlin). Input of the other partners (KNAW-DANS, Trinity College Dublin and TILDE) were gathered at the kickoff, midterm and final project meetings, through the monthly Project Member Board online conference calls, as well as asynchronously through the circulation of draft results.

2. Introductory Literature Review

How do scientific researchers structure and collect data? How do disciplinary epistemologies and data structuring and collecting processes relate to each other? WP4 of the K-PLEX project investigated scientific research on “emotions” by comparing different epistemic processes of academic knowledge production across a broad range of scientific disciplines. The research topic of “emotions” provides a fruitful topic for a comparative analysis of knowledge production, organisation and epistemics in the sciences, since it is explored by a broad range of disciplines comprising the humanities, the social sciences and the natural sciences. In the different disciplines, research approaches vary from focusing on the cultural constructedness of emotions to conceptualisations that emphasise the bodily experience of emotions and thus mark them as natural processes. In the comparison of several disciplines, the similarities and differences between epistemologies thus become quickly visible, just as the specificities of datafication, understood as the turning of real-world phenomena into data.

Scientific Thought Collectives and Styles

The exploration of science as a socially embedded enterprise pertains to the philosophy of science as well as science and technology studies (STS). Margaret Gilbert’s (2000) claim that scientific knowledge is socially constituted because it is partly derived from collective beliefs held by scientific communities is one of the more recent contributions to this discussion. The classic study “The Genesis and Development of a Scientific Fact” by the Polish physician Ludwik Fleck (1980, first print 1935) can be described as one of the first sociological examinations of scientific knowledge construction. Fleck profiled scientific research as a collective activity, focused on the mechanisms and customs in scientific communities, and coined the terms “Denkkollektiv” (“thought collective”) for the community in which scientists are organised, and “Denkstil” (“thought style”), which designates the readiness for directed perception characteristic of a collective of researchers. According to Fleck, thought styles shape the ways in which the members of a thought collective perceive and think about the world. This concept implies thought constraint, a shared understanding of what truth is, and the sole acceptance of evidence that are given in line with the thought style (“denkstilgemäße Auflösung”). Thought styles are therefore often incommensurable amongst members of differing thought collectives. Incommensurability here refers to shifts of meaning of terms, the reframing of conceptions, and to the incomparability and difficulties in evaluating knowledge claims of respective ‘other’ camps.

Ludwik Fleck’s analysis has influenced the well-known study by Thomas S. Kuhn, “The Structure of Scientific Revolutions” (1970, first print 1962). By focusing on out-of-date beliefs in the history of single disciplines and the differences between communities of scientists, Kuhn substantiated the differentiation of scientific schools of thought and their relation to each other by introducing the terms “revolution” and “paradigm”: “scientific revolutions are here taken to be those non-cumulative developmental episodes in which an older paradigm is replaced in whole or in part by an incompatible new one.” (92) “Paradigm shifts" do not necessarily make older paradigms obsolete, but lead to the coexistence of scientifically incommensurable ways of seeing the world. An important point Kuhn makes lies with the role of persuasion which accompanies the adoption of new paradigms: "Each group uses its own paradigm to argue in that paradigm's defence. [...] Yet, whatever its force, the status of the circular argument is only that of persuasion." (94) Moreover, Kuhn elaborates on the function of textbooks for scientific formation, and on popular science for a gain in legitimacy of a new paradigm. At the same time, he underlines the construction of long-standing historical traditions in textbooks as a means for disguising the significance of scientific revolutions.

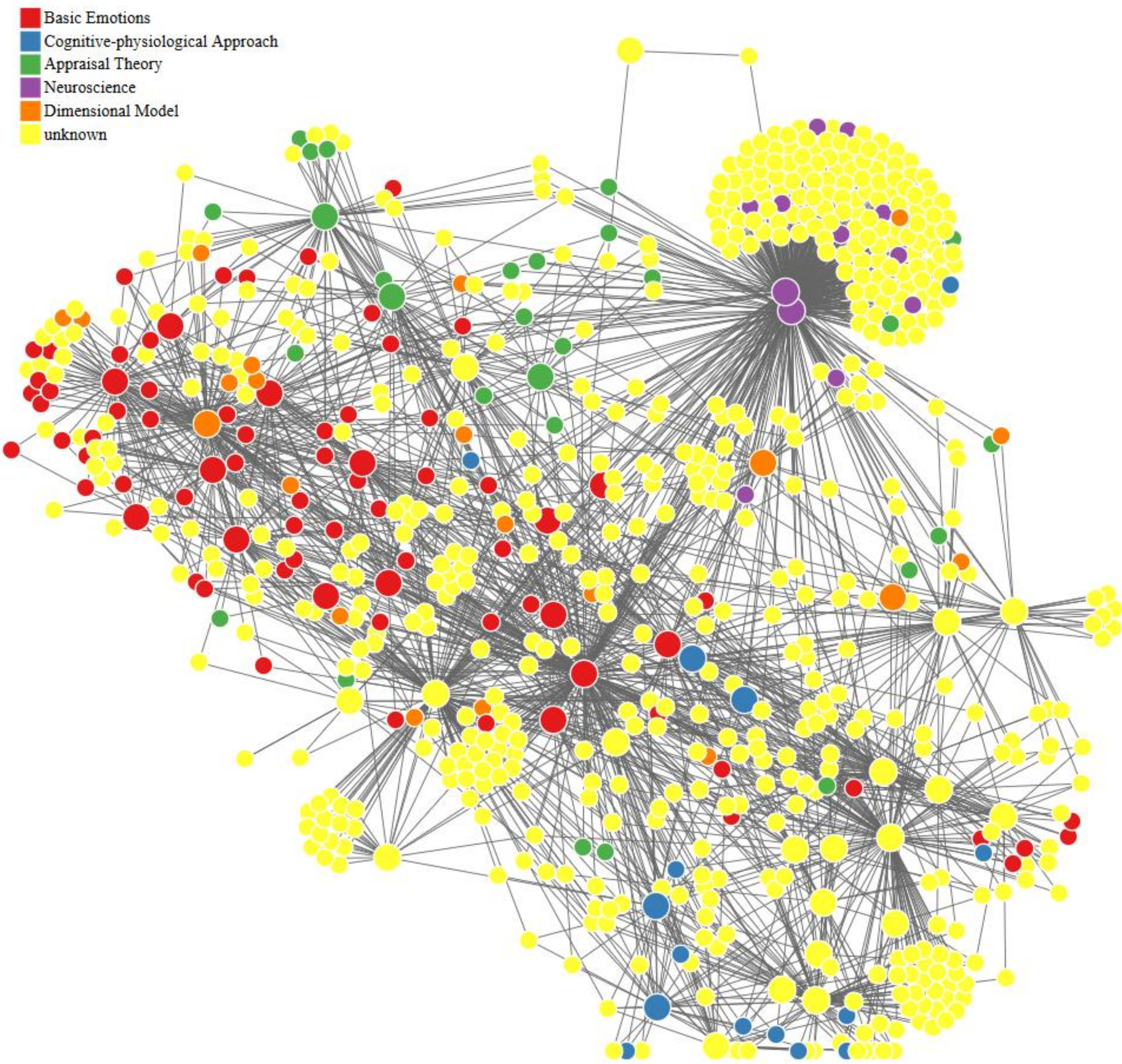


Fig. 1: Visualisation of major "thought collectives" (Fleck) or "schools" (Kuhn) within psychological emotion research.[1]

[1] Network generated from the citations contained within 46 classic studies in emotion research. These 46 studies were most often cited in textbooks published in the past 25 years. The graph reveals the opposition and

While Fleck's and Kuhn's theoretical concepts are grounded in the disciplines in which they were educated (medicine and physics respectively), the study "Laboratory Life" by Latour and Woolgar (1979) represents an ethnographic investigation of the social construction of scientific knowledge in biology. Latour and Woolgar analyse the processes in which scientific facts are being constructed and whereby all traces of knowledge production are deleted. Thus, scientific statements are cleaned from the social circumstances in which they emerged: "an important feature of fact construction is the process whereby 'social' factors disappear once a fact is established" (23). Scientific facts thus simultaneously mean what is at the same time fabricated and what is not fabricated: "fact is taken to refer to some objectively independent entity which, by reason of its 'out there-ness' cannot be modified at will and is not susceptible to change under any circumstances." (174/175) Not only taking into account the mechanisms of "inscription devices" (ibid.), but also the interplay of non-technical factors in the knowledge production process, research contexts will play an eminent role in the epistemologies in emotion research under scrutiny in this report. Our inquiry into the data–information–knowledge–wisdom hierarchy (DIKW) in emotion research will reveal the processes that lead to the transformation of data into information and of information into knowledge (Rowley 2007). Whether this hierarchy applies to all kinds of data and all methodological or epistemological approaches will be investigated across the scientific disciplines.

One of the rare studies to compare two different disciplines – experimental high physics and molecular medicine – led to the coinage of the term "epistemic cultures" (Knorr-Cetina 1999). The findings are based on an anthropological study involving participant observation with analysts in laboratories and interviews with scientific experts. In this report, we will take up the term "epistemic cultures", which has been defined by Knorr-Cetina as "different architectures of empirical approaches, specific constructions of the referent, particular ontologies of instruments, and different social machines" (3), thus analysing "cultures that create and warrant cultures" (1). Being aware of the compartmentalisation within disciplines (e.g. psychology), comprising a multitude of schools of thought, the term "epistemic cultures" will be employed carefully. Due to our meta-analysis within emotion research, encompassing more than a dozen different disciplines, the questions of whether there is something like disciplinary coherence or clear separations between epistemic cultures will be touched upon only selectively. However, our approach to see epistemologies as created through practice will permit discerning current commonalities and differences between and within scientific disciplines and related epistemologies.

Objectivities

Within differing "epistemic cultures", different norms and values are shared within a community of scientists. This also pertains to objectivity, which refers to a shared norm

incommensurability between the "Basic Emotions"-Approach (Ekman and others, in red) and the neuroscientific approach (LeDoux and others, in violet). This visualisation is the output of ongoing research within the K-PLEX project.

within an epistemic culture that internally serves the end to reach consensus amongst researchers, and externally provides legitimacy for the chosen epistemology. A typology of objectivities differentiates between a philosophical or absolute, a disciplinary, a dialectical and a procedural sense of objectivity (Megill 1994). Whereas an understanding of objectivity as an absolute, neutral authoritative view on truth is rejected by most researchers today, debates on which disciplines are better placed to getting at the truth of a certain phenomenon continue. To what extent disciplinary battles over the most adequate way of knowledge production are related to "epistemological insecurity" (ibid. 6) remains unclear. However, social scientists' and humanists' attempts to find a way out of the objectivity dilemma by recurring to dialectical objectivity can be seen as a consequence of the unsustainability of truth claims. The prevailing paradigm within the social sciences and the humanities today is questioning epistemic individualism and centres around intersubjectively and communicatively produced knowledge. The relativist position, assuming that a multitude of perspectives leads to an increased degree of objectivity (Fabian 1994) stands in contrast to a procedural understanding of objectivity. This becomes evident in Daston & Galison's (2007) explorations of scientific developments in the 19th century and the emergence of mechanical objectivity. The ideal of mechanical objectivity was developed as a "new configuration of epistemological convictions […] that aimed to quiet the observer so nature could be heard" (120). It aimed at repressing the wilful intervention of individuals and instead to emphasise procedures. Machines were seen as perfect embodiments of this new kind of objectivity, since they combined virtues like patience, tirelessness and industriousness. The emergence of mechanical objectivity also implied alterations on the side of the subject of the researcher. A new ethos developed, centred around a "morality of self-restraint" (185). The reformulation of the scientific self-evolving around practices including "training the senses in scientific observation, keeping lab notebooks, drawing specimens, habitually monitoring one's own beliefs and hypotheses, quieting the will, and channelling the attention." (199) This new epistemic virtue on the side of the researcher is termed "trained judgment" by Daston and Galison.

While conceptions of objectivity have considerably evolved since the period described by Daston and Galison, the basic distinction between mechanical objectivity and the objectivity of the scientific self sheds light on the heterogeneity of epistemic cultures used in emotion research. Mechanical objectivity can here best be illustrated by putting a research participant into a fMRI scanner used by neuroscientists. A huge research structure is being built in order to explore research participants' individual emotional responses to the stimuli presented in the scanner. On the other side of the objectivity spectrum (the side of the scientific self), anthropological emotion research represents a quite different approach: A solitary ethnographer conducts research within a culture that is initially alien to the researcher and may confront her or him with overwhelming complexity. Here subjectivities and relationality come into play, elements that are (supposedly) missing in the technical environments of laboratories and controlled experiments. The contrast between laboratory and field thus illuminates the extreme poles of differing "epistemic cultures" at play in emotion research. As Knorr-Cetina has pointed out, "laboratory practice entails the detachment of objects from their natural environment and their installation in a new phenomenal field defined by social agents" (Knorr-Cetina 1999, 27), whereas the context of research is completely different regarding the objectivity of the scientific self: "In particular, the relational element seems to be missing or interpreted differently in technical vocabularies – the relationship between the parts and the whole, between one object and others, and, most significantly, between objects and subjects." (Knorr-Cetina 1999, 113). Similar findings have resulted from ethnographic research in the artificial intelligence community. Due to technical and quantitative biases, preference for explicit models, the belief that there is only one correct interpretation and decontextualized thinking, knowledge engineers tend to "delete the social" (Forsythe 2001). "Epistemic dependence" (Pritchard 2015) is then not only knowledge-enabling (permitting the detection of correlations and causalities), but also knowledge-precluding (eliminating noise, ambiguities and contradictions).

Different types of knowledge require different types of justification. Whether researchers rely on empirical knowledge, so the information gained through language, behaviour or sensors, or on theoretical knowledge, so the information supplied by other researchers, has effects on the means of legitimisation. Different "epistemological standards" – "the social rule[s] that specif[y] under what conditions someone is entitled to make a knowledge claim of the given kind, [...] the conditions under which the circle is committed to authorising beliefs as knowledge" (Elder-Vass 2012, 218) thus depend on research methodology. Acknowledging that phenomena such as emotions and affects are socially, culturally and biologically constructed implies that there are multiple ways of framing them scientifically, methodologically, and epistemologically; and that researcher positionalities (how do they relate to emotions and affects as phenomena studied in methodological terms) cannot be neglected. Positivist approaches have grown out of style, as the claim to be able to detect exclusive causal relationships between variables, a priori excludes alternative explanations (see Elder-Vass 2012). Universalist ambitions in favour of generalisations and determinisms, as were implemented for example in the "universal Turing machine", have been deconstructed as being "not about discovering universals that are existent a priori, but about systematically increasing the scope of local principles" (Koch 2017, 16). If knowledge is understood as a matter of credibility, as the level of trust one accords to a particular epistemology, then we are inclined to embrace a relativist view on scientific truths that take into account that scientific procedures of knowledge construction can be multiply biased, hence carefully deconstruct and reflect on them (Henrich, Heine, and Norenzayan 2010).

Structural characteristics of the scientific field

Even though their studies were confined to a single discipline, Kuhn as well as Latour and Woolgar draw a picture of science as an arena in which competition between the different communities of protagonists constitutes the driving force of scientific progress. Kuhn (1970) noted: "Competition between segments of the scientific community is the only historical process that ever actually results in the rejection of one previously accepted theory or in the adoption of another." While Kuhn focuses on the competition between scientific communities and thus explains the emergence of new paradigms, Latour and Woolgar point out that even in the development of new research approaches competing forces are at work: “The elimination of alternative interpretations of scientific data and the rendering of these alternatives as less plausible is a central characteristic of scientific activity.” (Latour and Woolgar 1979, 40)

A major contribution to the scientific field in its entirety as an agonistic field stems from the French sociologist Pierre Bourdieu. In applying the field theory developed by him on the occasion of the French society of the 1960s, Bourdieu described the competitive struggle within the scientific field as a search for legitimacy, recognition, and autonomy, elaborating on asymmetric power distributions and monopolies, and characterising “strategies for conservation or subversion of the structure” (Bourdieu 1975, 27) in the scientific arena. In his description of the forces structuring the scientific field and the opposition between established actors and newcomers, dominant and dominated, holders and pretenders, he uses the terms “orthodoxy” and “heresy”. These terms serve a double purpose: On the one hand they allow him to carve out strategies to defend single theories as the “doxa” to be followed and to defame and marginalize competing theories, or to describe as “heresy” an approach that focuses on examining phenomena that can’t be explained in terms of the current “doxa”. On the other hand, these concepts imported from religious studies, enable him to show that claims to scientific truth take the form of professions of faith. Bourdieu explains the developments within a single discipline, but also the convergences and tensions between different scientific disciplines: “the field becomes the scene of a permanent revolution, but a revolution that is increasingly devoid of political effects.” (Bourdieu 1975, 33) Bourdieu’s insights are relevant for this report, because his theory enables us to explain the competition between, but also within scientific disciplines, the frictions arising within interdisciplinary research projects, and the peculiar relationship between basic and applied research. With regard to the latter opposition, it has to be noted that the testing of the efficiency of academic advances through the application of these approaches leads to a questioning of major theories on the one hand, and at the same time opens up a space for possible societal and political implications of these theories.

Exemplary case study: (Trans-), (Multi-), (Inter-) Disciplinary emotion and affect research

Research on emotions and affects serves as a prolific exemplary case study of aligning, competing, and clashing epistemologies in researchers’ attempts to turn real-life phenomena into data. With an implicit scholarly divide that ascribes the scientific research of physiological and non-verbal phenomena to the ‘inner disciplines’ (psychology, psychiatry, neuroscience, biology) and their performative, discursive and narrative dimensions to ‘outer disciplines’ (anthropology, cultural studies, literature, linguistics, performance studies, philosophy, sociology), with the latter positioning themselves at the critical science margins and (sometimes) meandering along the fine line between social science, humanities and art, the field is set for our critical metastudy into data(fication) and competing epistemic impacts.

Contemporary emotion research agrees on basic theoretical assumptions regardless of its scholarly origin: emotions are defined as bio-cultural processes that emerge when persons negotiate, engage or interact with someone or something, be that real or imaginary, be it related to the past, present or anticipated future (Dixon 2012; Engelen et al. 2009; Godbold 2015; Izard 2010, 2011; Lindquist and Gendron 2013; Matt 2011; Mesquita and Boiger 2014; Mulligan and Scherer 2012; Russell 2014; Stodulka 2017c). They are considered relational phenomena, where the experience and articulation of the self never exist without 'the other'. Epistemic dissent does not primarily arise from incompatible theoretical premises (except when we intentionally misread each others' arguments), but mostly results from different analytical scales: does the researcher focus on physiological arousal; individuals' experiences; or their encounters, communication practices and language patterns; or the transmission and circulation of emotions and emotion words within and between groups and collectives; or the feeling and display rules of collectives and societies; the emotion rhetoric of nation states; the social and cultural force of emotion words articulated in and between cultural and social contexts? Regrettably, this inevitable analytical prioritization often goes hand in hand with an artificial atomization of the phenomenon of 'emotion' itself when transformed into scientific data. This obstructs a trans-, multi-, or interdisciplinary emotion research that feeds into comprehensible, comparable and mutually beneficial scientific knowledge within and beyond different disciplines.

In what terms could emotions and related phenomena be defined from an integrated inner/outer sciences perspective? This is a particularly interesting question in emotion research, where manifold epistemologies converge, intersect and refute each other. In order to better understand this study a few preliminary conceptual notes seem necessary.

Emotions as folk theory. Emotions are more than verbally articulated symbols that hint to a deeper social and cultural meaning. They unfold as important embodied non-verbal communication and interaction practices. Besides words and prosodies, particular facial expressions and body postures are socialised by means of cultural transmission, intergenerational and peer negotiation. As bio-cultural processes (Röttger-Rössler and Markowitsch 2009) within and between persons, their bodily displays and verbal articulations are related to local display and feeling rules (Röttger-Rössler and Stodulka 2014; Stodulka 2017a, 2017b, 2017c). They are not just rhetoric analogies of cultural norms related to the articulation of emotion words.

Emotions are motivators for action and interaction that relate to social, cultural, economic and physiological needs and wants. Their display and articulation are both affected by and affect others. Emotions are crucial factors in relating or disconnecting people from each other. As bio-cultural processes they are pivotal in forming ties of companionship, establishing and reproducing animosities that can escape social or cultural logic. Non-articulated yet shared emotions can incite social movements, riots, or wars that escape the culturally explicable. Emotions are vital practices of navigating our everyday lives. They help persons to experientially assess their environments. The feelings that humans ascribe to physiological sensations make them seek, ignore, circumnavigate or avoid certain people and situations. If 'out of social or cultural tune', emotions can cause severe trouble to the person's and related others' health and well-being. Sometimes these irritations can develop into chronic states or so-called 'pathologies' and have to be treated by cultural, religious, medical and other experts. 'Emotions out of tune' are hardly articulated, and yet there can be striking non-verbal evidence that affected persons and their environments severely suffer. A more theoretical and systematic anthropology of emotion can capture all these different facets without having to fear an accusation to subjectively 'project' the anthropologist's Ethnocentric culture, mind or brain on those studied (Beatty 2005; Geertz 1983). What we need is more conceptual clarity.

What complicates the theorizing of emotions, besides its difficult systematic observation, documentation, and lucid translation into narrative text is a terminological mystification of emotion-related concepts. There has been little interest in compelling integrative theories of 'affect', 'feeling', 'emotion', or 'emotive' across major disciplines involved in emotion and affect research. Despite diverse scholarly origins and analytical scales, contrastive definitions of emotion-related phenomena can benefit the scientific analysis and understanding of human experience, behavior and speech (Kleinginna and Kleinginna 1981). Instead of rejecting concepts due to their 'alien' disciplinary backgrounds, their integration can add to the scientific comprehensibility and transparency. Which underlying theories scholars of different 'schools' or 'thought collectives' apply is not a matter of eclectic 'tool-kitting', but allies with preferences and *zeitgeist* vogues. For this report, the subsequent classification, which is based on this work package members' longterm experience in (inter-)disciplinary emotion and affect research, shall serve as theoretical framing.

Affect and feeling in science. 'Affects' are referred to as "nonconscious and unnamed, but nevertheless registered, experiences of bodily energy and intensity that arise in response to stimuli impinging on the body. (…) Affect, then, is the body's ongoing and relatively amorphous inventory-taking of coming into contact and interacting with the world" (Gould 2009, 19–20). Moreover, affects are considered opaque experiences, as something that we do not quite have language for, something that we cannot fully grasp, something that escapes us but is nevertheless in play, generated through interaction with the world, and affecting our embodied beings and subsequent actions. Sociologist Deborah Gould calls that "bodily, sensory, inarticulate, nonconscious experience affect" (ibid.). Accordingly, social psychologist Nico Frijda defines such processes as basic physiological arousals perceived as affective states as activated in all emotion-related human experiences (1994, 61). Gould writes "affect is what makes you feel an emotion" (2009, 22).

In an extension to affects, we contend that feelings are what humans subjectively ascribe to self-aware physiological arousals (affects), when they experience someone or something as pleasant or unpleasant. Feelings shall be defined as cognitively appraised affects. In the words of Antonio Damasio, a trained neuroscientist, 'feeling' is "some variant of the experience of pain or pleasure as it occurs in emotions and related phenomena; another frequent meaning refers to experiences such as touch as when we appreciate the shape or texture of an object" (2003, 3).

Although ‘affects’ are considered as self-aware physiological arousals and ‘feelings’ as their cognitive appraisals, they are relational to other bodies and environments. They are considered universal human capacities (Ekman and Cordaro 2011), but their physiological configuration is not necessarily identical between different persons or cultural contexts (Fessler 2004). Although human bodies, minds or brains share similar universal capacities, the physiological build-up and the situations that induce affects and feelings are related to biographical, social, political, and cultural dimensions. The physiological arousal that relates to ‘love’, for example, might not ‘feel’ the same nor are the social events that trigger the affect, or its connotations as pleasant or unpleasant necessarily similar within and across different cultural contexts (Jankowiak 1997; Röttger-Rössler and Engelen 2006). Compared to feelings, affects lack the physiologically aroused persons’ cognitive appraisals. In the original sense of the Latin word *afficere* (*ad-facere*; ‘to work on’ or ‘to influence’), affects are mere changes in the person’s physiological condition triggered by a stimulus. Feelings are considered as cognized affects, and yet, from a contrastive perspective, they lack the communicative capacities of ‘emotions’ in the form of culturally constructed, shared and circulated emotion words.

Emotion in science. Emotions are defined as bio-cultural processes. They relate physiological arousals and their cognitive appraisals with their surrounding local worlds in terms of a mutually shared cultural rhetoric. Moreover, emotions comprise of a cultural repertoire that enables persons to express their own and label other persons’ observable affects and articulated feelings in intersubjectively shared and understandable emotion words. Relating to their individual pre-experiences, biographies and sociocultural socializations, persons are able to exchange information through impulsive, learned, habitualised and staged emotions by means of words, facial expressions, gestures and body postures. Accordingly, anthropologist Linda Rebhun writes that “deliberation, rehearsal, and requirement are as integral to emotion as spontaneity and do not render it any less ‘true’” (1993, 137). In other words, even staged physiological arousals and cognized affects carry important cultural and social messages in the form of emotions. Orchestrated emotion displays can provoke social, cultural, economic or psychological consequences for oneself and related others. Within the daily politics of social life they can make up powerful tools in order to manipulate others for one’s own and related others’ gain. This social force can be achieved through the articulation of emotion words, facial expressions, and body language, also defined as ‘emotives’ (Reddy 1997).

3. Methodology

The aims of the survey and the interviews are as follows:

– To obtain detailed and contemporary knowledge on epistemic processes in various disciplines; the comparability of the answers is given through the cross-sectional topic of inter- and transdisciplinary emotion research.
– To understand the interplay between theoretical underpinnings of scientific workflows, the utilisation of research tools, methods and methodologies, and the design and potential barriers to institutionalised data structures and data sharing.

It is a well-known fact that different methods or framings of the object of research result in different findings (Misa 2009). Our methodological approach embracing both interviews and a survey is in its multi-perspectivity well suited to close this gap. The empirical enquiry into leading researchers' practices and narratives regarding cross-disciplinary collaboration in terms of methodologies, datafication, data management and sharing illustrates basic epistemological challenges to data aggregation in the context of messy, small-scale and big data sets.

3.1. Survey

The survey was designed to address the following research questions and hypotheses:

- Which aims do emotion researchers pursue with their research and what are their objects of research?

- What are the methods researchers employ in order to investigate emotions and affects? Are mixed method approaches common and if yes, which combinations of methods can be found?

- What kind of data and what volume of data does the research yield? Does the choice of methods and data structure depend on the disciplinary background of the researchers or on their theoretical assumptions?

- How frequent are interdisciplinary research groups that collaborate in terms of data sharing and which disciplines engage in data sharing?

- In what way does the size of research units, the funding and runtime of research projects influence research designs? What happens to the data once they are collected, created, cleaned and analyzed? Which challenges do emotion researchers face in regard to publishing and sharing their data?

3.1.1. Description of Survey

The survey was pre-tested and adapted before being sent to our survey participants. Our group of pre-testers was composed of two anthropologists, one psychologist, a statistician and a scholar from Theatre, Cinema and Media Studies. Three more scientists we had contacted (a sociologist, a psychologist and an educationist) were not available for the pre-test. As a result of our pre-test the number of questions were reduced and some of the questions clarified. We finally discussed the preliminary survey with a member of the statistical consulting team of Free University of Berlin.

The survey comprises of fifty questions, subdivided into the sections of (a) data and data processing, (b) methodology, (c) research organization, (d) sharing data and (e) personal information (approx. 30-45 minutes). To make the questionnaire as inclusive as possible most of the multiple-choice questions provided a wide range of answer categories (13 categories for “objects of research”, 8 categories for “kind of data”, 11 categories for “research methods”, etc.). Additionally, the additional category “other” was provided for many questions. The survey was completed with some open-ended questions, for example regarding the scientific aims, the key challenges or theoretical biases. Due to ethical and privacy issues, no questions concerning the countries of residence or names of research institutions were included. The survey was directed at emotion researchers of all disciplines. When filling out the survey the participants were asked to refer to their most recent research project. This enables us to better compare the researchers’ answers.

There are no figures concerning the number of emotion researchers currently working at universities and research organisations. Therefore, the sampling strategy employed was a mix of grab sampling and snowball sampling. Many of the researchers in our list were drawn from leading edited books in emotion research. These books comprised interdisciplinary handbooks in emotion research but also edited books by outstanding researchers in disciplines like literary studies, computer studies, sociology, social and cultural anthropology, history, philosophy and psychology. The list of emotion researchers was completed by participants of research clusters, networks and research centres. We created a list of 385 researchers, aiming to include all possible disciplines. Roughly clustered, 106 researchers on our list belong to the humanities, 22 to the natural sciences and 257 to the social sciences. This list – not being exhaustive – tries to include as many countries and institutions as possible. Most of the researchers we contacted personally are located at European universities or research centres. As we invited the emotion researchers to forward the weblink to our survey to colleagues, we do not know who was informed about our survey beyond the researchers we had contacted.

The online survey, accessible on a *SurveyMonkey* website, started on 31 August 2017 and was closed on 6 November 2017. The first invitation to participate in our survey was followed by three reminders in September and October. This was justified by the runtime of our online survey, starting during the summer break when many researchers were out of office. After the first three weeks 26 researchers had filled out our survey, the first reminder brought us 16 more datasets. The second reminder three weeks later was then written in

German for all German-speaking researchers (who constituted almost half of the researchers contacted) and in English for all other researchers. Additionally, we circulated the invitation among research clusters. As the number of datasets increased by 25 more participants by mid of October and our goal had been set at 100 responses we sent a last reminder, directed to each of the researchers personally. Hereby we attained 56 more responses. The total number of responses for our survey is therefore 123.

The feedback to our survey was predominantly positive, only few resigned because they were not active in emotion research anymore and few failed because of technical problems or because they attempted to fill in the survey after 6 November 2017. Twelve researchers had started with the survey but did not complete it. Those were either researchers from the humanities (philosophy, history, philology) or social scientists working with qualitative methods or only on a theoretical level (sociology, anthropology, political sciences). The reasons they gave for dropping out were that they felt the questions were not appropriate for their own approaches, but only for empirical or quantitatively working researchers. This becomes obvious in statements like: “I don’t find the questions to be very relevant for a cultural historical approach“, “I started answering the questions but then already on the 2nd page realised that they are geared to quantitative researchers, so I gave up” or “I began to fill in the survey few days ago but soon realised that it is so heavily targeted for empirical researchers that I had severe problems with giving sensible answers and finally gave up after 30 mins, not being even near finishing. I excuse for opting out; in brief, my research is theoretical and my data are others' studies, both theoretical and empirical”. Although the mean time spent for answering the survey was about 34 minutes, time constraints were another important factor for not participating in or finishing our survey.

Of the 123 survey responses 81 were completed. When comparing the number of humanities scholars, social scientists and natural scientists on our list with the number of those who have participated in our survey, it can be shown that whereas humanities scholars are underrepresented (every 6th humanities scholar participated in our survey), social scientists are adequately represented, and natural scientists are highly overrepresented (a third of all natural scientists contacted have filled in the survey).

3.1.2. Drop-out rate and analysis of related statements

Furthermore, the analysis of the dropouts is revealing with regard to the objects of research and the kind of data collected. Of the 29 survey participants who had indicated “history of emotions” as their object of research, 15 dropped out of the survey. This remarkable detail suggests that a considerable number of dropouts can be located within historians. The analysis of the dropouts’ scientific aims such as “insights into historical discourses on emotions and their significance for literary texts” or “a better understanding of how emotions and emotional expressions were integrated into social practice in early modern societies” substantiates this finding. Another interesting detail is that almost half of the survey participants who work with models (i.e. researchers from disciplines like psychology, cognitive science, computer sciences or biology) also dropped out of the survey. The according scientific aims of researchers working with models such as “clarify brain mechanisms of pleasure, desire and emotion” or “understanding how human decision-making processes can be simulated by computers” make it very likely that those researchers come from the above-mentioned disciplines. A more detailed analysis of the dropouts can give us further cues about the motives of the researchers. Interestingly most of the dropouts exited the survey at question 12 which elaborated on the role of theory within the research process. Aside from time allocation issues, we see the reasons in particular understandings of theory, either regarding theory as something that only incipiently influences the research process[2] or as accompanying the whole research process (which would make question 12 meaningless). Many other dropouts exited our survey at questions 5 and 6 which related to quality checks applied by the researchers. Two observations suggest that these questions functioned as knock-out questions for several emotion researchers. First, one third of drop-outs perform quality checks, conversely two thirds of the researchers who finished our survey engage in quality checks. Secondly, researchers with qualitative approaches apparently had difficulties with these questions, since they neither checked one of the supplied answers nor added examples of non-quantitative quality checks to the answer category "other".

Whereas the analysis of the dropouts provided only implicit information on probable reasons for exiting our survey, all researchers who completed the survey were given the opportunity to give us direct feedback on our survey. The last question in the survey invited them to comment on important aspects of our survey which they felt were lacking. Some researchers were rather critical towards our survey. Two survey participants complained about unfamiliar terms given without definition: “It used many terms that were unfamiliar to me and in need of definition so I am not sure those responses will be useful”. Others complained about missing answer categories, a bias towards quantitative research and a suggestive use of the term “data cleaning”. The definition of “data cleaning” provided was taken from Brine and Poovey (2013, 70) and describes data cleaning as the removal of “incorrect or inconvenient elements from the available data, supplying missing information, and formatting it so that it fit with other data”. Apparently, this definition does not distinguish between incorrect and inconvenient elements and can create the impression that any deletion or transformation of data is allowed when this is in favour of the underlying theoretical assumptions and hypotheses. Some researchers like a PhD student or two academics working in departments or large collaborative studies apparently had difficulties in answering questions concerning the organizational structures. A few researchers made propositions on how to improve our survey, for example by adding a “do not know” answer category or by asking questions about philosophical approaches to the topic.

As social science and humanities scholars engaging in critical epistemologies and reflexive scholarship we consider drop-out trajectories and typologies as valid knowledge in order to assess scholars’ hesitancy with regards to data quantification and a jargon that imitates

[2] See for example the following comment: “I also did not like the answer categories for the question about theory. I use theory to formulate hypotheses, so in a way it guides my data examination, but the answer data examination and interpretation sounds like making your data fit your theory”.

quantifying and essentializing ‘big data’ rhetoric shaped by the computer sciences. The comments and feedback speak a language of uncertainty, uneasiness and scepticism towards (big) data. A very specific understanding and use of the term “data” formed an obstacle for responding to several of the survey questions. Statements like the following one, shows the difficulties and ambivalent attitudes towards the term “data” as valid scientific concept: “I don't use quantitative data and statistical analysis. Researcher's relation to the ‘data’ may be different” show the difficulties and ambivalent attitudes towards the term “data”. This was not only manifested in feedbacks to the survey but also in the specifications within the “other” categories and open-ended questions. Section 4 and 5 will explain this in greater detail. Other comments provided insight into some of the reasons for skipping questions as the following statement shows: “I did not answer the question about standardised workflows. Of course, I use standards, but I do not totally standardise the workflow or the data”. Both surveys and interviews speak a discursive language of resisting and subverting the “data” concept, calling for more epistemological debates on “big data” also with reference to finding more integrative terminologies.

3.2. Interviews

The driving research questions for the interviews were as follows:

- Which aims do emotion researchers pursue with their research, which key challenges do they see?
- How do they assess the process of datafying emotions?
- Which benefits and challenges do they see in Big Data research or in large-scale analyses of emotions?
- What are their experiences with interdisciplinary collaborations?
- What are the obstacles they view in the integration of the available datasets?
- How do they view the history of emotion research, the cooperation between different theoretical strands and the emerging areas in emotion research?

WP4 generated a pool of questions that were then designed as semi-structured interviews adapted to our interviewees’ scientific aims, institutional background and objects of research. The mean duration of an interview was one hour (ranging from a minimum of 44 minutes to a maximum of 1 hour and 19 minutes). Researchers of various disciplines in the field of emotion research, located at European universities, research institutions or companies were contacted. The first of 15 interviews with 17 researchers (two interviews comprising two researchers) was conducted in June 2017, the last in January 2018. Where possible, the interviews were conducted face-to-face, with the exception of six interviews conducted either by Skype or telephone. All of the interviews were recorded and then transcribed using the transcription software “easytranscript”. The disciplinary backgrounds of our interviewees included (historical, social and cultural) anthropology, sociology, philosophy, (comparative developmental) psychology, neuroscience, computer sciences, language technology, computational linguistics, and software engineering. Four of our interviews were conducted with persons located in a public-private partnership or private companies applying science or developing their own apps. One interview was conducted but the transcript could not be used for our analysis because the consent was withdrawn by the researcher after the interview, indicating a dissatisfaction with the genre 'interview' and having said everything in a more pointed way in publications. Several requests for interviews remained fruitless. We contacted 23 researchers and developers repeatedly for an interview, but they were not available or did not respond to our request. It was especially challenging to find software developers, as well as to successfully conduct interviews with representatives of research funding bodies and big tech companies in order to gain insights into the structures of scientific knowledge production or their more applied dimensions. Regarding the research funding bodies we assume that the reasons for not participating in interviews can be located in the transversal character of the field of emotion research, since many research projects are crossing disciplinary boundaries while addressing particular questions there seem to be no specific guidelines for funding research on emotions and affects; moreover, funding bodies may follow policies not to grant interviews.

The total number of 15 interviews were transcribed, anonymised and sent to our interviewees for approval. Anonymization involved the deletion of the personal names of our interviewees and their research associates as well as the names of affiliated institutions. Furthermore, titles of books, journal articles or research projects in which our interviewees were involved were deleted.

3.3. Data Analysis

3.3.1. Survey

The survey data collected with *SurveyMonkey* was downloaded as an SPSS file for further processing and analysis. The survey data underwent data cleaning before we were able to process it further and start analysing it. Cleaning data, in our perspective, meant that we identified incomplete data sets, implausible answers or answers matching other questions than the ones they were attached to. Finding and defining missing information, especially for the multiple-choice questions, was another important step before a first descriptive analysis could be conducted.

3.3.1.1. Sample characteristics

Altogether 123 researchers have participated in our survey, 81 finishing it, though some questions were skipped by some of the survey participants.

Disciplines

The sample of researchers who completed the survey encompasses more than thirty disciplines, whereof the most common cited are psychology (20), sociology (10), linguistics (7), and literary studies (6). All the other disciplines were mentioned one to four times. Other disciplines include history, political science, computer science, biology, anthropology, philosophy, pedagogy, theatre sciences, cultural studies, pharmacy, medicine, nursing science, and cognitive science. Grouped into humanities, social sciences and natural sciences the overwhelming majority of survey participants (58) belongs to the social sciences, whereas less researchers (16) are located in the humanities and comparatively few (7) belong to the natural sciences. Our classification of social sciences is comprised of the following disciplines: psychology, sociology, pedagogy, cognitive science, political science, anthropology, linguistics, nursing science and medicine. The humanities include the disciplines history, literary studies, theatre sciences, philosophy and cultural studies. The natural scientists, who have participated in our survey, belong to the disciplines computer science, biology and pharmacy.

Career stage, age and gender

Regarding the professional position of researchers who completed our survey, the majority were professors (16) and associate professors (20), followed by postdoc researchers (28) and a rather small number of doctoral researchers (9). As the question on the researcher's position was part of the final section of our survey, we have no information on the positions of emotion researchers who exited the survey. The distribution of our survey participants' positions is reflected in age with most researchers (34) between age 31 and 40. Quite many researchers (14 and 15) are between age 41 and 50 and age 51 and 60. Rather few researchers (6 and 7) are either younger than 30 or older than 60. Of those survey participants who completed the survey 37 identified as female and 35 as male.

3.3.1.2. Data Cleaning

Diverging figures in the presentation of the results can be explained by missing values in the regarding variables. 20 out of 50 survey questions were either open questions or had the response category "other" to be specified by the survey participants if needed. For example, the question on the kind and volume of data collected turned out to be one of the trickier questions of our survey. Three researchers mentioned that they did not understand the abbreviations we had used for the data volume (KB, MB, GB and TB) and that their answers were therefore probably wrong. Other answers were equally surprising, for example audio files, images, or sensor data identified in kilobyte. Whilst we decided to set these answers as missings, in order to prevent the study from quantitative data distortion, their discursive language hints to scientific knowledges beyond data entities. Other implausible answers were found regarding quality checks and the monetary worth of equipment involved in research projects.

Data cleaning also involved completion of missing answers, especially regarding the disciplinary background of our survey participants, one of the most important variable for our analysis. By missing-data imputation we were able to infer the discipline of seven survey participants. The criteria applied were combinations of the following variables: the scientific aims (Q02), the theoretical biases researchers see in their work (Q21), the object of research (Q01), the three most important authors for the researcher's own research (Q15) and research unit composition (Q29).

The answers given in the "other" category had to be categorised, either by subsuming them under existing categories (i.e. subsuming the research method "text analysis" under "desk research") or creating new categories (i.e. the category "external restraints" as one of the reasons why researchers did not publish all of the results of their last research project).

3.3.1.3. Descriptive analysis and qualitative coding

Some of the variables had to be recoded because of the very fine-grained answer categories would make their analysis very difficult and would not yield any significant results. This problem applied for example to the questions dealing with the research unit's collaborations with researchers and institutions. The number of categories was hereby reduced from ten to four different categories in order to meaningfully correlate research units' collaborations with scientific disciplines. Additionally, indices were constructed for some of the variables, in order to differentiate between researchers with data volumes in kilobytes, megabytes, gigabytes and terabytes for example or between those with one, few and many research methods applied. For the analysis no weighting variables were applied. The open-ended questions regarding the scientific aims, the key challenges, problems of datafication, and theoretical biases were analysed qualitatively.

A first analysis of the 50 variables was done descriptively, this means that frequency tables for every variable were created. As most of our variables were nominally scaled, the range of appropriate measures was limited to the mode as a measure of central tendency and bar charts as visualisations of the answer patterns. Although our sample is comprehensive through its careful design and balanced recruitment of respondents and interviewees, the total population of emotion researchers is impossible to assess and therefore our sample is not representative and significance levels (p-values) have not been calculated. Statistical operations like chi-square tests, nonparametric statistical methods or logistic regressions had been excluded from our analysing tools. We focused on the distribution of variables presented in crosstabs and correlations of particular variables; for example, to assess whether the academic background of the researchers suggest differences in the theoretical approaches, the data collection methods, or the collaboration and data sharing with other researchers. With more than thirty different disciplines covered by our survey a detailed statistical analysis would be ethically misleading since it allows for identification of individual persons. We therefore assigned each of the researcher to either the group of humanities scholars, social scientists or natural scientists (see sample characteristics above).

3.3.2. Interviews

The transcribed and anonymised interviews were coded and analysed with the help of the software Atlas.ti. A preliminary set of codes was created by referring to our list of interview questions. More generally applicable codes were added that not only focused on epistemological aspects within emotion research, but which could also provide potential links to the other work packages of the K-PLEX project. These codes comprised e.g. “hidden data”, “uncertain data”, “complexity”, “context dependency” or “theoretical/methodological bias”. Each code within the codelist was provided with a content description, its properties or brief examples for reference. These codes, most of them grouped within eight code families, were applied deductively to the interview material, yet complemented by inductively emerging (in-vivo) codes. Ultimately, the code list comprised of altogether more than hundred codes (see Appendix 3).

Some of our codes were later merged with other codes in order to create a reasonably and comprehensively applicable set of codes. This applies e.g. to the code “software development” that was merged with the code “Coop researchers + developers” (Cooperation between researchers and developers in the development of tools) or to the code “voice analysis” that was merged with the code “speech analysis”. Some of the codes on our preliminary codelist had not been applied and were therefore deleted (e.g. “research policies” or “sampling methods”). Some codes turned out to serve no particular purpose, for example “blind spots”, were therefore deleted and the according citations were attributed with the more precise codes “knowledge gaps” or “conceptual gaps”.

In order to increase inter-coder reliability, each of the interview transcripts was coded by two of the work package members. This approach guaranteed the consistent application of the codes by each coder and enabled multiple interpretations, taking into account different layers and perspectives of analysis, keeping each other in check. Ultimately, we obtained thickly coded interview transcripts with more than six hundred citations. Memos written in Atlas.ti were very helpful for our analysis as they identified some of the overarching topics that might structure the presentation of our findings.

4. Findings and Results

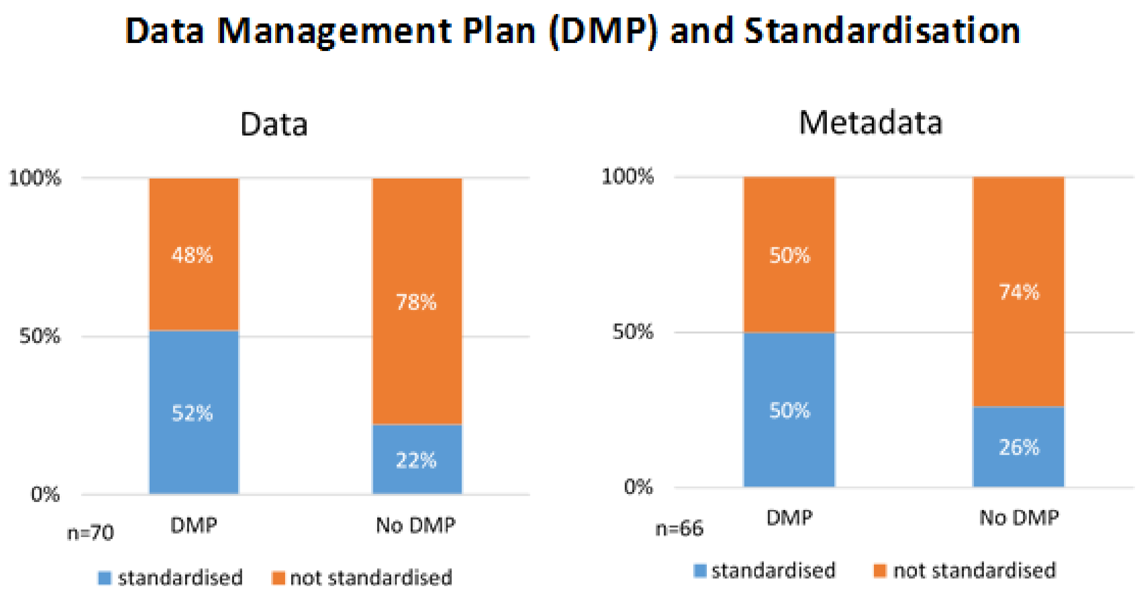
4.1. Survey results

The findings of our survey comprise both general results for all emotion researchers as well as an analysis of the commonalities and differences regarding researchers' disciplinary background, but also the theoretical underpinnings, methodological approaches, or organisational factors. Ultimately, our analysis conveys results on overarching issues, such as data definitions, the process of datafication and the loss of information in the course of the reduction of complexity, all issues that equally figure in the report of WP2. Common themes with WP3 can be located in the discussion on standardisation and the willingness to share data and other outputs of the research. The issue of translations and machine learning that is central to WP5's research was addressed by some of our interviewees, but did not come up in the survey. The same is true for the topic of big data that did not explicitly figure in the survey. Questions on data types and data volumes however allow us to draw conclusions on the differences in availability of data for scientific disciplines. A detailed analysis on the (potential) benefits and challenges of big data within emotion research can be found in section 4.2.5.

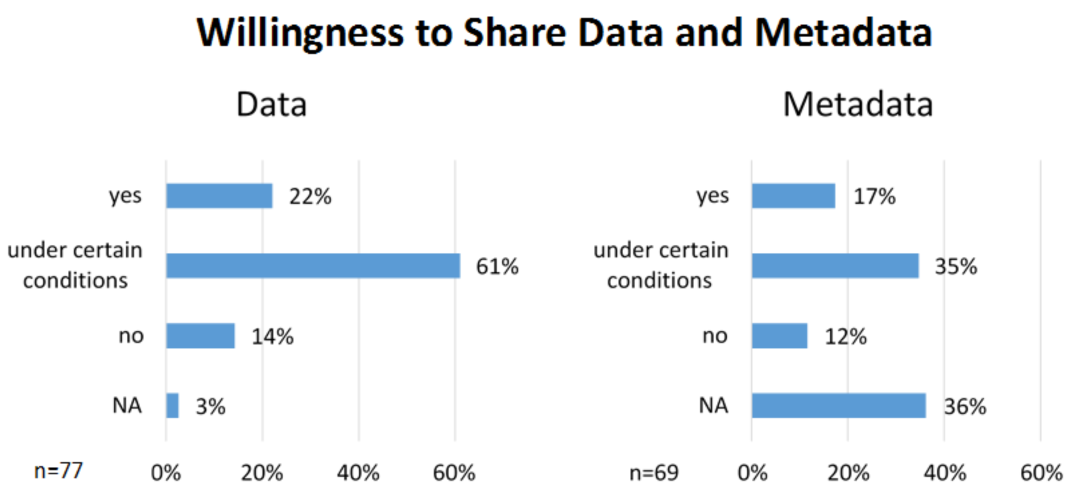
4.1.1. Sharing and processing data

In this section of the survey we focused on data practices of scholars in emotion research, especially the collection, transformation and dissemination of research data. Although the answers to these questions are not sufficient to clearly distinguish between and characterise epistemic cultures, the findings are revealing in terms of the differences between humanities, social sciences and natural sciences. We will first discuss the questions of standardisation, data reuse and data sharing before going into the details of the different kind of data created in emotion research and closing with an examination of divergent approaches to quality criteria.

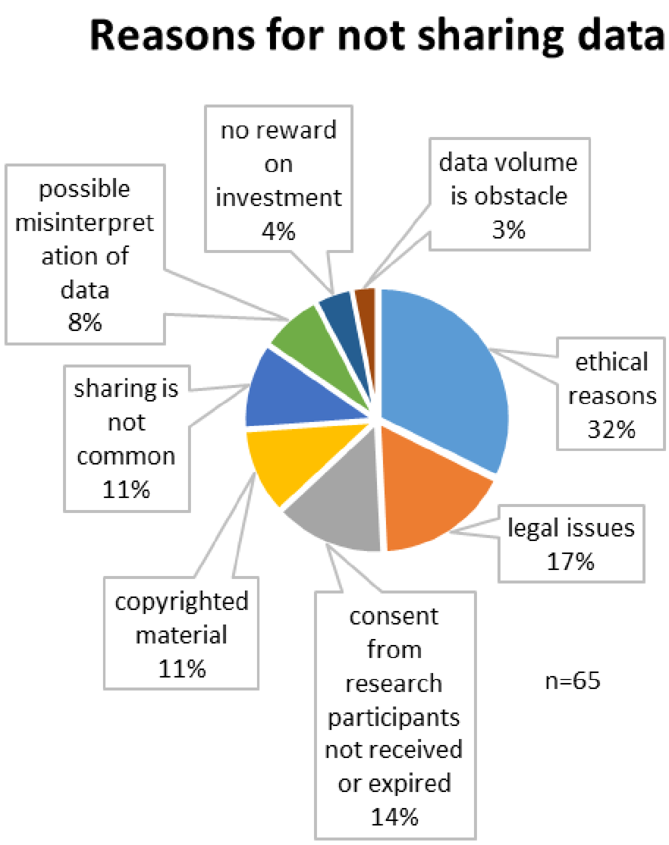
The research designs and organisation of data structures of a majority of research projects on emotions and affects are not standardised. The highly specific approaches in each of the research projects regarding the methods used and the kind of data collected could be one explanation of non-standardized workflows, data and metadata. Another possible explanation is, that because we had not provided a definition of the term "standardisation" in our survey, survey participants are not familiar with 'datafication' and 'big data' terminology. 64% of the participants state that their institution does not have or provide a Data Management Plan. It is worth noting that survey participants not having or not being aware of a Data Management Plan disproportionally often report to not follow standardised workflows. Even more clearly correlated with the lack of a Data Management Plan is the non-standardization of data and metadata. 78% of the researchers without a Data Management Plan work with unstandardised data; 74% of the researchers without a Data Management Plan with unstandardised metadata.



Nevertheless, this seems to be neither an obstacle for reusing their own data, which two thirds of the researchers indicated, nor is it an obstacle for sharing data and metadata with researchers from the same or other institutions, which many researchers (81% with regard to data and 52% with regard to metadata) would agree to do (under certain conditions).

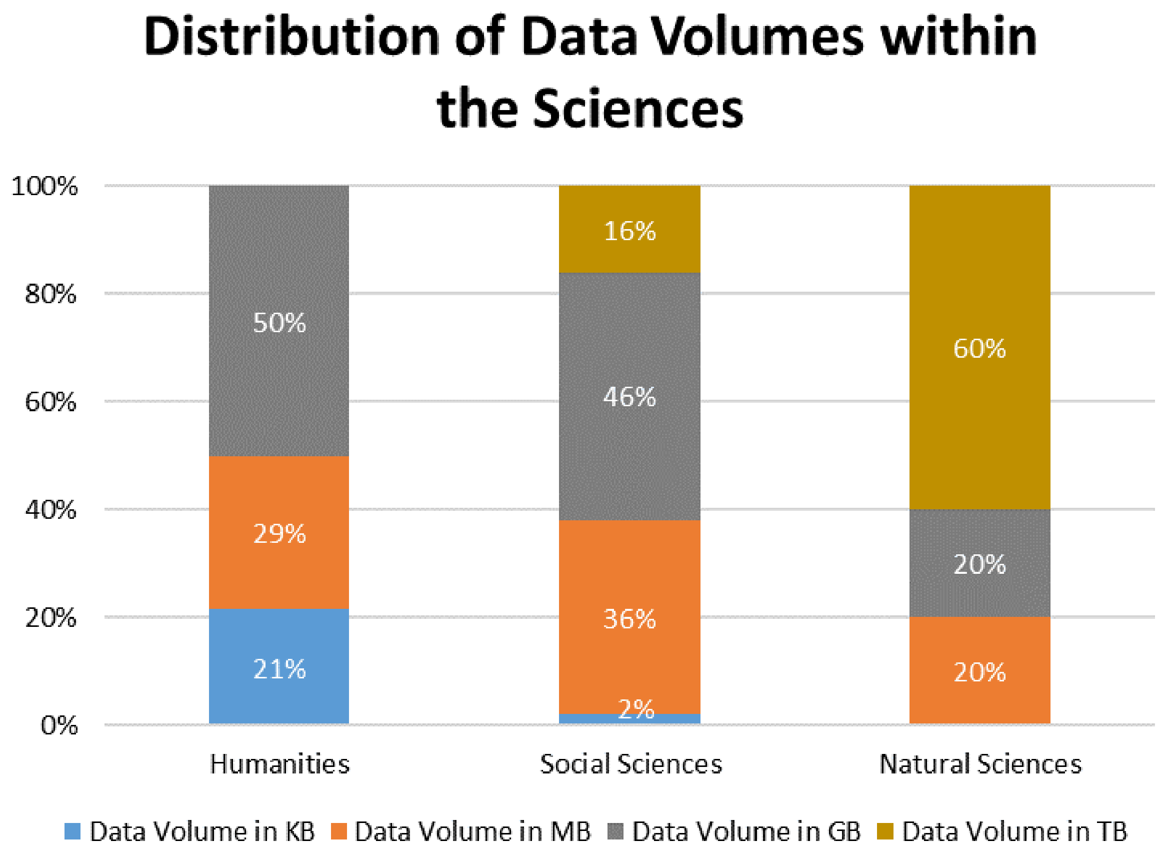


However, this general agreement to the principle of open data should not divert attention from the fact that respondents indicated important reasons for not sharing data. Most prominent are ethical and legal issues as well as concerns pertaining to copyright. Regardless of these reasons there are differences in the willingness to share data among the scientific disciplines. Almost a third of the humanity scholars do not intend to share data, metadata or other research results. The reluctance to use the term "data" that goes hand in hand with the reluctance to see the research objects as data (see answers such as "no data to share", "In my analysis I focused on a text theory which did not imply any 'data' in the empirical sense" or "You are interested in problems of data but this is not my kind of work") might explain this to some extent. A real 'culture of open science' can be found only among natural scientists, where 43% of the survey participants claimed that they shared all of their research outputs (under certain conditions).



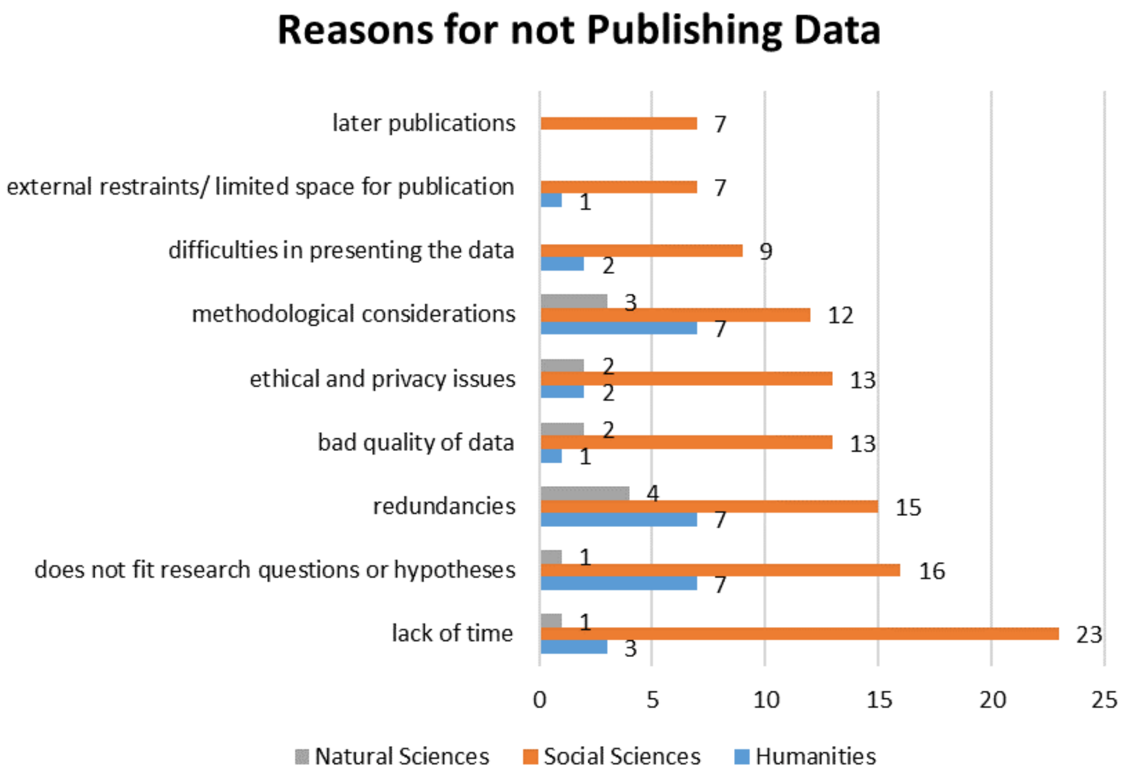
Most survey participants worked with text data (80 out of 123 researchers), both documents written by others, such as historical and literary sources or text collected on the internet, and text data created by themselves, such as interview and video transcripts or observation reports. Audio files, images, videos and spreadsheets were collected by about a third of the researchers. When asked about the importance ascribed to different kinds of data for their research, the majority of researchers see text data as the most important data. Almost all of the humanities scholars (81%) use text data and strikingly often it was indicated to be their most important data. Also 79% of the social scientists use text data but not necessarily as the predominant data, but rather as complementary data.

The second most important data source for researchers is behavioural data. For 22 out of 53 researchers who use behavioural data, these data are the most important data. These researchers tend to be either social or natural scientists. Behavioural data are rarely used in the humanities, with only two scholars stating that they use this kind of data. Video and audio data are used by 46 resp. 45 researchers. These kinds of data seem to be of secondary importance to researchers. Video data is mostly used by social and natural scientists, audio data is equally used by all researchers, independent of their disciplinary background. Neurocognitive and peripheral physiology data occupies the least cited data source of researchers. Only 33 resp. 31 researchers say that they use neurocognitive or peripheral physiology data and very often only as secondary data. Neurocognitive and peripheral physiology data is primarily used by social scientists (psychologists). In this regard, the differences between the disciplines are striking. While humanists often collect only one or two different types of data with rather low data volumes, natural scientists by the majority have several kinds of data in terabyte at their disposal. However, focusing exclusively on data volumes could potentially create a false impression of "dataphobia" within the humanities. The discussion in section 5 will further elaborate on the peculiarities of humanities sources and materials.



Differences also exist in the further processing of the data, especially with regard to data cleaning and quality checks applied. Few humanists (27%) stated that they were cleaning their data, whereas the majority of social and natural scientists stated that they did so. "Data cleaning" is at times associated with "data manipulation", an arbitrary act to make data fit with other data, which seems to have a negative connotation as this email feedback makes clear: "I doubt it very much that any self-respecting quantitative researcher would admit to manipulating their data! This is what your questions on p. 2 imply". Data cleaning is seemingly understood as unscientific when handling data, and less so as a necessary step within the processing of data that assures the accuracy, completeness, consistency (and uniformity) of a dataset. In the social and natural sciences on the other hand, more than half of the survey participants perform some sort of data cleaning. The criteria for excluding certain data points are explicitly formulated and the whole process of data cleaning is documented, as the following comment of one psychologist shows: "I do remove participants based on a-priori decision, but this is clearly stated throughout the manuscript". Closely related to the question on data cleaning is the question on quality checks, which are performed by the slight majority of all survey participants. Certain kinds of data, especially sensor data, computer code and spreadsheets seem to lend themselves well for quality checks. More than three-fourths of emotion researchers who work with these data confirmed the performance of quality checks. Accordingly, all of the natural scientists said that they conduct quality checks, the vast majority of social scientists (75%) do quality checks, but only two humanists stated that they applied quality checks. Most humanists (80%) seem to think that there are no appropriate quality checks for their research materials as they ticked the answer NA (not applicable). The answer categories provided in the survey, which mentioned four explicit statistical methods and a category for "other" types of quality checks might be accountable for a bias in the answers to this question, explaining qualitative or hermeneutic researchers' unfamiliarity with quality checks. In an extension to humanity scholars, the answers provided by social scientists who work with qualitative data were methodologically instructive: "qualitative improvement of ethnographic and qualitative methods", "reflection on how interviews were conducted" or "supervision for new co-workers in observation techniques". The same applies to quality checks mentioned by theoretically oriented researchers, both humanists and social scientists: "quality of aesthetic texts" or "empirical validity of descriptions in literary fiction". As these quality checks are predominantly framed within reflexivity discourses and only to a lesser extent as 'quality checks', they appear less standardised, although they follow disciplinary standards of plausibility, validity and reliability.

The survey conveys that most of the generated data, which are created in research projects are not being published. Less than a third of all emotion researchers use more than 75% of their data in publications. 29% of the survey participants stated that less than 25% of their data were presented in publications. The reasons for this are manifold: Lack of time is most often mentioned as an obstacle for social scientists. Data left out because it did not fit the research questions or hypotheses comes second and is a reason both for humanists and social scientists. Methodological considerations and redundancies were mentioned quite often and irrespective of the disciplinary background.



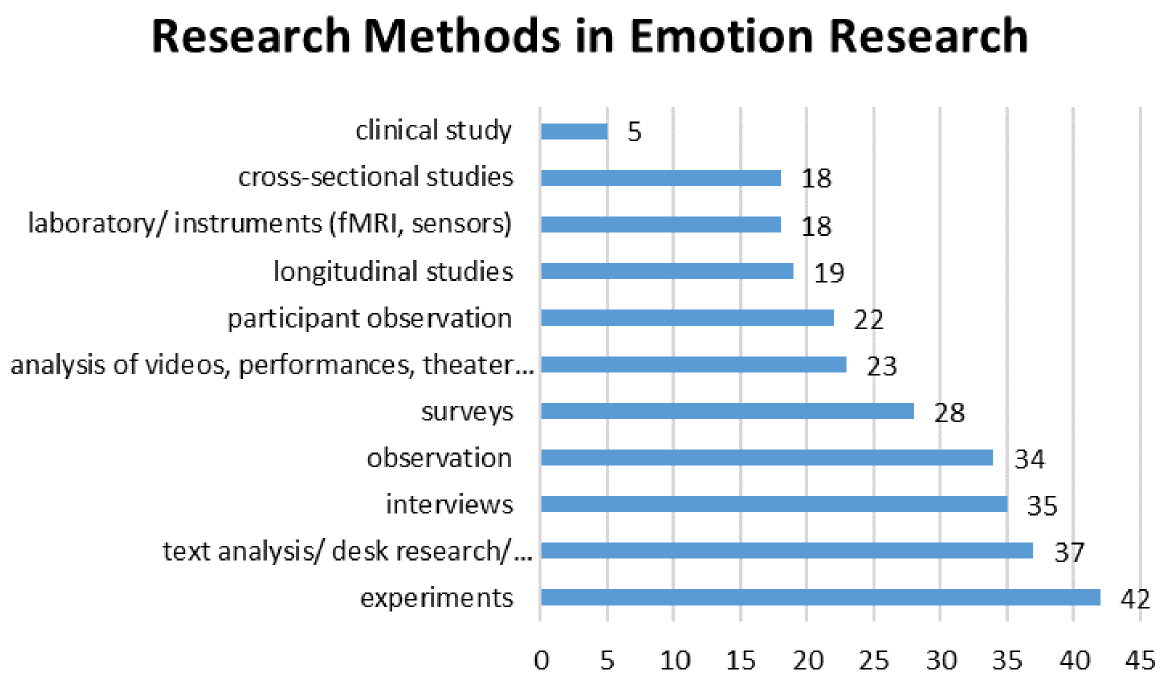
4.1.2. Epistemology and methodology

Epistemological differences can be found with regard to the scientific approach: generally, respondents divided their epistemologies into deductive, inductive and abductive reasoning.

The majority of social scientists (72%) and natural scientists (71%) are in favour of deductive approaches but also of an inductive approach in their research (76% resp. 71%). A mix of top down and bottom up approaches seems to be the predominant mode of research design for social and natural scientists. This stands in contrast to the humanists, where less than half of the researchers use a deductive approach, but two thirds an inductive approach. Survey participants were invited to position themselves within a rough classification of theoretical assumptions that can guide research on emotions. Interestingly the theoretical underpinnings match almost perfectly with the disciplinary background of our survey participants: Humanists and social scientists are in favour of relational approaches, situated affective states (humanists) or a combination of several theoretical approaches (social scientists). The natural scientists who participated in our survey in contrast believe that emotions are subjective and individual or adhere to the evolutionary function of emotions and to the dimensional model of emotions.

In how far does theory determine the process of knowledge creation in emotion research? There is unanimity with respect to the fact that theory determines the design of the study, the examination and interpretation of results as well as the write-up of the results. Whether theory enters the research process through the design of applications, tools and machines depends on the scientists' use of technologies. Three fourths of those who do not themselves develop tools and applications do not see theory influencing scientific practice at this point. This stands in contrast to those researchers who are engaged in technological innovations and who tend to acknowledge the influence of theory herein.

Respondents have indicated a variety of research methods pertaining to their area of expertise and disciplinary training. Experimental designs are the preferred method of researchers inspired by evolutionary theories or the dimensional model of emotions (Damasio and Carvalho 2013; Ledoux 1996; Russell 1980; Russell and Barrett 1999). Observations and interviews on the contrary are the selected methods for researchers advocating relational theories of emotion and affect (Kemper 1978; Hochschild 1979). The research methods most often cited are experiments, text analysis, interviews and observations.



The combination of research methods provides additional information on popular approaches within emotion research. One can distinguish between at least four different camps: researchers combining participant observation and interviews; researchers conducting both interviews and text or media analysis; researchers integrating cross-sectional and longitudinal studies; and researchers combining experiments with either surveys, observations, or laboratory methods such as fMRI and sensors. Although the majority of emotion researchers apply a combination of research methods, they do not associate the number of research methods applied with methodological triangulation. When asked about using methodological triangulation techniques to cross-check their findings, 60% of the survey participants replied with "no". Again, and in correlation with "data quality checks", this discrepancy is most probably related to disciplinary jargons, i.e. unfamiliarity with the term "methodological triangulation" (which is rooted in qualitative sociology) and not a statement against using a mixed methods approach.

With regards to research foci, those mostly mentioned in our survey were culture, social structure, language and facial expressions. Frequent combinations of research foci involve culture with either language, media, history of emotions or facial expressions; social structure with either language, political emotions or culture; and facial expressions with gesture or body language; and language with either political emotions, media or facial expressions.

4.1.3. Scientific aims

The aim to "understand" is the most frequently mentioned scientific aim of our survey participants (33 times stated) and can be seen as an indicator of a strong interest in basic research. What is it that emotion researchers want to "understand"? Some strive for conceptual contributions and aim at developing a theory or improving theories especially against the background of dichotomies and dualistic epistemologies. Two survey participants explicitly pointed to the interdisciplinary or even transdisciplinary nature of their scientific endeavour, one stating: "to use an interdisciplinary approach that allows us to address all stages of emotion (perception, processing, evaluation, interpretation and (self-)report", the other stating: "An integrated transdisciplinary account of emotion which incorporates socio-historical, phenomenological and organic aspects and which is philosophically informed". Many survey participants with a scientific background in the social sciences aim to investigate "emotional practices", discourses, social behaviour or collective emotions.

Some survey participants also deal with expressions of emotions, often with regard to cultural and language differences. Several emotion researchers are interested in the interdependencies of social dynamics and power dynamics, as to how social structures, institutions, organizations, and politics influence emotions. They claim to take a critical – or as one survey participant termed it "humanistic" – perspective, attempting to provide knowledge about "affective governance" for a social and cultural critique. Some of the researchers focusing on societal challenges, for example children and youth issues, healthcare use or migration, can also be assigned to this group. Others are interested in emotion regulation from a psychological point of view, emotion development or the functions of emotions. Last but not least some innovative research areas deal with the role of emotions in decision making as well as emotions in media and technological applications.

Summing up, scientific aims mostly focus on specific, well-defined, and particular research questions or objectives. The large majority of the survey participants concentrate on either solving conceptual and knowledge gaps, or contributing to existing theories. The aim to conduct meta-analyses, for example of the history of emotion research, was only rarely mentioned. The same applies to the establishment of a new scientific paradigm. Few survey participants stated explicitly that they were striving to gain "legitimacy for a social science on emotions".

4.1.4. Key challenges

When asked about the key challenges scholars see in their approach to emotion research, methodological challenges range at the top. Encompassing challenges related to both specific methodological approaches as well as the combination of different methods and the integration of data from various sources and dimensions. Many survey participants acknowledge the insufficiencies associated with their choice of methods with regards to a more integrative epistemology. Some of the methods mentioned in this regard are observation, text analysis, experiments and neuroimaging. Especially text analysis proves to be challenging as the following two comments illustrate: “How can we speak of affective dynamics, movement etc. when all we have at hand is a 'static' text?”; “tracing and assigning ‘emotions’ or ‘affects’ to words rather than to words uttered in a certain context”. In contrast, methodological approaches relying on interviews or the analysis of images and theatre performances were mentioned by very few researchers. How to integrate expression data and interview data or video, audio and physiological data into narrative and text-based approaches seems to be an unsettled issue. Several survey participants are concerned about questions of validity and reliability related to their methods, the huge amounts of data and data reduction, or the generalisation of research findings.

Whereas the former might speak to other domains of research, emotion researchers that intend to combine and integrate interdisciplinary epistemologies, face substantial methodological problems with regards to the phenomenon (of emotion) itself. The fact that some emotions “usually operate below conscious awareness in their actual practice” and “people can't always access and articulate their emotions” is a real challenge for scientific approaches. The following statement underlines the uncanny in emotional and affective phenomena: “the key challenges remain empirical, especially for Sociology, or, rather, how to integrate the theoretical insights and claims with talk, texts, and images that are not emotion, but more often than not proxy measures for emotion”. These methodological constraints lead to difficulties in the interpretation of the data: “Moreover, we have to find out what people really do when they (claim that they) refer to emotions. Do they specify an emotion or rather the cause(s) of a felt or sensed inner state or do they refer to a learned cultural concept that is said to be adequate in a given, described situation?” Some researchers went as far as to say that research on emotions and affects remains at large a groping in the dark, claiming that the research object appears to be too complex to be analysed by means of conventional evidence-based theory and methodology. There is even a hint of frustration that resonates in these comments. According to some survey participants, after several decades of emotion research the concepts used remain conceptually vague or even undefined: “We do not really know what emotion is and which emotions do exist. And we certainly do not know how to apprehend emotions. Scholars do what they can but success is missing”. This is a fundamental issue in non-integrative and particularistic emotion research, speaking a language for further interdisciplinary collaboration on eye-levels (where epistemologies are seriously, yet constructively debated, discussed and integrated).

The survey reveals that researchers are aware of the dissent in the definition of emotion and how to approach them scientifically. Whether these fundamental obstacles emerge from too specific research questions, mutually exclusive epistemologies, biases due to subjective understandings of emotions in everyday situations, or structural constraints (lack of time, money and research participants), will be further scrutinized in the analyses of the interviews.

4.1.5. Datafication and information loss

Datafication, in our survey is defined as “the process of collecting data out of real-world phenomena”. Most participants communicated this as a tricky task, involving several difficulties and shortcomings. Only two of the survey participants believe that their research approach remains unaffected by current or future challenges of datafication, stating: “I am not aware of many psychological studies where reduction/datafication leaves out complexity”, respectively: “Some researchers focus on the impact of 1 or 2 dependent variables to understand the phenomenon they sample. Others like me like to collect several related variables and do multiple regression to be in a position to interpret the impact / effect size of the observed dependent variable in the ecosystem considered”.

All other emotion researchers allude to one or several unresolved problems associated with datafication. Many researchers highlighted the loss of subjective, individual experiences and their relational dimension vis-à-vis context and method as problematic. Other researchers point to the non-linguistic bodily dimensions of knowledge as the following statement demonstrates: “One common issue might be the missing bodies (body language, gesture, tone etc.) from 'embodied' and 'relational' approaches that aim to study affective or emotional practices primarily through the collection and analysis of discourse, often without any attempt to 'square the circle' theoretically or methodologically”. Respondents related the loss of information in the process of datafication to the choice of traditional empirical methods. Survey participants with a social scientific background and applying methods such as interviewing and/or (participant) observation mentioned the omission of sensory information in the process of ‘coding’ or otherwise ‘essentialising’ contested social, cultural or historicised realities.

The problem of how to consider the temporal dynamics and sequences in the unfolding of social events and human experience is another issue brought up by our survey participants. The nuanced/differentiated answers to the question of datafication prove the high degree of reflexivity of emotion researchers from ethnographic social science and the humanities. Taking into account relational and interpersonal aspects of emotion experience and/or expression and communication in terms of “(ritualised) interaction strategies” or “the appeal character of emotional expression” reflects very well the complexity of the research object and the research context. Reading against the grain, the comments on datafication suggest that datafication is seen as an approximation to quantification. The following comment is illustrative: “Qualitative data collected in vivo can study socially situated practice that cannot be covered by that type of quantitative analysis, e.g. the relation between experience and expression of emotion”. Understood in this way, datafication is, according to the comments in our survey, inclined to emphasise aspects which most readily lend themselves to quantification and misses important dimensions and aspects of the phenomena studied. One researcher consequently tries to avoid datafication altogether: “The question assumes that emotions can be reduced to information, which they cannot in the research perspective I am applying”. The issue of data, datafication and its various definitions and understandings will be discussed in greater detail in section 5.

4.1.6. Theoretical biases

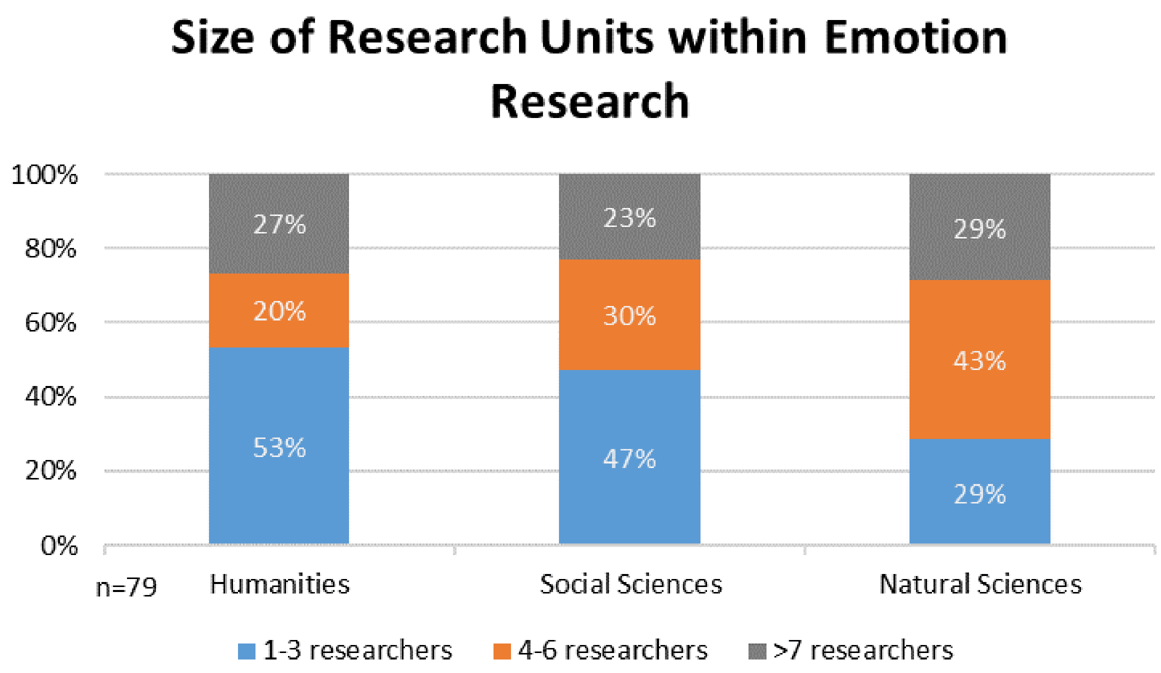
Whereas some of the survey participants remain vague in their answers regarding theoretical biases of their own work and point to “social science focused” or “the conceptualization of emotion and of particular emotions”, many researchers cited specific theories or models such as basic emotions, cognitive theories, constructionist approaches, systems theory, symbolic interactionism, appraisal theory or behavioural economics. The notable self-reflexivity and open communication of theoretical bias is a prominent result of the survey and relates to the critical stance towards datafication and monodisciplinary epistemology.

Moreover, biases are not only restricted to the selection of theories, but also to methodological choices. Hence, some of the survey participants mentioned “selection bias”, “reversal inference”, “the restriction of the possible number of in-depth interviews” – or the other way around – the neglect of certain methodological approaches, most dominantly physiological and neuropsychological measures. The problem of subjectivity bias is furthermore clearly stated in some of the comments. Biases are thus perceived in the broadest possible way, taking account of all the factors influencing a particular epistemological standpoint from which research is conducted and communicated.

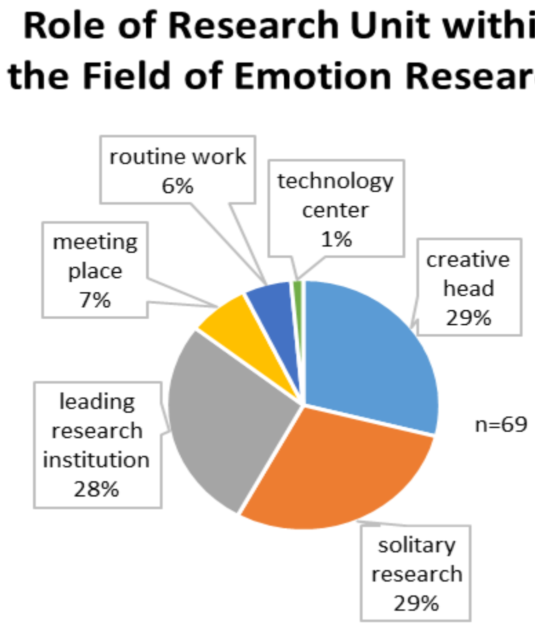
The identification of biases also reflects the prevailing paradigms in academia. Striking in this regard is the focus on emotional processes, openness, plurality, relatedness, or “an interest in transformation rather than in regression/stagnation”. The rejection of all kinds of reductionism “whether biological, psychological or sociological in nature” can be seen as another reference to an ideologically-founded legitimation. However, not all of the emotion researchers reported on theoretical bias. Some of the survey participants see the term “bias” as an accusation or scientific fraud (in the sense of an ‘impairment of objectivity’) and employ several narrative strategies to deal with it. While some adopted a laconic attitude: “That I seek to confirm my hypotheses”, others replied with an ironic comment: “None. I'm perfect ;)” or “I like when colleagues point these out to me at conferences or in reviews”. Still others reacted to our question by brushing away the issue of biases: “It's qualitative research so the usual criticism associated with it”. Eventually some researchers mentioned practical strategies to circumvent these biases, often pointing to the interdisciplinarity of the research unit, the willingness to revision the theoretical approach or using “tools that will allow to test the concurrent hypotheses of two competing models”. Interestingly one researcher, a psychologist, apparently opts for “agnostic data-driven approaches” and thus believes to avoid biases. To neglect the fact that the data structure results from methodological decisions about the collection, selection and processing of the data is rather problematic, as it places too much confidence in the representativeness of data samples.

4.1.7. Organisation of research

The vast majority of respondents works in very small research units: Almost half of our survey participants either work alone or in research units with less than three researchers. Only 23% of the emotion researchers who participated in our survey work in teams with more than seven scientists. The majority of humanists works in very small research units. Does this reflect the common approach in the humanities of individual researchers working in a highly specialised field with an idiosyncratic set of methods? Ethnographic research on humanists' research practices supports this argument, as many "perceive solitary work as a defining feature of humanities epistemology and methodology" (Antonijević 2015, 89). Or is it more an indication of the still marginalised position of emotion research within the humanities as this feedback by one survey participant would suggest: "I mostly work alone as my colleagues, with the exception of one guy, are not working in the philosophy of emotions"? The fact that almost half of the social scientists also work in very small research units supports this interpretation.



The very small size of research units is reflected in the role our survey participants attributed to their research unit: 29% see their research unit as doing solitary research and only 7% as a meeting place. Social scientists tend to see their research unit as a creative head, while humanists tend to identify it as a leading research institution.



The size of research units in emotion research also resonates with research funding in terms of amount and time span. With only a few exceptions funded publicly, most of the research projects receive modest amounts of funding (max. 150.000 €), but run for more than one year. 71% of the humanists belong to this group. On the other hand, well-funded and long-running research projects are disproportionately often directed by natural scientists. Though only seven natural scientists have participated in our survey, three of them are involved in well-funded and long-running research projects. Altogether the majority of survey participants (72%) are (very) satisfied with their institution's infrastructure.

A majority of emotion researchers – almost two thirds of our survey participants – work in interdisciplinary research units. Even scientists in very small research units are often engaged with other disciplines. Interdisciplinary collaborations often involve humanists and social scientists (21 times stated) or social scientists from different disciplines (16 times stated). Several research units in emotion research are also composed of social and natural scientists (9 times stated). A few research units associate researchers from the humanities and the natural sciences. However, within this group there are extraordinary research settings that combine in one case philosophers, literature scientists and biologists, or in another case psychologists, biologists, computer scientists and sociologists. An all-encompassing integrative approach involving scientists from all three camps seems to be rather exceptional. A remarkable feature of research units composed of humanists, social and natural scientists is the fact that all of them involve computer scientists. These mixed research units tend to focus on new research areas such as social robotics or video games and emotion regulation.

80% of the research units are well-connected and linked to other scientists, but in the majority of cases our survey participants' research units entertain only few institutionalised cooperations with external researchers and institutions. Many researchers have few institutionalised cooperations with researchers and also few loose cooperations with researchers. The distinction between few and many cooperations with researchers, drawn between less than eleven researchers and more than eleven researchers, results from the distribution of responses to this question showing a clear cut at the number eleven. Regarding the cooperation between the research units and other institutions there seem to be more institutionalised and loose cooperations, often involving more than four other institutions (25 times stated). As a considerable number of survey participants skipped this question it is hard to make conclusions for emotion researchers in general.

It is important to underline that relationships with other disciplines beyond the research unit do not necessarily hint to interdisciplinary collaboration per se. These alliances rather appear as multidisciplinary interactions and exchanges on particular topics. When asked about the nature of the relationships, the majority of the survey participants qualify them either as collaborative or consensual. Only in eight out of 38 cases conflicting relationships are reported despite some challenging collaborations between sociology, economy and anthropology, between psychology and biology; or between historians, sociologists, neuroscientists and anthropologists.

4.2. Results of the interviews

4.2.1. Key research areas and challenges in emotion research

We conducted 15 interviews with 17 interviewees; the disciplinary background of the researchers span from philosophy to German literature, anthropology, sociology, psychology, neuroscience, software engineering and computer science. Four of the interviews were led with researchers working in applied research; their disciplinary backgrounds are speech synthesis, computational linguistics, psychology, and affective neuroscience.

The scientific methods employed by our interviewees span from the development of theoretical concepts to text analysis, media analysis, interviews and surveys, speech and voice analysis, observations, facial measurement, experiments, physiological measurement, fMRI, and sensors. Many diverse concepts, such as empathy, compassion, enthusiasm, emotional practice, affective arrangements, existential feelings, or intimacy were used by our interviewees for the study of emotions and affects. Likewise the principal research topics of our interviewees span a broad range of research areas: emotion theory, social theory, religion and emotions, history of emotions, emotional rhythms and patterns in social media discussions, emotional governance in social media, emotion cultures, emotions as relational social processes, emotional socialisation, collective emotions, bodily mechanisms underlying emotion and emotion processing, alterations in social behaviour, patient populations with emotional disorders, expression of emotions in different kinds of species, human-machine interaction, artificial empathy, speech synthesis, imaginaries of human-robot interactions, and neuromarketing.

In this section we will first report on the conceptual gaps in the datafication of emotions and the epistemological challenges identified by our interviewees, followed by the topic of interdisciplinarity in emotion research; data integration, data sharing, and data reuse; benefits and challenges in Big Data research; and technology-driven research innovations.

In comparison with the survey, the interviews provided the chance to enquire in detail about the challenges of the datafication of emotions and to discuss epistemological questions. The guidelines for the interviews opened up a space for the interviewees to discuss issues that are rarely treated in publications. This becomes evident in the reflections e.g. on the gap between the measurement of emotion experience and the datafication of emotion expression, or in the thoughts presented about what cannot be datafied in the classic positivistic way. With respect to epistemologies, our interviewees contemplated about the incompatibility of epistemological approaches coming from different disciplines, on feedback loops in the adaptation between the research objects and the technologies used, and on the emotional implications of the research setting itself.

Bridging the gaps: Experience/Expression of Emotions

Our interviewees identified the gap between approaches focusing on the bodily experience of emotion and the expression of emotion as one of the most challenging questions in emotion research. This topic was reflected from the diverse disciplinary angles represented by our interviewees.

A researcher coming from psychology and the behavioural neurosciences stated: “And that is another question that is maybe a big problem to the field: what is the difference between the expression and actual feeling in emotion [...] I think it is really important to gather as much about the subjective individual experience that somebody has, as possible, to bring it together with the fMRI data. [...] Because our experience is much richer than on a scale from negative to neutral to positive, and this richness is kind of lost, when we don't ask more specifically.” An anthropologist studying historical sources tackled this topic: “I realised that there was going to always be a problem with the divide between emotional experience and emotional expression. This is a problem that the history of emotion has struggled with all the time and it is one of the reasons that people claim that you cannot really do a history of emotions, because you cannot access experience. So all we access is the expression.” The latter researcher saw this conceptual gap as one of the reasons why the discipline of Anthropology focused on the study of emotions: “And then when 09/11 happened it was like reality came crashing in: suffering, real danger, real fear; and that people realised that emotions were something that was beyond discourse, or deeper than discourse and that that was something we had to look at.” A sociologist also identified this gap as one of the most challenging questions: “And to me emotions are so interesting because they have this bodily experiential feeling component that also to a certain extend is not fully under people’s control. It’s something that rather happens to you than you wilfully choose, [...] usually you don't choose your emotions, I mean you can, you can work on them, but usually they just happen to you, right? So this involuntary automatic pre-reflexive non-discursive element, that is what interests me the most." Reflecting on the lack of concepts to account for certain dimensions of emotions, a researcher pointed to the environments in which emotions are experienced: "How are power structures in informal social settings, for instance, registering in affective experience or emotional experience on the individual? How does this work? What can we say about that and how can we research this?" And continued specifying this observation by pointing out concealed information contained in texts, which may be conceptualised as hidden data: "And then of course you also want to focus on texts, the way that language and text operate and how language can, on various levels, format affectivity in certain ways, but also bring in tacit dimensions, things that are not really explicit, things that are between the lines, things that are in the tone of voice, things that are in the overall narrative composition and that you kind of register without directly experiencing it as something that is manifest in front of you."

On a similar note, yet from a different epistemological perspective, a researcher with a background in software engineering described the conceptual challenges of algorithmic classification: "You can try to classify five or six basic emotions from that, but could you also classify the subtle changes in the interaction behaviour which a human would do in order to cope with the emotional behaviour of another human? Would you be able to formalise that and to put that into an instruction for an interaction handler or dialogue handler?" Moreover, our interviewees expounded a problem of scale by discussing whether the recognised emotion phenomena should better be ascribed to the level of personality structure: "I mean the problem you also have, is, that they [non-human primates] have different personalities. I mean personality research is a very hot topic at the moment, which means that [...] they might encounter the very same situation, but individuals might respond very differently depending on whether they are interested in novel objects for example or not." The same issue within humans was brought up by a software engineer: "Then we started looking into the personality and the granularity raises. So, the things that you have to be aware which translates into the things that you have to control for coming to clear laboratory experiments. They are growing exponentially. So basically, when I was predicting the degree of let's say extraversion or degree of agreeableness, these basic factors, big five from the personality, I encountered more and more and more context variables that I would need to basically take into account. The big challenge would be to find any kind of formalism or model that is actually able to incorporate all of these different characteristics. I would not even know how many of these parameters would be optimal to start with."

A final point brought in by our interviewees was the challenge of reconciling the focus on the individual person with the social, political and cultural context: "How do you conceptualise this sort of tension between individualism and a kind of sociality of emotions? That was one of my starting points. It is a long story of course; so at the one hand, you have this bare dimension of just identifying and characterising emotional phenomena, and on the other hand you go more into the contexts of political implications of certain emotional formations, where your research might have a critical intent, making visible certain problematic socio-political structures."

While the reflections presented above focus on the conceptual level, the epistemologies themselves and their limitations were also discussed as an issue by our interviewees. The experience of a researcher working on non-human primates and on comparisons between species led to the reflection on circular reasoning in epistemics: "But, and again this is the challenge of cross-species comparative research: So we might see the very same facial expression in another species and it might have a very different function at this other species. And then of course we can ask the question, what is the function in humans? And what is the function in other animals? But, [...] emotion expressions have been studied very differently in humans and other apes. [...] and so it's very difficult to get those two different strands of research together, because they address a different level of explanation, they ask different questions. [...] And with humans not only in emotion research, but the problem very often is if you work with your own species you think, you know what to expect. And then when we work with non-human primates we have to defend our stuff much more in terms of why do we think this is a gesture, why do we think they use it intentionally, why do we think this is an expression of happiness? Which is sometimes frustrating, but on the other hand it's also good, because we have to ask ourselves again and again: Are we [...] still using [...] the same scientific standards and comparable methods?"

There were two different viewpoints on the artificiality of experiments as a research setting. One researcher doubted that it would be possible to set up an experiment free from external intervention: "This is not done in a very good way, because [...] even if you do observational studies you influence the apes. I mean you should not interact with them, you should be a neutral person, but we all know, they get to know you". On the other hand, it was pointed out that experiments themselves are situations in which emotions are at play: "You could also say this sort of empirical research is itself a kind of an affective arrangement, because it breaks down certain phenomena into a thing that is manageable in an experimental situation." The same researcher went on explaining the feedback loops between the research participants and the technologies used for measuring emotions: "The other interesting side of this is that of course this has a formative effect. When your emotions are tracked according to empirical measures, individuals might attempt to play-act a little bit in line with these measurements, either to send the right messages to the machines or to kind of subvert, or fake it, in order to navigate it, but that is an interesting feedback effect. And then I would only say, with some historical consciousness, that this has always been the case with human emotions, they were always adapted to the social demands that were circulating around them. So there were always these sorts of habitual, habitus demands, or social etiquette, and they were always formative of what people experience about their emotions and how they are related and narrated there."

Bridging the gaps: Competing Theories

Another point brought in by a researcher was the friction between competing emotion theories; the tendency within the scientific field to claim orthodoxy for single theories triggered critique on this researchers' attempt to reconcile two competing approaches: "And among those who accepted that emotions have an impact on reading and have an impact on word processing, there was a very strong belief that the facts can be grouped on the dimensions of valence and arousal and that, basically that's it. So that you don't need anything else but valence and arousal to describe human emotion. And for me, so when I started publishing those effects, it was pretty tough to get those published, because there were basically established schools of thinking. So not real schools, more ways of thinking, which opposed those results pretty strongly. And I had a lot of discussions with researchers in the field that challenged my results, which was good, but also doubted my results even when they met all the challenges."

A topic mentioned mostly by scientists working in applied research was the pragmatic use of theory as the basis for developing specific applications. A software engineer explained the grounds on which decisions are taken: "In the sense of basic emotions, which can be identified and of course we can dispute about these five or six categories with which you are usually dealing with. Whether those are the ones you should be interested in or which are worth being classified. For many applications it is efficient, for example in call centres it might be sufficient to have angry vs. non-angry, that would be, you do not need to spend lots of effort on emotions which are not necessarily helpful for you because you cannot deal with them or because you will not observe them very frequently or something like that. But that is of course an application dependent decision you have to take." This researcher also described an uneasiness with emotion theories, which might be insufficient for the problems which confronted her/him: "if the ultimate aim is to steer the behaviour from the machine then you might be a little bit short-sighted to go for these emotion classes, just because we have them, because some psychologists or whatever people have defined them, because they are easy to describe and they have names and labels for it. For the engineers that is also quite heavy because then you have a precise problem. But if you do not know whether the problem you have tackled with is the solution to what you are actually after, it might be of no or little use to do it. We do it because that is a practical way to go forward, but it is not said that this is necessarily the best way to go forward." The point here is that these pragmatic decisions have implications on the frequency and distribution of emotion theories implemented in the applications. As another researcher explained to us, software developers tend to favour specific emotion theories: "There is still substantial debate over to what degree emotions are universal or not. However, you go to the affective computing engineers or to robotic engineers, and they are very much happy with this debate being finished for a number of reasons. I mean both technical reasons and economic reasons. There is an incentive to use universal theories of emotion. It is good for engineering. For them it is a simple solution. You can make universal machines, which are applicable and profitable across cultural boundaries, right? It is absolutely profitable." The same researcher pointed out that this observation led the research team to take the practices of the applied sciences into view: "Affective computing is for us an object of research. [...] So this perspective draws from science and technology studies; that is, we want to look at the cultural assumptions and the cultural practices being built into the science. And so affective computing is for us a scientific practice and a scientific object that we want to analyse in terms of the cultural dimensions. So affective computing is a very useful object through which to analyse what is happening culturally in theories of emotion and get back to science and popular culture in general."

4.2.2. Interdisciplinarity in emotion research

We did not only choose "emotions", or emotion research because they constitute a cross-disciplinary object alongside which different epistemologies, methodologies and disciplinary trajectories can be compared in our meta-analysis. Emotions and affects are probably more than any other phenomena subject to *interdisciplinary* research endeavours. Accordingly, our interviewees shared their ample experiences and reflections on the surpluses and challenges in interdisciplinary approaches, and commented on the chances and limits of operationalising interdisciplinary concepts in terms of integrative or holistic collaboration. In the statements provided by our interviewees, the controversial character of interdisciplinarity became more than obvious. This is perfectly understandable when one recalls that interdisciplinarity in scientific research is rather the exception than the norm; disciplines tend to distance themselves from each other, to structure themselves around certain topics, theories, or methodologies and to compete amongst each other for funding and public attention.

Interdisciplinary surplus: knowledge complexity

Contrary to this general tendency is the fact that emotions cannot be explored by a single discipline alone. The acknowledgment, on the side of our interviewees, of the existence of competing approaches and a certain 'tacit peace agreement' among scientific disciplines seem to result from this tension. Our interviewees often used the formulation "they have other research questions" when asked about other disciplines involved in emotion research, like in the following statement by a sociologist: "I think that is the important thing, we have different kinds of questions than let's say neuroscientists, or psychologists [...]. But that does not mean that we have to fundamentally disagree about what emotions are and what they do. It's just a different kind of perspective that leads to different things that we are interested in." It is also because of this inherent tension within the scientific field that the importance of interdisciplinarity is judged differently. One psychologist sees a boom in interdisciplinary emotion research: "But clearly it is important for psychology, it is one of the core areas because it brings together so many approaches, social approaches, cognitive approaches and so on. But philosophy has a major role, too, because it helps us to not fall into traps of definitional matters and force us to be precise. But also, we need the social sciences because psychologists often forget the social, even social psychologists, the social background. Anthropology is very important because of the cross-cultural issues. [...] I think the number of claims for the urgent need for more interdisciplinarity has gone up tremendously, something that did not exist before." An anthropologist, on the other hand, complained about the neurosciences' disinterest and inability in integrating other research approaches: "But neuroscientists cannot and do not want to. They just start asking different questions. So, I sort of arrived at the conclusion that maybe it is not worthwhile to try and talk to each other that intensely."

In the interviews, the perspectives on interdisciplinarity thus oscillate between visions of the future and sober estimations about its fruitfulness, between an accentuation of the surpluses and warnings on the challenges inherent in interdisciplinary research, and between sketches of holism and integration on the one hand and scepticism about structural limitations on the other. There was a consensus amongst many of our interviewees that for interdisciplinary research to be fruitful it needs a shared research framework and a shared theory as a common basis. One of the psychologists/neuroscientists elaborated on that: "I see there is the possibility [of interdisciplinary research], I would even go two steps further and say there is the absolute need for that. So both within the basic research as within the culture or the world that we live in. I think there is an absolute need of understanding or to understand what emotion is, how emotion is working. What is it that we are actually talking about. And I think for that it will really help to have clear definitions of what we understand, from what an emotion is. [...] So you should really start out with the theory and try to falsify this theory. And if you cannot falsify then that is good. And if you can falsify it then you have to adjust it. You have to publish your result and you have to adjust the theory and then try to build the baby steps to coming to better theories. And you have to start out broad. You have to start out with a very big, broad emotion, theory of emotion, trying to test that and then go deeper into the detailed level. [...] So that really, the framework within you are able to interpret it, is given by the theory." Interdisciplinarity was also the area where a philosopher, who is not working empirically, saw the specific role of his discipline: "And of course, as a philosopher I have the hunch that we are in need of concepts that work between theory, history and the empirical concrete experience, concepts that strike a balance between these poles without becoming vague or unspecific, and there are not that many concepts of that kind. And that is what philosophy can provide." This interviewee was also quite optimistic that it would be possible to develop overarching concepts in emotion research when referring to their own work: "the whole paper was written with the intent of contributing to an interdisciplinary initiative. And the background idea is that research needs concepts that are capable of elucidating new phenomena, or old phenomena in a new way, and that good concepts are capable of kind of merging or directing research in a certain direction without pre-figuring too much in the empirical domain, and certain concepts can affect a shift in the orientation, in this case quite simply from an overly individualist perspective to this sort of relational, local dynamic, orientation where you think that lots of aspects of the layout, or the kind of concrete entanglement of people and things is relevant."

On the other hand, some interviewees reported with a certain caution about their experiences in interdisciplinary settings; one of them described them as a kind of negotiation between differing epistemological approaches: "it's a very tricky field to work together in interdisciplinary research, [...] but it can be very fruitful, but only if everyone is willing to put it all onto a table and then mix it up and sort of learn, you know. This is an experience I had in two projects so far, that interdisciplinary research is very difficult, but if everyone is willing to learn from the others, it is actually quite [...] nice. But to do so [is] not easy, [...] and you have to give up some things that you came with, and you get new ones, and then you can work together.” Another researcher was overtly sceptical of the possibility to bring together diverging epistemologies in terms of collaboration between the social sciences and the natural sciences: “so it’s very difficult to get those two different strands of research together, because they address a different level of explanation, they ask different questions”, and the researcher substantiated it with respect to emotion theories: “I did not encounter an emotion theory yet that is really comprehensive and satisfies all the different facets of emotions, also those different, the cross-cultural-, and the cross-species-approach.”

Besides learning from each other in terms of getting a more comprehensive understanding of the phenomena under question and the methods used, the interviewees identified the vision of holism and integrative epistemologies as interdisciplinary surplus. One psychologist underlined the inspirational character of interdisciplinary exchanges: “I think it’s really, it’s really important and also because you/ by using other methods you also start to move out of your comfort zone and you see what the problems of your favourite methods are and you can learn a lot. It’s challenging and of course you, you might never be as good when you use for example a method from a different field, but I still think it’s very helpful, because it broadens your perspective and you may also see a certain phenomenon you observed in a completely new/ you might discover some new things [...] But, I think, to go back to your data and take a fresh new look from a different perspective is really, really important.” An anthropologist pointed to the mutual recognition and learning process in a research project with a neuroscientist: “There we were successful to really combine our different methodologies. I convinced the psychologist that we had to start with ethnographic methods. And with long-term research, long-term observation. And he was convinced: Okay, this is necessary and first we have to understand what's going on on the local level: What are their concepts, their ideas, their practices and so on? And then we can go and conceptualise experiments, field experiments. He convinced me that experiments are not so bad if they are adapted to the local situations/ might/ bring wonderful results, and interesting results.” Another anthropologist underlined the possibility of mutual enrichment across methodological boundaries, which may exist within or between scientific disciplines: “I think that we will still need qualitative methods. So, it's like the quantitative part can give you something and then you need qualitative stuff when you are framing the stuff, or when you try to dig deeper into what is it actually that you're interested in.” While talking about experiences gained in a cooperation between humanities and social sciences, one of the interviewees underlined the hope that these disciplines would complement each other in rather multi- than interdisciplinarity terms: “we don't have this problem to reduce the complexity. And it's easier to see the whole thing as a common project. Yeah? So, we all are aware that we/ in our disciplines all need/ process like a little piece of a puzzle. And, right? If you put it together, a more complete or holistic picture will emerge.”

Two of the researchers communicated the idea that interdisciplinary cooperation could serve the purpose of investigating each other's epistemologies, thus pushing the exchange to a metalevel beyond the actual research subject. A psychologist/neuroscientist put it this way: What "would also be interesting to see is if the process of research itself would be more subject to reflection. How do we come to this hypothesis, how do we come up with an operationalisation for our concepts, of empathy, of whatever emotion you want. How do we get there? [...] And that might be helpful to have somebody from the outside observing that, and helping reflect on that. It would be also an interdisciplinary part, let's say." The same was formulated by an anthropologist in a more pressing way, as a mission for the discipline itself: "I think here is really the point where anthropologists can and should do interventions. There is a group of researchers who are kind of like: big data is objective, or it gives us objective views of the world. And of course, we all know that that's not the case. But there is, for instance, there is certain artificial intelligence, even researchers who are saying that this is like the best time in history. Because we don't have to deal with the human bias anymore. That human is the problem in all, you know, knowledge production. So, I'm also (laughing) talking to those kinds of people (laughing). And I think the interventions that we can do is to demonstrate that there are so many different ways of understanding what is knowledge. What's the truth value of knowledge? Where is it coming from? How there are always biases. And we have to acknowledge them."

Interdisciplinary predicaments: knowledge reduction

While the possible surpluses of interdisciplinary endeavours seemed obvious to our interviewees, at the same time they presented differentiated opinions about the difficulties and challenges of interdisciplinarity, especially with respect to the harmonisation of epistemologies. One interviewee described the limited range of epistemologies and criticised reductionism as a result while underlining knowledge production processes as circular reasoning: "They took it for granted that there is something like a basic emotion. And this discussion, in my opinion, was circular. Because: What is a basic emotion? What is it? How many are there? What is the starting point? This is also maybe reducing the complexity. And is this basic emotion the first emotion or affective states of a new-born? So, then we have two: pleasant or unpleasant. [...] And what are the defining criteria for that? Yeah, but the other side was also a little bit reductionist. So, the constructivist's view to say: 'Biology doesn't matter. And we don't care about it. Everything is made by culture.' It's the same." A philosopher mentioned the possibility of a coexistence of differing perspectives without the chance of resolving them: "What are different data formats other than reality manifesting within different conceptual frameworks? [...] it is a ring of interacting, sometimes competing construals of reality that are all on the same level, but that carve up reality differently. So different data and knowledge universes kind of coexist, sometimes uneasily, but you don't really find a neat ordering where all fits in what goes on in research, in science and technology."

The reflections of the interviewees on the often reductionist epistemological basis of interdisciplinary projects even led to overt criticism and refusal to recognise the contributions of other disciplines. An anthropologist working in a Big Data research project reflected on the failure of interdisciplinary cooperation with the statement: “I think lot of the big data projects have failed miserably. They don't find the things that they wanted to find because they didn't have a theory. So, you need something to start with.” And another interviewee denied that a confluence of approaches would be possible: “What the humanities can contribute to the neuroscience study of emotion? Well, I don't know if they are really compatible. I think they would always have difficulties talking to each other, because they are working at different scales. My own thought on this has been: How can neuroscientists do these brain scans and not consider that the person that they are scanning is an individual person with a biography and cultural embeddedness and that sort of thing? You are not looking at a brain; you are looking at someone's brain! You can aggregate, I suppose, lots of data from a lot of different peoples' brains and arrive at some sort of average, you know, values, but still you are dealing with brains that are embedded in a certain time and space and society and you should take account of that.”

Interdisciplinary collaboration: structural dimensions

Beyond considerations of interdisciplinary surpluses and challenges, interviewees reflected on structural limitations of interdisciplinary endeavours characteristic of the scientific field. These thoughts ranged from fundamental reflections to organisational questions to the observation that interdisciplinarity might threaten a discipline’s identity. One researcher underlined the tendency of single disciplines to render an emotion theory in terms of absolutes, which can be understood as part of their struggle for legitimacy and recognition: “I think all the theories that have been proposed do have value. It's just that they all suffer from the fact that they claim that they are the only reasonable theory.” Another interviewee pointed in the same direction by contemplating on the economy of attention: “but the problem is sometimes that practitioners tend to set their own findings absolute and draw massive conclusions and say: ‘ok, now this is a leading paradigm’ and so on. This sort of battle for attention and resources ensues, and then it often becomes problematic. And sometimes this is then turned into an attack on the humanities and on conceptual understanding, when people claim that these things are empirically refuted, where it is just clear that you can dissect complex human phenomena in all sorts of ways and address various empirical channels.” A psychologist underlined the difficulties of bringing different methodological strands together within one discipline, mentioning that “traditionally sciences or disciplines are organised around individual response channels, so you have physiological psychologists that only do heart rate and so on. Or you have the neuro people who only do fMRI or the expression people who only work with video. So to some extent it is one of the major requirements for the future, to bring these together.” In this respect, the challenges are not only interdisciplinary in nature, but also have to do with the compartmentalisation and specification within disciplines. The more fine-grained the methods, research instruments and theoretical approaches, the more the principles uniting a discipline disappear and the more difficulties the proponents of the different schools of thought have in talking to each other. The same researcher shed light on the restrictions for interdisciplinary publications imposed by academic publishing: “I think the issue of really working in an interdisciplinary fashion requires to work on the same issue from different angles. And that I don't think has appreciably changed. What has changed is that there is a more realisation that it needs to be done, but whether it is really done is another issue. And I think the main reason is that there are no good publication outlets. If you do really serious interdisciplinary work, disciplinary journals will not take it and there are no interdisciplinary journals or only very few and not very prestigious ones. So, unless you create appropriate publication outlets nothing much will happen.”

Another point brought forward as a structural limitation were the difficulties of organising research in larger research units, influencing the relationships established between disciplines and researchers: “So interdisciplinarity [...] always comes with dependencies in a way, between the people, new dependencies, and so you have again power relations within an interdisciplinary project that are different to purely disciplinary projects”. Finally, one researcher recounted from own experiences working as a social scientist with neuroscience, pointing towards the fundamental questioning of each discipline involved. Describing this erosive process for anthropology: “And [the neuroscientist] said: ‘You are so right, this is so important, but we cannot do this. We have this brain scanner. And it's too complex. We have to design a common project with two variables.’ To be able to/ that it fits into this scan thing. This was the end of [...] collaboration. I said: ‘It's, sorry, but it's too stupid for us. I cannot do it!’ Yeah, it's my own grave in my own discipline if I reduce this complexity to these two things you can see in your scan.” But there were also consequences for the other discipline involved: “We had this scan thing. We HAD to use it. It was a must, an imperative. And especially the neuroscientists, they couldn't say: ‘No, all we learned from the sociologists/ our work is under-complex. And so (laughing) we will not use it any longer.’”

In view of what has been reported above, it should have become clear that our interviewees were cautious to state that a holistic approach to emotions will emerge out of interdisciplinarity. The spectrum of answers ranges from overt denial of such a possibility to a thoughtful affirmation containing restraints, or moving the prospect of it to the far future. One of the more optimistic researchers stated: “I would say it is possible. It is possible. I learned a lot through my collaborations with the natural sciences. [...] Of COURSE, in such an interdisciplinary context, we can/ maybe we get a little bit closer to the complexity of reality. But we will never be able to represent it. We can just try to get close.” Other researchers narrowed the frame and identified concrete research objects, such as “we as sociologists, we quite often or we usually with the methods that we are using, we are not getting to people’s bodily feelings and experiences, so we are mostly stuck with looking at different ways of expressing emotions, communicating emotions, talking about emotions [...].” Sceptical about so-called holistic approaches, an anthropologist explained her/his standpoint by referring to the relative nature of truth in scientific research which results out of competing approaches: “I am sort of trying to figure out how it is that we can say one set of things about emotions, like they are private and they should be private, cause we know this to be true. And at the same time, we can say another set of things about emotions and we also know them to be true. And it is just the opposite. And I think it is because we have competing ideologies about emotions. And they just sort of exist side by side and we just live with that and we sort of, you know, go back and forth between them."

4.2.3. Datafication and the loss of information

As we have seen, researchers have expressed both fascination and scepticism with respect to the possibility to implement an integrative research framework to investigate emotions and affects. Scepticism is extended to – and at times also nurtured by – the possibilities and limitations of current datafication processes and agendas. When asked, all interviewees were astonishingly outspoken about the limitations of their approaches and the inherent biases due to the underlying theoretical assumptions and the technical specificities of collecting and structuring data and analysing it. Researchers across all boards were well aware that datafying emotions might contribute to the reduction of knowledge complexity.

General agnostics

The appraisal of the datafication processes ranged from blunt disenchantment to elaborate reflections about the limitations imposed by scientific epistemologies, technological possibilities, and data integration processes. A researcher working with Big Data stated laconically: "I don't think that much has been lost in the datafication of emotions because they have not been very well datafied", pointing to the methodological tools responsible for it the researcher remarked: "Yes, they're too rudimentary [...], way too simplistic and anybody who kind of claims to have datafied emotions, is probably exaggerating hugely." Another researcher, who was also engaged in research on Big Data, took the theoretical assumptions and models into perspective: "What I can say is that the models, as far as I know, that have been used in dataficated emotion research are very, very simple, they are usually completely void of any cultural differences between people, social backgrounds of people, something like this, so a very, very rough method is being used for everyone, and this alone lets me doubt about the objectivity. [...] So there is a lot lost in translation, to come back to your question, and I would even say that on the one side the affects that one person has, and what's being taken out of that into the machines has nothing to do with each other, it's a total ambiguity, at least". This statement explicitly addresses the social construction of facts and contests the congruence between subjective experience and "objective" measurement. By pointing to the unscientific way in which Big Data is collected and analysed without any theoretical underpinnings, a researcher underlined the disproportion between the amount of data to hand and what can be taken out of it on the basis of theoretical assumptions: "The greater problem, to be honest, is that we have a lot of data that we cannot make sense of. I mean we collect tons and tons of data and most of that is basically unused because we don't have enough theory to interpret it [...]. That for me is the biggest problem, the datafication itself."

Specified scepticism

Scepticism with respect to the comprehensiveness of datafication was uttered by the interviewees in relation to several levels of the epistemic process. A point made referred to the common problem that only a part of the available data can be considered as containing signal while other parts have to be seen as noise. With respect to speech analysis, a researcher remarked: "In emotion research you usually have few strong emotional reactions. So, most of the time, if you observe an interaction between two speakers or between a speaker and a system then you usually have, I don't know, in ninety-something percent of the time you do not have any strong emotional responses, although the user might have some underlying affective state, some underlying emotion but you might not be necessarily able to extract that from the speech [...] one of the big problems in emotion research, I think, is the data which can be used for dealing with emotions. And this data is very imbalanced, it is very much biased towards non-emotional instances and there are very few emotional instances in the data. And if you build a system like an automatic classifier[3] then you have to deal with this imbalance." Another interviewee working in the same research area pointed to the loss of information during the analysis of speech: "You could say I have a certain level of arousal for example or valence or something like that, which you try to classify. And then you have a kind of regression problem, or you go for distinct classes and then you have a classification problem. And of course, you lose information on that way because you try to formalise the problem, because you want to build an easy classifier or regressor. You lose information."

Beyond the challenge of the signal/noise ratio, the interviewees underlined what is lost in datafication. Depending on the epistemology used, this loss may pertain to the reduction of the richness of the individual experience of emotions in the fMRI scanner, the abundance of explicit knowledge in the memory of a researcher working in the field, or the broader dimension of affect encompassing emotions experienced within interactive episodes. Pointing to the conceptual gap between emotions experienced by test persons and the dimension which can be captured by a machine, a neuroscientist remarked: "So you have a little bit, some information about the subjective emotion that somebody feels in the scanner, but [it] should be taken to a further level [...]. Because our experience is much richer than on a scale from negative to neutral to positive, and this richness is kind of lost, when we don't ask more specifically. There are not really good ways how to do that." Referring to ethnographic epistemologies instead of cognitive and affective neuroscience, another interviewee pointed to the limits of exhaustively datafying and documenting the explicit knowledge of the researcher: "First, from an anthropological view [...], from a view of a field researcher, I would say a lot is lost. [...] in the best case, I can make a film of an emotion episode. So, I have a body movement, a gesture, the facial expressions, the voice, the tonality and so on. So, I have already a lot of things I can document but it's also only a part of the story. [...] And this is not in the film, is not in the field notes. But it's not lost, as long as I'm working with the data." This interviewee also pointed to the epistemic relationship between the researcher and the researched (brains, body fluids, persons, communities, societies, cultures, spaces, places, objects and phenomena) and thus carved out why the process of datafication

[3] For explanations on terms like automatic classifiers or regression see Hastie, Tibshirani, & Friedman (2009).

inevitably implies disruption and distancing: “We had all these ‘writing culture’[4] discussions on subjectivity. And that we have always to see the data we produce in relation to the researcher. And his or her standpoint in the landscape, or standpoint in the situation, in the field. And these discussions about data storage imply that data is independent from the researcher. And from an anthropological point of view, I would say this is a step back.”

While the statements above pointed to data loss, there were also references to what seems to be completely out of reach of datafication. Scepticism was especially uttered by researchers when reflecting on the relational and situational character of emotions. One interviewee pointed to the circular reasoning resulting from particular epistemologies and underlined that the broader dimensions of affect fall out of their range: “Things get lost in the wake of the tendency to identify measurable markers of emotion. This practice short-circuits the definition of certain types of emotion [...] And of course that is not nothing, of course they will find something, and if they're good, they will find a certain affective texture in my appearance, but I would say that is not what we mean when we speak of our affectivity, when we talk about our feelings. [...] Rather, I would say, affect is always a thing of being together in a situation, of course having a history, which is an individual history, educational learning history and ontogenesis, but also in a context in a certain culture and that is kind of coded in our emotion, sedimented in them and, I think, if you lose this dimension because you cannot measure it, well, then so much the worse for your perspective.” Another interviewee brought to attention the implicit knowledge of researchers themselves that influences the interpretation of the episode: “That's the point I think, it's not in my explicit knowledge. The explicit knowledge I can note. I can transfer it to data. But this implicit knowledge is out of reach [...] The fieldnotes I am making and all these materials, all this documentation stuff functions as a kind of exogram or external memory storages or something like that. That means the sensual qualities of fieldnotes, photographs or objects from the field have the capacity to trigger implicit memories or the hidden, embodied knowledge of the researchers.”

Finally, two interviewees remarked on the consequences of complexity reduction in emotion research; one noted a possible shift of epistemologies through the adaptation of human behaviour in the interaction with a machine or application: “But then when you look what actually happens around those [self-tracking] techniques is that, yes, the kind of mechanical objectivity is the beginning. That’s where it starts. But then when you start working with the numbers something else emerges. We have called this ‘situational objectivity’: That all of a sudden, the objectivity is not so objective anymore. So, epistemologically it is a kind of a journey. You start from somewhere where facts are facts and you're trying to objectify something. And then you end up in this kind of Harawaynian idea that, okay, knowledge is situational.” The other pointed to the implications for society with respect to large-scale applications: “I don't think that there is a true possibility of matching emotions and data. [...] if you do this, you really discriminate the complexity of a human being into a very rough scheme. And therefore [...] I think it's a big problem. But the other thing, since it is being

[4] ‘Writing culture’ relates to a turn within anthropology since the 1980s that focuses on reflexivity, deconstruction and the uncertainties researchers encounter in ontological, epistemological and representational terms (see James et al. 1997).

done on a large scale, in many different contexts, I mean, it's a reality, you know? So this has very, very tense repercussions on the reality again, because of course the data plays back and does something. [...] you know the face recognition works on the assumption [...] of a normativity and so everyone is modelled against a norm, or a normativity [...], and from that emotions are being subtracted.” Quite obviously the possible consequences for scientific work and for the society as a whole require further exploration.

Aside from precisely formulated scepticism in pointing towards what exactly is lost in datafication in terms of knowledge alienation, reduction and information loss, or to dimensions not contained in data or only tacitly contained in data, outlooks were also presented on how the reduction of complexity in the process of datafication could be compensated for: “So for now we are treating all the information coming from Big Data separately, so we are treating the text information separately from the image and for example the reflection of the behaviour of the people. Everything is in the distinct. And we will now [...] get models that are trained by different sources at the same time. So then we can of course, or probably, we will be able to even better detect emotions.”

4.2.4. Data integration, data sharing, data reuse

Having attended to interdisciplinarity, the perspectives on holistic and integrative emotion research, and the limitations imposed by the datafication of emotions, this section focuses on data integration and data sharing/data reuse. Despite the existence of the EmotionML standard, established by the World Wide Web Consortium (W3C), it became obvious that this standard is not widely used in research. Our interviewees are aware of the possibilities and the advantages of sharing data from an abstract-theoretical perspective, but scholars across all disciplines also identified several structural limitations of sharing research data. A common feature which has been named by researchers to oppose data sharing is that data cannot be seen as being independent from the context in which they were collected, a point which was already mentioned above in section 4.2.3.

The necessity of having a common theory as the basis for data integration and data sharing was mentioned by a researcher who is working in a large interdisciplinary research endeavour: “It's the theory and methodology. Technique could be a tool to organise it, but first you have to think about the ways you will organise the data”, They also explained the concrete procedures used to diminish the resistances to data aggregation across several scientific disciplines involved: “during this first period we all tried to establish data management structures within the projects. Because these projects are all team projects. So, they have to work together. But that's not so complicated. We store our protocols and films, and whatever on our common server. and we have these data discussing sessions. So, we know about the data-eliciting contexts, and we can exchange us. And so, we know how to read the data even of another person. But this is limited. I can do this maybe with ten persons, maybe twenty, but then it's/ twenty is too much already.”

From our survey we had learned that a majority of research projects don’t use standardised data formats, which is a result of the multiplicity of epistemologies used; it can therefore be concluded that the W3C standard EmotionML is not widely used. This finding stands in contrast to the statement by one interviewee, who explained to us: “It has been used by many universities, laboratory experiments, there are these examples on the website of W3C in Freiburg, I think. For example, there are some models and some companies, like there is nViso in Switzerland, they detect emotion from facial/ like the idea is that customers watch product videos and then you can tell how much they liked the product.” This interviewee even mentioned a project by a private company which used EmotionML: “It was a pilot study on customers in call centres, so that in the end you can measure how many angry customers you had for certain products and this is done offline. So, at the end of the day, so the customers would not be molested by any wrong, erroneous feel after, emotional detection and their privacy would not be disturbed”. Another of the researchers interviewed was also familiar with EmotionML and pointed out reasons for the poor acceptance of the standard: “The shortcoming of course is, I guess for example, in our lab, most people even don’t know this, so there was not much impact. Why was there not much impact, or not so much impact? Because it is not so easy to use. So, all these XML things, or EmotionML is a markup language which is like XML, it blows up your data. So for example if you have a three-letter-word, which is some kind of emotional word, then you have a bracket with a longer word before and a bracket with a longer word with a slash after it and so it blows up your documents and your texts. [...] the standardisation first of all gives you a format. So everyone has to use this format, and if someone is using it, so the others are in principle able to understand it. But then you have to, with the standard you have to catch all the different aspects. And emotions have a lot of different aspects as you probably know of course. [...] So to catch all this, this was a big, big challenge I think for this standard. And usually you [inc.] for that the standard is correct on the one hand of course, on the other hand it should be complete. And this completeness makes it so big.”

Several aspects that describe the potential strengths inherent in sharing or reusing data were mentioned by our interviewees. For example, the possibility of testing models that have been obtained from one dataset on another dataset, which was mentioned by an expert on emotional synthesized speech: “Yes, there is cross data, we did research on that and we did it. There is cross database reliability also. [...] So yes, you can generalise emotional data if it is somehow related, if it is from the same domain that you want to recognise this kind of expression.” Another benefit of data sharing was the improvement of methodologies by cross-disciplinary exchange which enables a fresh look onto data: “We had a gesture project [...] and we used our coding scheme and we established reliability. So we had two different coders state all the same thing which is good. But then [...] we worked with people from linguistics and they used a certain coding scheme they adapted from sign language studies [...] to code hand movement. And then we realised that [...] our coding scheme [...] was not detailed enough to capture very subtle movements and so we had to redefine gestures. So, for example we didn’t differentiate whether they used a fist or a flat hand. And then they said: ‘Look, it makes a difference in terms of the function the gesture has.’ And so we basically went back to our original data [...], I think this is a good thing, [...] it doesn’t mean that we had to basically throw away our results of the previous study, but we could say okay, [...] we continue to develop our methods we included in another discipline. And so this [...], we suggest, needs to be changed. So, I think, unless you really made a really big mistake and your statistics you did them not correctly, so this is a problem. But, I think, to go back to your data and take a fresh new look from a different perspective is really, really important." As an advantage on the methodological side, the possibility of multiple readings of the same dataset was emphasised: "This is the good thing about observational data, it takes [...] a long time to collect them and to code them, but once you have them, you can re-analyse them from like, you can ask different questions and so we do this quite often, I have to say. And so, we [...] have now a big data set along (inc.) on infant development and it's a huge data set and different people work on it, with different questions. So, some look at mothers' behaviour, some at infants'. Some look at interactions with other group members and so on. So you can [...] reuse the data and ask different questions". This interviewee underlined that the sharing of large datasets – which can in this case be compared to Big Data since they consist of terabytes of video data – is still in its infancy: "So there have been attempts to at least share video data and make them accessible to other researchers, [...] it's starting to change, but it's still a long way to go. And, I mean the advantage is really, it could save so much time, if people would basically join forces and say: 'Hey, I have this data set, let's/ we analyse it!' [...] And the disadvantage is of course, you have to be very careful in terms of [...] methods to collect your data. [...] particularly in gesture studies, everybody is using their own definition. So we have to be careful when you code your data, that you use the same definitions and variables and so on. So this is the challenge I see, but I'd say that the advantages, [...] the benefits are much bigger than the costs. And it should be done, absolutely, yes."

The limitations to data sharing and reusing described by our interviewees are located on different levels related to theory, methodology, epistemology and data management. A neuroscientist identified the lack of a consistent theory as a reason for these: "I think there are theoretical issues. For instance, when you talk about empathy. The field is very diverse and how it uses the term empathy and whatever it is. It varies extremely, really. And this is really a problem to the field, because it is hard to integrate different results and to integrate the different research that is out there." Beyond this issue, the dependency of data on the context in which they were collected was often mentioned by our interviewees; one researcher pointed to the polysemy of texts as an obstacle for reuse: "I published a study where we try to really get into words that can trigger positive and negative emotions. And that often related to different meanings of the word". Another researcher reminded of the danger of an amplification of existing biases in large datasets resulting out of data integration: "Another outcome might be that since you have so many different sources of data it would seem like a very strong match of one emotion, but in the end it's only a problem of the translation again that the persons that you have been surveying did have some whatever kind of characteristics".

A researcher in software engineering explained the difficulties which may arise when the data collected stem from laboratory settings instead of being collected in everyday scenarios: "Basically, if you just take a clean corpus of speech recordings and you try to learn, let's say, for any kind of XY-company. Dialogue systems are based on this speech. So that is not the quality that is normally transmitted when you do a phone call. That is only studio quality, high quality. And so, we have to have all of the noise, all of the different components in between of the transmission chain, either model or in realistic ways recorded, so that you [...] actually welcome this noise inside and then say: Okay, that might contain largely the real problem and now let's see how to solve this. Which is then in many cases completely different from the laboratory’s way of solving a problem.” One of the researchers working with Big Data mentioned that in machine translation it is the availability of parallel texts coming only from one specific domain which can form an obstacle to adequately treating emotions. Further explaining that machine learning produces suboptimal results with respect to an adequate translation of emotions if the machine is trained with text data hardly containing emotionally charged content. These training data can therefore be described as a biased database. “Machine translation is done there also with neural nets and you have to train them. So, to train machine translation you have to have parallel texts. Parallel texts are documents that are written down in one language and that are translated correctly into another language and then you can say this sentence is translated to this sentence in the other language. And you have to have huge amount of this data. And then you can train this machine translation tool. So this is how for example Google does it. And everything that you know where, where machines are good at translation, they are always trained like that. So, where do you get this data from? This is the main issue. Because you won’t find a lot data for example with tweets that are translated, [...] you just won’t find it. So, where do these data come from? They come from the European parliament for example, because there everything that is written down there [...], every speech and things like that is translated, and it is written down, so we get this data. And this data is free to use. And so the machine translation algorithms are trained with this data. But, as you said, this data is not very emotional. So in the end, machine translation really has no aspect of emotions per se in it, because of the training data. So if you translate for example a funny joke from English to German, in German it probably won’t be funny anymore. And so this is where it completely falls apart. So, there is no emotion in it.”

Finally, there are pragmatic reasons that stand in the way of preparing data for the reuse of other researchers: “But that is absolutely time-consuming. So, it sounds very simple, but, I think this is really [...] a big limitation for the whole project of the data storage. [...] To externalise all our knowledge from the field protocols so that other persons are able to do something with that, to understand it, would take weeks.”

Privacy, ethical issues, and also trust are another central issue related to data integration, sharing and use, particularly in emotion research. The anthropologist cited above illustrated that these concerns apply to both researcher, research and the researched: “Also the privacy of a researcher. (...) This question, I think, is VERY important. So, there are so many things you (...) you are told as a person. So, I tell it to you, but not to everyone. And you may use it, but YOU may use it. Because I'm sure that you will say it in the right way. But not anybody else. So, I cannot put it on a data platform.”

4.2.5. Benefits and challenges in Big Data research and large-scale analyses of emotions

It is notable that not many of the researchers who participated in the interviews said that they would be working with Big Data. Three out of 17 interviewees reported to be involved in current or recent projects on Big Data, which were mostly stemming from social media. The majority of our interviewees expressed their uncertainty about a clear definition of Big Data. They had a conventional understanding of certain features of Big Data, as being drawn from the internet/social media and characterised by the three V's (volume, velocity, variety). The result of such a conventional understanding is that very large data sets (such as video collections or aggregated fMRI data from the neurosciences) are not termed “Big Data” by scientific researchers. We will stick to the terminological distinction between “Big Data” and “very large data sets” here, thus indicating the difference between Big Data and data collected for scientific research purposes and according to a research question.

Even if they were not working with Big Data in strict terms, our interviewees reflected on potential benefits and challenges of Big Data in emotion research. Several interviewees highlighted the possibility of Big Data to open up new research questions that could not have been asked before. In discussing Big Data as a resource for analysis, our interviewees often remarked on the consequences of the fact that Big Data are not being collected for research purposes or according to research questions. It was at this point where it became obvious that in the conception of our interviewees data are inseparably linked to the epistemological process. Our interviewees thus underlined that the character of research would be different if they worked with Big Data: more exploratory in nature, their research would become data-driven rather than theory-driven; the nature of Big Data cuts the possibility to infer on causal explanations and narrows the focus onto correlations (or spurious correlations). Frictions arise because scientists from all disciplines have an understanding of research as being driven by research questions and hypotheses; the research process is held up as methodologically controlled navigation through *terra incognita*. This clearly stands in contrast to the rather unoriented exploration of correlations between variables in decontextualized Big Data, or when insights come serendipitously. For these reasons our interviewees discussed Big Data as a rather insufficient information base which does not resolve the problems characteristic of the datafication process itself. More data do not necessarily lead to more insights, nor are Big Data devoid of epistemic limitations, especially with respect to questions of representativeness or bias.

Even though our interviewees presented a conventional understanding of what Big Data in general might be, there was no consensus amongst them about how Big Data on emotions would look like. One of the researchers stated the following: “I think big data would be for example if you would record yourself, you took audio databases and perhaps wear some physical biosensors at the same time so you could be more sure about results and also that could be interesting and it would give you larger sums of data.” On the other hand, another researcher with a background in anthropology pointed out that large datasets on emotions would necessarily need to imply a theory and a conception of a model of personality structure to analyse these data: “The problem is I think this category of ‘emotional data’ does not exist yet, culturally speaking. [...] So the idea that you can have something like an emotional profile: this is what is quite interesting to us, to see if something like this does develop. A kind of personality. You know, what is one's 'affective profile' or 'emotional profile'? And do we now have – just like we have kind of classic psychology personality studies – certain kinds of people? Are you the 'achiever' or one other of the VALS personality[5] or consumer types? Then maybe you have the emergence of these kinds of emotional types, which are important in terms of big data, right? Terms to order the big data into brackets and categories." A third researcher pointed to the uneven distribution of data between academic research and the research units of the big tech companies as a structural problem which has its effects on knowledge production: "Just gathering data because you can is something not very reasonable for me, right? And many of the big data sets, for example service providers have or Google has might be usable for specific reasons, the purchase behaviour of people or whatever, but it is not desirable for me if I want to pursue my own research which is then the speech related data. So, there is data collections and I do not know if speech data collections would be called big data, so that is already a question mark. I guess it would still be called a database, even if it is a huge database, it would not be considered big data. So, the big data is a different kind of data, data types, right? But of course, these companies or entities, organizations also, they have a big advantage if they have the access to this kind of data. You have for example a clear example with speech recognition performance, you have only a couple of big players on this planet which is Google which is Apple which is Nuance, that basically own massively big data sets. And now I am saying it myself, so huge datasets, speech data sets and leveraging these datasets they are able to basically build the best speech recognition systems. They also are very active in research, but not necessarily with externalising all of the data, right? But with participating in the knowledge exploration, basically in the scientific process, yes, but not really sharing the data."

The potential benefits of research on larger data sets collected according to scientific methods described by our interviewees mostly referred to taking larger groups of people into perspective and thus enhancing representativeness. These views became clear in statements like "one is that you get more reliable data. Of course, if you look at smaller samples you are more prone to find spurious results, of course, which are not real in a sense. So it makes your, besides stronger/ And on the other hand you can look more at inter-individual variability also". And in the observation of an interviewee doing research with nonhuman primates: "The more individuals you [...] add, then you can use different types of analysis and for example for us it's also because most of our data are interactions, and individual A might behave very differently depending on whether it interacts with B or C. So we also have to use different methods depending on whether we look at single individuals or interactions between individuals. So absolutely, yes. So in terms of the bigger the data set becomes, we can also use more sophisticated methods." One interviewee expressed a differentiated position on how Big Data might be useful if it was combined with concise theory, methodology and context-related epistemology: "So in many cases when I saw affective computing, what they did is they basically used advanced statistics, machine learning, things like that, to find relations

[5] "Values and Lifestyle", a research methodology proprietary to SRI International; see https://www.sri.com/sites/default/timeline/timeline.php?timeline=business-entertainment#!&innovation=vals-market-research.

between a pre-defined stimulus set and their data. And then it's basically correlational evidence that they scaled and then used, put to use. But that is something that, I think even nowadays and especially within the future that is something that is not enough. So you need an understanding of [...] how you can use your data to understand why this response was given, why a person reacted, felt in a certain way. And if you combine that, so if you do basically, the big data approach in combination with solid theoretically founded or theoretically grounded research. Then you have a really valid and valuable approach." Once again, an exclusively data-driven approach is not seen as beneficial to scientific research. The theoretical framing of the concepts under investigation is seen as absolutely necessary. Thus, an anthropologist described Big Data as a mere trigger for research: "I mean it tells us something. From my perspective, because I am interested in the qualitative dimension, it often gives me a starting point. You know, you have sort of an overview, a big broad overview".

Regarding the new research questions enabled by Big Data, researchers noted that Big Data allows the emotional dynamics within populations to be considered: "Some projects [...] work with traces persons left in social media. Also, to investigate how kind of social emotion movements evolve." This was extended in terms of the temporality and sequence of emotion experience and expression by another researcher: "And what we wanted to study was emotional waves and rhythms in the discussion and [...] we have done a lot of experimentations so mainly in Finnish because the data set is in Finnish. So, it's kind of easier to start thinking about emotional vocabulary in Finnish. So, one of the things that we did for instance is that we looked at when people talk about things that could be associated with fear or worry or happiness and we looked at rhythms: daily rhythms, weekly rhythms, monthly rhythms, yearly rhythms." Big Data are seen as potentially providing new insights for emotion research which might come up serendipitously: "And for some reason in this social media site that Tsunami generated the first recognisable wave of hate speech. And now we are trying to go back to that with everybody who remembers what actually happened. And understand why and how does something like that generate a tale that is so emotional and so negative? Because you would think that this would generate a tale of sorrow, but it actually didn't. So, there were a lot of people who were actually saying that: 'These people deserved it.'" In another example, the observation of a massive drop in the amount of data at a certain point of time attracted the researchers' curiosity to investigate the phenomenon: "Okay, so then we know 2004, 2005 there is something, the data breaks for some reason. I tried to find people who would tell about, you know, why this happened, but basically, it's unexplained. Either the service somehow slowed down for some reason. One of them might have broken. We don't know. Other kinds of brokenness-instances were bots."

When asked about the challenges that research on Big Data poses, our interviewees reflected on the range of each kind of data and their differing capacity to respond to research questions. Big Data may provide an opportunity to analyse the behaviour of users visiting a website, but they do not provide insights that alternative approaches open up: "Because with the behavioural data you don't get any information about how they feel. You just get information of whether they stick on the website or whether they move away from it. [...] so for each method, be it neuroscience, be it Big Data, be it qualitative and quantitative research, for each method there are certain questions very important, very helpful and answer a lot of questions. And there are other questions, where it doesn't help.” According to our interviewees, more data or Big Data do not necessarily help to answer crucial research questions. This may be due to the limitations characteristic of current analytic approaches: “They have collected all the Twitter responses at the American election, millions of tweets and are now thinking of doing a more reasonable sentiment analysis than what is usually done. Because again, usually sentiment analysis is positive/negative. You really need a much more sophisticated tool. I think, these kinds of approaches are of value, but only if you do it right and only if you know the limitations.” Another researcher, a software engineer, expressed his discomfort with Big Data in that it does not necessarily allow to navigate research into anticipated directions: “I think there is also a danger in the data, because it may happen that you define your problems on the basis of the available data. So, you have certain databases and then you define what you want to do with them. [...] And more important gets the problem you might be able to solve with it, but it might not necessarily be the real problem. I am not against spending effort and money into the collection of big or whatever databases, but I would be very cautious in defining the problem on that basis. [...] for many of the practical problems we have there are no Big Data available. [...] And this, in my understanding, [...] is the danger if you just say okay this is the data I have so I am just dealing with this problem, but you do not find a general solution for a very similar problem because it is just based on data. You do not have a mechanism behind afterwards. [...] Big Data might open up a more, a greater space for research, but still you cannot be sure that the answers you might find or insights you might find will answer your original question. So the question is something that logically needs to be driven forward, right, we want to move in one direction. We steer basically our research and we know what we want to explore, so Big Data can help, but it is no automatism that the more data, the more answers will come.” A final challenge for Big Data research, was identified as an exclusion from technical innovation which is largely confined to the Anglo-Saxon world: “because a lot of the advances are happening in English language. And, you know, some people say that this is what actually protects us in the datafied world for instance. Because, you know, Finnish language is like/ no data giants are putting money to actually detecting what we are doing here in Finnish. So, we're made marginal in that sense. Marginal as targets of surveillance. But also marginal in terms of getting the benefits from these innovations.”

The preceding analysis makes it clear that the exclusive reliance on Big Data is seen as a problem for academic research. This uneasiness results from the specific character of Big Data as not being structured or collected according to research questions or following established epistemologies: “I mean this is the sociologists’ dream then so to say, yeah. Because usually it’s the other way around: You have a host of questions and you have no data. You don’t know how to answer those questions. Now it’s the other way around: You have all this data, but you don’t have the questions. And if you don’t know, what you want to know, then, what people are doing, they are just/ it’s like, they are finding sorts of patterns, they are/ you know, but it’s not really that there is/ Yeah, that is what I am missing: What are the interesting questions?” This circumstance is not compensated by the advantages of Big

Data, “I mean this is the big game of Big Data, of how you/ or why everyone who says I do Big Data speaks of it and gets money and stuff, because it's a very cheap way to correlate datasets and then find new things. But the question remains – if you don't have a question then why do you look for an answer?” Beyond their own research questions, the limited explanatory power of Big Data is seen as an epistemic deficit: “What do you do with the patterns emerging from big data processing? If you have totally big data analysis, you have so many patterns that you need extremely valuable hints at what the relevant patterns are and then you need a process of, kind of, testing and matching and checking what you can do with the patterns. This has all to go into it and there is always variance and I am not sure that big data can generate all the relevance criteria itself, like a bootstrapping process. The intelligence of pattern checking and relevance detection has to come from somewhere else, and there will be competing perspectives and purposes.”

Moreover, Big Data are not seen to be capable of compensating for the limitations inherent in the datafication process itself. This became obvious in the remark of a researcher reflecting on the ambiguity in Big Data with reference to emoticons and emojis: “And the biggest problem we found was that you can never know/ There is always the binary of serious and ironic. The result is the same. There is an angry face that has been clicked on, but you do not know if it is real or not – I mean real – in what mode this expression is taking place. Also the laughing face, when it was used was very hard to interpret, because you did not know whether the person was laughing with the joke or laughing at the person, so it is deceptively precise.” Another researcher repeated the warning that Big Data would reduce the complexity of emotions: “One of the most glaring examples is of course the social media fashion of having likes and dislikes. That is constituting a lot of the Big Data and I think this is a terrible simplification, emotions are much more complex than that. And there is a general tendency that I observe that people really focus on either the like or dislike or the emoji kind of business where you think that you can classify things in a very simple fashion. In some sense that is going back to basic emotions in a very primitive way. The danger is to forget the complexity of the emotional phenomena, for example, the fact that very often you have mixed states, as emotions are very rarely ‘pure’. In daily life they are most of the time mixed or blended in some sense.”

4.2.6. Technology-driven research innovations

In the conceptual phase of this work package we decided to extend the interviews beyond the basic research conducted by academic disciplines onto applied research and private companies that attend to emotions. On this basis we were able to take emerging research areas of technology-driven innovations into account. These research innovations are prompted by advances in artificial intelligence research (e.g. machine learning, availability of neural nets) on the one hand and by the availability of Big Data for training these machines on the other. One of our interviewees described these recent developments: “In the last two, or three, or four years there was a change in artificial intelligence research because/ suddenly because of this Big Data we had, as the name is saying, we had access to a lot of data, which is driving our research into a more data driven direction. So before that we were trying to build some models, so mainly we crafted models to resemble so to say reality and to simulate things, and now we are more data-driven and learn from these data."

While the core of the scientific field is focusing on basic research and addresses knowledge gaps for example in the neurosciences or in the social sciences (the latter focusing on relationality and the affective dimensions of society and social behaviour), our interviews exposed applied research with a focus on emotions and artificial intelligence as a dynamic driver of technological innovation. Even though we were not able to conduct interviews with representatives of the big tech companies, the answers provided by the interviewees made obvious that economic interests underlie these recent developments, aiming to achieve the general goal of improving human-computer interaction (HCI) or human-machine interaction. While this research trajectory does not easily fit with research aims and epistemologies employed in basic research, it is yet unclear how these advances will influence research in the latter field.

From our interviews we learned that emotion research in the field of human-computer interaction focuses on the development of artificial agents (such as dialogue systems like embodied conversational agents or sensitive artificial listeners, or tangible implementations like robots), as well as on the interaction between humans and the artificial agents themselves. The task of applied research is therefore to improve artificial agents in order to make them more human-like and to explore the relationships between humans and artificial agents. The latter research task turned out to be a departure into the unknown, since the role of artificial agents is not yet defined and it is therefore not easy to see which forms the relationships between humans and artificial agents will take. The interviews revealed that the artificial agents currently in use reify emotion and personality theories as well as assumptions about human communication in general, all of which are coming to the surface when the human-computer interaction is examined. Our interviewees identified current challenges and potential benefits for society beyond a better acceptance of technology. Finally, they speculated on ethical issues possibly emerging in the future of this rapidly developing field.

When asked about the tech companies' intentions with respect to emotions in applied research, the scientists interviewed by us (software engineers, speech processing researchers, computational linguists) often answered "to enhance human-machine communication". One researcher explained: "So this is completely new business for them [the private companies], and why is it so good for them? So, the most natural way for humans to communicate is by a voice. [...] so you have these short dialogues with these tools. But this is something that is still not very satisfying for a human to interact with. So it would be better, and there are a lot of scenarios that you can maybe think of, to have real dialogues with these things. [...] And this is where they want to go, they want to make these things more natural. [...] it's important to deliver emotions to people, so that they get trust into the technology so to say. So if there is no trust, then people won't simply use this technology, so. And the companies are keen on getting people using their technology, so this is where all this emotion research comes in." Another researcher added: "As soon as there is a voice talking to you, you predict and you associate a personality with it", and gave an example: "In many call centres you will first be confronted with the system: with the chatbot or whatever you would like to call it, we would call it spoken dialogue system. And this would run fully automatically without any human intervention. And then there is a kind of warning system in the background which detects if the user speech is getting angry and then at a certain level you would try to forward such a call to a human operator which might be better in dealing with those emotions than the system can. [...] And humans have more, I do not know how you would call it 'Fingerspitzengefühl', sensitivity for how to behave socially adequate in order to deal with emotions and this is something which is in my opinion not really dealt with correctly by machines at the moment." This applied research can go far beyond the mere application of emotion theories, as another researcher pointed out: "Ok, there must be some greater overview, notion, attitude towards these kinds of affective states. How we internalise them, how we react towards them. And that was basically that PhD topic of the personality recognition. As a way of basically leveraging from the emotional knowledge that we basically have. And here you can also see the complexity quite easily. So we have done some experiments that we had, the personality of any person judging an another's person personality, right?" Research can thus go in two directions. Either emotion and personality recognition done by machines, or the design of artificial agents, which may be 'embodied conversational agents' or 'sensitive artificial listeners': "The project that I think of, they have developed four different characters, with different personalities. So one is more dismissive, and one is more aggressive and one is always sad, or negative, and one is more positive. So they have these four characters with four different personality styles and they react differently, depending on your emotion." Beyond the development of applications which can be implemented in the internet or on mobile devices, tangible products like robots represent another research area. This field of investigation has been characterised as largely unexplored yet: "I presume that we will find similar things with companion robots, but again the means and ends that companion robots are developed to serve are unfixed and undetermined yet. So like in any technology, whether it be social media platforms, hardware devices, or software, you know there are always people – this is just a common point made not only by me – that people use technologies in unpredictable ways, right? People do things with social media or software that you wouldn't expect them to do. And so there is another kind of feedback loop between users and designers and this is how technology develops. So even though the designers of robots like 'Pepper'[6] presume that 'Pepper' will serve certain kinds of needs – you can see the kinds of needs the presumed 'Pepper' will serve quite clearly by looking at some of the commercials that SoftBank puts out. But how people actually use 'Pepper' is probably safe to say it is probably going to be quite different than how engineers imagine. It will definitely be different in the short term because 'Pepper' simply cannot do those things that they have presented 'Pepper' as doing in ads. So what is going to come out of that? We don't know. I mean that is why there is need for this kind of ethnographic research, because this is the space where the means or the services or the I don't know, raison d'être of the companion robot will be defined." While the latter explanations were provided by an anthropologist working on emotion robots, nearly the same observation was made by a

[6] Companion robot capable of emotion recognition, developed by SoftBank Robotics. See, https://www.ald.softbankrobotics.com/en/robots/pepper.

software engineer: “So if you use Alexa or some other of these chatbots, they of course have a certain behaviour which may elicit emotions. [...] so you might even really develop strategies of how to deal with conversational systems, which are not necessarily designed for making you emotional, but they might have this effect and you might use that in your communication. I think we are not so far from it and people who develop these systems they have to be aware and they have to develop strategies of how to deal with that.”

The multiplicity of human behaviour and the variety in human reactions towards artificial agents have two effects. First, the emotion theories and assumptions built into them by their developers become visible and identifiable for humans. An anthropologist hinted to related challenges with regards to the cultural dimension of imagining robots: “The thing is, design is not uniform in Japan. Certainly, you see a lot of different kinds of robots, humanoid robots being developed in Japan. And [some scholars] would argue that you can certainly see certain cultural assumptions, very clear cultural assumptions built into different models. So with ‘Pepper’, who suggests a kind of value placed on adolescence, the same kind of adolescence that you see in a lot of the classic anime and manga, like ‘Tetsuwan atomu’ (‘Astro Boy’) or something like this. [...] And it is clear that there are certain mainstream ideals of mass media beauty which are serving as the model for these creations. So there are different values, which are being built into different objects, I think.” Second, the use for which these artificial agents were designed and how they are actually used don’t necessarily match. Even if there is no clear role for these artificial agents, the emerging interactions between humans and machines may turn out quite unexpectedly: “So what you have then is a different kind of interacting, a different kind of intimacy. That’s why we use this term ‘technological intimacy,’ or ‘technological transformations of intimacy.’ So different kinds of interaction we expect are going to elicit different kinds of feelings, which aren’t necessarily human-human feelings but they’re human-machine hybrid feelings. [...] There are a lot of different actors: some human, some non-human, and you get a kind of, you know, emergent form of affective exchange that you have to analyse as, I think, a complex hybrid object. [...] That is why I think you have to understand these spaces of interaction as kind of hybrid spaces: they are not human-human, they are not human-machine, they are kind of just this weird new emergent kind of relational space, composite, or assemblage.”

Another interviewee, developing an app, affirmed this changing role within human-computer interaction: “But if I have an app that is not a social partner, it’s my personal companion, it’s like my, my diary, it’s like/ I mean, and this is like an assumption that I would put in the room: A smartphone is sort of, it becomes kind of a part of myself after a while.” Within this context, the term “artificial empathy” came up. Our interviewees explained that there is no empathy on the side of the machine. The display of compassionate emotions by a robot has to be understood as pretension: “And a lot of his interactions and other robots like ‘Pepper’ are basically functioning in terms of a kind of performance of empathy [...] A behaviour performance essentially, yeah. A very specific one, so not one that is learning from a certain profile and adjusting, at least not in the consumer space where ‘Pepper’ operates now. Right now, there are very fixed, planned responses.” Next to this anthropological view another interviewee added: “I mean machines can take rational decisions, but they are not empathic.

But this is the new thing, you know. Like imagine machines would be empathic and they could really not only on a rational basis influence your decisions, they can also do it on another level, which is much more indirect but very smart. And I mean/ there are of course economic reasons for this." In the context of unclear roles or unclear purposes for which the artificial agent is designed for, their development is driven by visions and imaginations rather than clear-cut functions, as the anthropologist cited above explained: "As in a lot of fields where you have new technologies, it is driven by the imagination of what these things could potentially do. [...] The way we imagine it is more like a feedback loop. That the way people react with other people – these assumptions, imaginaries, expectations, norms – are built into the technologies. The assumptions of what robots should be there for, what means they serve, are being built into their capacities." Furthermore, the differences between developing applications and designing robots are of importance: "What it means to have 'artificially intelligent software' is a different set of concerns than when you implement that into a figurative robot – a robot with a figure or a form, I should say. Because then all of a sudden you are taking work which is primarily done on emotion modelling, right? At the software level you are working on models, for example something like the attention schema theory, which is a way to try to model attention, and thus consciousness, in artificial intelligence. [...] then you have a whole different set of questions because you are talking about now mimetic representation, mimetic symbolism, and performance. It is so much of how people interact with their people and bodies. So much of how people interact with people emotionally and read emotional cues is because of the aesthetics. It is because of behaviour, because of performance of what another thing looks like."

While these explanations give an idea of the complexity of the whole field of applications, our interviewees provided examples of the challenges they face, e.g. the question of majority bias: "As humans learn from examples, machines learn from examples. So if you have a stack of examples you basically need to put them into some categories because that is how machines learn, by categories, by examples. But when you ask 20 people is this sample emotionally coloured and would it be anger or would it be joy or would it be whatever emotion or whatever affective state. Basically, you see the people they diverge, they have different opinions. So, what we go for in this stage at, let's say, this stage of development of AI, we go for the majority of it. So, we train the system that is able to recognise anger by a prototype of anger that also 80 percent of our testers have assigned anger to. So, that machine will be very good in dealing with the majority form of anger but it will not be able to differentiate any example or any exceptional forms or any context dealing with this kind of anger. [...] So, the AI might be moving on forward to with a quite considerable speed, so we are achieving, but we are only able to achieve with this one direction and what is basically left out is the whole granularity complexity when different examples coming into the context causing different shapes of action, causing different demands that we would like the machine to actually know and to follow the different path, we do not have the path". Another challenge formulated by the interviewees was enabling the artificial agent to find an adequate response while avoiding the manipulation of its user: "And when you come to applications, in future times my smart home at home would try to gently speak with a little bit, you know, coloured emotion with you. Imagine you are getting angry. So how do you react if your smart home will dare to try to calm you down? I guess as a human you would be able to recognise that now your smart home will try some strategy with you. So, what's your reaction towards this? So, then I was basically talking about this to professor [...] and he said yeah: 'Do I want to have my smart home talking gently angry with me, I am not sure.'" The complexity of the tasks and the challenges ahead led one of the researchers, working in a public-private partnership, to sceptically reflect on the capability of AI to process the complexity of emotions in the near future: "But what I don't think is that they, at least when we are still using the technology that we are using now, I think there will always be no place for real creativity within these tools that we are developing, because as I said the neural nets are just mappings from one, one input area to one output area. So there is no place for real creativity. And so when we are for example talking with each other, we immediately/ so you see my emotions and you feel it somehow, you can't really make, say: 'Ya this was the point when he was friendly and then there was this phase', it's not explicit. You just feel it, and your internal process is doing something with it and then you react somehow to it. And there is a lot of creativity in this reaction, which is coming not only from our talk now, but which is coming from experiences that you have in the world. So, so much comes together. And no computer will."

Beyond a better acceptance of technology and research on human-computer interaction, our interviewees identified therapeutic uses as possible fields of application and identified potential societal benefits: "So loneliness is a real big issue and artificial intelligence that is always there for me, is like a friend, I can switch it on and off whenever I want to have it or not, would be a good thing to help me with that, if it works. Like I said, I myself am a little bit sceptical somehow, that it cannot really replace human interaction, but that is something that remains to be seen. And as loneliness and self-management is one of the critical issues of most mental disorders, I would say, also that of course there is a lot of potential for helping people to self-manage and not feel so lonely, with artificial intelligence, in this mental-disorders-field." Another interviewee, a representative of a patients' empowerment movement, was optimistic about the ability of the learning system under development to deliver an effective behavioural therapy: "So you can tell the program what you did and the program analyses how the activity helps and when it helped and how it changed your emotions. And this way the companion should get smarter and smarter. And so it's a mix of individual input, what you did. And methods that are proven to enhance for example the mood or to reduce anxiety or to boost gratitude."

Because this field of human-computer interaction is still emerging and developments in the near future can hardly be anticipated, our interviewees were reluctant to share their reflections on possible ethical issues and pointed to their thoughts being speculative and anticipatory. Where emotions and emotional attachment come into play, ethical issues can arise, as one researcher underlined: "I think there is a certain human propensity to link with objects, with pets, with gadgets, whatever, and to establish relationships with those things. I think the most critical and interesting questions here are ethical ones, in the very moment. I mean, elderly care certainly is something, but then you also/ there is a colleague [...], she very successfully uses artificial companions for people with Alzheimer's disease. And they seem to be hugely effective, so it's on the one hand it's just, okay, we don't care about the elderly, we have our artificial companions to take care of them. So there is both ethically very questionable practices that may arise". One of the researchers expressed the opinion that the interests of private companies would not stretch beyond increased economic profits: "Coming back to the dialogue systems and emotional things, for now I think all companies if they try to kind of manipulate people, they are doing it like they are doing it in advertisements. So to bring people to buy something. So, just to earn money. I don't see, for the moment I don't see like a big thing behind this where they want to manipulate people to do things that they originally do not want to do." A sociologist was more articulate about the possible frictions between economic interests and the attachment of the users to empathising chatbots: "Nobody says it's a problem that people think cats empathise with their owners, right? It's/ on the one hand it always seems to be so weird, because it's technology. I think the important or the critical thing here is, because/ I mean, cats are usually not commercially employed or used for other things. If those apps and technologies are used for/ in terms of exploiting that for some other cause, then we have those questions". One point of conflict might therefore be between collecting data for learning purposes and privacy preservation: "So when you listen to someone, like the CEO of SoftBank speak at conferences, you hear him talk about how 'Pepper is a learning robot' and how 'Pepper is connected to you now in the artificial cloud and he has AI learning capacities.' And so the idea that they articulate is that these robots will be connected, they will learn from their interactions with other people, they can share that data, although he is also careful to say that no private data will be collected".

5. Discussion and Conclusions

Epistemic Dissonances

The findings of the interviews and the survey show that most of the researchers acknowledge that their understanding of emotions and affects is limited by the particular epistemologies, methodologies and theories they take on as their object of research. The preceding sections illustrated that the interdisciplinary character of emotion research corresponds with a multitude of scientific positionalities, research structures and organisation. The disciplinary backgrounds or epistemic cultures can be seen as the primary factor in the social construction of scientific facts as they shape the formulation of the research questions. The subsequent process of knowledge construction moreover comprises of choices of theoretical frameworks and the selection and combination of specific methods. The way theoretical concepts are operationalised and methodologically applied highly influences the nature of the data acquired or created and the subsequent analysis and interpretation thereof. Consequently, the outcomes of epistemological processes depend on a number of decisions taken upfront, which explains why the findings of different research projects are limited in their scope and applicability and are often difficult to replicate. And yet, integrative perspectives on these results promise kaleidoscopic landscapes of knowledge. These can be aggregated into large datasets if multiple contexts that shape the construction of data structures are considered from the point of curatorial perspectives of storage, sharing and reuse.

Datafication

Researchers are well aware that the research object of ‘emotion’ and ‘affect’ as a whole, encompassing all possible aspects and dimensions, cannot be investigated in their research. The datafication of phenomena like affects and emotions therefore always entails the reduction of complexity and the loss of information. The one does not work without the other – they are mutually constitutive. Datafication, when implying the *selection* of data was primarily seen as a problem for empirical researchers. The distinction between signal and noise works as a valid metaphor in this regard: that is to say the distinction between meaningful data in a certain theoretical and methodological sense and data, that is spared from the outset or cleaned in the processing of the data. In order to fully grasp a phenomenon, information is needed on how both signal and noise come to existence, and how they mutually constitute each other based on structural definitions of epistemic difference: what is considered as relevant data by the researchers, and what is not? Humanists who work on theoretical levels and thought experiments often take the written outcomes of other researchers as their starting point and so reverse the DIKW pyramid, expanding on previous knowledge without referring to it as ‘data’. Humanists prefer to talk about ‘research material’ or ‘primary’ and ‘secondary sources’. The materials accessible and reusable for humanists are in a way opaque: Containing derived data or argumentative elements well-presented within narratives. These materials do not allow for drawing conclusions on the “raw data”. Their data have already been datafied by other thinkers and theorists and so identifying texts as data would duplicate the process of datafication. Denying the equalisation of texts with data can thus be an expression of recognising the limited influence humanists have on the framing of the underlying information and knowledge in their material. This applies also to humanists working with other sources like images, audio, or video material. The fact, that these sources do not stem from their own empirical inquiry but rather are the products of others, could explain the clear positioning against the term “data”. Where does data(-fication) start, and where does it end then? Some social scientists who participated in our survey equally rejected the term “data” and expressed their unease with “datafication”. On the one hand this scepticism of the social scientists results from reflections on the shortcomings of datafication, especially the disembodiment and disentanglement of data. The translation of emotions and affects into data is inevitably reductionist as these real-world phenomena are overly complex by nature. Reductionism in terms of selection of a research object, the adoption of an epistemological focus and the choice of appropriate methods is not so much the problem. What is problematic is the lack of reflexivity loops that can increase knowledge complexity by adding neglected information before, during and after datafication. On the other hand, the social scientists’ discomfort to use the term data can also be seen in connection with a particular empirical research methodology. This pertains to an understanding of “data” as decontextualized and depersonalised “data” obtained from controlled experiments conducted in laboratory settings. Epistemological perspectives that extend their focus also to the relational and situational factors in the constitution of emotions stand in contrast to this data-driven approach. Moreover, for researchers, who usually adopt qualitative approaches, datafication stands for the quantification of emotions and affects. In this perspective datafication is not only reductive but in its simplified translation of real-world phenomena into numbers, it is furthermore prone to rankings, ratings, scorings and screenings and therefore highly problematic in ethical and political terms.

Generally speaking, humanists’ and social scientists’ positionalities within the data processing chain affects their relationship with data and datafication. The absence of research technologies and the reliance on the researcher as embodied instrument within these two scientific approaches is an essential difference to the natural sciences. Unlike in the natural sciences, where shareable technological devices often go hand in hand with the establishment of data and workflow standards, in the humanities the preconfiguration of data are not considered a part of the epistemic process. The idiosyncratic nature of the knowledge creation processes complicates the (inter-)disciplinary exchange on data processing and data analysis methodologies. This idiosyncrasy results from a certain opacity on the side of the humanities, since “there is little evidence to show exactly how the humanities disciplines fulfil their epistemic mission” (Edmond, Bagalkot, and O ’Connor 2016, 3) The particular strength of humanists – the presentation of data embedded in their relative contexts – does not necessarily become more significant when the amount of data increases. Moreover, the integration of large datasets and comparative approaches favours quantitative methods in need of standards and baselines in order to develop theoretical significance. It is not necessarily the quantity of data that poses problems to humanists and qualitative and ethnographic social scientists focusing on cultural and language differences. Rather, these problems are the result of the related standards that accompany data and which are to be developed from within these epistemic cultures.

The tacit or implicit dimensions in the data that are known to the researchers but usually are not found in publications seem to be less of a concern as long as the data remain in use by the researchers or research units who collected or created the data. Even if not all details along the datafication process (starting with the operationalisation of concepts, the selection and combination of methods, the adaption of research tools to the specific inquiry, the collection, processing and analysis of data) are documented, the researchers involved will be aware of their assumptions, experiences and revised approaches. Moreover, their stock of implicit knowledge encompasses the reasons for decisions made against particular methodological approaches. Knowledge about exclusion criteria usually remain hidden, be it because of immanent critique, strategic or pragmatic reasons. Once these data are shared with others, reused or integrated with other data tacit knowledge is lost, if it is not transparently contextualised and annotated (and that again brings about ethical challenges of what knowledge is confidential and hence not to be shared, and which is not, and can be reused ethically even in future generations, when political and academic regimes transform and change). The valuable insights we gained from our interviewees and survey participants shed light on this problem. Specified in terms of subjectivity or "situated objectivity" (Williams 2015) the researchers, many of them anthropologists, reflected on the shortcomings of datafying their own experiences and perceptions in the actual encounters with their research participants during fieldwork. A challenge to all empirically working emotion researchers, both interviewees and survey participants, was the resistance of underlying affective states of researchers and research participants to datafication. Besides the difficulties in expressing or communicating individual perceptions of emotions – partly due to emotional regimes that exert pressure on individuals and groups – these hidden dimensions were characterised as most difficult to capture. Emotion seemingly stands to affect in a similar vein as does data and narrative – whereas emotion/data can be standardised and hence run the risk of oversimplification and essentialism, affect/narratives resist standardisation in its current practices and policies. The tension between these two epistemological positions creates a dynamic academic climate that – in its current manifestation – divides scholars into dichotomies of 'for/against' datafication. The K-PLEX project speaks a different and more reconciling language: critical yet respectful interdisciplinary collaboration can create bridges between opposing camps – if only there was enough awareness to support these collaborative efforts between data sciences, computer sciences, the humanities and the social sciences within institutionalised structures of educating future researchers, archivists and developers.

Heterogeneity of research approaches

A topic that was prominent in the survey results is the heterogeneity of methodological approaches. There are different combinations of methods to explore emotions and affects. That the collection of data does not happen in a standardised manner may be due to these very specific methodological approaches as well as the widespread adoption of an inductive approach. The constant adaption of methods to address the particular research questions, the changing socio-cultural environments, technological improvements and the current state of the art in emotion research provokes context-adaptive methodologies that are difficult to subsume under current procedures of standardisation. The compartmentalisation of the research field emotions and affects can thus explain the tailored solutions many researchers embrace. At the same time these methodological choices impose limits on the datafication process and thus restrict the range of what can be datafied.

Context

According to both our survey participants and our interviewees, information loss in the process of datafication also depends on the choice of methods, according to both our survey participants and our interviewees. The single focus on either a specific method like sentiment analysis, facial measurement, fMRI, speech analysis, etc. or one kind of data such as text data, sensor data, images or audio data leads to the selective masking of aspects that cannot be covered by the particular approach. There exists a dependence on facilitating technological instruments which may be insufficient as these tools can perpetuate the problem of selective masking. These tools often cannot deal with ambiguous or even contradictory meanings and can miss connotations inherent in the data. The significance of meanings and connotations is only revealed through adequate contextualisation. By contextualisation we mean both the consideration of the context of data as well as the context of the researchers. Context thus implies the historical, political, social, cultural and linguistic embeddedness of the data. Depending on the research setting context can also mean the natural context (whether the data were collected in the laboratory or in the field) or the situational context of origin of the data. Regarding the researchers, knowledge about their positionalities and subjectivities as well as their research interests and aims would foster the reusability of data.

Information loss may occur at all stages of the datafication process, but classification may have the most lasting effects. The *a priori* reduction of a phenomenon to distinct categories such as the reduction of a person’s wide array of affective experiences and feelings into basic emotions clearly restricts extensive knowledge to predefined (and potentially misleading) categories. Rigid classification schemes not only have consequences on scientific research, but also shape public discourses on affects and emotions. Too rigid or too reductionist scientific classifications have social consequences and are hence political. Big Data approaches to emotions in social media were therefore criticised by the majority of emotion researchers not only as oversimplified but also as questionable in ethical and political terms. A mood tracking app that provides a selection of a dozen different emotions has the potential of norm-setting and personal governance in the mental health care arena, education and employment sectors. This becomes obvious in the binary reduction to like/dislike or the limited choice of expressing emotions with emojis in social media.

Conceptual gaps

Dualistic conceptions of emotions and affects, whether positive-negative as for example in a textual sentiment analysis or the juxtaposition between emotional experience and emotional expression, were commonly identified as reductionist. These restrictions on a conceptual level help to deal with complexity but at the same time create blind spots. Conceptual gaps were identified both in very concrete omissions from the theoretical framework and methodological investigation as well as on a meta-level. Particular issues mentioned relating to publicly non-observable and masked aspects of affect and emotion often focused on the bodily dimensions, the phenomenon of mixed emotions and the complexity of interpersonal dynamics and communication. Furthermore the question of how to take into account individual differences, personality types or emotional phenotypes, that often do not coincide with conventional grouping criteria such as age, gender, social background, economic income, or profession was also defined as a conceptual gap. On a meta-level it was either theoretical approaches which were criticised for simplifying or the reduction of the concepts of “emotion” and “affects”. A few researchers proposed solutions to close conceptual gaps. Some named specific approaches such as practice theory, neurophenomenology or constructive design work. Others accorded interdisciplinary cooperations a high potential to overcome deadlocks. And finally, a few researchers recognised postcolonial approaches that acknowledge the perspectives of the racialised and epistemologically “other” as a possible solution.

Biases

There were several kinds of disciplinary or epistemological biases identified by emotion researchers. These biases were partly attributed to the approaches in other disciplines, partly admitted for their own research approaches.

First and foremost, biases result from the use of theoretical models that claim universally valid results and facts, although they are deeply rooted in Eurocentric or ethnocentric ‘Western’ reasoning. This potentially global impact may have serious consequences. If the emotions of large populations are measured on the basis of universal theories, then normativity is the result, and obvious cultural differences cannot be registered. The societal implications and repercussions of such a universalist approach have already been discussed in emotion research on the occasion of the theory of “basic emotions” developed by Paul Ekman. Science historian Jan Plamper has drawn long lines from Ekman's claim to identify distinctive universal signals and his examination of facial expressions of emotions in the 1970s to Ekman’s involvement in the U.S.-American anti-terror program SPOT (“Screening Passengers by Observational Techniques”, (see Plamper 2012, 191). The use of such a universal theory and its benefits for questions of national security has led to an extensive debate after 09/11. If the very same approach is used nowadays in products developed by the big tech companies and other private companies, a discussion involving citizens and politicians on the societal repercussions of such techniques has yet to be conducted.

Second, biases – if in accordance with our interviewees and survey participants are understood as results of methodological decisions – were strongly related to the machines used for emotion measurement and the laboratory settings in which these research tools are deployed. Researchers exclusively relying on fMRI or speech recognition software as well as researchers conducting research in laboratory settings in general, identified explanatory limitations due to their controlled experimental research design. Due to the high costs associated with the technical instruments, the majority of experiments are being conducted in exclusively 'Western' (including Japan, Singapore and China), Educated, Industrialised, Rich, and Democratic (WEIRD) countries (Henrich, Heine, and Norenzayan 2010) thus increasing the bias in the data structure from a global perspective. Another predominantly methodological bias can be termed "quantitative bias" (Forsythe 2001; Lash et al. 2016). Not neglecting cultural or language differences or social backgrounds, this bias runs the risk of naturalising these differences. Quantitative methods tend to overgeneralise their results for social groups while staying analytically on the surface and not necessarily fulfilling the requirements for drawing conclusion on causal relationships. What is true for quantitative data becomes even more crucial for Big Data. The inference from behavioural and micro-narrative data collected on a social media platform to the affects, emotions or feelings of the users is still a highly speculative exercise despite joining forces of various disciplines.

Finally, a bias termed "majority bias" (Feinerman, Haeupler, and Korman 2017; Mukherjee, Sen, and Airiau 2009), refers to the definition and singling out of emotions as bounded entities that are easy to define, to assess (imagine you had to describe how you feel right now while reading this report, your emotions might be mixed) and to translate into applications that target the health or productivity of persons, communities or whole societies, without taking their ambiguity into account. This bias is relevant for the development of technologies and programming of machines which is closely related to the quantitative bias and is gaining in weight with the amount of data available. Since datafication and technological applications currently work along decontextualized standardization which targets bounded prototypes of particular emotions, therefore researchers take those emotional expressions into account when building new technologies that are most likely identified by test persons in an unanimous way (see "quantitative bias"). The consequences of the "majority bias" are (at least) twofold: on the one hand the cleaning of noisy, ambiguous data creates biased datasets, on the other the technological implementation of emotional prototypes into technological instruments and detection measures results in a bias of emotion recognition. Without systematic scrutiny of data contexts, instruments to measure emotions will remain preconfigured in multiply biased ways, and run the risk of detrimental misrepresentation and manipulation of human experience.

Knowledge gaps

Despite the theoretical and methodological efforts made by emotion researchers to better understand emotions, there is a number of unresolved issues within this field. One knowledge gap noted by our interviewees and survey participants was the inadequate knowledge on brain functions in terms of emotions, which is mainly a problem within cognitive and affective neuroscience, but also touches the issue of affects. The same applies to the question of whether affective behaviour is the result of genetic inheritance or the result of a social inheritance transmission. Knowledge gaps were also identified with regard to the dynamics of collective emotions, especially how emotions are shared, how they spread out, both in human and non-human primate populations. Some knowledge gaps were mentioned on behalf of future developments and their societal impacts, such as the ways in which the increase of human-machine interaction or the widespread use of artificial empathic agents might shape communities and societies. Within the humanities it became clear that the availability of data very much restricts what can be known about emotions and affects. Particularly in historical approaches the way emotions were expressed in former times can be investigated with text data, but how emotions were experienced can only be examined to a limited extent.

Data reuse and data sharing: shifting standards of contextualisation

One of the findings of the survey is that two thirds of the survey participants are of the opinion that their data are reusable for researchers coming from other disciplines and who use the same instruments and methods. In contrast to this finding, several limitations to data sharing and data reuse have been identified. These restrictions can be found on different levels: the structure of the data and metadata themselves or issues of integrating data, but also obstacles resulting from the organisation of research, or ethical and legal restrictions.

Although the work package did not focus on data and metadata formats and their specific structures, this study illustrates that a multiplicity of research epistemologies leads to a plurality of data and metadata formats. This conclusion is substantiated by the lack of standardisation of data as identified in the survey as well as by the observations made in the interviews. To mention one example, the W3C standard format EmotionML is rarely used in academic research. There seems to be a contradiction between the affirmation that data are reusable and a lack of standardisation. Possible explanations for this contradiction are the fact that few researchers use data other than their own and therefore are not aware of the necessity of standards for successful sharing of data, and on the lack of adequate standards for particular epistemological approaches. Further collaboration is needed on the question of how best to add information on the research context and on the epistemologies implemented in the data collection process, and on the development of methodologies for capturing the research context.

One result of the heterogeneity of data and metadata formats is the challenge of integrating data from various sources. At first glance this may appear to be a specific challenge posed by emotion research with its diverse approaches to physiology, brain activity, or the various forms of expressing, communicating and interpreting emotions. But it is also obvious that the more comprehensive the phenomenon under research is, the more complex and pressing the question of data integration will be, especially in the human sciences. Interviewees pointed to the necessity of having a comprehensive theory as a basis for data integration. While it remains to be seen how this consistent theory may contribute to the operationalisation of data formats for the purpose of their integration, it will certainly contribute to a harmonisation of data structures. If the communication amongst researchers is enhanced with the aim of a better integration of data, this aim will certainly contribute to improved data reuse as well. Though this goal seems to be laudable, researchers should be aware of the possibility of an amplification of existing biases through data aggregation. In this respect, academics can certainly learn from the discussions around biases in Big Data.

Limitations to data reuse and data sharing may lie beyond the questions of data formats and data aggregation. Especially in large interdisciplinary research projects or on the institutional level obstacles may arise out of the organisation of research. As the survey has shown, two thirds of the participants stated that their institution does not have a Data Management Plan. While this may not apply to the project level due to guidelines provided by funding institutions, the provision of transparent and epistemology-sensitive procedures as well as best practice examples promise to create incentives for data sharing and reuse. Furthermore, the example of emotions demonstrates that there may be legal restrictions to or ethical issues in sharing data. This especially applies to questions of privacy, anonymisation and the possibility of de-anonymisation of data. Once again the context in which data are collected comes in: while it may be easier to solve these issues in situations where technical devices are used, scenarios in which researchers interact with research subjects beyond a measuring device require more careful practices, since it is not only the privacy of the research subject which is at stake, but also the privacy of researchers themselves.

Incongruity of terms and concepts

Survey results showed that academic researchers do not necessarily have a thorough command of basic terms of IT language, such as fluency with abbreviations designating the volume of the data at their disposal, or acquaintance with terms like “data cleaning”. At first glance this looks like a terminological issue, but the incongruity of terminologies points to the incongruity of concepts as well, as the example “quality checks” shows. It is self-evident that humanities’ researchers and qualitatively working social scientists apply procedures to check the quality of their data and even use terms common in statistics. This becomes obvious in examples like “validity” or “reliability”. Judging the validity or reliability of sources is essential in the historical sciences, and in anthropology, and the results of these preliminary works inform the embedding of statements taken from the sources or informants into the critical discourse of a scientific study. Yet even if the terms used are the same in different scientific disciplines, the methods used are not congruent with each other. While in the computer sciences quality checks are performed by applications, in the humanities and part of the social sciences these procedures cannot be formalised in a way that enables delegation of the task to the machine, since for example contextual information is used to estimate the reliability of the source. The example of quality checks therefore shows that the attempt to share a common language between different disciplines might at best end up in a mutual awareness of research methods.

Another issue deserving attention is the dominance of statistical techniques for performing quality checks within the social sciences. The evaluation methods that dominate the discourse focus on measures such as p-values, correlation coefficients and cross-validation. Qualitative social scientists are familiar with the principles of these procedures, albeit they apply them differently in their methodological approaches. The consistency of explanations and verifications, whether in forms of inter-rater reliability or the matching of findings, is a common aim among many researchers, but the terms to speak about it and the way quality criteria are expressed (in numbers or in a narrative) are very diverse. Attempts to provide an equivalent framework for statistical and qualitative quality checks, operating with criteria like credibility, transferability, dependability and confirmability (Lincoln and Guba 1985) have not found acceptance within the qualitative social sciences. However, recent discussions on the validity of statistical measures can be seen as supporting the call for more reflexivity in the use of research methods. When psychologists acknowledge that questions of plausibility, validity, and reliability are too complex to be controlled automatically, there is a real chance to put an end to "mindless statistics" (Gigerenzer 2004). The challenge for qualitative social scientists would then be to provide enhanced reflexive tools that not only focus on literary representations or issues of conceptual rigor and logical consistency, but that can further discussions on dialectical knowledge formation, the ever-changing context within which research occurs. The dimensions that qualitative social scientists can add to the discussion on quality standards extends the usual limitations of the choice of variables, the sampling and the number of research participants, and they include reflections "after the fact". The disclosure of epistemic interests and adaptations of research methods to the particular research context as well as reflexions on positionalities and the role of theoretical assumptions on the interpretation of data can be enumerated here. Moreover, in view of data storage and reuse, ethical questions, especially with regard to privacy concerns and potential political implications, have to be taken seriously.

Big Data challenges

From our survey we learned that 16 out of 123 researchers have data with a volume of at least 1 TB; the majority of natural scientists amongst the survey participants reported to have data of this volume at their disposal. We took this point up in our interviews where it turned out that such data need not necessarily be Big Data in the conventional sense; these could also be very large datasets of video recordings or data collected in the neurosciences doing fMRI studies. The difference between Big Data and data collected in the sciences became obvious insofar as Big Data are not collected according to a specific research question or methodology. This can be termed a structural similarity between Big Data and the data used in research done by humanists: data can be antecedent to the epistemological process, they need not form the output of a research methodology aiming at collecting and analysing data according to a specific theory. In the interviews we observed a certain cautiousness on the side of our interviewees with respect to Big Data, which stemmed on the one hand from an uncertainty about the definition of Big Data, and on the other from the challenge of dealing with data that were not collected for research purposes. The fact that Big Data are antecedent to the epistemic process of science (yet not for computer scientists) necessarily creates friction with scientific approaches where they are collected as part of the empirical research process. In the case of humanities' researchers, who are used to dealing with data they have not collected themselves, the challenge consists of implementing interdisciplinary cooperation, since humanists are mostly not trained to deal with Big Data themselves. Rather, they need collaborate with information scientists to analyse these data. The process is improved if the latter group also are willing to understand the language of humanities or social science scholars.

For these reasons it is not surprising that our interviewees, three of whom have been engaged in Big Data research projects, presented differentiated views on Big Data, balancing benefits and challenges. While the surplus of emotion research on Big Data was identified as opening new research questions such as tracing emotional waves over time, exploring dynamics within groups, or potentially providing new insights into collective emotions, objections were raised. Interviewees questioned the capacity of Big Data research to answer questions that are usually treated within a certain research framework and on the basis of a given theory; the impossibility to infer group characteristics from Big Data, since representativeness is impaired due to an unknown basic population; the limited explanatory power of Big Data as containing only information on human behaviour; or the difficulties of steering research on the basis of data which should better be investigated in an exploratory manner open for serendipitous findings. Against the background of these challenges, the opposition between the approach of social scientists – well acquainted with stochastic data models – and the approach maintained by information scientists – using algorithmic models that treat the data mechanism as unknown – becomes apparent. These two different camps, or "epistemic cultures" (comp. Breiman 2001) have already been described above in section 2. Again, collaboration of various stakeholders in the domains of information, data, cultural, humanities, and other sciences is a promising enterprise if mutual brokers are involved.

Use of standard data formats

The finding from our survey that the use of standardised data in emotion research is uncommon corresponds with the interview findings on the poor acceptance of the W3C standard EmotionML. The technical reasons for the low impact of this standard – the XML format requires coverage of the diverse aspects of emotions and blowing up the data – stand in contrast to the statement of one of our interviewees involved in the W3C Emotion Markup Language specification, that the standard is used in academic research and by private companies. There is certainly the need for further enquiry into the question of who uses this standard and into the reasons why it is not more common amongst emotion researchers. Differing "cultures of formalization" (van Zundert et al. 2010) in the computer sciences and the humanities which align with particular ways of approaching complexity and uncertainty might help in explaining this gap. Making humanities' specific formalisations that are implicit in argumentative structures explicit through the use of computational methods might appear to be an alienating process for humanities scholars. In other words, this standard reflects the lack of theoretical and methodological agreement amongst emotion researchers by comprising markup for a variety of emotion vocabularies (categories, dimensions, appraisals, action tendencies). Thus, it consolidates several epistemologies that compete with each other in the academic arena. The tendency within the scientific field to set single theoretical approaches as absolutes and to ostracise competing approaches certainly contributes to the reduced acceptance of the W3C standard format. In contrast, in the applied sciences and in the research done by private companies, where the decision on which approach to use is taken on a pragmatic and economic basis, such considerations play a secondary role. The flexible application of diverse approaches or even their combination may lead to the desired outcome; This stance may run counter to academic orthodoxy. While this explanation, coming from a theoretical viewpoint, may clarify why the use of the W3C standard is uncommon in the academic field, it has to be questioned whether the myriad of heterogeneous epistemic approaches currently used in academia will ever be homogenised into a few broadly accepted standard data formats. Again, this calls for the development of encompassing emotion theories which form the basis for a data and metadata format yet to be designed in careful collaboration.

Challenges for interdisciplinarity in emotion research

Interdisciplinarity was seen both as providing substantial benefits in emotion research while raising new challenges at the same time. With regard to potential benefits interdisciplinary cooperation could possibly reveal each others' tacit knowledge. In the interviews the potential contributions of some disciplines such as philosophy to clarify the concepts used, or the possibility of anthropology to complement and expand neuroscientists' approaches, were particularly highlighted. Interestingly interdisciplinary cooperation on a theoretical and conceptual level was estimated to be easier than in empirical research. Some disciplines presumably compatible on a theoretical level such as neuroscience and philosophy may turn out to be oppositional when it comes to the integration of data acquired by both disciplines. One challenge for interdisciplinary research thus concerns mutually benefiting, influencing and supporting research methodologies that create particularistic data that can be integrated into reusable data organised along shared epistemological standards. The role attributed to theory is a further point of discussion closely related to this issue. Scientific disciplines based on highly formalised models such as contemporary psychology argued for a deductive approach to the investigation of emotions and affects. This stands in contrast to disciplines like anthropology or history, which often pursue inductive approaches, well adapted to the cultural contexts or the sources available. Whether interdisciplinary research on emotions can work according to a "grounded theory" approach is highly controversial. The challenge of conducting interdisciplinary research can thus also be presented as a matter of scale. Eventually one difficulty in interdisciplinary research will have to do with the compromises each of the participating disciplines has to make. In particular, those disciplines relying on costly technological instruments might not want to abstain from using their scanners and other technical equipment. This is certainly one of the most important challenges in interdisciplinary emotion research, which illustrates that structural factors influence the modes of interdisciplinarity: the competition for funding, the lack of high-ranked journals publishing interdisciplinary results and the difficulties of organising large-scale interdisciplinary research units can be mentioned in this regard.

While interdisciplinary approaches need not necessarily be holistic, it is interesting to compare the statements made by our interviewees regarding these diverging fields of discussion. Several interviewees were both sceptical about the feasibility of interdisciplinary research and the probability of establishing holistic approaches in emotion research. We wonder, what researchers actually understand by ‘holism’? Their statements show that disciplines covering a broad spectrum of theoretical and methodological approaches tend to define their disciplinary approach as holistic. This perspective supports an image of data being perfect, all-encompassing and truthful, thus denying the reduction of complexity inherent in the datafication process. At the same time emotion researchers are well aware of the fact that a holistic theory or framework does not yet exist. There are two striking examples: a failed harmonisation of nature/culture-focused approaches, and the incompatibility of emotions as private internal states and emotions as relational by character. These examples clearly show that a holistic perspective or a “view from nowhere” (Nagel 1986) can hardly be achieved. In addition, since scientific disciplines apply for funding, the tendency to claim “truth” and the revelation of all-encompassing knowledge as well as claims of holism have to be understood in terms of marketing strategies. Therefore, the term ‘integrative epistemologies’ is perhaps more adequate in this regard.

The exceptional position of the applied sciences

Within the scope of our study, the exceptional position of the applied sciences has to be foregrounded. This observation arose from the interviews conducted with researchers working in the applied sciences or in private companies. With the creation of artificial agents and research on human-machine interaction, this research field can be described as a driver of innovation in a quickly developing field. The dynamics of research on emotions in artificial intelligence applications and human-computer interaction is fuelled by private companies’ economic interests, in general aiming at optimising the impact of human-computer interaction. Thus, new research areas have come into existence, be it chatbots, sensitive artificial listeners, embodied conversational agents, or robots, or the whole field of reciprocal exchanges and alignments between humans and AIs. These new fields bring new possibilities for collecting and analysing emotion data, but also raise questions of ethics and privacy with respect to AI applications’ quickly growing capacities to understand and interpret humans’ behaviour and emotions. The lack of interest of representatives of the big tech companies (Apple, Google, or Microsoft) in conversing with our work package collaborators indicates a certain opacity on the side of global economic players. However, it has become more than obvious that this field is of utmost importance for STS studies of the near future, since the feedback loops between users, developers, and the artificial agents form an interesting research topic in itself. Finally, although the use of AI and algorithms is not yet very common in academic emotion research, the repercussions of these recent developments and innovations for the academic field cannot yet be predicted. What can be anticipated is that a continued gap between economy-, information science-, humanities- and ethnographic/social scientific-driven research keeps leading to epistemic, social, political and cultural deadlocks. Furthermore, our interviewees carefully discussed the impacts of economic interests and possible consequences when overly contrived emotion theories, methodologies, and datafication standards are translated into applications that target core values of persons and societies (health, job, education). Although private companies are still in favour of emotion theories that claim universal validity due to their promise of global applicability of the products under development, this work package report illustrates that a more integrative perspective on science, data, and economy is multiply promising, if it includes the humanities and ethnographic/social science research in future research endeavours.

This report has carved out many ways by which datafication leads to the reduction of complexity of the research object "emotions", such as theoretical and methodological biases, the loss of information on the context, relationality, localities and historicities, conceptual gaps, limits to interdisciplinarity, the irreconcilable dichotomy between nature and culture, or the resistance of certain dimensions to quantification. Moreover, the multiplicity of epistemic approaches and the entrenchment of academic disciplines from each other contribute to asymmetric power structures and to exclusive approaches within the ivory tower. Where datafication reduces complexity, these structural factors add up to a marginalisation of complexity. Although the findings reported here may nurture skepticism towards interdisciplinary research projects, it has at the same time become obvious that exchanges across disciplinary boundaries on theories, research questions, methodologies, and limitations to epistemologies as well as mutual learning in interdisciplinary settings may still be an adequate choice to overcome these shortcomings.

6. Recommendations

In taking the cross-disciplinary research subject "emotions" and "affects" as an example, this report has illustrated how the datafication of these phenomena leads to the reduction of complexity. This reductionism is inevitable due to the limitations imposed by the epistemologies underlying the examination of emotions and affects and due to the biases that result from methodological choices. Structural factors of the scientific field, especially the dissection into disciplinary approaches and the challenges of interdisciplinary research, further aggravate these shortcomings and lead to a marginalisation of complexity.

We consider a comprehensive transparency of research contexts and provisions to tie context-related and relevant information back to the research data as key to overcoming the limitations of reductionism. A comprehensive understanding of contexts includes the epistemologies, methodologies and technologies used to select, structure and collect data during research; the researchers' theories, hypotheses, disciplinary backgrounds, positionalities, subjectivities and localities; as well as the historical, cultural, political, and linguistic characteristics of the research setting in which data collection took place.

A package of measures to increase complexity, to foster mutual understandings of research findings, and to capture the contexts therefore extends itself onto all levels of the research process: from (1) the provision of an integrative research framework which forms the basis of interdisciplinary research projects, (2) the testing of available or the development of new standards for data and metadata, (3) the development of a data passport to integrate the context into the provided data when data sharing and reuse is intended.

Recommendation 1: Nurturing Interdisciplinarity and Integrative Research

Research on emotions is a powerful example where research is not confined to a single discipline. Interdisciplinary research projects are common and open up promising perspectives to increase the complexity of the datafication processes. *Researchers* should strive for integrative emotion research not only in terms of a consistent terminology and concordant concepts, but also within a comprehensive theoretical approach and a shared (yet multifarious) methodological framework. This promises to enable research that matches the complexity of the research object, while facilitating the integration of the various context-related aspects of the envisaged research, and fostering methodological reflections across disciplines. An encompassing theory that does not marginalize particular epistemologies, but integrates them into an overarching framework can serve as a basis for data integration and has the potential to promote data reuse.

Recommendation 2: Developing methodologies for context-sensitivity through institutionalized training

We recommend the development of methodologies for capturing the context in which data were structured, collected, or created. These methodologies and procedures should reflect in a systematic way the epistemic limitations and reductions inherent in datafication processes, acknowledge the circumstances of data collection, and the positionalities of those creating knowledge. *Researchers* should be enabled to provide contextual information in the metadata accompanying the data themselves or in the repositories in which they are stored. Standard formats for data and metadata need not be understood as narrowing and obstructive, but as a means to overcoming disciplinary data silos. Interdisciplinary research projects provide the best thinkable frame to facilitate systematic reflection on epistemic limitations and reductions inherent in datafication processes, to develop methodologies and procedures on how to capture contexts, to collect best practices on how to make data fit for data sharing, to test the use of available standard formats and to design new inclusive standards which are considered to be appropriate. Therefore such research projects should be encouraged and supported by *research funding bodies*. An alternative to this bottom-up approach would be the funding of projects to develop data passports to be attached to data within repositories. These data passports should contain information on data provenance, origin and processing, data creators, methodologies employed and theoretical assumptions that lead to the case specific construction and collection of data, and how these were interpreted and analysed. *Research institutions* should ensure that the repositories and infrastructures they maintain provide the possibilities to add metadata or data passports.

Universities and research institutions that provide training for data scientists should ensure that curricula contain modules that teach the students to explore the contexts in which data were collected, especially beyond academia. Data scientists should be taught ethnographic methods to explore the context in which data were produced, and they should be capable of establishing detailed descriptions of these data and the cultures around them, including the implicit, hidden, and thus invisible classifications contained in data sets, as well as the social circumstances and processing steps that have been eliminated from the datasets during their collection.[7]

Recommendation 3: Institutionalizing sustainable data sharing and reuse

Documentation and storage of research data is often a demand made by funding bodies financing research projects. Preparing research data in a sustainable way for sharing and reuse is laborious and does not have an immediate return for the scientists who collected them, especially when they leave the research institution after the project ends. For these reasons researchers may be reluctant to prepare the data collected by them for storage. In

[7] For further elaborations on these issues see the following two contributions on the K-PLEX blog: https://kplex-project.eu/2017/06/02/has-anyone-ever-analyzed-big-data-classifications-for-their-political-or-cultural-implications/ and https://kplex-project.eu/2017/03/21/how-can-data-simultaneously-mean-what-is-fabricated-and-what-is-not-fabricated/.

contrast, institutional data management offices and libraries accumulate knowledge over time about best practices in storing data and licences appropriate to be used for research data sets. *Research institutions and organisations* should therefore establish data management offices or departments at their libraries and develop institutional templates of research data management plans. These offices or library departments should also provide guidance to the researchers working in projects on how best to preserve their research data beyond a particular epistemological approach. Furthermore, they should consult research projects on the use of metadata or data passports and the appropriate licences to be used in compliance with the funding agency, the data repository, or the chosen publisher (e.g. in the case of peer-reviewed journals). A focus should also be placed on the establishment of workflows, congruent with research data management processes, and the promotion of research data management skills. *Universities* should develop curricula containing courses on methodology, in which the reuse of data is tested. Moreover, they should encourage the creation of textbook material documenting best practices of how data are reused and analysed in meaningful ways in order to make the utility of data reuse visible.

Research funding bodies should request larger research projects to create the position of a data scientist within teams dealing with both quantitative and qualitative research data. As there is a great demand for data scientists from the side of the economy and data scientists might therefore be hard to find, the training of junior researchers would form an alternative to satisfy the need of expertise in data processing, integration, and sharing. These data scientists should develop procedures that improve the deposit of research data including the captured context in repositories, harmonise data organisation and analysis procedures and develop analysis tools that can be applied to research data. They should document the experiences gained in larger research contexts and disseminate best practices. This action will also enable researchers to design data structures from the point of their reusability and not only from the point of their capacity to answer particular research questions and in accordance to the chosen epistemology and methodology.

Recommendation 4: Making data literacy attractive

Scientific enquiries and interdisciplinary research endeavours have increased in complexity over time. It seems thus crucial for research teams to find a *lingua franca* that enables communication on data and related terms. However, the establishment of glossaries that map terms used in different disciplines onto each other does not provide an easy solution to this issue, since the concepts underlying these terms are mostly not equivalent. *Research funding bodies* should therefore invite tenders for the establishment of systemic glossaries and introductory materials to facilitate a fluency in the different meanings of terms and encourage critical reflexivity among researchers. Systemic glossaries should not only elaborate on the terminologies and their specific meaning in different disciplines, they should also foster mutual understandings of discipline-specific standards regarding quality checks, validity, reliability, or datafication. *Research institutions and organisations* should complement their curricula with training programs providing introductory knowledge and skills for scientific researchers related to data science essentials. Moreover, they should provide certificates for acquired skills and issue researchers' passports to document methodological, epistemological and theoretical experience and know-how.

Recommendation 5: Critical Systematic Research on Big Data

The analysis of Big Data is mostly the task of data scientists familiar with the specific techniques relevant for conducting such examinations, or of interdisciplinary research teams combining social sciences or humanities' researchers with information scientists, and statisticians, or IT specialists. However, the competencies acquired in interdisciplinary research groups have not informed data science training programs. So far, data science is a blend of domain expertise, analytics, and engineering, but it does not comprise of elements of social sciences' and humanities' knowledge. *Universities and institutions providing training for data scientists* should ensure that the particular strengths of the humanities, the ethnographic and qualitative social sciences become part of data science curricula, for example the awareness of the contexts in which data were collected, the question of non-representativeness of Big Data, critical approaches to datafication, the societal repercussions of classifications contained in high-dimensional datasets, or specific competences in the mining of text data. Such topics should become standard modules in data science training courses.

Recommendation 6: Decolonizing data

Empirical emotion research is conducted not only within the borders of the EU, but also in and about communities, societies and cultures of non-European countries. Such research aims at investigating in a context-sensitive way the cultural construction of emotions as well as the research participants' subjectivities, historicities and situatedness. Data collected in emotion research generally contains a tension between the internal (emic) perspectives of research subjects, which are directly inscribed into the data, and the questions and theoretical concepts of researchers imposing themselves onto these data. This tension inevitably invokes questions on the side of the research participants about ownership, cultural property, access, and the possibility to withdraw data. While the EU's General Data Protection Regulation (GDPR) becomes enforceable from May 2018 onwards and thus provides a framework for European citizens with respect to personal data, it is unclear which laws and rules apply for research in non-European research contexts. *Future ICT projects* comprising anthropologists, psychologists, and jurists are recommended to tackle this issue and explore related questions. These questions do not only relate to judicial subjects, like possible conflicts with moral rights, personality rights, privacy, and non-conformity with the GDPR, but also to questions of data storage, data sharing and reuse. Once the transition of data from an original to a non-original environment takes place, the multifarious question of the traceability of the source arises. Which opportunities should data repositories provide with respect to contextual information and data elicitation by non-European research participants? Which amendments to current data archiving practices are deemed necessary? Which possible issues arising here go beyond the hitherto existing commitments in ethical codes and concern stages within the data lifecycle not yet considered? While the sensitivity of these issues is immediately evident with respect to emotion research, the questions posed here go far beyond the narrower range of data on emotions. And while the global scope of this section becomes evident in transcultural and transcontinental research and raises important juridical and ethical issues, these challenges pertain to every process of research where narratives, stories, observations and data travel through reductionist epistemologies from origin to archive to possible reuse.

Recommendation 7: Taking culture and context seriously in applied research on emotions

This report has spoken in favour of context-rich and therefore culturally sensitive data on emotions in order to overcome the limitations imposed by current reductionist datafication processes. In contrast to this, applied research tends to favour universally applicable emotion classifications, because private companies are interested in globally deployable products which are profitable across cultural boundaries. Since data-driven applied research aims at the development of artificial agents, machine learning (ML) is involved, which in turn is in need of large datasets as input for training purposes. If more fine-grained solutions for such applications are desired which are appropriate for respectively different cultural contexts, the need for large high-quality datasets containing fine-grained emotion classifications arises, as does the need for contextualized data not prone to errors, biases and inconsistencies related to radical reductionism. A *future ICT project* is recommended, which explores the possible ways in which academic research can create and provide such contextualized datasets for use in applied research, e.g. in public research institutions focusing on artificial intelligence or private tech companies. This ICT project would tackle at least two interconnected challenges: First, how can the analysis of large datasets (e.g. collections of videos), which are currently manually coded and annotated in emotion research, be enhanced through artificial intelligence techniques, thus transferring expert knowledge available mainly in the applied sciences back into basic research? Second, if there is a lack of emotion data resources for particular cultural contexts, one has to ask which techniques could be applied – such as bootstrapping – or developed in order to expand these small datasets and generate the models and rules necessary to satisfy the needs of machine learning, thus balancing data inequalities. The ICT project would further the exchanges and collaboration between applied science, currently forming the technological avantgarde in emotion research and the academic arena, in order to also support culture-sensitive and contextualized technological advances in data-driven public and private sector endeavours relevant for the European economy.

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Annexes

Annex 1: K-PLEX WP4 Survey questions

We would like to address your most recent research on emotions. The following questions are targeted against this background.

A) Data & Data Processing

1. What is your object of research? Please check all that apply.

facial expression

gesture

body language

peripheral physiology

affective dimension of prosody

language

brain activity

social structure

media

culture

voice

history of emotions

political emotions

other (please specify):

2. Which scientific aims do you pursue with your research?

3. What kind of data did you collect in your most recent research project? Please guess the data volume for each category of data.

text	KB | MB | GB | TB
spreadsheets	KB | MB | GB | TB

audio files	KB | MB | GB | TB
videos	KB | MB | GB | TB
images	KB | MB | GB | TB
models	KB | MB | GB | TB
computer code	KB | MB | GB | TB
maps	KB | MB | GB | TB
other (please specify):	KB | MB | GB | TB

4. Do you clean[8] your data?

yes

no

5. Are you doing quality checks?

yes

no

not applicable

6. What do these quality checks look like? Please check all that apply.

Missing at random

Outliers

Plausibility checks

summary / descriptive statistics

check for NAs (no answers)

other (please specify):

[8] Cleaning: Removing incorrect or inconvenient elements from the available data, supplying missing information and formatting it so that it fit with other data.

7. Does the collection of data in your most recent research project follow standardized workflows?

yes

no

8. Are workflows synchronized among team members in your research group?

yes

no

not applicable

9. Are the data themselves standardized?

Are the metadata themselves standardized?

yes

no

10. Please guess: What percentage of your data is presented in publications?

0–25%

26–50%

51–75%

76–99%

100%

11. Why didn’t you use all of your data? Please check all that apply.

bad quality of data

does not fit research questions or hypotheses

methodological considerations

difficulties in presenting the data

redundancies

ethical and privacy issues

lack of time

other (please specify):

B) Methodology

12. At which point in the research process would you say does theory determine or re-enter your practice? Please check all that apply.

design of the data structure

design of the study

design of applications/tools/machines

examination and interpretation of the results

write-up of the results

elsewhere

13. Which theoretical underpinning guides your research?

evolutionary function of emotions

emotions can be located in a dimensional model

emotions are relational

emotions are subjective and individual

language provides for an adequate expression of emotions

emotions are situated affective states

other (please specify):

14. In your opinion: Which kind of information is being left out in the process of 'datafication'[9] of emotions?

15. Please cite the three most important authors for your research.

[9] http://www.mydatafication.com/2016/10/what-is-datafication.html The process of collecting data out of real-world phenomena

16. Please indicate your research methods. Please check all that apply.

observation

experiments

clinical study

laboratory/ instruments (fMRI, sensors)

cross-sectional studies

longitudinal studies

surveys

interviews

analysis of videos, performances, theater plays

desk research/ computational/ data repositories in the internet

participant observation

other (please specify):

17. Please rank the following data according to their importance for your research. Rank only the items that apply.

behavioural data

neurocognitive data

peripheral physiology

video

audio

text data

other

18. Do you use methodological triangulation techniques to cross-check your research findings?

yes

no

19. What do you see as key challenges in your approach to emotion research?

20. My research approach is:

deductive (testing hypotheses)

inductive (generating hypotheses)

abductive (probabilistic reasoning)

21. Which theoretical biases do you see in your work?

22. Do you document observations by maintaining personal logs/ memos/diaries?

yes

no

23. Do you develop tools and applications?

yes

no

24. Which aims do you pursue with the development of tools and applications? Please check all that apply.

match a certain research question / hypothesis

improve existing tools/apps

make interdisciplinary / collaborative research possible

other (please specify):

25. What kind of influence do you have on the design and development of tools and applications?

none

limited (consultancy)

provided the basic idea

permanent dialogue during development

C) Research Organisation

In this section we would like to know more about your working environment and the institution you are working in.

26. Size of the research unit working on emotions:

1–3

4–6

7–11

12-25

>25

27. Size of whole institution/ department:

<23

24–36

36-72

73-120

>120

28. Is your research unit composed in an interdisciplinary way?

yes

no

29. Of which domains/disciplines is your research unit composed?

30. Is your research unit linked to other external researchers?

yes

no

31. With how many researchers does your research unit collaborate? Please check all that apply.

< 5 institutionalised cooperation □ | loose cooperation □

6–11 institutionalised cooperation □ | loose cooperation □

12–35 institutionalised cooperation □ | loose cooperation □

36–50 institutionalised cooperation □ | loose cooperation □

> 51 institutionalised cooperation □ | loose cooperation □

32. With how many institutions does your research unit collaborate? Please check all that apply.

1–3 institutionalised cooperation □ | loose cooperation □

4–6 institutionalised cooperation □ | loose cooperation □

7–9 institutionalised cooperation □ | loose cooperation □

10-12 institutionalised cooperation □ | loose cooperation □

> 12 institutionalised cooperation □ | loose cooperation □

33. In which way does your research unit relate to other disciplinary fields beyond your academic organization?

- Discipline 1 (please specify):….: □ collaboration | □ consensus | □ contestation

- Discipline 2 (please specify):….: □ collaboration | □ consensus | □ contestation

- Discipline 3 (please specify):….: □ collaboration | □ consensus | □ contestation

34. What do you see as the role of your research unit within the field of emotion research?

creative head

leading research institution

meeting place

technology center

routine work

solitary research

35. Does your institution have a Data Management Plan (DMP)?

yes

no

36. Rough indication of funding received for the most recent project (in Euro):

10–50.000

51.000–150.000

151.000–500.000

501.000–1 Mio

more than 1 Mio

Time span:

3–6 months

7–12 months

13–24 months

25–36 months

more than 36 months

Public/private/public-private:

public

private

public-private

37. How do you judge the infrastructure of your institution with respect to the necessary technological equipment, personal and financial resources to undertake research activities?

very good

good

mediocre

poor

very poor

38. Rough indication of monetary worth of equipment involved

D) Sharing Data

39. Have you ever reused data from your own previous research endeavours?

yes

no

40. Are your data reusable for other researchers/disciplines?

yes

no

41. Specify to whom the data will be useful. Please check all that apply.

researchers from the same discipline / with same instruments and methods

researchers from other disciplines / with the same instruments and methods

all other researchers

42. Do you intend to share your:

data: yes □ | under certain conditions □ | no □ | NA □

source code: yes □ | under certain conditions □ | no □ | NA □

metadata: yes □ | under certain conditions □ | no □ | NA □

qualitative and quantitative codes (code book in Atlas.ti, MAXQDA, SPSS...): yes □ | under certain conditions □ | no □ | NA □

software tools: yes □ | under certain conditions □ | no □ | NA □

43. Who should have access to your data? Please check all that apply.

everybody with access to the internet

researchers from other institutions that provide access

only researchers from my research institution other (please specify):

44. There are many reasons not to share data. If you don’t intend to share them, why wouldn’t you do so?

ethical reasons

legal issues

copyrighted material

no reward on investment

sharing is not common

data are outdated

data volume is obstacle

consent from research participants not received or expired

possible misinterpretation of data

other (please specify):

E) Personal Information

45. What is your position / job title?

46. Academic background (discipline)

47. Highest Degree

48. Age

<30

31–40

41–50

51–60

>60

49. Gender

male

female

no answer

50. Is there anything we did not ask and you think would be important to add?

Thank you for taking our survey!

51. How did you like our survey?

Poor

Fair

Good

Very Good

Annex 2: K-PLEX WP4 Guidelines for Interviews

Scientific researchers in various disciplines

1. Which aims do you pursue with your research?

2. Which key challenges do you see in emotion research?
   a) How crucial is the lack of a congruent definition of “emotion” resp. overlaps in definitions of “emotion”, “affect”, “feeling”, “emotive”?

3. We have observed a tendency of ‘datafication’ of emotions. What kind of information do you think is lost in this process?
   a) What are the benefits/challenges of large-scale analyses of emotions?
   b) In the field of emotion research, has use of big data tools and methods created research questions that could not have been asked before?

4. May we ask you to give a short overview of the history of emotion research?
   a) How many different traditions are there in emotion research? What are the differences and commonalities?
   b) Is there any theoretical approach that has been rejected (falsified)? Rightly, or wrongly?

5. Which theories/methods would you say are dominating the field of “emotion research” today and why is that so?
   a) From your perspective which approaches yield scientifically most reliable data?
   b) Do all approaches develop hypotheses that can be empirically tested?
   c) What do you consider as empirical evidence?
   d) What does tacit knowledge mean for scientific approaches to emotions?
   e) How important is popular science for the success and authority of science?

6. How would you describe the structure of the research field “emotions”? What actors, and research networks sustainably influence scientific discourse?
   a) To what extent is an intergenerational change within the research networks taking place?
   b) Do the actors/research networks refer to each other or is there a certain non-consideration of the research findings of opposed actors?

7. Which potentials and surpluses do you see in interdisciplinary research on emotions?
   a) Which disciplines make crucial contributions to emotion research and should therefore

be highlighted in interdisciplinary research networks?
b) Regarding the highly specific research questions and the large amount of scientific studies would it even be possible to attain a holistic representation of emotions?

8. What has not been attained yet in emotion research?

Officers / staff of research funding bodies

1. Along which criteria do you select and fund research projects in emotion research?

2. What are your main requirements for project applications in the area of emotion research?

3. How do you evaluate the quality of project applications in the area of emotion research? Which criteria do you use?

4. Which key challenges do you see in emotion research?

5. Which societal and economic interests do you see in advocating funding of emotion research?
   a) What is your approach to data sharing, open access, and open license concerning the content and tools developed within the projects you fund?

6. Do you advocate interdisciplinary research projects on emotions? If yes, can you give an example?

7. Would you advocate steered funding in emotion research?

8. How do you evaluate the impact of the projects you funded in the area of emotion research?
   a) What is the usual life cycle of the projects you fund?

Representatives of private companies

1. Which key challenges do you see in emotion research?

2. What research trajectories do you see developing in emotion research as a result of incorporating big data tools and methods?

3. What do you see as key challenges of developing big data tools for emotion research?

4. Which economic interests do you see for advocating emotion research?

5. Do you advocate interdisciplinary research projects on emotions? If yes, can you give an example?

6. Do you think that it will be possible someday to create artificial consciousness and feelings?

Software developers

1. Which key challenges do you see in emotion research?

2. Please describe your software development project/s!
   a) Describe your research process: what are the inputs, what tools or processes do you use to interrogate them, and how do you formulate the results of that interrogation into findings or insights, and what do they look like?

3. Do/did you develop the project in dialogue with researchers / experts in emotion research? Is/was there a coordinator of the project?
   a) If yes, what is your experience about the interaction between researchers and tool developers? If no, what is your vision about the interaction between researchers and tool developers?

4. What are/were the project aims and which role do/did emotion analysis play in them?

5. Which theoretical underpinnings / basic assumptions guide your software development project/s?

6. What served as the empirical database for the software development?
   a) How do you analyse the data? Do you develop your own encoding scheme / data structure or do you orient yourself at established standard format with metadata?
   b) How do you deal with cultural differences/language differences?

7. In your view, which features should an emotion research tool have? What makes for an effective emotion research tool?
   a) How do you evaluate the quality of emotion research tools and data? Which criteria do you use?

8. How would you describe the ‘weak points’ or ‘blind spots’ in the design of your software project?
   a) Do unexpected things happen?
   b) Algorithms are said to work in a precise and reliable way. Have you experienced any shortcomings of algorithms, e.g. in the interaction with human beings or other algorithms?

9. Do you think that it will be possible someday to create artificial consciousness and feelings?

Annex 3:

WP4 Derived and Constructed Variables for the Analysis of Survey Data in SPSS

Q03_index

Data Volume Index (What volume of data did you collect in your most recent research project?)

1 Data Volume in KB

2 Data Volume in MB

3 Data Volume in GB

4 Data Volume in TB

Q03_sum

How many different kinds of data did you collect in your most recent research project?

Answers ranging from 1 (one type of data collected) to 8 (eight different types of data collected)

Q26_rec

Size of the research unit working on emotions

Recoded from:	To:
1–3 4–6 7–11 12-25 >25	1-3 4-6 >7

Q27_rec

Size of whole institution/ department

Recoded from:	To:
<23 24–35 36-72 73-120 >120	<23 24–35 36-72 >73

Q31_comp

With how many researchers does your research unit collaborate?

Recoded while defining few = less than 11 researchers and many = more than 11 researchers into the following four categories:

1 few institutionalised and few loose cooperations

2 few institutionalised and many loose cooperations

3 many institutionalised and few loose cooperations

4 many institutionalised and many loose cooperations

Q31_comp

With how many institutions does your research unit collaborate?

Recoded while defining few = 1-3 research units and many = more than 3 research units into the following four categories:

1 few institutionalised and few loose cooperations

2 few institutionalised and many loose cooperations

3 many institutionalised and few loose cooperations

4 many institutionalised and many loose cooperations

Q36_rec

Research project funding

Recoded into the following four categories:

1 short runtime (less than 12 months) and low funding (less than 150.000 Euros)

2 short runtime (less than 12 months) and high funding (more than 150.000 Euros)

3 long runtime (more than 12 months) and low funding (less than 150.000 Euros)

4 long runtime (more than 12 months) and high funding (more than 150.000 Euros)

WP4 Code List for the Qualitative Analysis of Interviews Used in Atlas.ti

Code Name	**Code Definition**	**Examples**
Academic Publishing	e.g. pressures like “publish or perish”	
Affective arrangements	Philosophical concept	
Affective turn	Affective turn that has taken place in the sciences since the 1970s	
Algorithms		
Ambiguous data	Data that can be interpreted in more than one way, data that can have more than one meaning, also for mixed emotions	
Anomaly	Observation which stands in contrast to theoretical assumptions	
Applied research		
Appraisal Theory	Appraisal Theory	

Artificial agents	personal assistants, embodied conversational agents, sensitive artificial listener, chatbots	
Artificial empathy		
Artificial Intelligence		
Attributionist approach	Observing/noting which emotions are attributed to an actor/actors/by other actors (observation logs and text/visual analysis)	
Basic Emotions	Basic emotion theory	
Basic research		
Big Data benefits	Benefits of large-scale data analysis	
Big Data challenges	Challenges of large-scale data collection and analysis	
Big Data definitions	Definitions given for big data	
Classifications	Encoding scheme	
Clinical study		
Cognition + emotion		
Collective Emotions		
Compassion		
Complexity		
Conceptual gap	Gap between f.ex. experience and expression of emotion; missing of	

	concepts	
Confessional tale	Narrative strategy that is dominated by the self-absorbed researcher	
Constructionist approach	Constructionist emotion theory, situational approach	
Context dependency	Dependency of interpretations on the context of data	
Coop researchers + developers	Cooperation between researchers and developers in the development of tools	
Cultural/language differences	Strategies applied to deal with cultural and language differences	
Data cleaning	Removing incorrect or inconvenient elements from the available data, supplying missing information and formatting it so that it fit with other data	
Data definitions	Definitions given for data	
Data loss	Loss of information in the process of data collection, processing or analysis	
Data reuse		
Datafication	Turning real-world phenomena into data	

Debated Knowledge	This type of knowledge is based on information supplied by others, but is justified by evaluating a set of (potentially competing) testimonies, invoking specific standards of inquiry to justify our evaluation. This is the standard applied (often, for example, by academics) to claims for which we have inadequate empirical evidence and reason to doubt any single source of testimony.	
Deductive vs. inductive		
Dimensional model	Valence-arousal approach of emotions	
Discipline's contribution	Contribution of a discipline to interdisciplinary research	
Economic interests	Private companies' economic interest in developing a tool	
Emerging research questions	New research questions that have not been asked before	
Emotional ambivalence approach	Under which conditions ambivalent emotions are generated and transformed, and some become dominant – starting by looking for emotional exaggeration, denotative hesitancy, mixed metaphors, irony, the Janus face of each emotion	
Emotional Practice	How emotions are practiced, related to practice theory	
Emotional regime approach	Reveal the obligatory feeling rules, how they position and shape bodies in space, embodied or emotional costs of conforming and departing, "justificatory emotions" and "escapist emotions"	

Emotional regulation	Emotional regulation, incl. emotional dysfunctions, such as depression, anxiety disorders	
EmotionML	XML standard used for the annotation of emotions	
Emotions in Media		
Empathy		
Empirical knowledge	Knowledge that we expect to be justified by reference to sensory perception (combined with background beliefs about categories and their application where necessary).	
Epistemology		
Ethical Issues		
Existential feeling	Philosophical concept	
Experiments	Method used to measure emotions	
Facial expressions	Object of research	
Facial measurement	Methods used to measure facial expressions	
fMRI	Method used to measure emotions	
Hidden data		
History of Emotions	Emotions in historical perspective	
Holistic vs. specific	Is a holistic representation of emotions possible despite the multiplicity of	

	specific research questions?	
Humanities vs. natural sciences	Differences between humanities and natural sciences (technically and data-driven approaches)	
Human-machine interaction	Includes also human-robot interaction	
Impressionist tale	Narrative strategy that has a dramatic vignette	
Interactionist approach	Observing/noting which emotions are expressed and attributed by actors to each other, noting one's own concurrent emotions, as well as when relevant circulating and shared emotions emerge (observation logs or text/visual analysis, supplemented by interviews and documents)	
Interdisciplinarity challenges	Challenges of interdisciplinary research	
Interdisciplinarity surpluses	Surpluses of interdisciplinary research	
Intimacy		
Interviews +surveys	Method used to measure the expression of emotions	
Introspective knowledge	knowledge that we expect to be justified by introspection. This includes, for example, knowledge regarding one's own pain, emotions, and beliefs.	
Knowledge gaps	Knowledge gaps in the research field	
Laboratory vs. Field		

Machine learning	construction of algorithms that can learn from and make predictions on data through building a model from sample inputs; can be divided into classification & regression (stochastic data models) and neural nets/deep learning (predictive approach with unknown data mechanism)	
Media Analysis	Method used to measure the expression of emotions	
Observations	Method used to measure the expression of emotions, i.e. Facial expressions, gestures	
Open data	FAIR data (findable, accessible, interoperable, reusable data), Sharing of data, open license	
Particular vs. general	Research focusing on a idiosyncratic spatial-/historical context vs. universal patterns	
Personality structure	personality traits	
Phenomenology	Theoretical approaches to experience and consciousness, also taking into account empathy and intersubjectivity	
Physiological measurement	Methods used to measure physiological responses, e.g. EEG, EMG	
Physiological responses	Object of research	
Political Emotions	Object of research	
Popular Science Impact	Importance of scientific results' communication to a lay public for the authority of science	

Positivist-expressionist approach	Observing/noting which emotions an actor expresses, treating expression as emotion data (observation logs and text/visual analysis); causalities	
Posture	Object of research (also: bodily expressions, body language)	
Practical knowledge	Knowledge that we expect to be justified by evidence that 'it works'. This is a standard for judging knowledge about ways of doing things.	
Privacy Issues		
Private Emotions	Subjective dimension of emotions, uniqueness	
Project aims	Goals of projects in applied research	
Publisher's restraints	Restraints by publishers, e.g. on new approaches, significant results	
Qualitative Approach		
Quality checks	(Statistical) methods applied to check reliability, validity, etc.	
Quantitative Approach		
Reliability	consistency of measurement, i.e. intercoder agreement	
Research aims	Scientific targets pursued by a scholar	
Research challenges	key challenges in conducting research, e. g.. lack of a congruent definition of a concept	

Research funding	Criteria for research funding	
Research history	History of emotion research in a specific domain or discipline	
Reviewing	Process of reviews of research projects and outputs	
Sensors	Method used to measure emotions, i.e. Eye tracking, infrared camera	
Signal-noise		
Small Data benefits	Benefits of small-scale data collection and analysis	
Small Data challenges	Challenges of small-scale data analysis	
Social behaviour		
Societal benefits	Benefits of specific research for society	
Speech and voice analysis	Method used to measure emotions	
Supplied knowledge	This type of knowledge is based, for the individual holding it, on information supplied by others, and is justified by invoking the authority of the sources from which it was obtained. This is standard that is widely used for knowledge claims regarding facts and theories for which we have no, or insufficient, personal empirical evidence.	
Text analysis	Method used to measure the expression of emotions, e.g. sentiment analysis	
Theoretical/methodological bias	Bias attributed to preferences in particular theoretical or methodological approaches	

Theory-driven	Research that is guided by theories, ideas	
Uncertain data	Meaning of data is unresolved	
Validity	Accuracy of measurement (is measured what is supposed to be measured?) i.e. construct validity, content validity, criterion validity	
Vocal expressions	Object of research	

CODE GROUPS	**Code Group Definition**	**Codes within the group**
ARTIFICIAL INTELLIGENCE		Machine learning Artificial Empathy Artificial intelligence
CONCEPTS IN EMOTION RESEARCH		Empathy, Compassion, Enthusiasm, Emotional Practice, Affective Arrangements, Existential feeling, Intimacy
EMOTION THEORIES	Theoretical Approaches in Emotion Research	Appraisal Theory Basic Emotions Dimensional model (Val-Ar) Constructionist approach Phenomenology
QUALITY OF RESEARCH DATA		Reliability Validity

EPISTEMIC CIRCLES	Which specific claims may be treated as knowledge	
EPISTEMOLOGICAL CIRCLES	Epistemological standards that are used to justify the assertion that a belief is knowledge.	
EPISTEMOLOGICAL TYPES OF KNOWLEDGE		Introspective knowledge Empirical knowledge Practical knowledge Supplied knowledge Debated Knowledge
OBJECT OF RESEARCH		Emotions in Media Facial expressions History of emotions Physiological responses Political emotions Posture Vocal expressions

RESEARCH APPROACHES		Positivist-expressionist approach Attributionist approach Interactionist approach Emotional regime approach Emotional ambivalence approach Taboo emotions approach Quantitative approach Qualitative approach
RESEARCH METHODS	Methods applied to conduct research	Observations Experiments Facial measurement Physiological measurement fMRI Media analysis Interviews + surveys Sensors Speech+voice analysis Text analysis
NARRATIVE STRATEGIES		Realist tale Confessional tale Impressionist tale