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Understanding the Personality of Contributors to Information Cascades in Social Media in Response to the COVID-19 Pandemic

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Abstract—Social media have become a major source of health information for lay people. It has the power to influence the public’s adoption of health policies and to determine the response to the current COVID-19 pandemic. The aim of this paper is to enhance understanding of personality characteristics of users who spread information about controversial COVID-19 medical treatments on Twitter.

Index Terms—Personality traits, Sentiment analysis, Information cascades, Social media, COVID-19

I. INTRODUCTION

In social media, information cascades appear when information flows develop hops due to comments on a comment of the initial tweet or its retweet that evokes comments [7]. Information cascades have been studied in politics and economy because in politics and financial markets a sequence of decisions made by different agents based on the imitation of the choice of agents ahead of them may cause major

Moreover, the study on personality characteristics of persuasive individuals [5] has demonstrated that the individuals with high scores on Extraversion and Openness are more likely to be persuasive during debates as opposed to those with a high score on Neuroticism. According to another study on persuasive argument prediction using author-reader personality characteristics [6], reader Extraversion, Agreeableness, and Conscientiousness can be good indicators of persuasive arguments. Our interest in the relationship between personality characteristics and persuasion is motivated by the fact that individuals initiating cascades with their statements in tweets are more likely to be persuasive in their arguments.

II. BACKGROUND

II describes the background of the work carried out, Section III presents the original dataset and methodology of the study undertaken, Section IV reports and discusses the obtained results, and Section V concludes the paper.

In social media, information cascades appear when information flows develop due to comments on a comment of the initial tweet or its retweet that evokes comments. Information cascades have been studied in politics and economy because in politics and financial markets a sequence of decisions made by different agents based on the imitation of the choice of agents ahead of them may cause major
societal change or a disaster \[8\]. When making a decision, the agent follows the stream regardless of their preferences and interests with no attempt to verify or reconsider information and act irrationally and impulsively \[8\]. The agents involved in an information cascade do not make one decision after another, they decide to join the activity straight after they receive a signal about the choice of those ahead of them and estimate the crowd of those who had chosen to join the activity and their experience \[9\]. The cascades in social media were classified by \[10\]. The authors distinguished two types of information cascades according to the direction of the information flow: (1) a further development of the initial tweet by followers (F-cascade); (2) a retweet that moves the information flow to another feed attracting more users to comment and share the initial information (RT-cascade) \[10\]. As such, this makes it possible for the cascades to develop from person to person through word of mouth. When transferring information, a social network user needs to follow the rules and formatting of the platform design, and often shortens the initial tweet, paraphrases its text, includes emojis, etc. \[11\]. These transformations lead to information distortion; the distortion of information in cascades is extremely high due to the irrational behaviour of the cascade participants. In information cascades on social media, distortion appears when an original message is transformed from hop to hop \[12\].

In studies of information distortion in social media, researchers have shown a connection between users’ psychological traits and their willingness to reconsider information about COVID-19 published on the social media platform \[13\], \[14\]. Users who skip reconsideration share unverified information even if they could recognize errors and fake news. The users – ‘re tweeters’ lack analytic cognitive style and follow their intuition in information evaluation \[13\]. The information cascade participants who spread distorted information have a certain set of common psychological traits that come to light in their way of writing \[15\].

The correlation between the linguistic features of a text or speech generated by an individual, and the individual’s personality traits has been studied since Jungian experiments in the middle of the previous century. But it was only in the last quarter of the century that the standard procedures of text analysis and standard psychological tests established grounds for obtaining reliable results. However, the correlation is still unclear due to the impact of discourse and pragmatic factors on text generation. Topic, genre, recipient and communicative intention determine the text peculiarities including lexical choice and syntax structure. In social media, the effect of discourse is weakened by less restricted norms of conversation and the specific design of online communication. Studies of users’ blogs and microblogs in social media show various possibilities of extracting personality characteristics from short texts aimed at searching for Big Five features through using pronouns and emotional words, auxiliary verbs and words reflecting discrepancy \[15\]. Extraverts prefer positive emotion words and compliments showing more agreements than introverts \[16\]. Conscientious people tend to strictly verbalise their ideas and thus avoid discrepancies, negative emotions and hesitations \[15\]. Openness to experience reveals itself in objectivity and the disregard of first personal pronouns \[15\]. However, the COVID-19 pandemic affects communication in social media forcing users to discuss particular topics and express mostly negative emotions on the platforms. Users show emotional involvement in conversation on research and treatment of the coronavirus. Moreover, they neglect grammatical rules and norms of syntax in short tweets. Therefore, analysis of semantic categories in the tweets provide reliable data to describe the users’ personality profiles when in a stressful environment the personality traits are not seen clearly.

III. DATASET AND METHODOLOGY

In this Section, the dataset that was created and used for analysis will be presented. Second, the methodology used to reveal the psychological profiles of active contributors to the discussions about COVID-19 treatments will be described.

A. Data Description

We have collected 10 million tweets in English, including 141,866 tweets with distinct text. Twitter API \[1\] was queried via Logstash \[2\] with the following terms: ['“science retraction”, “chloroquine”, “hydroxychloroquine”, “Raoult”, “remdesivir”, “tocilizumab”, “favipiravir”, “Avigan”, “azithromycin”, “azithromicine”, “#HCQ”, “Axemal”, “Dolquine”, “Quensyl”, “Hydroxychloroquinum”, “Hydroxychloroquin”, “Hydroxylorquin”, “Montagnier”, “Hydroquin”, “Quinoric”], in order to cover the topic of controversial medical treatment of COVID-19 \[17\]. The tweets were published in the period between 30/03/2020 and 13/07/2020. In this dataset, 2,159,932 users were found to publish tweets in English.

Among these users, seven categories were selected (see statistics in Table I):

1) 192 users with the highest number of tweets about controversial treatments from our dataset (top);
2) 431 users with the most quoted tweets about controversial treatments (most_quoted);
3) 339 users with the most retweeted tweets about controversial treatments (most_rt);
4) 247 verified users with the highest number of tweets about controversial treatments (verified);
5) 196 users randomly selected from a set of users who published between 1 and 50 tweets about controversial treatments in our dataset (rnd_1_50);
6) 183 users randomly selected from a set of users who published between 50 and 500 tweets about controversial treatments in our dataset (rnd_50_500);
7) 292 users who published tweets in the cascades with a depth of at least four hops (cascade_depth_4).

https://www.elastic.co/fr/logstash
https://about-twitter-verified-accounts
TABLE I: Number of users and tweets in the overall dataset and in its subset with only original content

<table>
<thead>
<tr>
<th></th>
<th>top</th>
<th>most_quoted</th>
<th>most_rt</th>
<th>verified</th>
<th>rnd_1_50</th>
<th>rnd_50_500</th>
<th>cascade_depth_4</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>All tweets</td>
<td># users</td>
<td>192</td>
<td>431</td>
<td>339</td>
<td>247</td>
<td>196</td>
<td>183</td>
<td>292</td>
</tr>
<tr>
<td></td>
<td># tweets</td>
<td>38,357</td>
<td>85,450</td>
<td>67,150</td>
<td>49,236</td>
<td>37,094</td>
<td>36,488</td>
<td>57,344</td>
</tr>
<tr>
<td>Original content (min 10 per user)</td>
<td># users</td>
<td>127</td>
<td>429</td>
<td>338</td>
<td>234</td>
<td>180</td>
<td>124</td>
<td>286</td>
</tr>
<tr>
<td></td>
<td># tweets</td>
<td>9,898</td>
<td>61,064</td>
<td>47,514</td>
<td>28,154</td>
<td>15,995</td>
<td>7,329</td>
<td>35,378</td>
</tr>
</tbody>
</table>

The majority of users have only one tweet about controversial treatments in the dataset (see Fig 1a). However, many users published more than 500 tweets (Fig 1b). After a closer look at these tweets, it could be seen that in many cases the text is the same but a short link to an external web page is different even though it points to the same external resource. These tweets are published within a short interval (a few seconds), therefore, it is supposed that they are generated automatically. That is why users who published less than 500 tweets were also analysed. Verified users often published between 1-10 tweets about controversial treatments. Twitter verifies the authenticity of public interest accounts, e.g. accounts maintained by public figures (music, acting, government, politics, religion, journalism, media, etc.). In general public figures published less than 50 tweets about controversial treatments (Fig 1c). Therefore, it was decided to analyse users who tweeted with the same frequency as public figures considering that it is a normal tweeting rate (not bots). Information cascades appear on social media when a number of users choose the same option while sharing information by retweeting or quoting an initial tweet [10]. Information cascades were created based on tweet replies and quotations, and cascades with a depth of at least four tweets were selected in order to have balanced categories. The users who participated in these cascades were added to the set of users under analysis, making the total number of selected users 1,880. The choice was limited by the number of free queries in IBM Personality Insights service that we used to predict users personality traits. For each user, the Tweepy module was used to retrieve the last 200 tweets. To extract the personality traits of the users under consideration, the concatenated texts of tweets for each user were passed to IBM Personality Insights service.

B. Personality Traits

Personality traits were extracted by analysing the textual content of the last tweets of the participants of information cascades. From each of the seven aforementioned user categories, we selected those who had at least 10 user-generated tweets (i.e. retweets were excluded), in order to ensure the minimum text length for analysis. Such user generated content then constitutes the user profile for this study (see Table I for statistics per category).

To predict users’ personality traits, the publicly available IBM Personality Insights service was used, similar to the works of [6], [13]. This service infers psychological characteristics of an individual based on the analysis of the input text they generated. It was trained mainly on social media datasets, such as Reddit and Twitter (e.g. see [19]). The inference is performed with respect to three personality models:

- **Big Five** personality traits (agreeableness, conscientiousness, extraversion, emotional range, openness) each coupled with six facets detailing the corresponding trait: general dimensions characterising an individual’s engagement with the world [20]. See Table II for lower level facets of the personality traits (as provided in [4]).
- **Person’s Needs** (excitement, harmony, curiosity, ideal, closeness, self-expression, liberty, love, practicality, stability, challenge, structure): universal aspects of human behaviour reflecting the desires that people aim to satisfy via the consumption of a certain product or a service [21].
- **Personal Values** (Self-transcendence / Helping others; Conservation / Tradition; Hedonism / Taking pleasure in life; Self-enhancement / Achieving success; Open to change / Excitement): motivating factors and principles of people’s lives [22].

Fifty-two personality characteristics can be obtained using this classifier. The results for this study are reported based on the percentile scores for all these characteristics.

C. Case Study Methodology

For expert study, five users per category were selected (5 users × 7 categories = 35 in total) among popular users who have original content about controversial treatment of COVID-19. The number of retweets were considered as a popularity measure. Among these 35 users, there were 14 verified accounts. A psycho-linguist manually analysed 200 recent tweets per user along with 100 the most frequent words from the concatenated tweets of each user.

For the psychological descriptions, a reliable set of linguistic units (mostly words) associated with a particular trait were used. The sets are represented as dictionaries or lexicons received in experimental studies and through content analysis of texts produced by those who filled in questionnaires to define the personality profile [23]. The dictionaries and lexicons were worked out for Jungian psychological types, which psychologists and psychotherapists have been applying in their studies and practical work [24]. In typology, Jung constructed four oppositons to distinguish psychological types based on the preferences in activity, information processing, reasoning and planning [25]. For the purpose of this study, the opposition of ‘Thinking - Feeling’ matches the criteria for expertise personality profiles of the Twitter users who participated in the
information cascade generation. The opposition describes the difference between logical thinking and consideration based on social norms and attitudes. The first one is associated with analytic cognitive style, which is needed for critical analysis of information from unreliable sources [14]. Based on Seegmiller’s dictionary (1987), where the sets of verbs for thinking and feeling types were included, the frequent verbs in tweets were analysed grouped into three semantic classes: (1) acts of perception; (2) mental processes and actions; (3) emotions and feelings. The latter group corresponds to Feeling type. To strengthen the reliability of the expertise, adjectives and nouns with emotional connotations were extracted. Thus, for each user, a list of verbs and other words with emotional connotations was received. In each tweet, the analysis procedure included a comparison of frequent words denoting emotions and feelings with those referring to mental and perception activity in the tweets of each user. We evaluated the personality profile as Thinking, Feeling or Neutral according to the prevalence of a certain group of words. A user’s personality was characterised as Thinking when verbs referring to mental and perception activity prevailed over the words with emotional connotations and verbs denoting feelings and emotions. When the prevalence was not essential, characterisation of the personality was avoided. The Thinking type is correlated with Conscientiousness and Emotional stability since the use of verbs of cognitive processes and insight shows significant negative correlation with the Dark Triad traits [26].

### IV. Results

This section will present the results of the study.

**A. Users’ Personality Profiles**

First, the results of classification of users were studied w.r.t. three personality models, as described above. Fig. 4 depicts the averaged users’ profiles in terms of personality models and categories depicted.

It can be seen that all considered categories share the same general tendency for most of the dimensions. Thus, the active contributors to information cascades have a tendency to score high on Openness, Extraversion, and Neuroticism. While Extraversion and Openness traits align well with previous studies on the relation between user’s engagement in social media and personality [3], [4], Neuroticism may at first seem more surprising, but this could be explained by the context of COVID-19 pandemic that engenders messages of fear, loneliness, depression, anger, uncertainty, and grief, among others. Thus, it is reflected in terms of the facets of Neuroticism, where users score extremely high on Anger, and slightly less on Anxiety, Depression, Vulnerability, and Self consciousness.

Mind that the individuals we are dealing with have actively taken part in the discussions of treatments. Note however, that people who score low on emotional stability are less likely to be considered credible or persuasive [6], [27], and therefore, effective in arguments. In contrast, the same context gives rise to the expression of Sympathy (facets of Agreeableness), Self-efficacy and Orderliness (facets of Conscientiousness), and an increase in Activity level (facets of Extraversion). Moreover, the users tend to score very high on the majority of facets of Openness. There is also a tendency for Openness to change in terms of Values.

Interestingly, the need for Curiosity stands apart. At the same time, the given context of pandemic and isolation influences such facets as Stability, Structure, Excitement, Harmony, Love, and Closeness, on which the users score extremely low.

As for individual tendencies considered category-wise, it was noted that two categories, namely verified (yellow) and

### TABLE II: The lower level facets of Big Five personality traits [4]

<table>
<thead>
<tr>
<th>Big Five Trait</th>
<th>Lower Level Facets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Openness</td>
<td>Imagination, Artistic interests, Emotionality, Adventurousness, Intellect, Liberalism</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>Self-efficacy, Orderliness, Dutifulness, Achievement-striving, Self-discipline, Cautiousness</td>
</tr>
<tr>
<td>Extraversion</td>
<td>Friendliness, Gregariousness, Assertiveness, Activity level, Excitement-seeking, Cheerfulness</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>Trust, Morality, Altruism, Cooperation, Modesty, Sympathy</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>Anxiety, Anger, Depression, Self-consciousness, Immoderation, Vulnerability</td>
</tr>
</tbody>
</table>

---

[Image 1: Number of tweets per user]

- **Fig. 1: Number of tweets per user**

1. Greater than average tendency for a given dimension / characteristic.
Correlation between Jung categories and personality traits

verified gets the highest scores among other categories on Conscientiousness and Extraversion, and the lowest on Neuroticism, while rnd_I_50 is the opposite. The same tendencies can be found in terms of the facets of Conscientiousness, such as Cautiousness, Self-efficacy, Self-discipline, Achievement striving; Assertiveness and Activity level (facets of Extraversion), Trust and Sympathy (facets of Agreeableness). On the other hand, rnd_I_50 score the highest on all facets of Neuroticism, Values such as Hedonism, Openness to change, Self-transcendence, and Needs, such as Liberty, Ideal, and Self-expression. This duality is not surprising, as most of the verified accounts belong to public figures, while the majority of users constituting rnd_I_50 category are lay people.

B. Psycholinguistic Case Study

The results of the annotation of the users’ tweets with Jung categories can be seen in Table III. To respect privacy, user IDs are not provided, nor is the text of tweets due to the paper limit.

The results of this analysis are summarised in Fig. 3. It shows the proportion of original texts in 200 recent tweets of 35 users. It can be seen that the Thinking class tends to have more original tweets than Feeling users or users we could not categorize (Neutral).

In order to align these results with the personality traits of the same users, we estimated the correlation between Jung categories and the personality traits (see Fig 2). It can be seen that Thinking positively correlated with Openness to change, Neuroticism, and Curiosity, while being negatively correlated with Agreeableness, Extraversion, and Conscientiousness. The latter is a rather surprising finding, which is due to the fact that the users in our dataset score low on Conscientiousness. In contrast, Feeling is positively correlated with Conscientiousness, Agreeableness, Stability, and Closeness. We consider that the opposition ‘Thinking - Feeling’ can provide additional nuances of a user’s personality, which may be especially enriching when dealing with discussions that result in information cascades.

V. Conclusion

In this paper, we investigated the personality characteristics of users who were spreading information about controversial COVID-19 medical treatments on Twitter. It was noted that the context of the pandemic accentuates the expression of emotional instability. Thus, the recent tweets of the active users who contributed to the information cascades about COVID-19 treatments tend to exhibit a user tendency to score high on Neuroticism. The differences in personalities of public figures versus lay people when tweeting were also highlighted. Moreover, the psycholinguistic analysis on a sample of popular and active users showed the prevailing tendency of the original content when the users belong to the class of Thinking.

Future work will consider user personality traits and use sentiment analysis to predict information distortion within cascades.

Acknowledgment

We would like to thank Bilel Benbouzid and Marianne Noël for the idea of studying controversial treatments of COVID-19 and for their participation in building the initial Twitter query.
Fig. 4: Averaged personality traits of user categories regarding various dimensions of personality models
<table>
<thead>
<tr>
<th>user_description</th>
<th>verified</th>
<th># original</th>
<th># RT</th>
<th>Jung category</th>
</tr>
</thead>
<tbody>
<tr>
<td>New York Times Bestselling Author, Columnist for Newsmax, Attorney, Talent Agent, Law Professor and Former Keyboard Player for the Temptations. President, Judicial Watch. (These are my personal views only!) Coming soon: A Republic Under Assault: <a href="https://t.co/g13e9h34ga">https://t.co/g13e9h34ga</a></td>
<td>True</td>
<td>143</td>
<td>57</td>
<td>Feeling</td>
</tr>
<tr>
<td>The official Twitter of <a href="http://t.co/HJOFeYodXw">http://t.co/HJOFeYodXw</a></td>
<td>True</td>
<td>138</td>
<td>62</td>
<td>Neutral</td>
</tr>
<tr>
<td>Drug discovery chemist and blogger Note: all opinions, choices of topic, etc. are strictly my own – I don’t in any way speak for my employer (or anyone else). Covering the latest news in all fields of science. Tweets by @wwrfd, @ThatMikeDenison and @Kate_Travis. Publisher @society4science. See also @SNStudents. Ever vigilant to stop the forces of darkness overwhelming Australia. PRAISE BE! ...</td>
<td>True</td>
<td>194</td>
<td>6</td>
<td>Thinking</td>
</tr>
<tr>
<td>UFOs</td>
<td>False</td>
<td>176</td>
<td>24</td>
<td>Feeling</td>
</tr>
<tr>
<td>Infectious Diseases Clinical Pharmacist, Drug therapy expert, providing up to date information #IDTwitter &amp; #COVID19, KAMC @NGHAnews HCQ does NOT work, CRE OXA-48 Jesus, Democracy, and Capitalism. Mensa. Data Scientist w/PhD in Prognostication. Follow me for Hydroxychloroquine COVID-19 news. Not about me, it’s about us! #GOD, #FAMILYFIRST #PROLIFE #TRUMPSUPPORTER #MAGA #KAG #ANIMALLOVER #SUPPORTOURMILITARY #SUPPORTOURVETERANS #SUPPORTMENANDWOMENINBLUE #DigitalSoldier #QAnon #KAG #MAGA <a href="https://t.co/wDZeL7T6zW">https://t.co/wDZeL7T6zW</a> No lists !!!</td>
<td>False</td>
<td>152</td>
<td>48</td>
<td>Neutral</td>
</tr>
<tr>
<td>I pursue happiness through many creative activities. Pottery and Argentine Tango are two of them. Love, truth, happiness, and freedom for ALL. <a href="https://t.co/4rJme6xNZk">https://t.co/4rJme6xNZk</a> @DougChris58 on Parlor</td>
<td>False</td>
<td>129</td>
<td>71</td>
<td>Thinking</td>
</tr>
<tr>
<td>'Kindness is not weakness.' Small business person, activist, cook, critical thinker, big picture thinker, singer, and writer. I don’t have time for rude people. It’s pronounced oh-sting. Michigan politics reporter for @BridgeMichigan. Email <a href="mailto:joosting@bridgemi.com">joosting@bridgemi.com</a> or reach out via DM, Signal or WhatsApp. Nephrologist in Scotland. Virologist and Infectious Diseases physician at the University of Michigan. Proud father of 3. Opinions are my own. Former D.C. bureau chief for Investor's Business Daily, Hoover Institution media fellow, author of several books, including bestselling INFRINGEMENT</td>
<td>False</td>
<td>129</td>
<td>71</td>
<td>Thinking</td>
</tr>
<tr>
<td>Lawyer ● Patriot ● Civil Rights Activist ● Journalist ● Bro/Bruh ● 1.5M on IG #MAGA School Safety Advocate. NOW: @TeamTrump That NY Cackling Conservative sings too! #Trump2020 Mon-Fri scope-6pm est <a href="https://t.co/JO34ny43i">https://t.co/JO34ny43i</a> kbq225 <a href="https://t.co/sY2Zh3Wo3">https://t.co/sY2Zh3Wo3</a> Journalist, storyteller, and lifelong reader. A Texan, by birth and by choice. Author of WHAT UNITES US <a href="https://t.co/obwukT5WuM">https://t.co/obwukT5WuM</a> Capitalist ● Cuban Born ● Proud American ● Medical Field ● Photography ● @realdonaldtrump ● Sarcasm ● America First ● Parker @CarlosSimancas ● TAKE THE OATH!</td>
<td>False</td>
<td>149</td>
<td>51</td>
<td>Neutral</td>
</tr>
<tr>
<td>President, @FreeThinkerProj — @ShopRightOrDie — UA ’24 — Contact: <a href="mailto:cj@cjpearson.org">cj@cjpearson.org</a> Red, White and Blue music makers <a href="https://t.co/sysBEBnOR">https://t.co/sysBEBnOR</a> Host of ‘HighWire’ with Del Bigtree, Producer of Vaxxed: From Cover-Up To Catastrophe, Former Emmy winning producer of The Doctors. The voice of the people. Sorry, people. Listen to the Common Sense podcast through the link below, <a href="http://t.co/">http://t.co/</a></td>
<td>False</td>
<td>156</td>
<td>44</td>
<td>Thinking</td>
</tr>
<tr>
<td>Mom, author, host, The Ingraham Angle, 10p ET @FoxNews. Retweets do not = Endorsements Proudly serving the people of California’s 43rd District in Congress. Chairwoman of the House Financial Services Committee (@FSCDems) Medical Degree, Columbia University. COVID-19 research. Not medical advice.</td>
<td>False</td>
<td>190</td>
<td>10</td>
<td>Neutral</td>
</tr>
</tbody>
</table>