



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

Diana Nurbakova, Liana Ermakova, Irina Ovchinnikova

► To cite this version:

Diana Nurbakova, Liana Ermakova, Irina Ovchinnikova. Understanding the Personality of Contributors to Information Cascades in Social Media in Response to the COVID-19 Pandemic. 20th International Conference on Data Mining Workshops, ICDM Workshops 2020, Sorrento, Italy, November 17-20, 2020, Nov 2020, Sorrento, Italy. 10.1109/ICDMW51313.2020.00016 . hal-03122001

HAL Id: hal-03122001

<https://hal.science/hal-03122001>

Submitted on 26 Jan 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

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

Diana Nurbakova

LIRIS UMR 5205 CNRS

INSA Lyon - University of Lyon
Villeurbanne, France

diana.nurbakova@insa-lyon.fr

Liana Ermakova

HCTI - EA 4249

Université de Bretagne Occidentale
Brest, France

liana.ermakova@univ-brest.fr

Irina Ovchinnikova

Sechenov First Moscow State Medical University
Moscow, Russia

ovchinnikova.ig@lmsmu.ru

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

Social media have become a major source of health information for lay people and have the power to influence the public's adoption of health policies and determine the response to the current COVID-19 pandemic. [1] demonstrated that robots accelerate the spread of true and false news at the same rate as humans, implying that it is humans, not robots, who are responsible for spreading fake news and controversial information. Information circulation on social media has peculiar features due to message structure (length and format) and user behaviour (rules of sharing information, access to commenting on the message, etc.). Twitter users are able to share, cite short messages and add comments on them. Sharing and commenting on a hot topic tweet may result in producing an information cascade. Commenting on tweets and retweeting are two different behavioural strategies of users according to their personality and psychological type [2]. Although some research has been carried out in the field of microblog user profiling, research on the psychological characteristics of Twitter users is still an open challenge.

It has been shown that people with different personality characteristics show different information spreading behaviours in social media, for instance, in terms of retweets [3] or question answering [4]. Thus, individuals with high scores on traits such as *Conscientiousness*, *Openness*, and *Modesty* are more likely to retweet the information [3]. *Extraverted*, *agreeable* individuals *seeking excitement* are more likely to respond to questions, unlike people scoring high on *Conscientiousness* [4].

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.

We conduct a qualitative exploratory study with the objective of investigating how an individual's personality influences their participation in information cascades about controversial COVID-19 treatments on Twitter. Through the analysis of the tweets of public figures who triggered information cascades, and the reactions of other contributors to these cascades, we investigate how the personality characteristics of the participants of these cascades influence their behaviour on social media when dealing with health information. More precisely, we focus on the following research question: *What are the personality characteristics of the most active contributors in information cascades about controversial COVID-19 treatments?*

The remainder of the paper is organised as follows: Section 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.

II. BACKGROUND

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

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 – 'retweeters' 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 API¹ was queried via Logstash² with the following terms: [*"science retraction", "chloroquine", "hydroxychloroquine", "Raoult", "remdesivir", "tocilizumab", "favipiravir", "Avigan", "azithromycin", "azithromicyne", "#HCQ", "Axemal", "Dolquine", "Quensyl", "Hydroxychloroquinum", "Hydroxychloroquin", "Hidroxicloroquina", "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 D):

- 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 verified³ 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*).

¹<https://developer.twitter.com/en/docs/twitter-api>

²<https://www.elastic.co/fr/logstash>

³<https://help.twitter.com/en/managing-your-account/about-twitter-verified-accounts>

TABLE I: Number of users and tweets in the overall dataset and in its subset with only original content

| | | top | most_quoted | most_rt | verified | rnd_1_50 | rnd_50_500 | cascade_depth_4 | TOTAL |
|---------------------------------------|----------|--------|-------------|---------|----------|----------|------------|-----------------|---------|
| All tweets | # users | 192 | 431 | 339 | 247 | 196 | 183 | 292 | 1,880 |
| | # tweets | 38,357 | 85,450 | 67,150 | 49,236 | 37,094 | 36,488 | 57,344 | 371,119 |
| Original content (min 10 per user) | # users | 127 | 429 | 338 | 234 | 180 | 124 | 286 | 1,718 |
| | # tweets | 9,898 | 61,064 | 47,514 | 28,154 | 15,995 | 7,329 | 35,378 | 205,332 |

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 Tweepy⁴ 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 Insights⁵ service was used, similar to the works of [6], [18]. This service infers psychological character-

istics 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 \times 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 oppositions 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

⁴<http://docs.tweepy.org/en/latest/api.html>

⁵<https://cloud.ibm.com/apidocs/personality-insights>

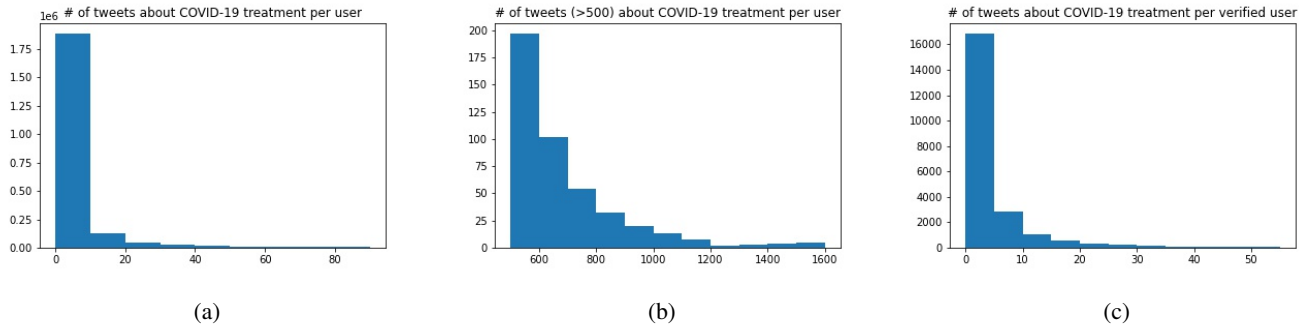


Fig. 1: Number of tweets per user

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

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

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 high⁶ 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

⁶Greater than average tendency for a given dimension / characteristic

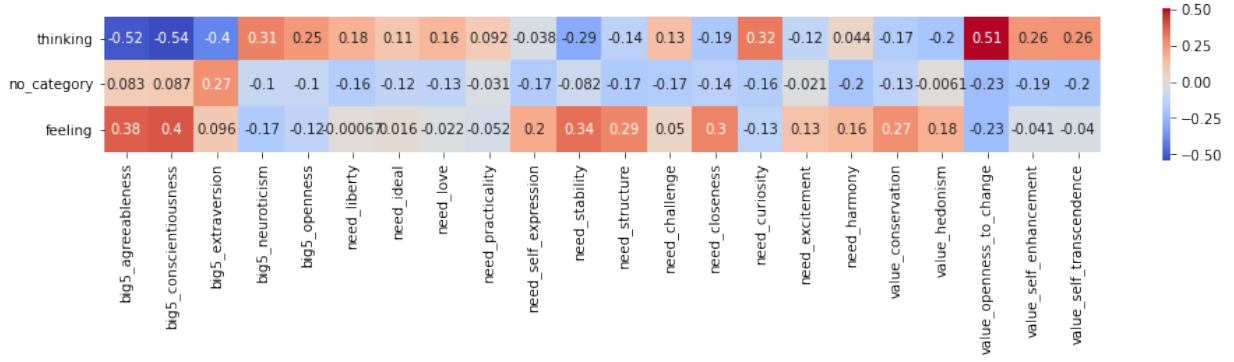


Fig. 2: Correlation between Jung categories and personality traits

rnd_1_50 (cyan), to some extent exhibit opposite tendencies, while still following the same general trends. For instance, *verified* gets the highest scores among other categories on *Conscientiousness* and *Extraversion*, and the lowest on *Neuroticism*, while *rnd_1_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_1_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_1_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.

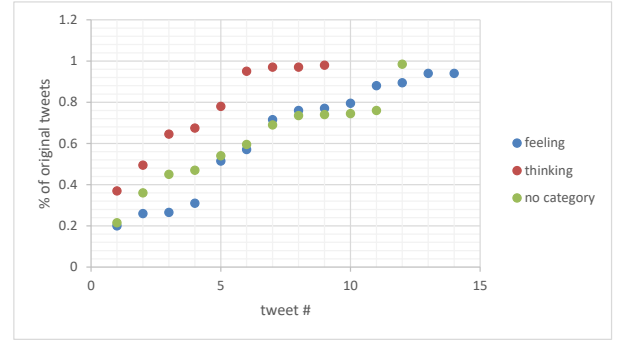


Fig. 3: Proportion of original texts in 200 recent tweets

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.

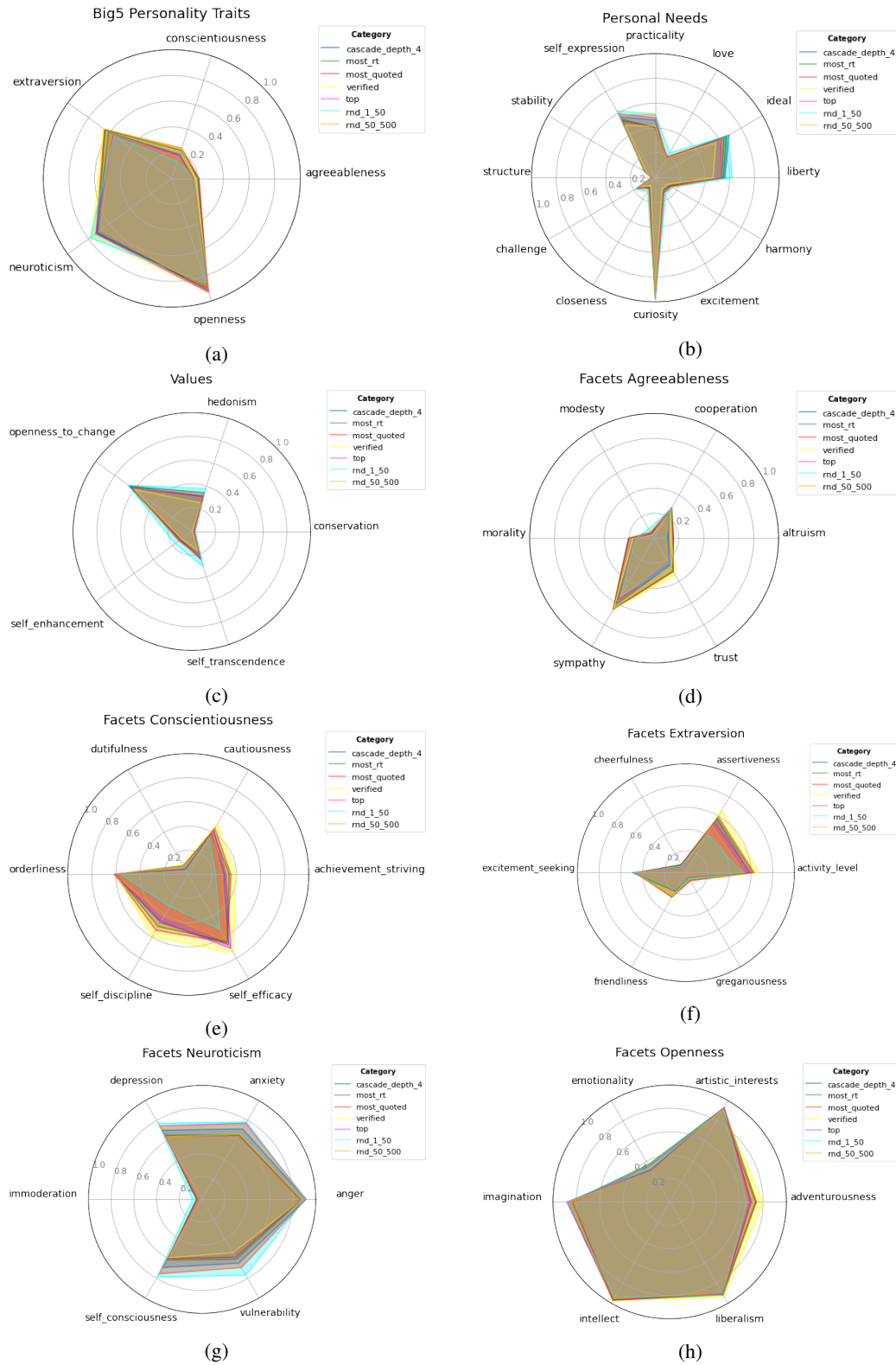


Fig. 4: Averaged personality traits of user categories regarding various dimensions of personality models

TABLE III: Results of the annotation of user tweets with Jung categories

| | user_description | verified | # original | # RT | Jung category |
|-----------------|---|----------|------------|------|---------------|
| verified | New York Times Bestselling Author, Columnist for Newsmax, Attorney, Talent Agent, Law Professor and Former Keyboard Player for the Temptations. | True | 143 | 57 | Feeling |
| | President, Judicial Watch. (These are my personal views only!) Coming soon: A Republic Under Assault: https://t.co/S0oL7Z0oI2 | True | 138 | 62 | Neutral |
| | https://t.co/g13e9b34ga | True | 197 | 3 | Neutral |
| | The official Twitter of http://t.co/HJOFeYodXw | True | 99 | 101 | Thinking |
| | 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). | True | 194 | 6 | Thinking |
| top | Covering the latest news in all fields of science. Tweets by @wwrfd, @ThatMikeDenison and @Kate_Travis. Publisher @society4science. See also @SNStudents. | True | 176 | 24 | Feeling |
| | Ever vigilant to stop the forces of darkness overwhelming Australia. PRAISE BE! | False | 108 | 92 | Neutral |
| | ... | False | 152 | 48 | Neutral |
| | UFOs | False | 129 | 71 | Thinking |
| | Infectious Diseases Clinical Pharmacist, Drug therapy expert, providing up to date information #IDTwitter & #COVID19, KAMC @NGHAnews HCQ does NOT work, CRE OXA-48 | False | 196 | 4 | Thinking |
| md_50_500 | 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! | False | 40 | 160 | Feeling |
| | #GOD, #FAMILYFIRST #PROLIFE #TRUMPSUPPORTER #MAGA #KAG #ANIMALLOVER #SUPPORTOURMILITARY #SUPPORTOURVETERANS #SUPPORTTHEMENANDWOMENINBLUE | False | 62 | 138 | Feeling |
| | #DigitalSoldier #QAnon #KAG #MAGA https://t.co/wDZeL7T6zW No lists !!! 🇺🇸🔥🇺🇸🔥🇺🇸🔥🇺🇸🔥🇺🇸 | False | 43 | 157 | Neutral |
| | Hater of Govt/institutional lies/injustice, whichever side of the spectrum. Will support even those with whom I disagree over unjust demonisation and attacks. | False | 90 | 105 | Neutral |
| | I pursue happiness through many creative activities. Pottery and Argentine Tango are two of them. Love, truth, happiness, and freedom for ALL. | False | 149 | 51 | Neutral |
| md_1_50 | https://t.co/4rJme6xNZk @DougChris58 on Parlor | False | 53 | 2 | Feeling |
| | '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. | False | 94 | 106 | Neutral |
| | It's pronounced oh-sting. Michigan politics reporter for @BridgeMichigan. Email joosting@bridgemi.com or reach out via DM, Signal or WhatsApp. | True | 119 | 81 | Neutral |
| | Nephrologist in Scotland. | False | 74 | 126 | Thinking |
| | Virologist and Infectious Diseases physician at the University of Michigan. Proud father of 3. Opinions are my own. | False | 135 | 65 | Thinking |
| most_rt | Former D.C. bureau chief for Investor's Business Daily, Hoover Institution media fellow, author of several books, including bestseller INFILTRATION | False | 114 | 86 | Feeling |
| | Lawyer • Patriot • Civil Rights Activist • Journalist • Bro/Bruh 🇺🇸 1.5M on IG #MAGA | False | 154 | 46 | Feeling |
| | School Safety Advocate. NOW: @TeamTrump | True | 179 | 20 | Feeling |
| | That NY Cackling Conservative sings too! #Trump2020 Mon-Fri scope-6pm est- https://t.co/JOI4gny43i kbq225 https://t.co/yW2Zbn3WOa | False | 188 | 12 | Feeling |
| | Journalist, storyteller, and lifelong reader. A Texan, by birth and by choice. Author of WHAT UNITES US. https://t.co/uhwukT5WuM | True | 156 | 44 | Thinking |
| most_quoted | Capitalist • Cuban Born • Proud American • Medical Field • Photography • @realdonaldtrump • Sarcasm • America First • Parler | False | 52 | 148 | Feeling |
| | @CarlosSimancas • TAKE THE OATH 🇺🇸 | True | 103 | 97 | Feeling |
| | President, @FreeThinkerProj — @ShopRightOrDie — UA '24 — Contact: cj@cjpearson.org | False | 152 | 48 | Feeling |
| | Red, White and Blue music makers https://t.co/syo3BEBnOR | False | 188 | 4 | Feeling |
| | Host of 'HighWire' with Del Bigtree, Producer of Vaxxed: From Cover-Up To Catastrophe, Former Emmy winning producer of The Doctors. | True | 194 | 6 | Thinking |
| cascade_depth_4 | The voice of the people. Sorry, people. | True | 159 | 40 | Feeling |
| | Listen to the Common Sense podcast through the link below. 🇺🇸 | False | 72 | 14 | Neutral |
| | Trained extensively in diagnosis and treatment of human disease. Interest in politics. Contributor to 'The Debbie Aldrich show'. | True | 147 | 53 | Neutral |
| | Husband, father, grandfather | True | 148 | 52 | Neutral |
| | Mom, author, host, The Ingraham Angle, 10p ET @FoxNews. Retweets do not = Endorsements | True | 190 | 10 | Thinking |
| | 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. | | | | |

REFERENCES

- [1] S. Vosoughi, D. Roy, and S. Aral, "The spread of true and false news online," *Science*, vol. 359, no. 6380, pp. 1146–1151, 2018, publisher: American Association for the Advancement of Science _eprint: <https://science.sciencemag.org/content/359/6380/1146.full.pdf>. [Online]. Available: <https://science.sciencemag.org/content/359/6380/1146>
- [2] T. C. Marshall, N. Ferenczi, K. Lefringhausen, S. Hill, and J. Deng, "Intellectual, narcissistic, or Machiavellian? How Twitter users differ from Facebook-only users, why they use Twitter, and what they tweet about," *Psychology of Popular Media*, vol. 9, no. 1, pp. 14–30, 2020, place: US Publisher: Educational Publishing Foundation.
- [3] K. Lee, J. Mahmud, J. Chen, M. Zhou, and J. Nichols, "Who will retweet this? automatically identifying and engaging strangers on twitter to spread information," in *Proceedings of the 19th International Conference on Intelligent User Interfaces*, ser. IUI '14. New York, NY, USA: Association for Computing Machinery, 2014, p. 247–256. [Online]. Available: <https://doi.org/10.1145/2557500.2557502>
- [4] J. Mahmud, M. X. Zhou, N. Megiddo, J. Nichols, and C. Drews, "Optimizing the selection of strangers to answer questions in social media," *CoRR*, vol. abs/1404.2013, 2014. [Online]. Available: <http://arxiv.org/abs/1404.2013>
- [5] S. Oreg and N. Sverdlid, "Source personality and persuasiveness: Big five predispositions to being persuasive and the role of message involvement," *Journal of Personality*, vol. 82, no. 3, pp. 250–264, 2014. [Online]. Available: <https://onlinelibrary.wiley.com/doi/abs/10.1111/jopy.12049>
- [6] M. Shmueli-Scheuer, J. Herzig, D. Konopnicki, and T. Sandbank, "Detecting persuasive arguments based on author-reader personality traits and their interaction," in *Proceedings of the 27th ACM Conference on User Modeling, Adaptation and Personalization*, ser. UMAP'19. New York, NY, USA: Association for Computing Machinery, 2019, p. 211–215. [Online]. Available: <https://doi.org/10.1145/3320435.3320467>
- [7] M. H. Ribeiro, K. Gligorić, and R. West, "Message Distortion in Information Cascades," Feb. 2019. [Online]. Available: <https://arxiv.org/abs/1902.09197v2>
- [8] S. Bikhchandani, D. Hirshleifer, and I. W. R. work(s):, "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy*, vol. 100, no. 5, pp. 992–1026, 1992. [Online]. Available: <http://www.jstor.org/stable/2138632>
- [9] A. D. Vany and C. Lee, "Information Cascades in Multi-Agent Models," 1999.
- [10] W. Galuba, D. Chakraborty, K. Aberer, Z. Despotovic, and W. Kellerer, "Outtweeting the Twitterers - Predicting Information Cascades in Microblogs," 2010, conference Name: 3rd Workshop on Online Social Networks (WOSN 2010) Number: CONF. [Online]. Available: <https://infoscience.epfl.ch/record/149269>
- [11] D. Boyd, S. Golder, and G. Lotan, "Tweet, Tweet, Retweet: Conversational Aspects of Retweeting on Twitter," in *2010 43rd Hawaii International Conference on System Sciences*, Jan. 2010, pp. 1–10, ISSN: 1530-1605.
- [12] S. Kumar and N. Shah, "False information on web and social media: A survey," *CoRR*, vol. abs/1804.08559, 2018. [Online]. Available: <http://arxiv.org/abs/1804.08559>
- [13] B. Bago, D. G. Rand, and G. Pennycook, "Fake news, fast and slow: Deliberation reduces belief in false (but not true) news headlines," *Journal of Experimental Psychology: General*, vol. 149, pp. 1608–1613, 2020. [Online]. Available: <https://doi.org/10.1037/xge0000729>
- [14] G. Pennycook, J. McPhetres, Y. Zhang, J. G. Lu, and D. G. Rand, "Fighting COVID-19 Misinformation on Social Media: Experimental Evidence for a Scalable Accuracy-Nudge Intervention," *Psychological Science*, vol. 31, no. 7, pp. 770–780, Jun. 2020, publisher: SAGE Publications Inc. [Online]. Available: <https://doi.org/10.1177/0956797620939054>
- [15] F. Mairesse, M. A. Walker, M. R. Mehl, and R. K. Moore, "Using Linguistic Cues for the Automatic Recognition of Personality in Conversation and Text," *Journal of Artificial Intelligence Research*, vol. 30, pp. 457–500, Nov. 2007. [Online]. Available: <https://jair.org/index.php/jair/article/view/10520>
- [16] C. K. Chung and J. W. Pennebaker, "Revealing dimensions of thinking in open-ended self-descriptions: An automated meaning extraction method for natural language," *Journal of Research in Personality*, vol. 42, no. 1, pp. 96–132, Feb. 2008. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S0092656607000451>
- [17] M. Noel, L. Ermakova, P. Rammaciotti, A. Perrier, and B. Benbouzid, "Controverse scientifique," 2020. [Online]. Available: <https://dpa.hypotheses.org/controverse-scientifique>
- [18] J. Herzig, G. Feigenblat, M. Shmueli-Scheuer, D. Konopnicki, and A. Rafaeli, "Predicting customer satisfaction in customer support conversations in social media using affective features," in *Proceedings of the 2016 Conference on User Modeling Adaptation and Personalization*, ser. UMAP'16. New York, NY, USA: Association for Computing Machinery, 2016, p. 115–119. [Online]. Available: <https://doi.org/10.1145/2930238.2930285>
- [19] J. Chen, G. Hsieh, J. U. Mahmud, and J. Nichols, "Understanding individuals' personal values from social media word use," in *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing*, ser. CSCW'14. New York, NY, USA: Association for Computing Machinery, 2014, p. 405–414. [Online]. Available: <https://doi.org/10.1145/2531602.2531608>
- [20] P. Costa and R. McCrae, "The revised neo personality inventory (neo-pi-r)," *The SAGE Handbook of Personality Theory and Assessment*, vol. 2, pp. 179–198, 01 2008.
- [21] P. T. Kotler and G. Armstrong, *Principles of Marketing*, 15th ed. Prentice Hall, 2013.
- [22] S. Schwartz, "Basic human values: Theory, measurement, and applications," *Revue Française de Sociologie*, vol. 47, pp. 929–968, October 2006. [Online]. Available: <https://doi.org/10.3917/rfs.474.0929>
- [23] R. A. Seegmiller and D. L. Epperson, "Distinguishing Thinking-Feeling Preferences Through the Content Analysis of Natural Language," *Journal of Personality Assessment*, vol. 51, no. 1, pp. 42–52, Mar. 1987, publisher: Routledge _eprint: https://www.tandfonline.com/doi/pdf/10.1207/s15327752jpa5101_4. [Online]. Available: https://www.tandfonline.com/doi/abs/10.1207/s15327752jpa5101_4
- [24] Y. Li, J. Medwell, D. Wray, L. Wang, and L. Xiaojing, "Learning Styles: A Review of Validity and Usefulness," *Journal of Education and Training Studies*, vol. 4, no. 10, pp. 90–94, Aug. 2016, number: 10. [Online]. Available: <http://redfame.com/journal/index.php/jets/article/view/1680>
- [25] C. Jung, *Psychological Types*, ser. Routledge Classics. Taylor & Francis, 2016. [Online]. Available: <https://books.google.fr/books?id=SPgwdQAAQBAJ>
- [26] C. Sumner, A. Byers, R. Boochever, and G. J. Park, "Predicting Dark Triad Personality Traits from Twitter Usage and a Linguistic Analysis of Tweets," in *2012 11th International Conference on Machine Learning and Applications*, vol. 2, Dec. 2012, pp. 386–393.
- [27] R. L. Falcione, "The factor structure of source credibility scales for immediate superiors in the organizational context," *Central States Speech Journal*, vol. 25, no. 1, pp. 63–66, 1974. [Online]. Available: <https://doi.org/10.1080/10510977409367770>