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

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 API[1] was queried via Logstash[2] with the following terms: *[”science retraction”, ”chloroquine”, ”hydroxychloroquine”, ”Raoult”, ”remdesivir”, ”tocilizumab”, ”favipiravir”, ”Avigan”, ”azithromicyn”, ”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 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[3] 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	# users	127	429	338	234	180	124	286	1,718
(min 10 per user)	# 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 Tweepy[4] 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[5] service was used, similar to the works of [6], [18]. 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].

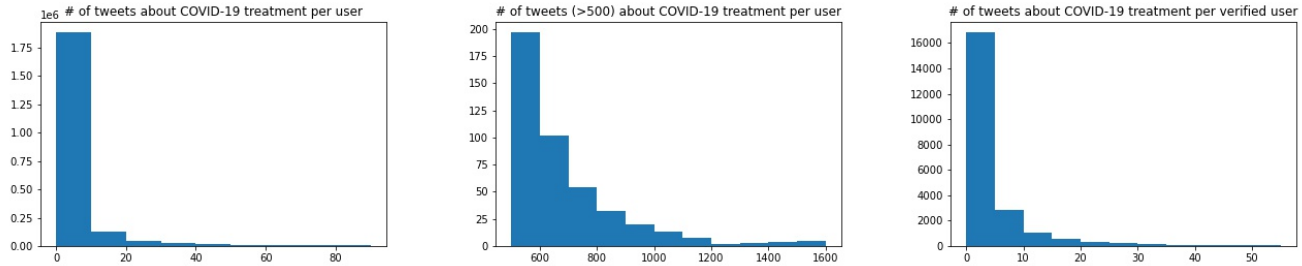
Fifty-two personality characteristics can be obtained using this classifier. The results for this study are reported based on the percentile scores for all these characteristics.

C. *Case Study Methodology*

For expert study, five users per category were selected (5 users $\times$ 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



(a) (b) (c)

Fig. 1: Number of tweets per user

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

Big Five Trait	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 high[6] 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

[6] Greater than average tendency for a given dimension / characteristic

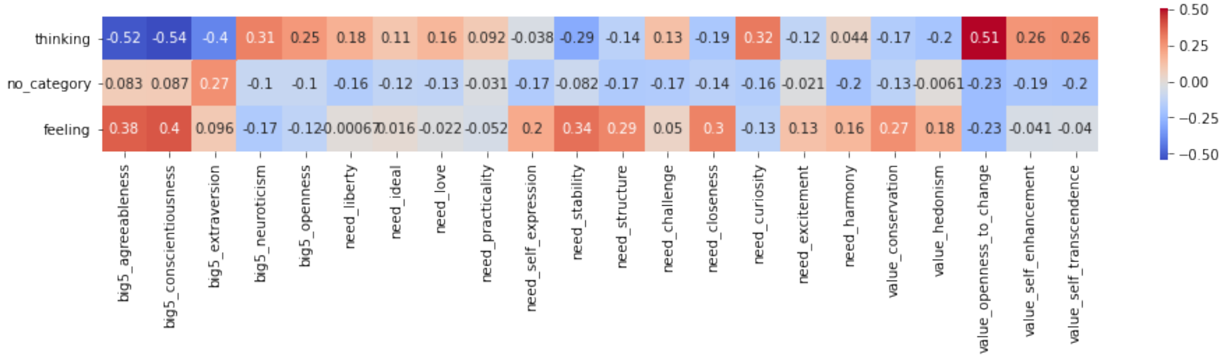


Fig. 2: Correlation between Jung categories and personality traits

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.

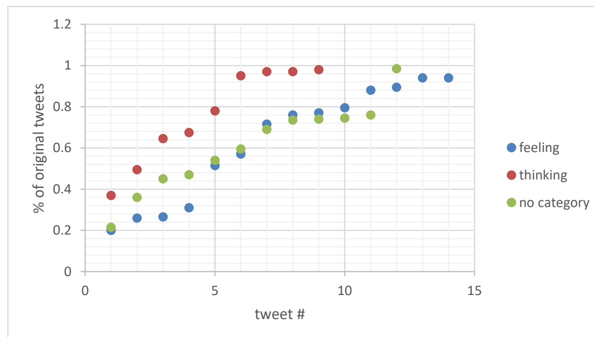


Fig. 3: Proportion of original texts in 200 recent tweets

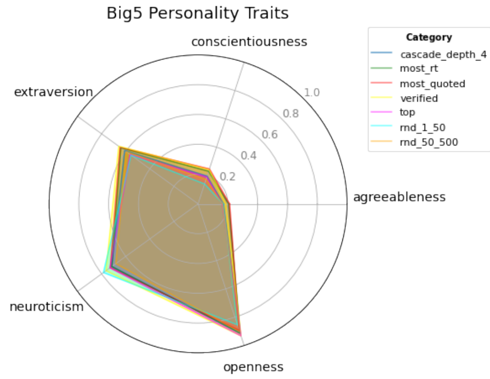
V. Conclusion

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.



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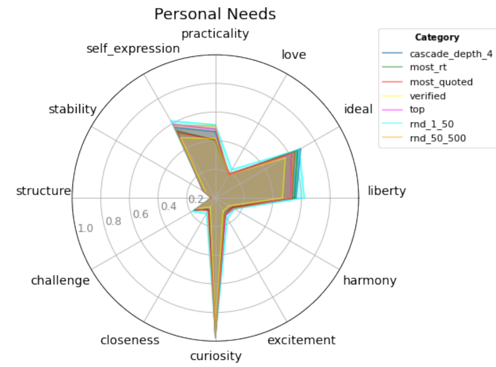

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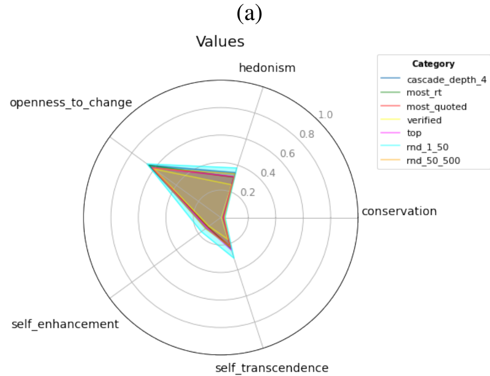

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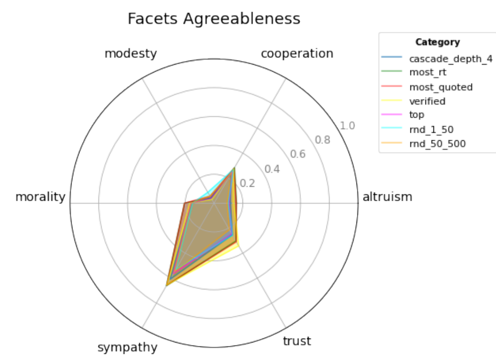

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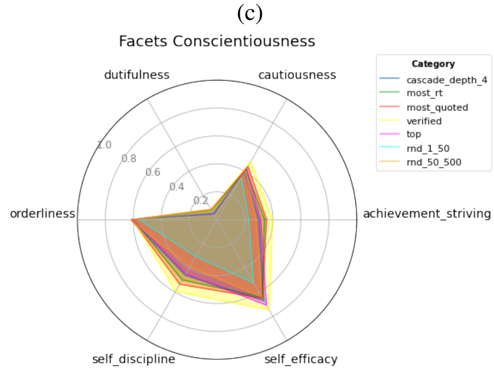

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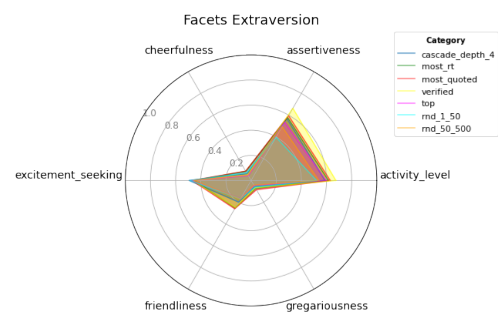

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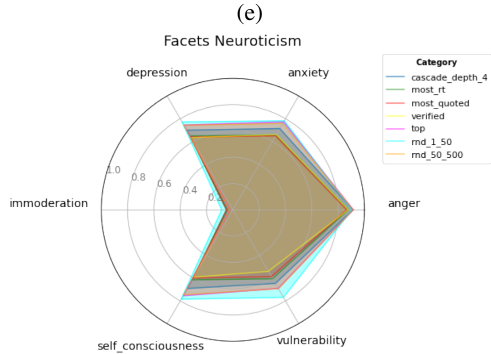

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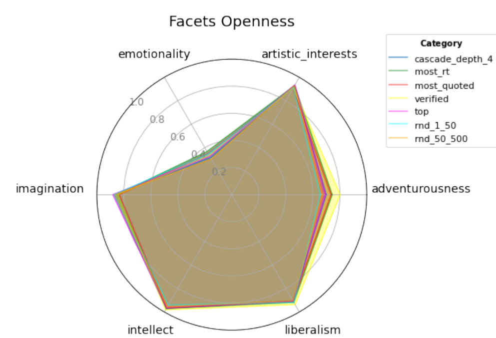

(h)

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 https://t.co/g13e9b34ga	True	138	62	*Neutral*
	The official Twitter of http://t.co/HJOFeYodXw	True	197	3	*Neutral*
	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	99	101	*Thinking*
	Covering the latest news in all fields of science. Tweets by @wwrfd, @ThatMikeDenison and @Kate_Travis. Publisher @society4science. See also @SNStudents.	True	194	6	*Thinking*
top	Ever vigilant to stop the forces of darkness overwhelming Australia. PRAISE BE!	False	176	24	*Feeling*
	...	False	108	92	*Neutral*
	UFOs	False	152	48	*Neutral*
	Infectious Diseases Clinical Pharmacist,Drug therapy expert, providing up to date information #IDTwitter & #COVID19,KAMC @NGHAnews HCQ does NOT work, CRE OXA-48	False	129	71	*Thinking*
	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	196	4	*Thinking*
rnd_50_500	#GOD, #FAMILYFIRST #PROLIFE #TRUMPSUPPORTER #MAGA #KAG #ANIMALLOVER #SUPPORTOURMILITARY #SUPPORTOURVETERANS #SUPPORTTHEMENANDWOMENINBLUE	False	40	160	*Feeling*
	#DigitalSoldier #QAnon #KAG #MAGA https://t.co/wDZeL7T6zW No lists !!! 🇺🇸💥 🇺🇸💥🇺🇸💥🇺🇸💥	False	62	138	*Feeling*
	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	43	157	*Neutral*
	I pursue happiness through many creative activities. Pottery and Argentine Tango are two of them. Love, truth, happiness, and freedom for ALL.	False	90	105	*Neutral*
	https://t.co/4rJme6xNZk @DougChris58 on Parlor	False	149	51	*Neutral*
rnd_1_50		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/JOl4gny43i 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 @CarlosSimancas ● TAKE THE OATH🇺🇸	False	52	148	*Feeling*
	President, @FreeThinkerProj — @ShopRightOrDie — UA '24 — Contact: cj@cjpearson.org	True	103	97	*Feeling*
	Red, White and Blue music makers https://t.co/syo3BEBnOR	False	152	48	*Feeling*
	Host of 'HighWire' with Del Bigtree, Producer of Vaxxed: From Cover-Up To Catastrophe, Former Emmy winning producer of The Doctors.	False	188	4	*Feeling*
	The voice of the people. Sorry, people.	True	194	6	*Thinking*
cascade_depth_4	Listen to the Common Sense podcast through the link below. 🇺🇸	True	159	40	*Feeling*
	Trained extensively in diagnosis and treatment of human disease. Interest in politics. Contributor to 'The Debbie Aldrich show'. Husband, father, grandfather	False	72	14	*Neutral*
	Mom, author, host, The Ingraham Angle, 10p ET @FoxNews. Retweets do not = Endorsements	True	147	53	*Neutral*
	Proudly serving the people of California's 43rd District in Congress. Chairwoman of the House Financial Services Committee (@FSCDems).	True	148	52	*Neutral*
	Medical Degree, Columbia University. COVID-19 research. Not medical advice.	True	190	10	*Thinking*

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