

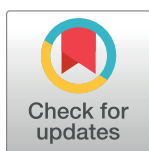
RESEARCH ARTICLE

Too much focus on your health might be bad for your health: Reddit user's communication style predicts their Long COVID likelihood

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Abstract

Long Covid is a chronic disease that affects more than 65 million people worldwide, characterized by a wide range of persistent symptoms following a Covid-19 infection. Previous studies have investigated potential risk factors contributing to elevated vulnerability to Long Covid. However, research on the social traits associated with affected patients is scarce. This study introduces an innovative methodological approach that allows us to extract valuable insights directly from patients' voices. By analyzing written texts shared on social media platforms, we aim to collect information on the psychological aspects of people who report experiencing Long Covid. In particular, we collect texts of patients they wrote BEFORE they were afflicted with Long Covid. We examined the differences in communication style, sentiment, language complexity, and psychological factors of natural language use among the profiles of 6,107 Reddit users, distinguishing between those who claim they have never contracted Covid-19, those who claim to have had it, and those who claim to have experienced Long Covid symptoms. Our findings reveal that people in the Long Covid group frequently discussed health-related topics before the pandemic, indicating a greater focus on health-related concerns. Furthermore, they exhibited a more limited network of connections, lower linguistic complexity, and a greater propensity to employ emotionally charged expressions than the other groups. Using social media data, we can provide a unique opportunity to explore potential risk factors associated with Long Covid, starting from the patient's perspective.

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1. Introduction

Post-acute sequelae of Sars-CoV-2 infection (PACS), widely known as Long Covid—is a chronic disease referring to individuals struggling with long-term symptoms after a COVID-19 infection [1], which affects “at least 65 million individuals worldwide. . . , with cases increasing daily” [2]. COVID-19 is a viral-onset illness spread through the coronavirus (SARS-CoV-

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2); approximately 10% of those affected develop Long Covid with more than 200 possible symptoms that affect the organism [2]. The most experienced symptoms of affected people are, for example, fatigue, chest pain, headache, abnormal breathing, anxiety, depression, and decreased physical performance [3, 4]. Furthermore, patients stated that Long Covid affects their mental health due to the constantly changing course of the illness and its symptoms [5]. Thus, many affected people cannot return to work or maintain a social life [6], leading to permanent employment loss and increased hospitalization worldwide [7, 8]

Long Covid significantly impacts public health and people's lives, which "is placing an increased burden on individuals and societies" [4]. Therefore, researchers and healthcare professionals put much effort into investigating links to other post-viral illnesses to increase knowledge on risk factors for prevention and medical treatments for recovery strategies [2, 4]. Given that there are not yet validated effective Long Covid treatments for recovery [2], prevention strategies that focus on reducing possible risk factors become relevant for contributing to public health [8].

Previous research investigated possible risk factors determining a higher probability of individuals falling ill with Long Covid. Such Long Covid traits are: sociodemographics as women, the elderly, and individuals with lower socioeconomic status are at higher risk of developing prolonged symptoms [1]; the severity of Covid -19 disease as hospitalized patients and patients at greater risk [9]; medical comorbidities as patients with obesity, asthma, and diabetes are at greater risk [1, 2, 10] and the vaccination status as the vaccinated population is at lower risk [1, 2, 10]. Although these studies provided valuable contributions to identifying risk factors that predict Long COVID, 'fully understanding complex and multifaceted health conditions requires approaches that capture and amplify the voices of those affected' [8]. Therefore, more prospective research from the patient's perspective considering social traits, such as social exchange and Covid long haulers, is required to increase our knowledge of possible risk factors that distinguish between people being affected by long-term Covid symptoms and those not after a SARS-CoV-2 infection [8].

With this work, we propose a methodological approach that allows us to capture insights directly from patients' voices by extracting information about possible risk factors from written texts posted on social media platforms.

Following Thompson et al. [11], the uncertainty of Covid long haulers due to missing medical cues leads to more people using social media as a crowdsourced medicine. Therefore, social media data can help "to better understand Long Covid from the perspective of patients" [12]. For example, affected people reported long-term loneliness [13], changes in social support [14], and antisocial behavior [3, 15, 16] that may be illustrated through changes in the communication style and the network structure of social media users. As Sarker and Ge [12] determined, before Long Covid, people communicated much on health-related issues on Reddit, while after being infected, participation was reduced, resulting in a decreasing network structure and communication. Social media platforms like Reddit provide a reasonable basis for Long Covid studies [12, 17]. This lets us assume that social media data might be appropriate to derive possible social traits of Long COVID by exploring the communication style and the social network structure within user profiles. This also refers to the calls of Nittas et al. [8] and Burton et al. [18] to use long-term investigations to better understand Long Covid from the patient's perspective.

Considering this scenario, our objective is to investigate possible social traits of COVID-19 patients that influence the possibility of a Long Covid disease. With the help of text analysis and Social Network Analysis (SNA), we analyzed 6.107 Reddit users' profiles, comprising their posts or comments, by comparing the differences within the communication style and network structure of people who claim that they have never contracted Covid -19 (No Covid

Group, NC), those who maintain that they have had it (Covid Group, C), and those who claim that they have experienced Long Covid symptoms. The aim is to identify social factors that classify covid long haulers (Long Covid Groups, LC). An innovative feature of our analysis is that we identified the Covid status of a large random sample of Reddit users, and then collected their texts from the time before Covid existed.

To identify changes in the communication style and network structure that differentiate Reddit users belonging to the NC, C, and LC groups, we used textual characteristics of the user profiles and SNA metrics based on a constructed social network graph (representing our independent social traits variables). We used a pairwise comparison to investigate differences regarding our three groups (NC, C, and LC as dependent variables). Furthermore, we performed logistic regression models to determine the impact of different social traits variables on the probability of belonging to LC group.

The paper is organized as follows. In Section 2, we discuss the theoretical background and the development of hypotheses. In Section 3, we illustrate the method, describing the data set, data collection, and the construction of independent and dependent variables. In Section 4, we present the results and discuss them in Section 5. Finally, in Section 6, we show the main contributions of the work, highlighting its limitations and possible future developments.

2. Theoretical background and hypotheses development

Following our aim to investigate Reddit user profiles' communication style and network structure as possible social traits of Long Covid, we provide hypotheses guiding our analyses based on related work.

We start with our basic assumption that social media data can be used to predict the health of its users. This is based on well-established research. For example, Choudhury and De [19] examined social factors driving social support for the mental health of Reddit users, and Shen et al. [20] investigated early signs of depression among Twitter users. Given that social media platforms provide a rich source of user information based on user-generated content comprising their feelings and thoughts [19, 20], research began to use social media platforms for public health studies [21, 22]. In the context of Covid or Long Covid, there is also initial research using social media data. For instance, Sarker et al. [17] extracted self-reported Covid-19 symptoms of Twitter users; Sarker et al. [12] elaborated Long Covid symptoms of Reddit users. Reddit is especially appropriate for Covid-related studies, as the social media platform with 48 million active monthly users exhibits several Long Covid groups (organized in subreddits, such as r/covidlonghaulers with over 30,000 members) [12]. Therefore, our work builds upon the assumption that Reddit's social media platform provides a reasonable basis for analyzing the social traits of Long Covid.

Looking deeper into possible relations between the communication style and the probability of coming down with Long Covid, we searched for mental health studies demonstrating how anomalies within communication can indicate chronic diseases. In general, while positive emotions can be associated with immunity against specific diseases, negative emotions can be related to an increased risk of developing a disease [20, 23]. For example, depressed people often express more negative emotions when communicating on social media [20]. A positive emotional style can predict resistance to illness after experimental exposure to rhinovirus or influenza A virus, which are other viral-onset illnesses compared to COVID-19 [24]. Given that—similar to depression—Long Covid can be related to chronic diseases and—similar to Influenza A virus—to a viral-onset illness with a significant impact on mental health [1, 2, 12], equal effects can be assumed. Hence, we formulate this first hypothesis to see whether:

H1: *Long Covid users express more negative emotions compared to Covid-19 users (not having long-term symptoms).*

Following Zhao and Zhou [25], COVID-related content in social media can be associated with users having worse mental health. Following the authors, users searching for disease-related content reported more significant disaster stressors. In comparison, people more concerned with organizing leisure activities and communicating about family and hobby-related content on social media reported higher well-being and less stress [26, 27]. This is consistent with research on linguistic traits of an individual's health (see, for example, Pennebaker and King [28] who determined a causal link between the use of words by individuals and their health or illness). Hence, excessive use of social media for information and communication about health-related topics, such as the coronavirus pandemic, can impact perceived disease symptoms. This is also known as hypochondriacal beliefs affecting disease progression [29–31]. Mahat-Shamir et al. [32] confirmed the mediation effects of hypochondriasis symptoms of social media users in the context of the COVID-19 pandemic. Hence, we assume similar effects for Covid long haulers:

H2: *Long Covid users express more health-related topics on social media than Covid-19 users.*

Concerning further possible social traits of Long Covid within the communication style of social media users, we elaborate on the language and communication style of the posted content. Before the coronavirus pandemic, psychological studies investigated how linguistic complexity can predict emotional stress [33]. Following Karabin et al. [34], in the context of the Covid-19 pandemic, there has been “a steady increase [in linguistic complexity] from the pre-pandemic level throughout the first year of the global lockdown”. The results were contrary to the author's assumption that linguistic complexity will decrease with infection, given that a loss of cognitive function is associated with COVID-19. This might be because sick people tend to demonstrate a greater length of postings to provide clear and detailed information regarding their physiological and psychological health status [35, 36]. This demonstrates a priority on communication clarity leading to linguistic complexity in terms of word counts and direct communication but not in terms of using polished language with complex words to express their thoughts, since sick people face greater levels of stress (Suefeld & Rank 1996). Since Covid long haulers are uncertain about how to deal with the varying symptoms during their long-term illness [5] leading to a greater use of social media for medical research [11], affected people might try to overcome this uncertainty by adding value through clear and direct postings explaining their illness resulting in a higher word count of verbose language and a more direct communication style. Hence, we assume:

H3: *Long Covid users use more verbose and direct language than Covid-19 users.*

In addition to having communication style as one possible social traits increasing the probability of coming down with Long Covid, we also believe that social media exposure somewhat predicts Long Covid illness. For example, healthy people's communication activity is higher than that of non-healthy ones [19]. In the context of COVID-19, Gao et al. [37] determined that social media engagement and mental health are frequently interrelated. Although self-promotion through social media can benefit mental health [38], cognitive overload with COVID-19 information or misinformation can also result in cyberchondria as “shar[ing] news without verifying its reliability” [39]. Hence, highly active social media users require healthy skepticism [39]. Therefore, users with high engagement within social media might have a reduced probability of developing Long Covid. However, the study of Nicholls and Yitbarek [40] examined that social media engagement does not necessarily lead to more preventive behavior during

the COVID-19 pandemic. Since lethargic behavior can be one post-Covid syndrome [41], Covid long haulers might demonstrate lower engagement within social media. Thus, we assume the following.

H4: Long Covid users have lower social media communication activity (posting, commenting) than Covid-19 users.

Besides the communication activity on social media, how individuals are connected with other users (referring to the network structure) can further affect their health [42]. For example, social support and social connectedness on social media are related to lower levels of depression and anxiety [43]. Thereby, “depressed users tend to build a close network of trusted people to share their mental health issues”, whereby “a lower value indicates fewer interactions” [42]. In the context of the COVID-19 pandemic, people experience loneliness by having less contact with friends [44]. This can lead to mental health problems, such as poorer physical performance or more chronic conditions [45]. Hence, ‘students who kept all-around contact with friends during the lockdown declined in loneliness, whereas students who had little contact or did not (video) call friends did not’ [44]. Additionally, especially Covid long haulers reported long-term loneliness [13], reduced social support [14], and antisocial behavior [15, 16, 46], so we assume:

H5: Long Covid users have fewer social media connections than Covid-19 users and are less central in the social network.

In summary, while the first three hypotheses (H1-H3) are related to the communication style of social media users as social traits of Long Covid, the last two hypotheses (H4-H5) are related to the network structure of social media users.

3. Methodology

The purpose of this research is to understand how the communication style and network position of Reddit users differ between those who have Covid, Long Covid, and those who have never been infected. In this Section, we present our study design based on the methodology used by Shen et al. [20] in their depression detection research, with slight adjustments based on the proposals of Chancellor & De Choudhury [23] regarding how to improve social media-based public health studies. Fig 1 presents the complete process, detailed in the next paragraphs.

3.1. Data collection

To obtain our initial dataset, we used the Pushift API, a community-driven Reddit API. We collected information between 1 January 2018 and 1 May 2022. Subsequently, the collected data were divided into two datasets according to their publication date. The first contains all user posts made before the advent of the pandemic (from January 2018 to 1 January 2020). Consequently, the second includes the posts published after the arrival of the pandemic. This second dataset allowed us to label the pre-pandemic posts into three distinct groups of users: users who declared that they did not develop Covid symptoms (No Covid group); users who claimed to have Covid without developing Long Covid (Covid group); users who declared that they developed Long Covid (Long Covid group).

All the posts included in the analysis are written in English. To identify whether a user belongs to one of the three groups, we followed the approach of Chancellor & De Choudhury [23], illustrated in Fig 2.

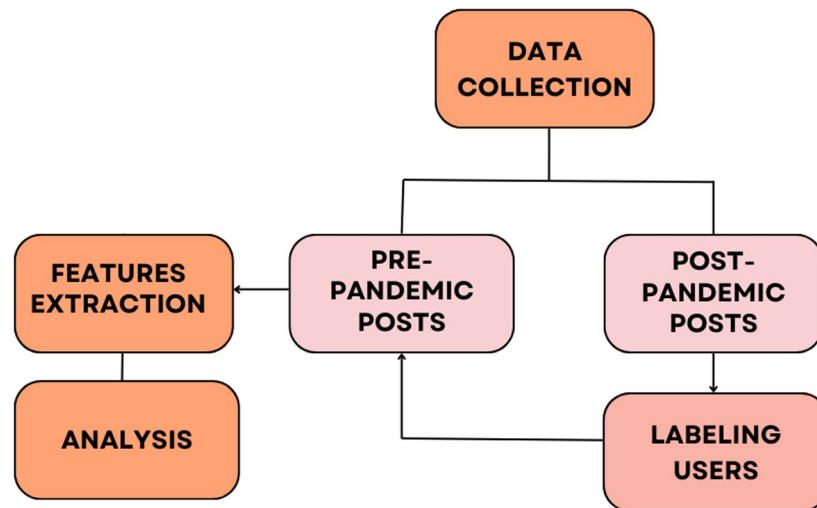


Fig 1. Research framework.

<https://doi.org/10.1371/journal.pone.0308340.g001>

In brief, to create the Long COVID group, we identified 2,986 users who posted on the *covidlonghauers* Reddit forum. Accordingly, we collected all their posts published in this sub-group. The forum has been previously validated by Sarker & Ge [12] for its representation of people with Long Covid symptoms.

The two remaining groups (i.e., Covid and No Covid) are constructed by selecting authors of randomly selected Reddit posts. In the random selection process, all posts within the given timeframe have the same chance of being selected. The random selection is done without replacement. The criteria for categorizing a user as COVID-positive are the active participation in a subforum dedicated to COVID-19-positive patients and a user's explicit declaration of being infected with COVID-19. Users meeting these criteria are allocated to the Covid group, while those who have never posted in a Covid subreddit and have never explicitly stated

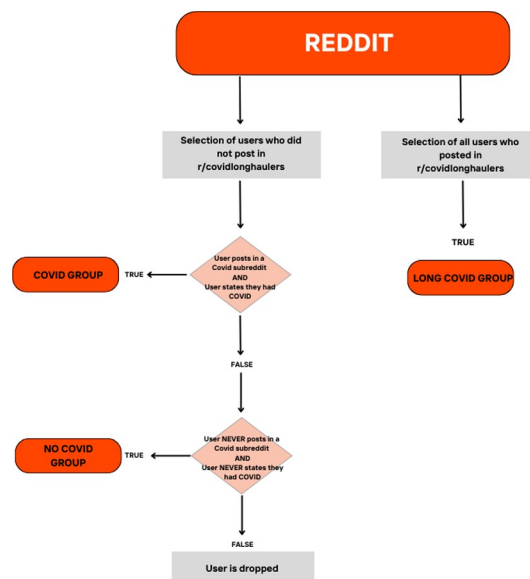


Fig 2. Construction of the three user groups.

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that they are infected with COVID-19 are assigned to the No-Covid group. In all other cases, the user is dropped. For the first criterion, we listed all subreddits in our data that had the word COVID in it, and identify COVID-19 subreddits dedicated to people infected by the virus. For example, our list includes: r/COVID19positive, r/COVID19, and r/CovidVaccinated sub-reddits. The second criterion is based on a regular expression. This method has been employed in several studies on identifying disease infections on social media, as demonstrated by Chancellor et al. [23]. The aim of this approach is to identify users expressing thoughts regarding their COVID-19 infection. In the, S1 Fig provides several examples of regular expressions used to identify mentions of COVID-19 infection in user posts, while S2 Fig illustrates an example of how these indicators allow us to identify mentions of COVID-19 infection in user posts.

For the validation phase, we manually reviewed 500 posts to ensure the classes were correctly assigned. During the initial phase, we noticed classification errors stemming, for example, from the definition of “being infected”. If a user stated “My father was infected” instead of “I was infected” the classification was incorrect. With the aid of manual review, we refined the regular expression until the issues identified during validation were resolved. Once all major issues were addressed and posts from randomly selected users were consistently assigned to the correct categories, we completed the validation process.

This snowball approach has been used successfully by Chancellor & De Choudhury [23] to identify mental health-related subreddits.

3.2. Features extraction

To extract the variables related to the SNA and linguistic aspects of the NC, C, and LC groups, we processed the first dataset, i.e., the one containing posts published by users before the pandemic, from January 2018 to January 2020. To respect the privacy of the users in our sample, we first anonymized the users' names to protect their identities and safeguard their health information related to COVID-19 infection. After classifying users into groups and extracting their pre-pandemic posts, we assigned each user a unique ID, ensuring that specific names were not retained in our internal databases. Additionally, we did not make the analyzed texts public. Instead, we present only aggregated measures that describe the characteristics of the three groups, ensuring that the textual content of individual users cannot be traced back to them. Numerical results are publicly available at Figshare (10.6084/m9.figshare.25251316).

3.2.1. Network construction and SNA variables. We constructed a social network graph considering users' interactions in our database. The graph consists of nodes representing users and edges representing comments exchanged between two users. The network is weighted according to the number of comments user i makes to user j 's posts. To construct a network, the recipient of a post was set as the original poster triggering the response. When it was not possible to directly identify the recipient of a post, we made the corresponding subreddit a virtual recipient of a post. Using this methodology, we constructed a comprehensive network that includes users and subreddits as nodes, with posts or comments as connecting edges. This network representation allowed us to analyze centrality metrics and gain insights into the prominence of users within the platform.

The social network features were retrieved using Griffin, a web-based social network analysis tool [47]. The variables *messages sent* and *messages received* provide quantitative measurements of the total number of messages sent and received by each user in our study. To further analyze these communication data, we explored the concepts of *in degree* and *out degree* centrality [48]. In degree centrality quantifies the number of incoming arcs directed towards a user i , specifically representing comments made by any user in response to user i 's posts.

Conversely, out degree centrality captures the number of outgoing arcs originating from a user i . In addition, we calculated *betweenness centrality*, which measures how often a node occurs on all shortest paths between two nodes [49].

To account for interaction times, we calculated *ego art*, which measures the average response time of the user, and *alter art*, which is the average response time of all other users to user i [50].

We also considered two sets of variables to measure the language's complexity (Section 3.2.2) and identify different dimensions of the language content (Section 3.2.3).

3.2.2. Language complexity and informativeness. Over the years, numerous studies have used textual metrics to explore the complexity of human language from social media posts [51–53]. In line with these works, we have measured user language complexity based on the three variables. The first is *Word Count*, representing the total number of words users post. It is a proxy for language richness and complexity [54, 55]. Building upon the findings of Lewis & Frank [51] and Owens & Wedeking [52], we included the variable *Six-Letters*. This variable measures the percentage of words in each post with a length greater than six letters. A higher share of long words is associated with communicative sophistication and thus increases language complexity [52]. Lewis & Frank [51] also supported the inclusion of this variable, which demonstrated that longer words refer to conceptually more complex meanings. The first two variables proved to be connected to the educational background of people. Several authors, such as Béland et al. [56], Le Dorze and al. [57], and Mackenzie [58] shed light on the positive impact of education on the length of text used to describe images or the completeness of their descriptions. Consequently, *Word Count* and *Six-Letters* can be interpreted as proxies for educational attainment. Higher linguistic complexity monitored with these variables can also indicate higher user education [59]. Lastly, we introduced a measure of the average informativeness of a user's post, i.e., *Document Informativeness*. It is calculated using the term frequency-inverse document frequency (TF-IDF) metric. The idea is that user posts contribute novel information when they incorporate words not commonly found in other posts and when the intended message is effectively conveyed without uninformative text. Therefore, the frequency of occurrence of each word is multiplied by the logarithmically scaled inverse fraction of the posts that contain that word. The informativeness for each post analyzed is calculated as follows:

$$\text{Document Informativeness} = \frac{1}{n} \sum_{w \in C} f_w \log \frac{N}{n_w}$$

Where N represents the total number of documents in the corpus (referring to a user's posts); n is the total number of words that appear on a user's post; C indicates the set of these words; f_w is the frequency of a specific word w , and n_w is the number of posts where the word w appears.

We employed standard text preprocessing techniques before calculating the three metrics (word count, six letters, and document informativeness). This involved eliminating stop-words, which typically add little value to the meaning of a sentence, as well as punctuation and special characters. Additionally, we converted all words to lowercase and extracted stems by removing word affixes using the Natural Language Toolkit (NLTK) Snowball Stemmer algorithm [60], as recommended by Jivani [61].

3.2.3. Sentiment and psychological aspects of natural language use. The language individuals use daily can reveal significant aspects of their social and psychological spheres [62]. To uncover psychological markers from users' posts on Reddit, we use a quantitative approach based on the idea that language characteristics can be counted and statistically analyzed [63–

[66]. Our quantitative text analysis is based on previous evidence that words people use convey psychological information or represent their emotional states or opinions. Following this approach, we measured language sentiment and other dimensions using the Python programming language and Linguistic Inquiry and Word Count (LIWC) software [67].

The selected variables fall into two distinct categories of language *style* and *content*—each possessing unique psychometric and psychological properties.

According to the definition of Tausczik and Pennebaker [55], *style words*, also known as function words, consist of auxiliary verbs, interrogative verbs, prepositions, pronouns, and articles, which we explain in the following.

The *auxiliary verbs*, such as “can”, “could”, “must”, “should”, “may”, “might” and “would”, are mainly used in English to express ability, permission, possibility, obligation, necessity, intention, prediction, or probability [68]. By analyzing the frequency of these verbs, we can gain insight into the narrative style of a user's language. Brandt and Herzberg [35] highlighted that a higher occurrence of auxiliary verbs indicates a more dynamic use of language, often involving personal anecdotes.

Other markers of a dynamic narrative style are *pronouns*. We measured the frequency of the first-person pronoun *I*, commonly used when expressing oneself or referring to one's perspective or actions. Its frequency can exhibit associations with factors such as depression, illness, and, more broadly, self-oriented focus [69]. In particular, Bucci & Freedman [70], Rude et al. [71], and Stirman & Pennebaker [72] demonstrated that people who are more vulnerable to depression tend to use first-person pronouns more frequently when expressing their feelings compared to those who are less susceptible to depression. Furthermore, how individuals use pronouns can vary depending on their level of social connection [69, 73]. Using more first-person singular pronouns indicates a more egocentric narrative focus and a more personal communication style. On the other hand, using more second- and third-person pronouns, such as *You* and *She / He*, can represent a user's level of social engagement [62]. This is why we also measured the frequency of second- and third-person singular pronouns.

The use of *Articles*, such as “a”, “an”, and “the” is another variable that can provide valuable information about the level of detail in the comments. Indeed, it is a proxy of a user's categorical language, which indicates that they use more formal language and provide precise and complex descriptions [35]. Greater use of articles is also associated with users' gender [74], with studies showing that men tend to use more articles than women [75–77].

The dimension *Interrogatives* refers to the presence of interrogative words or phrases in comments, such as “who”, “what”, “where”, “when”, “why” and “how”. This dimension indicates a user's level of curiosity or interest [67].

In addition to these *style words*, the second category of variables consists of *content words* comprising nouns and many descriptive adjectives. From a psychological standpoint, the first category, *style words*, reflects how users communicate, while *content words* convey their expressed opinions (e.g., sentiment), emotional states (e.g., anger, affection, feel) or interests (e.g., leisure) [55]. In the following, we describe the variables belonging to this category.

Sentiment is a variable derived from sentiment analysis, a natural language processing technique that aims to extract, convert, and interpret opinions from a text, classifying them as positive, negative, or neutral [78]. We used the VADER lexicon, which is a pre-built sentiment analysis tool that assigns sentiment scores to the entire post. Our measure ranges from -1 (negative) to +1 (positive) and is a crucial aspect in understanding the overall tone of a text.

Anger counts the frequency of words that express feelings of anger and aggression, such as “angry”, “hateful”, “annoyed”, and “frustrated”. This variable has been incorporated in various studies to map the nature of social media communication before, during, and after the Covid-19 pandemic [79, 80]. A higher presence of these terms indicates worse health. On the other

hand, a branch of literature dedicated to repressive coping argued the opposite [81]. It suggested that individuals who avoid using negative words when describing their emotions are at a greater risk of experiencing subsequent health problems [81].

The *Affection* variable is associated with focusing on emotional states and the well-being of an individual; it refers to the overall emotional tone or mood experienced by a user. Braun et al. [82] found that higher values of positive-affect language characterize texts produced by users with higher emotional intelligence.

Feel is related to the emotional tone and expression in language. This variable measures the degree to which individuals use the language of sensations. It includes words such as “hard”, “cool”, and “felt” [28].

Leisure reflects users' engagement in leisure activities and their desire to discuss such topics on social media. This dimension includes words such as “game”, “fun”, “play”, and “party”, and it has been utilized in numerous psycholinguistic studies about the Covid-19 pandemic, e.g., Gandino et al. [83] and Su et al. [84].

The presence of words indicative of basic psychological needs, desires, and motivations is measured by *Drives*. This dimension includes words related to achievement, power, affiliation, and other fundamental drives that shape human behavior [67].

Reward is related to expressing rewards, incentives, positive goals, and approaches [67]. The idea is that individuals with high-reward attention may be more motivated during the pandemic to take preventive measures to achieve positive health outcomes. This variable has the potential to offer valuable information on the approach taken by various groups of subjects.

Risk refers to the extent to which language use reflects a willingness to take chances or engage in risky behavior; it captures the presence of words and phrases associated with risk-taking, adventure, and daring activities [67]. We introduce this dimension to understand how many individuals from the three groups were more risk-oriented before the pandemic.

Family is associated with a focus on family dynamics and support; it includes words related to family relationships and roles, such as “mother”, “father”, “sister”, and “brother”. Past studies have shown that individuals who use family-related words in their writings are perceived as extraverted [85, 86]. Moreover, valuable research for our work comes from Gutanku et al. [26]. They explored the language of psychological stress with a dataset of social media users and found that stressed users post about family time less frequently than users who are not stressed.

Differentiation concerns the amount of words that reflect cognitive complexity and differentiation in language. It includes words such as “or”, “but”, “if”, and “not” [67].

Insight represents the extent to which a person gains new understanding, knowledge, or self-awareness about themselves or their experiences; it is related to a user's level of self-reflection and introspection. As suggested by Ogden and Cornwell [54], insight expressions may reflect the participants' willingness to analyze topics that are personal to them.

Lastly, *Health* includes words related to physical and mental health, such as “doctor”, “sick”, “pain”, and “therapy”; it focuses on a user's perception of their physical well-being. Brown et al. [29], Ferguson et al. [30], and Pauli & Alpers [31] demonstrated that individuals with hypochondriacal beliefs tend to process health-related information more extensively than those without such beliefs. Using this dimension, we want to investigate whether individuals who have experienced Long Covid exhibited more significant health concerns before the pandemic; this could imply greater control and thus a greater likelihood of discovering that the preexisting symptoms of Covid-19 are associated with Long Covid.

3.3. Overview of study hypotheses and models

To sum up, we used the variables described in Section 3.2.1 to verify the last two hypotheses (*H4-H5*), while the variables included in Sections 3.2.2 and 3.2.3, which are related to the communication style and the psychological aspects of Reddit users, are used to check the first three (*H1-H3*).

To understand the user communication profiles within the No Covid, Covid, and Long Covid groups, we performed the Kruskal-Wallis one-way analysis of variance. Furthermore, pairwise comparisons with a Bonferroni correction were performed.

In addition, we performed logistic regression models to identify the network and textual characteristics that distinguish individuals who have experienced Long Covid from those who have only contracted Covid without developing Long Covid symptoms. Consequently, our dependent variable describes the user's Long Covid class membership. It takes the value of 1 if labelled Long Covid or 0 if the user belongs to the Covid class.

[Table 1](#) provides an overview of the research hypotheses

4. Results

In [Fig 3](#) we show the distribution of pre-pandemic posts extracted and analyzed for each group. In total, we collected the posts of 6.107 Reddit Users, of which 2.986 belonged to the Long Covid group, 592 belonged to the Covid group, and the remaining 2.529 belonged to the no Covid group. Consequently, we extracted 984.625 posts, 23% belonging to the Covid group, 32% to the Long covid group, and the remaining 45% to the no covid group. On average, the pre-pandemic posts of each Covid user is 363,09 with a standard deviation of 489,87. Users in the Long Covid group have an average posts count of 104,76 with a standard deviation of 228,34. Lastly, individuals in the No Covid group show an average Reddit post of 166,36 posts, with a standard deviation of 349,87.

As presented in [Table 2](#), our findings indicate that all centrality metrics significantly differ between the three groups. However, the interaction variables (ego art and alter art) were not statistically significant in distinguishing users. Additionally, of the three variables related to language complexity, only six-letter was statistically insignificant. Similarly, the variables you, drives, and reward did not appear to differ among the three groups of users. Individuals who have contracted COVID-19 exhibit elevated values in all variables in social network analysis. Specifically, their communication style is characterized by more auxiliary verbs and articles and a higher frequency of third-person singular pronouns. On the contrary, subjects in the Long Covid group tend to use more first-person singular pronouns and interrogative forms. Regarding content, COVID users discuss family and risk more frequently than their counterparts. In addition, their posts contain more anger-related words, distinguishing them from the other groups. Interestingly, those who develop Long Covid exhibit the lowest average for the

Table 1. Research hypotheses and variables.

Hypothesis	Formulation
H1	Long COVID users express more negative emotions compared to COVID-19 users.
H2	Long COVID users express more health-related topics on social media compared to COVID-19 users.
H3	Long COVID users use a more verbose and direct language compared to COVID-19 users.
H4	Long COVID users have lower social media communication (posting, commenting) activity compared to COVID-19 users.
H5	Long COVID users have lower connection to social media user networks compared to COVID-19 users.

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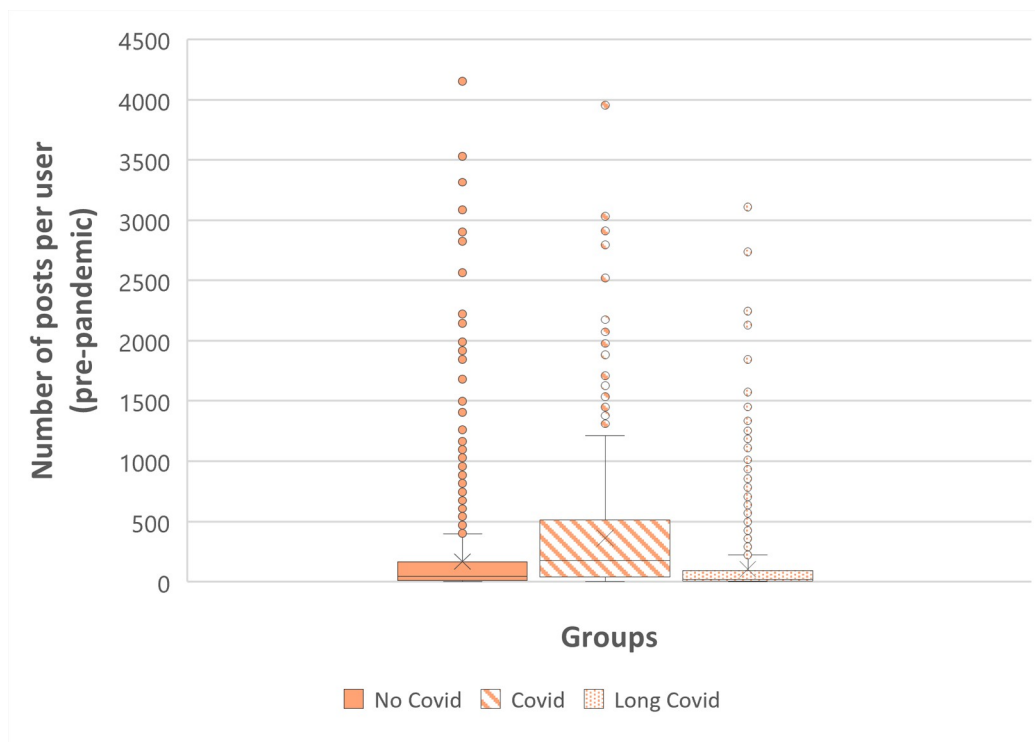


Fig 3. Number of pre-pandemic posts per user.

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anger variable but the highest for sentiment and feeling. Meanwhile, individuals without COVID have the highest mean for the affected variable; they tend to discuss leisure more frequently but use fewer insight words. However, users in the Long Covid group exhibited a greater focus on health even before the pandemic, as seen from the mean values of this dimension.

We performed seven logistic regression models to test the hypotheses described in Section 2. Table 3 shows an overview of the regression results.

The first three hypotheses aim to explore variations in the psychological aspects of natural language between Long Covid and Covid users. For this purpose, we created Model 1 to test whether there are differences between the use of negative expressions (*H1*), the use of health-related words (*H2*), and the use of more verbose and direct language (*H3*). Consequently, this first model includes all the variables presented in Section 3.2.3. On the other hand, Model 2 examines the impact of language complexity variables to address the third hypothesis. The findings from Model 2 suggest that language complexity variables do not play a significant role in classifying subjects with Long Covid, except for the Word Count. Indeed, the value of McFadden's R^2 for this model is the second lowest among the seven models we have created. Looking at the goodness of fit of Model 1, we note that the model explains about 8.1% of the variance in the data. This indicates that the psychological dimensions explain a low percentage of the total variance, leaving a significant proportion unexplained.

The following three models were employed to investigate the impact of Reddit users' social network structures as further social predictors predicting the likelihood of being in the Long Covid group using SNA variables (*H4-H5*). We constructed three distinct models due to the collinearity of the variables related to the number of messages sent and received by a user, its degree, and betweenness centrality metrics. The results reveal that Model 3 explains more of

Table 2. Kruskal-Wallis independent samples tests.

Variable	Groups	N	Mean	Sig.	Post hoc analysis		
					No Covid	Covid	Long Covid
Messages sent	No covid	2529	164.98	0.000		***	***
	Covid	592	362.47		***		***
	Long covid	2986	103.88		***	***	
Messages received	No covid	2529	10.22	0.000		***	***
	Covid	592	15.47		***		***
	Long covid	2986	2.55		***	***	
In degree	No covid	2529	1.26	0.000		***	***
	Covid	592	2.35		***		***
	Long covid	2986	0.72		***	***	
Out degree	No covid	2529	134.04	0.000		***	***
	Covid	592	294.92		***		***
	Long covid	2986	91.28		***	***	
Betweenness	No covid	2529	232397.45	0.000		***	***
	Covid	592	537101.29		***		***
	Long covid	2986	222191.16		***	***	
Ego art	No covid	2529	0.05	0.729			
	Covid	592	0.11				
	Long covid	2986	0.01				
Alter art	No covid	2529	0.05	0.025		*	
	Covid	592	0.24		*		**
	Long covid	2986	0.02			**	
Word Count	No covid	2529	21.63	0.000		***	***
	Covid	592	29.17		***		***
	Long covid	2986	34.75		***	***	
Six Letter	No covid	2529	0.27	0.904		***	***
	Covid	592	0.26		***		
	Long covid	2986	0.26		***		
Document Informativeness	No covid	2529	5.13	0.000		***	***
	Covid	592	4.94		***		
	Long covid	2986	4.89		***		
Auxiliary Verbs	No covid	2529	7.370	0.000		***	***
	Covid	592	8.383		***		***
	Long covid	2986	8.044		***	***	
I	No covid	2529	4.294	0.000		***	***
	Covid	592	3.754		***		***
	Long covid	2986	4.644		***	***	
You	No covid	2529	2.470	0.066			
	Covid	592	2.302				
	Long covid	2986	2.492				
She/He	No covid	2529	0.922	0.000		***	**
	Covid	592	1.062		***		***
	Long covid	2986	0.986		**	***	
Articles	No covid	2529	4.840	0.000		***	***
	Covid	592	5.704		***		***
	Long covid	2986	5.327		***	***	

(Continued)

Table 2. (Continued)

Variable	Groups	N	Mean	Sig.	Post hoc analysis		
					No Covid	Covid	Long Covid
Interrogatives	No covid	2529	1.583	0.000		***	**
	Covid	592	1.623		***		*
	Long covid	2986	1.646		**	*	
Sentiment	No covid	2529	0.144	0.000		***	***
	Covid	592	0.117		***		***
	Long covid	2986	0.184		***	***	
Anger	No covid	2529	1.08	0.000		***	***
	Covid	592	1.10		***		***
	Long covid	2986	0.84		***	***	
Affection	No covid	2529	8.95	0.000		***	***
	Covid	592	7.57		***		***
	Long covid	2986	8.36		***	***	
Feel	No covid	2529	0.69	0.000			***
	Covid	592	0.55				***
	Long covid	2986	0.71		***	***	
Leisure	No covid	2529	1.96	0.000		*	***
	Covid	592	1.74		*		***
	Long covid	2986	1.48		***	***	
Drives	No covid	2529	7.304	0.133			
	Covid	592	7.018				
	Long covid	2986	7.076				
Reward	No covid	2529	1.883	0.872			
	Covid	592	1.732				
	Long covid	2986	1.831				
Risk	No covid	2529	0.473	0.000		***	***
	Covid	592	0.595		***		***
	Long covid	2986	0.546		***	***	
Family	No covid	2529	0.41	0.000		***	*
	Covid	592	0.45		***		***
	Long covid	2986	0.39		*	***	
Differentiation	No covid	2529	2.650	0.000		***	***
	Covid	592	3.204		***		***
	Long covid	2986	3.052		***	***	
Insight	No covid	2529	1.921	0.000		***	***
	Covid	592	2.038		***		***
	Long covid	2986	2.268		***	***	
Health	No covid	2529	0.49	0.000		***	***
	Covid	592	0.59		***		***
	Long covid	2986	0.88		***	***	

Note: Independent-Samples Kruskal-Wallis Test. Asymptotic significances are displayed. Post hoc analysis: pairwise comparisons with a Bonferroni correction.

*** $p < 0.001$

** $p < 0.01$

* $p < 0.05$

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Table 3. Logistic regression models.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)
Auxiliary Verbs	0.927*** (0.888–0.967)					0.924** (0.881–0.970)	0.926*** (0.887–0.966)
I	1.149*** (1.093–1.208)					1.111*** (1.049–1.175)	1.123*** (1.070–1.191)
You	1.012 (0.948–1.080)					1.002 (0.933–1.076)	
She/He	1.034 (0.951–1.124)					1.056 (0.960–1.161)	
Articles	0.937* (0.891–0.986)					0.922** (0.871–0.977)	0.942* (0.895–0.992)
Interrog	1.086 (0.996–1.184)					1.112* (1.009–1.226)	1.111* (1.003–1.230)
Sentiment	6.970*** (3.439–14.127)					3.596** (1.547–8.360)	3.850** (1.716–8.64)
Anger	0.847** (0.767–0.937)					0.873* (0.782–0.974)	0.889 (0.799–0.988)
Affection	1.041* (1.004–1.079)					1.065** (1.021–1.111)	1.073** (1.031–1.117)
Feel	1.228* (1.027–1.469)					1.306* (1.053–1.619)	1.324* (1.065–1.647)
Leisure	0.936** (0.890–0.984)					0.954 (0.906–1.006)	
Drives	1.036 (0.989–1.085)					1.0345 (0.982–1.089)	
Reward	0.933 (0.854–1.018)					0.944 (0.854–1.042)	
Risk	0.938 (0.834–1.048)					0.937 (0.831–1.057)	
Family	0.819** (0.717–0.935)					0.811* (0.706–0.933)	0.830** (0.733–0.940)
Differtiation	0.921* (0.856–0.990)					0.889** (0.820–0.964)	
Insight	1.120* (1.014–1.237)					1.082 (0.969–1.208)	
Health	1.486*** (1.269–1.740)					1.517*** (0.970–1.208)	1.542*** (1.291–1.841)
Word Count		1.012*** (1.008–1.017)				1.012*** (1.006–1.018)	1.010*** (1.005–1.016)
Six Letter		2.222 (0.426–11.682)				5.277 (1.006–1.018)	4.020 (0.578–27.952)
Document Informativeness		0.851* (0.745–0.972)				0.884 (0.726–1.075)	
Messages sent			0.998*** (0.998–0.998)			0.998*** (0.998–0.999)	0.998*** (0.998–0.999)
Messages received			0.989*** (0.982–0.995)			0.986*** (0.980–0.993)	0.987*** (0.981–0.993)
In degree				0.870***			
Out degree				0.998***			
Betweenness					1* (0.999–1)		
Ego art			1.016 (0.958–1.077)	1.012 (0.956–1.072)	0.956 (0.897–1.019)	1.001 (0.933–1.074)	

(Continued)

Table 3. (Continued)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)
Alter art			0.982 (0.933–1.034)	0.975 (0.932–1.020)	0.948 (0.905–0.992)	0.987 (0.937–1.040)	
Constant	2.946*** (1.566–5.539)	6.149*** (3.254–11.621)	7.855*** (7.026–8.783)	8.331*** (7.407–9.370)	5.132*** (4.695–5.611)	4.407 (0.841–23.083)	1.752 (0.728–4.218)
McFadden's R2	0.081	0.018	0.093	0.0892	0.004	0.160	0.155
N	3578	3578	3578	3578	3578	3578	3578

Note: Odds ratios from logistic regression analysis to determine the impact of our variables on the probability of belonging to the Long Covid group. CI: Confidence Interval.

*** $p < 0.001$

** $p < 0.01$

* $p < 0.05$

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the analyzed phenomenon, which justifies our choice of considering the messages sent and messages received instead of in degree and out degree in the final models. Furthermore, we found that the average response time is not significant in making a distinction between the Covid and Long Covid groups, unlike betweenness centrality.

To capture the maximum amount of information and comprehensively understand the phenomenon, we included all the variables considered for analysis in the sixth model. It is the full model, whereas Model 7 is more parsimonious and only includes the best combination of significant variables. McFadden's R2 is significantly higher for these two models than for those considering only the separate block of variables, thus suggesting that the study of social interaction and the analysis of linguistic characteristics play a role in distinguishing people in the Covid and Long Covid groups.

5. Discussion

From the evidence of the Kruskal-Wallis analysis, we can deduce that users who stated that they developed symptoms of COVID-19 have the highest level of messaging activity among the three groups. This group interacts with more users within their social network, suggesting a broader range of connections and engagement. We also note that these users have the highest values of linguistic complexity, a higher number of auxiliary verbs, and articles characterizing their posts. This indicates a more formal and precise communicative style [35]. Based on their post content, we note that they tend to utilize more expressions related to anger, risk, and family compared to users who have not had COVID-19 or users with Long Covid. Hence, even before the pandemic, they express or discuss their frustrations, dissatisfaction, or negative emotions more frequently than other groups. This finding aligns with several studies linking negative emotions, such as anger, to an increased likelihood of developing a disease, e.g., Cohen et al. [24], De Choudhury & De [19], and Shen et al. [20]. Moreover, these users used more words associated with risk, probably because they were more aware or concerned about potential life risks. The increased usage of expressions related to the family could reflect their personal values and the significance of familiar relationships in their lives.

Users in the No-COVID group tend to have a more extensive and refined communication vocabulary. Their posts are typically more intricate and informative while also incorporating emotional language. There is a greater emphasis on leisure activities within their contents, while they use fewer words related to the category *insight*. These results are consistent with the

finding of Pennebaker et al. [87], who demonstrated that decreased use of insight words, e.g., “know”, “how”, and “think”, is associated with better health conditions. In addition, individuals who have not developed COVID symptoms are likely to be more engaged in leisure activities, implying higher levels of positive affect and life satisfaction and, consequently, higher life well-being [27].

Consistent with the findings of the regression models, our work suggests that individuals in the Long Covid class generally exhibit lower messaging activity than those with only Covid, both in terms of sending and receiving messages. The signal coming from the betweenness centrality values also agrees with this. The Long Covid users have less messaging activity. On the other hand, individuals in the Covid class play a more critical role in facilitating communication between other network users. This result confirms our hypotheses 4 and 5 regarding the lower involvement of Long Covid users in their social network than those in the Covid class. Moreover, individuals in the Long Covid class tend to express themselves using more words in their posts. Despite the length of their comments, there are fewer articles and auxiliary verbs but many interrogative forms. These linguistic characteristics offer valuable insights into their communication style. For instance, the reduced usage of articles may suggest a direct and concise communication approach, where conveying information takes precedence over specific details. Similarly, the decrease in auxiliary verbs might indicate a preference for straightforward and assertive statements, focusing on essential information rather than hypothetical scenarios [35].

A odds ratio greater than one for the interrogative dimension suggests a higher tendency to ask questions or seek information from others in their online communication [67]. This result confirms our hypothesis 3. Moreover, it is in line with the studies of Suedfeld & Rank [88] about the “disruptive stress hypothesis”. They supported the idea that when people experience significant stress, their thinking becomes less complex. According to the disruptive stress hypothesis, individuals with high stress levels might try to solve problems with simpler, less complicated thinking because stress disrupts and simplifies information processing. Consequently, since the communication style of individuals reflects the type of their thoughts, we could associate the simpler communication style with the higher stress level of users who belong to the Long Covid class. The heightened frequency of singular pronouns underscores the significance of personal experiences, thoughts, and emotions shared by these individuals [69]. This evidence is confirmed by the significant dominance of variables like feel and affect.

Long Covid users use more emotional language, compared to users with Covid, which can include a wide range of emotions, such as happiness or excitement, and tend to share in their posts the general state of the feelings they are experiencing. Among the emotions that are not significant for identifying Long Covid subjects is anger. Long Covids' comments are sparse in words such as “angry”, “hate”, “annoyed”, and “frustrated”. At the same time, the overall sentiment of their posts tends to be predominantly positive. The lower frequency of negative emotions in the posts of users with Long Covid compared to those with Covid denies our hypothesis 1, but it is consistent with the literature on repressive coping [81]. According to this theory, people who do not use words with negative emotions are at a higher risk of subsequent health problems than those who use at least some words with negative emotions. Moreover, it is interesting to consider these results in light of past research that states that individuals more vulnerable to depression tend to use first-person pronouns more frequently when expressing their feelings compared to individuals who are less susceptible to depression [70–72]. This could indicate that individuals who develop Long Covid are already more likely to experience intense emotional distress before the onset of the pandemic. In addition, how individuals utilize pronouns can vary depending on the level of social connection [69, 73]. As previously mentioned, users of Long Covid tend to employ more first-person singular pronouns,

indicating a more self-centered narrative focus and a more personal communication style. An odds ratio lower than one of the family measure also shows that discussing family relationships on social media is not a prominent characteristic or topic for individuals in the Long Covid class. Based on the result of Gutanku et al. [26], which associated the lower occurrence of family-related words with more significant stress in individuals, it is plausible to suggest that Long Covid users are more susceptible to stress. In contrast, in the content posted before the pandemic, subjects in the Long Covid class were already mainly talking about health. This finding implies that health was already a significant concern or interest for these individuals even before their experience with Long Covid. It suggests that individuals who develop Long Covid symptoms may have a greater tendency towards hypochondria. Research conducted by Brown et al. [29], Ferguson et al. [30], and Pauli & Alpers [31] have shown that individuals with hypochondriacal beliefs tend to process health-related information more extensively than those without such beliefs. This heightened processing may facilitate the retrieval and written elaboration of health-related information. It is also aligned with Zhao & Zhou [25], who reported that users posting and searching for solely Covid-related content demonstrated worse mental health. Moreover, the preexisting focus on health-related concepts may have empowered them with a greater sense of control, leading to their eventual discovery of having Long Covid symptoms. Our analysis shows that Long Covid users express health-related topics more than Covid users. This confirms the validity of our hypothesis 2.

Fig 4 provides an overview of the hypotheses formulated and examined in this study, differentiating between those that were validated and those that were not supported by our findings.

6. Conclusions

Through this research, we have expanded our understanding of some possible social determinants of Long Covid, contributing valuable insights for developing effective prevention strategies.



Fig 4. Supported and unsupported hypotheses.

<https://doi.org/10.1371/journal.pone.0308340.g004>

6.1. Theoretical and practical implications

By analyzing social media data from Reddit user profiles, we offer unique perspectives on potential risk factors associated with Long Covid. Since our investigation delves into the shifts in communication styles and network structures from Covid to Long Covid users, it has broader implications for Covid studies. Indeed, it reveals that individuals developing COVID-19 exhibit a wider range of connections and engagement within their social network, elevated levels of linguistic complexity, and a higher tendency to use expressions related to negative emotions. Moreover, our study helps to create psychological profiles related to Long Covid patients, highlighting that people who developed Long Covid often discussed health-related topics before the pandemic. Hence, it suggests that those users may have a greater tendency towards hypochondria, which aligns with previous research on how hypochondriacal belief impacts disease progression [29, 30].

Our analysis leverages an automated methodology incorporating social network analysis, text mining, and natural language processing. The data we selected offers a significant advantage in characterizing the communication and psychological profile of individuals who have reported contracting COVID-19 and developing Long Covid, providing a perspective directly centred on patients' voices.

In particular, the findings discussed in the previous Section can be integrated into patient history records, capturing data produced when patients were unaware of being observed. By extracting characteristics from social media, we can reduce the bias inherent in traditional survey instruments like structured questionnaires, leading to more informed decisions. As Zhao and Zhou [25] suggest, if these investigation methodologies are designed and applied on a large scale, it can enhance preventive and reactive intervention measures in health crisis management. Furthermore, the profiling of the three user groups appears to align with existing theories regarding patient lifestyle management. This information may offer healthcare providers additional data to support their decisions and medical advice for patients. For instance, the findings from the No-Covid group suggest that engaging in physical activity might help prevent infectious diseases like COVID-19. Encouraging an active lifestyle that includes various recreational activities could be beneficial. These proactive measures may enhance immune function and reduce the risk of experiencing long-term effects after a COVID-19 infection [89].

Finally, in light of the health crisis caused by COVID-19, our research provides evidence to support the effectiveness of using analytical tools based on social media data. Indeed, an automated tool that allows healthcare providers to quickly extract patient information and categorize them could greatly help prioritize interventions at such critical times, optimizing the patient management process.

6.2. Limitations and future perspectives

This work has some limitations that also point to future research direction. Exploring different social media platforms with diverse demographics could help reduce any biases resulting from Reddit's potential misrepresentation of the general population. For example, Reddit does not allow us to extract information about users' geo-location. In addition, due to the lack of descriptive information about the users, we could not gather additional data on factors such as age, gender, or level of education, which might affect, for example, the probability of having Long Covid symptoms. Introducing these control variables would enhance the study's robustness. In addition, our choices at the user classification step can be enhanced by incorporating additional criteria. Future work could involve expanding the selection to include subreddits dedicated to Long COVID, thereby capturing active users in other forums focused on related discussions. To enhance the robustness of our dictionary for detecting user-declared COVID-

19 infections, future work could involve expanding keyword variants, incorporating idiomatic expressions, updating symptom-related terms, and integrating machine learning models for contextual understanding.

Additionally, our reliance on the Reddit dataset limits our ability to include information about pre-existing health conditions that may increase susceptibility to developing Long Covid. As Jacobs et al. [90] suggested, it is crucial to consider comorbid conditions such as asthma, chronic constipation, reflux, seasonal allergies, rheumatoid arthritis, depression/anxiety, in addition to age, gender, race, and smoking. These factors proved to be significantly associated with the development of Long Covid. Therefore, future research should explore incorporating additional variables beyond those proposed in our current study. One potential approach is to complement our social media analytics with interviews and questionnaires targeting individuals who have experienced COVID-19 symptoms and Long Covid. An ideal strategy would involve mapping their ego networks while comprehensively analyzing the discrepancies between online social networks and real-life social networks. Another interesting analysis might also consider different categories of people with Long Covid, based on their symptoms. It could be that our predictors may more accurately anticipate psychological aspects related to the disease, such as depression or feeling tired, rather than more physiological aspects, such as a taste or hearing disorder.

[89], Finally, although this study focused on factors predicting the likelihood of Long Covid, those factors may also be appropriate to predict general health anxiety, especially considering the heterogeneity of Long Covid symptoms [91]. As illustrated in the introduction, individuals affected by Long Covid often exhibit symptoms similar to those of depression or migraine, including headache and anxiety, and thus, similar predictors [3, 4, 12]. This overlap could suggest that the same factors predicting Long Covid might also influence broader health diseases. Therefore, future research should aim to provide more detailed insights into the specific symptoms and predictors differentiating Long Covid from other illnesses, employing an approach that prioritizes depth over breadth. This, in turn, could lead to more accurate treatment and recovery strategies and could further inform target interventions.

Supporting information

S1 Fig. Examples of the regular expressions used to detect user COVID-19 infection. S1 Fig provides examples of regular expressions employed to identify mentions of COVID-19 infection within user posts. Regular expressions (regex) are patterns used to match character combinations in strings. In the context of detecting COVID-19 infection mentions, these regex patterns are designed to capture a variety of ways users might refer to their infection status. (TIF)

S2 Fig. Example of COVID-19 infection indicators. S2 Fig illustrates in blue an example of indicators we used to identify mentions of COVID-19 infection in user posts. (TIF)

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References

1. Peluso MJ, Deeks SG. Early clues regarding the pathogenesis of long-COVID. *Trends Immunol.* 2022 Apr; 43[4]:268–70. <https://doi.org/10.1016/j.it.2022.02.008> PMID: 35272932
2. Davis HE, McCorkell L, Vogel JM, Topol EJ. Long COVID: major findings, mechanisms and recommendations. *Nat Rev Microbiol.* 2023; 21[3]:133–46. <https://doi.org/10.1038/s41579-022-00846-2> PMID: 36639608
3. Alwan NA, Johnson L. Defining long COVID: Going back to the start. *Med.* 2021 May; 2[5]:501–4. <https://doi.org/10.1016/j.medj.2021.03.003> PMID: 33786465
4. Astin R, Banerjee A, Baker MR, Dani M, Ford E, Hull JH, et al. Long COVID: mechanisms, risk factors and recovery. *Exp Physiol.* 2023 Jan 22; 108[1]:12–27. <https://doi.org/10.1113/EP090802> PMID: 36412084
5. Garg M, Maralakunte M, Garg S, Dhooria S, Sehgal I, Bhalla AS, et al. The Conundrum of 'Long-COVID-19': A Narrative Review. *Int J Gen Med.* 2021 Jun; Volume 14:2491–506. <https://doi.org/10.2147/IJGM.S316708> PMID: 34163217
6. Kaatz M, Springer S, Schubert R, Zieger M. Representation of long COVID syndrome in the awareness of the population is revealed by Google Trends analysis. *Brain Behav Immun - Health.* 2022 Jul; 22:100455. <https://doi.org/10.1016/j.bbih.2022.100455> PMID: 35373158
7. Malta G, Cirrincione L, Plescia F, Campagna M, Montagnini C, Cannizzaro E. Long-Term COVID: Case Report and Methodological Proposals for Return to Work. *Sustainability.* 2022 Jul 29; 14[15]:9332.
8. Nittas V, Gao M, West EA, Ballouz T, Menges D, Wulf Hanson S, et al. Long COVID Through a Public Health Lens: An Umbrella Review. *Public Health Rev [Internet].* 2022 Mar 15; 43. Available from: <https://www.ssph-journal.org/articles/10.3389/phrs.2022.1604501/full> <https://doi.org/10.3389/phrs.2022.1604501> PMID: 35359614
9. Chan Sui Ko A, Candellier A, Mercier M, Joseph C, Schmit JL, Lanoix JP, et al. Number of initial symptoms is more related to long COVID-19 than acute severity of infection: a prospective cohort of hospitalized patients. *Int J Infect Dis.* 2022 May; 118:220–3. <https://doi.org/10.1016/j.ijid.2022.03.006> PMID: 35257903
10. Arjun MC, Singh AK, Pal D, Das K, G A, Venkateshan M, et al. Characteristics and predictors of Long COVID among diagnosed cases of COVID-19. Thanachartwet V, editor. *PLOS ONE.* 2022 Dec 20; 17[12]:e0278825. <https://doi.org/10.1371/journal.pone.0278825> PMID: 36538532
11. Thompson CM, Rhidenour KB, Blackburn KG, Barrett AK, Babu S. Using crowdsourced medicine to manage uncertainty on Reddit: The case of COVID-19 long-haulers. *Patient Educ Couns.* 2022 Feb; 105[2]:322–30. <https://doi.org/10.1016/j.pec.2021.07.011> PMID: 34281723
12. Sarker A, Ge Y. Mining long-COVID symptoms from Reddit: characterizing post-COVID syndrome from patient reports. *JAMIA Open [Internet].* 2021 Jul 31; 4[3]. Available from: <https://academic.oup.com/jamiaopen/article/doi/10.1093/jamiaopen/oaab075/6362522> <https://doi.org/10.1093/jamiaopen/oaab075> PMID: 34485849
13. Sulemana AS, Nguyen TXT, Lal S, Khan MSR, Kadoya Y. Loneliness during the COVID-19 Pandemic: A Comparison of Urban and Rural Areas. *Sustainability.* 2023 Aug 10; 15[16]:12218.
14. Hossain MM, Das J, Rahman F, Nesa F, Hossain P, Islam AMK, et al. Living with "long COVID": A systematic review and meta-synthesis of qualitative evidence. Canzan F, editor. *PLOS ONE.* 2023 Feb 16; 18[2]:e0281884. <https://doi.org/10.1371/journal.pone.0281884> PMID: 36795701
15. Lohmann PM, Gsottbauer E, You J, Kontoleon A. Anti-social behaviour and economic decision-making: Panel experimental evidence in the wake of COVID-19. *J Econ Behav Organ.* 2023 Feb; 206:136–71. <https://doi.org/10.1016/j.jebo.2022.12.007> PMID: 36531911

16. O'Connell K, Berluti K, Rhoads SA, Marsh AA. Reduced social distancing early in the COVID-19 pandemic is associated with antisocial behaviors in an online United States sample. Verona E, editor. PLOS ONE. 2021 Jan 7; 16[1]:e0244974.
17. Sarker A, Lakamana S, Hogg-Bremer W, Xie A, Al-Garadi MA, Yang YC. Self-reported COVID-19 symptoms on Twitter: an analysis and a research resource. J Am Med Inform Assoc. 2020 Aug 1; 27[8]:1310–5. <https://doi.org/10.1093/jamia/ocaa116> PMID: 32620975
18. Burton C, Dawes H, Goodwill S, Thelwell M, Dalton C. Within and between-day variation and associations of symptoms in Long Covid: Intensive longitudinal study. Fatouros IG, editor. PLOS ONE. 2023 Jan 19; 18[1]:e0280343. <https://doi.org/10.1371/journal.pone.0280343> PMID: 36656830
19. De Choudhury M, De S. Mental Health Discourse on reddit: Self-Disclosure, Social Support, and Anonymity. Proc Int AAAI Conf Web Soc Media. 2014 May 16; 8[1]:71–80.
20. Shen G, Jia J, Nie L, Feng F, Zhang C, Hu T, et al. Depression Detection via Harvesting Social Media: A Multimodal Dictionary Learning Solution. In: Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence [Internet]. California: International Joint Conferences on Artificial Intelligence Organization; 2017. p. 3838–44. Available from: <https://www.ijcai.org/proceedings/2017/536>
21. Yadav S, Ekbal A, Saha S, Bhattacharyya P. Medical sentiment analysis using social media: towards building a patient assisted system. In: Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018). 2018.
22. PAUL MJ, SARKER A, BROWNSTEIN JS, NIKFARJAM A, SCOTCH M, SMITH KL, et al. SOCIAL MEDIA MINING FOR PUBLIC HEALTH MONITORING AND SURVEILLANCE. In: Biocomputing 2016 [Internet]. WORLD SCIENTIFIC; 2016. p. 468–79. Available from: http://www.worldscientific.com/doi/abs/10.1142/9789814749411_0043
23. Chancellor S, De Choudhury M. Methods in predictive techniques for mental health status on social media: a critical review. Npj Digit Med. 2020 Mar 24; 3[1]:43. <https://doi.org/10.1038/s41746-020-0233-7> PMID: 32219184
24. Cohen S, Alper CM, Doyle WJ, Treanor JJ, Turner RB. Positive Emotional Style Predicts Resistance to Illness After Experimental Exposure to Rhinovirus or Influenza A Virus. Psychosom Med. 2006 Nov; 68[6]:809–15. <https://doi.org/10.1097/01.psy.0000245867.92364.3c> PMID: 17101814
25. Zhao N, Zhou G. Social media use and mental health during the COVID-19 pandemic: Moderator role of disaster stressor and mediator role of negative affect. Appl Psychol Health Well-Being. 2020; 12[4]:1019–38. <https://doi.org/10.1111/aphw.12226> PMID: 32945123
26. Guntuku SC, Buffone A, Jaidka K, Eichstaedt JC, Ungar LH. Understanding and measuring psychological stress using social media. In: Proceedings of the international AAAI conference on web and social media. 2019. p. 214–25.
27. Vine V, Boyd RL, Pennebaker JW. Natural emotion vocabularies as windows on distress and well-being. Nat Commun. 2020 Sep 10; 11[1]:4525. <https://doi.org/10.1038/s41467-020-18349-0> PMID: 32913209
28. Pennebaker JW, King LA. Linguistic styles: Language use as an individual difference. J Pers Soc Psychol. 1999; 77[6]:1296–312. <https://doi.org/10.1037/0022-3514.77.6.1296> PMID: 10626371
29. Brown HD, Kosslyn SM, Delamater B, Fama J, Barsky AJ. Perceptual and memory biases for health-related information in hypochondriacal individuals. J Psychosom Res. 1999 Jul; 47[1]:67–78. [https://doi.org/10.1016/s0022-3999\(99\)00011-2](https://doi.org/10.1016/s0022-3999(99)00011-2) PMID: 10511422
30. Ferguson E, Moghaddam NG, Bibby PA. Memory bias in health anxiety is related to the emotional valence of health-related words. J Psychosom Res. 2007 Mar; 62[3]:263–74. <https://doi.org/10.1016/j.jpsychores.2007.01.015> PMID: 17324674
31. Pauli P, Alpers GW. Memory bias in patients with hypochondriasis and somatoform pain disorder. J Psychosom Res. 2002 Jan; 52[1]:45–53. [https://doi.org/10.1016/s0022-3999\(01\)00295-1](https://doi.org/10.1016/s0022-3999(01)00295-1) PMID: 11801264
32. Mahat-Shamir M, Pitcho-Prelourentzos S, Kagan M, Kestler-Peleg M, Lavenda O. Adjustment Disorder in the Face of COVID-19 Outbreak: The Impact of Death Anxiety, Media Exposure, Fear of Contagion and Hypochondriasis Symptoms. OMEGA - J Death Dying. 2023 Sep 29; 87[4]:1189–206. <https://doi.org/10.1177/00302228211034372> PMID: 34324401
33. Saslow LR, McCoy S, van der Löwe I, Cosley B, Vartan A, Oveis C, et al. Speaking under pressure: Low linguistic complexity is linked to high physiological and emotional stress reactivity. Psychophysiology. 2014 Mar 20; 51[3]:257–66. <https://doi.org/10.1111/psyp.12171> PMID: 24354732
34. Karabin M, Kyröläinen AJ, Kuperman V. Increase in Linguistic Complexity in Older Adults During COVID-19. Exp Aging Res. 2023 Mar 9; 1–19. <https://doi.org/10.1080/0361073X.2022.2163831> PMID: 36892044

35. Brandt PM, Herzberg PY. Is a cover letter still needed? Using LIWC to predict application success. *Int J Sel Assess*. 2020 Dec 11; 28[4]:417–29.
36. De Choudhury M, Kiciman E, Dredze M, Coppersmith G, Kumar M. Discovering Shifts to Suicidal Ideation from Mental Health Content in Social Media. In: *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* [Internet]. New York, NY, USA: ACM; 2016. p. 2098–110. Available from: <https://dl.acm.org/doi/10.1145/2858036.2858207>
37. Gao J, Zheng P, Jia Y, Chen H, Mao Y, Chen S, et al. Mental health problems and social media exposure during COVID-19 outbreak. Hashimoto K, editor. *PLOS ONE*. 2020 Apr 16; 15[4]:e0231924. <https://doi.org/10.1371/journal.pone.0231924> PMID: 32298385
38. Ernala SK, Labetoulle T, Bane F, Birnbaum ML, Rizvi AF, Kane JM, et al. Characterizing Audience Engagement and Assessing Its Impact on Social Media Disclosures of Mental Illnesses. *Proc Int AAAI Conf Web Soc Media* [Internet]. 2018 Jun 15; 12[1]. Available from: <https://ojs.aaai.org/index.php/ICWSM/article/view/15027>
39. Laato S, Islam AKMN, Islam MN, Whelan E. What drives unverified information sharing and cyberchondria during the COVID-19 pandemic? *Eur J Inf Syst*. 2020 May 3; 29[3]:288–305.
40. Nicholls N, Yitbarek E. Trust in social media and COVID-19 beliefs and behaviours. Chen Z, editor. *PLOS ONE*. 2022 Oct 13; 17[10]:e0275969. <https://doi.org/10.1371/journal.pone.0275969> PMID: 36227887
41. Mahmud R, Rahman MdM, Rassel MA, Monayem FB, Sayeed SKJB, Islam MdS, et al. Post-COVID-19 syndrome among symptomatic COVID-19 patients: A prospective cohort study in a tertiary care center of Bangladesh. Zivkovic AR, editor. *PLOS ONE*. 2021 Apr 8; 16[4]:e0249644. <https://doi.org/10.1371/journal.pone.0249644> PMID: 33831043
42. Yazdavar AH, Mahdavinejad MS, Bajaj G, Romine W, Sheth A, Monadjemi AH, et al. Multimodal mental health analysis in social media. Zhao J, editor. *PLOS ONE*. 2020 Apr 10; 15[4]:e0226248. <https://doi.org/10.1371/journal.pone.0226248> PMID: 32275658
43. Seabrook EM, Kern ML, Rickard NS. Social Networking Sites, Depression, and Anxiety: A Systematic Review. *JMIR Ment Health*. 2016 Nov 23; 3[4]:e50. <https://doi.org/10.2196/mental.5842> PMID: 27881357
44. Lorijn SJ, Laninga-Wijnen L, Engels MC, Lodder GMA, Veenstra R. The development of adolescents' loneliness during the COVID-19 pandemic: The role of peer status and contact with friends. Ballarotto G, editor. *PLOS ONE*. 2023 May 26; 18[5]:e0286085. <https://doi.org/10.1371/journal.pone.0286085> PMID: 37235574
45. Zhang Y, Luo A, Hou L, Chen S, Zhang W, Schwartz A, et al. Crisis response during the COVID-19 pandemic: Changes in social contact and social participation of older Americans. Martell ME, editor. *PLOS ONE*. 2023 Jul 27; 18[7]:e0284935. <https://doi.org/10.1371/journal.pone.0284935> PMID: 37498870
46. Awal MR, Cao R, Mitrovic S, Lee RKW. On analyzing antisocial behaviors amid covid-19 pandemic. *ArXiv Prepr ArXiv200710712*. 2020;
47. Gloor PA. *Happimetrics: Leveraging AI to Untangle the Surprising Link Between Ethics, Happiness and Business Success*. Edward Elgar Publishing; 2022.
48. Freeman LC. Centrality in social networks conceptual clarification. *Soc Netw*. 1978 Jan; 1[3]:215–39.
49. Brandes U. A faster algorithm for betweenness centrality. *J Math Sociol*. 2001 Jun 1; 25[2]:163–77.
50. Gloor PA. Inside Media Individual Collaboration (IMIC). In: *Sociometrics and Human Relationships* [Internet]. Emerald Publishing Limited; 2017. p. 391–403. Available from: <https://www.emerald.com/insight/content/doi/10.1108/978-1-78714-112-420171015/full/html>
51. Lewis ML, Frank MC. The length of words reflects their conceptual complexity. *Cognition*. 2016 Aug; 153:182–95. <https://doi.org/10.1016/j.cognition.2016.04.003> PMID: 27232162
52. Owens RJ, Wedeking JP. Justices and Legal Clarity: Analyzing the Complexity of U.S. Supreme Court Opinions. *Law Soc Rev*. 2011 Dec; 45[4]:1027–61.
53. Jurafsky Martin. *Speech and language processing: An introduction to natural language processing, computational linguistics, and speech recognition*. prentice hall; 2007.
54. Ogden J, Cornwell D. The role of topic, interviewee and question in predicting rich interview data in the field of health research. *Sociol Health Illn*. 2010 Nov; 32[7]:1059–71. <https://doi.org/10.1111/j.1467-9566.2010.01272.x> PMID: 20942822
55. Tausczik YR, Pennebaker JW. The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods. *J Lang Soc Psychol*. 2010 Mar 8; 29[1]:24–54.
56. Béland R, Lecours AR. The mt-86 β aphasia battery: A subset of normative data in relation to age and level of school education. *Aphasiology*. 1990 Sep; 4[5]:439–62.

57. Le Dorze G, BÉDard C. Effects of age and education on the lexico-semantic content of connected speech in adults. *J Commun Disord*. 1998 Jan; 31[1]:53–71. [https://doi.org/10.1016/s0021-9924\(97\)00051-8](https://doi.org/10.1016/s0021-9924(97)00051-8) PMID: 9421767
58. MacKenzie C. Adult spoken discourse: the influences of age and education. *Int J Lang Commun Disord*. 2000 Apr 1; 35[2]:269–85. <https://doi.org/10.1080/136828200247188> PMID: 10912255
59. Mulder K, Hulstijn JH. Linguistic Skills of Adult Native Speakers, as a Function of Age and Level of Education. *Appl Linguist*. 2011 Dec; 32[5]:475–94.
60. Perkins J. Python 3 Text Processing With NLTK 3 Cookbook. Python 3 Text Processing With NLTK 3 Cookbook. Birmingham, UK: Packt Publishing; 2014. 304 p.
61. Jivani AG. A comparative study of stemming algorithms. *Int J Comp Tech Appl*. 2011; 2[6]:1930–8.
62. Pennebaker JW, Mehl MR, Niederhoffer KG. Psychological Aspects of Natural Language Use: Our Words, Our Selves. *Annu Rev Psychol*. 2003 Feb; 54[1]:547–77.
63. Popping R. Computer-assisted Text Analysis [Internet]. 1 Oliver's Yard, 55 City Road, London England EC1Y 1SP United Kingdom: SAGE Publications, Ltd; 2000. Available from: <https://methods.sagepub.com/book/computer-assisted-text-analysis>
64. Smith CP, Atkinson JW, McClelland DC, Veroff J. Motivation and personality: Handbook of thematic content analysis. Cambridge University Press; 1992.
65. Weber RP. Basic content analysis. Vol. 49. Sage; 1990.
66. West MD. Theory, method, and practice in computer content analysis. Vol. 16. Greenwood Publishing Group; 2001.
67. Pennebaker JW, Boyd RL, Jordan K, Blackburn K. The development and psychometric properties of LIWC2015. 2015.
68. Jaime A, Pérez-Guillot C. A Comparison Analysis of Modal Auxiliary Verbs in Technical and General English. *Procedia - Soc Behav Sci*. 2015 Dec; 212:292–7.
69. Pennebaker JW, Lay TC. Language Use and Personality during Crises: Analyses of Mayor Rudolph Giuliani's Press Conferences. *J Res Personal*. 2002 Jun; 36[3]:271–82.
70. Bucci W, Freedman N. The language of depression. *Bull Menninger Clin*. 1981; 45[4]:334. PMID: 6176285
71. Rude S, Gortner EM, Pennebaker J. Language use of depressed and depression-vulnerable college students. *Cogn Emot*. 2004 Dec; 18[8]:1121–33.
72. Stirman SW, Pennebaker JW. Word use in the poetry of suicidal and nonsuicidal poets. *Psychosom Med*. 2001; 63[4]:517–22. <https://doi.org/10.1097/00006842-200107000-00001> PMID: 11485104
73. Berry DS, Pennebaker JW, Mueller JS, Hiller WS. Linguistic bases of social perception. *Pers Soc Psychol Bull*. 1997; 23[5]:526–37.
74. Newman ML, Groom CJ, Handelman LD, Pennebaker JW. Gender Differences in Language Use: An Analysis of 14,000 Text Samples. *Discourse Process*. 2008 May 15; 45[3]:211–36.
75. Gleser GC, Gottschalk LA, John W. The relationship of sex and intelligence to choice of words: A normative study of verbal behavior. *J Clin Psychol*. 1959 Apr; 15[2]:182–91. [https://doi.org/10.1002/1097-4679\(195904\)15:2<182::aid-jclp2270150219>3.0.co;2-7](https://doi.org/10.1002/1097-4679(195904)15:2<182::aid-jclp2270150219>3.0.co;2-7) PMID: 13631110
76. Mehl MR, Pennebaker JW. The sounds of social life: A psychometric analysis of students' daily social environments and natural conversations. *J Pers Soc Psychol*. 2003 Apr; 84[4]:857–70. <https://doi.org/10.1037/0022-3514.84.4.857> PMID: 12703653
77. Mulac A, Wiemann JM, Widenmann SJ, Gibson TW. Male/female language differences and effects in same-sex and mixed-sex dyads: The gender-linked language effect. *Commun Monogr*. 1988 Dec; 55 [4]:315–35.
78. Drus Z, Khalid H. Sentiment Analysis in Social Media and Its Application: Systematic Literature Review. *Procedia Comput Sci*. 2019; 161:707–14.
79. Storey VC, O'Leary DE. Text Analysis of Evolving Emotions and Sentiments in COVID-19 Twitter Communication. *Cogn Comput [Internet]*. 2022 Jul 28; Available from: <https://link.springer.com/10.1007/s12559-022-10025-3>
80. Chew NWS, Lee GKH, Tan BYQ, Jing M, Goh Y, Ngiam NJH, et al. A multinational, multicentre study on the psychological outcomes and associated physical symptoms amongst healthcare workers during COVID-19 outbreak. *Brain Behav Immun*. 2020 Aug; 88:559–65. <https://doi.org/10.1016/j.bbi.2020.04.049> PMID: 32330593
81. Jamner LD, Schwartz GE, Leigh H. The relationship between repressive and defensive coping styles and monocyte, eosinophile, and serum glucose levels: support for the opioid peptide hypothesis of repression. *Psychosom Med*. 1988; 50[6]:567–75. <https://doi.org/10.1097/00006842-198811000-00002> PMID: 2853404

82. Braun N, Goudbeek M, Krahmer E. Lost in transmission? Self- and other-annotation of emotional words. *Acta Psychol (Amst)*. 2022 Sep; 229:103713. <https://doi.org/10.1016/j.actpsy.2022.103713> PMID: 35988301
83. Gandino G, Civilotti C, Finzi S, Gaboardi M, Guazzini A, Novara C, et al. Linguistic markers of processing the first months of the pandemic COVID-19: a psycholinguistic analysis of Italian university students' diaries. *Curr Psychol [Internet]*. 2023 May 19; Available from: <https://link.springer.com/10.1007/s12144-023-04737-4> <https://doi.org/10.1007/s12144-023-04737-4> PMID: 37359583
84. Su Y, Xue J, Liu X, Wu P, Chen J, Chen C, et al. Examining the Impact of COVID-19 Lockdown in Wuhan and Lombardy: A Psycholinguistic Analysis on Weibo and Twitter. *Int J Environ Res Public Health*. 2020 Jun 24; 17[12]:4552. <https://doi.org/10.3390/ijerph17124552> PMID: 32599811
85. Koutsoumpis A, Oostrom JK, Holtrop D, van Breda W, Ghassemi S, de Vries RE. The kernel of truth in text-based personality assessment: A meta-analysis of the relations between the Big Five and the Linguistic Inquiry and Word Count (LIWC). *Psychol Bull*. 2022 Nov; 148[11–12]:843–68.
86. Mehl MR, Gosling SD, Pennebaker JW. Personality in its natural habitat: Manifestations and implicit folk theories of personality in daily life. *J Pers Soc Psychol*. 2006; 90[5]:862–77. <https://doi.org/10.1037/0022-3514.90.5.862> PMID: 16737378
87. Pennebaker JW, Mayne TJ, Francis ME. Linguistic predictors of adaptive bereavement. *J Pers Soc Psychol*. 1997; 72[4]:863–71. <https://doi.org/10.1037//0022-3514.72.4.863> PMID: 9108699
88. Suedfeld P, Rank AD. Revolutionary leaders: Long-term success as a function of changes in conceptual complexity. *J Pers Soc Psychol*. 1976 Aug; 34[2]:169–78.
89. Ranasinghe C, Ozemek C, Arena R. Exercise and well-being during COVID 19 –time to boost your immunity. *Expert Rev Anti Infect Ther*. 2020 Dec 1; 18[12]:1195–200. <https://doi.org/10.1080/14787210.2020.1794818> PMID: 32662717
90. Jacobs ET, Catalfamo CJ, Colombo PM, Khan SM, Austhof E, Cordova-Marks F, et al. Pre-existing conditions associated with post-acute sequelae of COVID-19. *J Autoimmun*. 2023 Feb; 135:102991. <https://doi.org/10.1016/j.jaut.2022.102991> PMID: 36634460
91. Ziauddeen N, Gurdasani D, O'Hara ME, Hastie C, Roderick P, Yao G, et al. Characteristics and impact of Long Covid: Findings from an online survey. Sutcliffe CG, editor. *PLOS ONE*. 2022 Mar 8; 17[3]: e0264331. <https://doi.org/10.1371/journal.pone.0264331> PMID: 35259179