Cognitive and Linguistic Aspects of Digital Media

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Cognitive and Linguistic Aspects of Digital Media

Cognitieve en taalkundige aspecten van digitale media

Thesis

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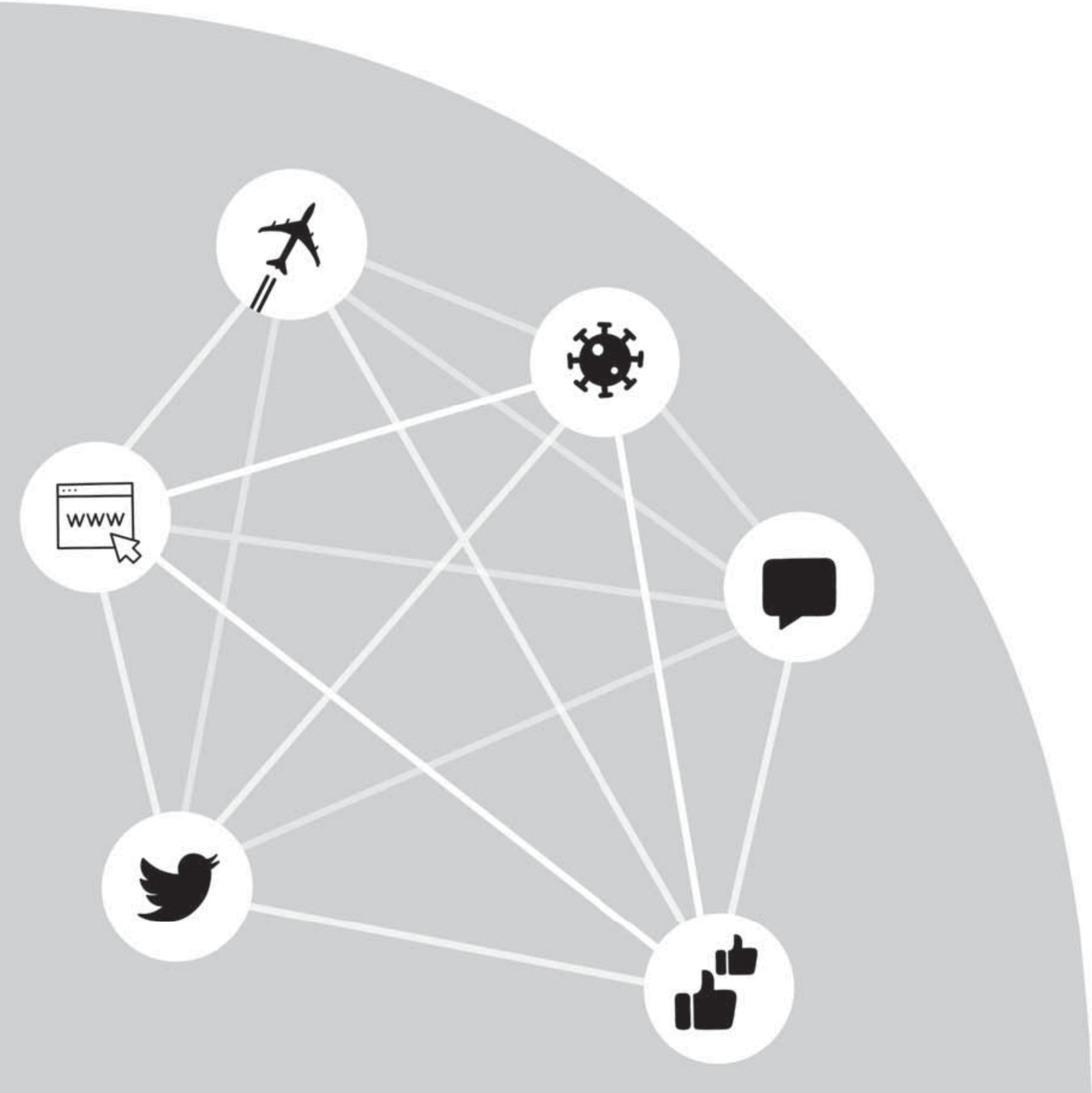
CHAPTER 1



General introduction

“Knowledge is power”, a statement so well recognized one might consider it to be overused. The cliché signifies a wide consensus that knowledge is important. In fact, technological innovations that facilitate the ability to share knowledge are associated with major improvements in human prosperity throughout history. For instance, the advent of the printing press helped to disseminate knowledge much more efficiently and accurately, as it made the tedious and error-prone process of hand copying obsolete. The printing press instigated the scientific revolution because it provided a method to accurately mass-publish data and formulas (Eisenstein, 1982; Leed, 1982). Therefore, there was an opportunity for scientists to share knowledge and to form a collective movement, devoting energy to reach new scientific breakthroughs rather than trying to reinvent the wheel. Printing technology also enabled the publication of the first newspapers, allowing more people to be aware of current events and affairs (Nelson, 1998). Furthermore, mass-printed books would spread novel ideologies and criticisms against the established order, such as during the Protestant Reformation (Roos, 2019). Thus, printing revolutionized how information could be exchanged, and therefore, had world-altering effects.

The advent of the Internet represents a continuation of this trend, marking a significant leap forward in the efficiency and speed of information exchange. People are no longer constrained by the slow and expensive traversal of books from publishers to readers, which required human couriers and horse wagons. In the present-day, information can be transmitted using electromagnetic energy (e.g., Wi-Fi, 5G, fiber optic networks), traveling the digital highway at the speed of light. This means internet users can both request *and* receive the information they need in the blink of an eye, from any habitable place on earth. This capability to freely share and consume information is the cornerstone of the current digital age. Multimodal information can be converted into streams of digital data that are transmitted across a vast network of interconnected devices. This technological innovation has drastically improved the human ability to communicate, transcending the former constraints of distance and time. A “simple” connection to the Internet provides access to a wealth of information and knowledge on any topic.

The sheer ease with which people can exchange information through the Internet indicates an inevitable and increasing cognitive dependency on this technology. Any fleeting question can be resolved in a matter of seconds using search engines, online libraries, and educational websites. In combination with the convenience of a mobile device, the Internet provides an ever-present opportunity to acquire a basic understanding about any topic. In addition to this cognitive dependency, people are becoming more socially dependent on the Internet because it revolutionized how people can communicate with each other. Social media platforms, messaging apps, and email have made it easier and faster to connect with people from all over the world. Online conversations can take place irrespective of the distances between interlocutors and are sometimes even preferred over face-to-face interactions (López de Ayala López et al., 2022). These technological affordances are just the tip of the iceberg when it comes to the impact of the Internet on society, as there is a myriad of applications (e.g., open access publications, online journalism, topical news aggregation, forums, video sharing, digital learning environments, e-commerce, targeted advertisements, digital transactions, currencies, movie and music streaming services, online gaming, live traffic navigation, identity management systems, mobility as a service, product reviews, online travel agencies, online dating services, delivery services, geosocial networking, and work from home).

As digital media have become more ubiquitous, they are now deeply connected to the sociocultural aspects of daily life. Consider the contemporary behavior of people in public spaces, being predominantly occupied with their mobile phones. The use of these devices makes these mundane moments more pleasurable. Consequently, people have the pervasive habit of using their phones very frequently. A study from 2012 by Oulasvirta and colleagues revealed that people checked their phone with an average of 34 times per day. A more recent study by Beierle and colleagues (2020) indicated this frequency to be 72 times per day. The desire to use a mobile phone has even been associated with similar neural processes as those observed in addiction, such as activation of the mesolimbic pathway (i.e., the reward pathway) of the brain (Sharma et al., 2020; Westbrook et al., 2021). This means that the use of digital technology is not just convenient but also highly rewarding. Not surprisingly, digital media are becoming increasingly ingrained into people's daily lives. In the year 2011, adults in the U.S. spent approximately three and a half hours per day using digital media. This approximation increased to eight hours and five minutes per day in 2021, which is a staggering increase of 127% in only ten years (Gutman, 2023).

The exponential surge with which the Internet has come into practice is also reflected by the sheer number of people who use it: more than five billion within just three decades (Petrosyan, 2023). Many of these users have become adept at utilizing digital media in their lives. Each user has personal motivations, preferences, and even a unique digital "footprint" based on their history with the Internet (Cahn et al., 2016). This user data is essential for most internet companies' revenue models, which are predominantly based on targeted advertising. To derive more profit, these companies aim to proliferate user engagement by personalizing the user experience of their platform. This personalization is achieved using feed algorithms that automatically match the displayed content with personal preferences of the users, amplifying the types of content people find interesting and reducing exposure to other contents. As a result, users become more exposed to specific topics of content they find more exciting and/or which engender certain emotions that they pursue deliberately or implicitly. This means that, despite digital media being used by the masses, the individual user's experience can be highly personal.

Since the Internet has both sociocultural and personal affordances, it serves an integral part of people's daily routines. This omnipresence of the Internet has affected language as well, imbuing new meanings to words such as *influencer* and *follower*. The ubiquity of these digital-age semantics instigate colloquial views and opinions on how the Internet affects its users. For example, the term *influencer* refers to a social media celebrity who promotes a certain lifestyle and has many *followers*. Thus, social media platforms are generally perceived as a means to reach and influence a global audience. These types of colloquial views tend to appreciate what the Internet can offer to society, such as the notion that it harbors freedom of expression, information agency, and personal identity. However, there are also more dystopian views which regard the Internet as a channel to exert control over the masses, to infringe privacy, to deceive, or to engender confirmation bias (Krishen et al., 2017; Petrescu & Krishen, 2020).

An example of a dystopian view of the Internet is the concept *echo chamber,* which refers to the notion that social media platforms are closed systems that reinforce preexisting beliefs while limiting exposure to opposing views (Gentzkow & Shapiro, 2011). From a utopian perspective, however, such a closed system might be considered as a form of information agency. That is, users are "safeguarded" from ideas and facts that make them feel uncomfortable, and they encounter types of information they prefer. These opposing views about the Internet are likely to be two sides of the same coin; the major technological shift of the digital age has accelerated information exchange and has increased personal information agency. This revolution in the way people encounter and process information has profound cognitive implications, that can be considered to be both beneficial but also potentially harmful.

As discussed above, digital media have greatly changed the way people can communicate with each other and have drastically increased both the pace and the scope in which information can be exchanged. The psychology of digital media, then, makes an intriguing domain of research due to its multifaceted nature, societal relevance, and ongoing impact on individuals and communities. By investigating how people engage with and are affected by digital technologies, this contributes to a better understanding of contemporary human behavior. Despite the colloquial views, which are instigated by the sheer ubiquity of digital technologies, a robust scientific foundation for the psychological effects remains elusive. This is mainly due to the swiftness with which digital media have come into practice, as they have been globally deployed within a relatively brief timeframe. The current thesis aims to fill this gap and investigates how social media and Internet users are affected both linguistically and cognitively.

In the realm of cognitive psychology, the study of text production, processing, and comprehension serves as a cornerstone for understanding how individuals engage with written information. Text production involves the generation of written content, encompassing processes such as planning, drafting, and revising. Cognitive psychologists explore the cognitive mechanisms underlying these processes, shedding light on factors that influence the quality and efficiency of written communication. Furthermore, text processing refers to the mental operations involved in interpreting and extracting meaning from textual information. This includes tasks such as word recognition, syntactic parsing, and semantic integration, all of which contribute to the ability to comprehend written text. Understanding the intricacies of text production and processing is essential for elucidating how individuals construct meaning from written materials and navigate linguistic information in various contexts.

Transitioning to the digital realm, the study of cognitive and linguistic processes takes on new dimensions and challenges. With the advent of digital media, individuals are increasingly exposed to a wide array of textual content across digital platforms, ranging from social media posts to online articles and multimedia presentations. This shift has prompted scholars to investigate how digital technologies influence text production, processing, and comprehension. For instance, the dynamic nature of digital media allows for real-time interaction and collaboration, which may impact how individuals produce and interpret textual content. Additionally, the multimodal nature of digital communication, incorporating text, images, videos, and hyperlinks, introduces complexities in information processing and cognitive engagement. Exploring these nuances provides valuable insights into how cognitive and linguistic processes operate in the context of digital environments, shaping our understanding of human communication and interaction in the digital age. From this broad perspective of digital media's influence on cognitive and linguistic processes, this thesis explores social media communication, social cues on news websites, information processing during the COVID-19 pandemic, and conspiracy ideologies on the Web. The next section of this introduction presents an overview of the studies reported in the following chapters.

Language usage on X

Chapter 2 of this thesis focusses on the linguistic aspects of social media platforms, where unique lexical rules emerge. The language that people use on certain social media platforms is constrained by a limited message length. Consequently, people have developed strategies to abbreviate and shorten their messages. These types of text adaptations originate from earlier technological limitations in mobile communication, and even earlier telegrams. For instance, SMS messages had a maximum size of 140 bytes, and therefore, a length limit of 140 characters with eight bits per character. This motivated people to be creative with their phrasing and character use to condense information into smaller text sizes. Social media platforms such as X (formerly known as Twitter) inherited this message length limit from mobile messaging. The brevity of X messages remains a defining feature of the platform. In **Chapter 2**, we investigate how the language usage on X (retrospectively referred to as Twitter throughout this chapter) was affected by an increase in the maximal message length.

Opinionated online environments

In traditional psychology, it is well established that people can be influenced by the opinions and behaviors of their peers. For example, studies on social peer-pressure have shown that some individuals tend to conform to the opinions and behaviors of the majority group (Asch, 1951, 1955, 1956; Bond & Smith, 1996). Expectedly, this behavior might also exist in the digital age. Especially since social media create opinionated environments in which information is publicly evaluated and reflected on by various social media users. Consider how contemporary news sites often have social features such as *user reactions* and *Likes*. Such feedback from the audience was impossible in traditional media channels such as radio, television broadcasts, and newspapers. Social media platforms can publish information within a public space and even encourage users to share their opinions and interpretations. Thus, social media users are not just exposed to new information; they are also exposed to the reactions, beliefs, and ideas from peer users. **Chapter 3** investigates the effect of peer user social cues (i.e. *Likes* and user reactions) on the processing of news content, using an online experiment.

Digital media and the COVID-19 pandemic

Chapter 4 reports a study that was performed in response to the COVID-19 pandemic, which instigated a novel research domain focusing on its sociopsychological effects. The pandemic had drastic consequences on people's daily routines. Recurring lockdowns, curfews, and social distancing policies further accelerated the use of digital media to stay connected with the outside world. For those who were in social isolation, the Internet could even be used to acquire basic needs, which eliminated the requirement to go outside altogether. As a result, the pandemic instigated a surge of online shopping and delivery services (Wang et al., 2021).

Importantly, people's media usage and the way they gather and interpret information became even more consequential. Specifically, the beliefs, the opinions, and the interpretations about the events surrounding the pandemic situation would invoke behaviors that in some cases could be harmful for society, such as ignoring health-policies against the spread of the coronavirus (Duarte, 2020). As such, establishing a better understanding of (pandemic) information processing behaviors and the related cognitive traits was considered as a valuable endeavor of inquiry. In **Chapter 4**, we examine two distinct cognitive traits in relation to the way people search and evaluate information about COVID-19. Specifically, the Need for Cognitive Closure (NCC) and the Need for Cognition (NC; Cacioppo et al., 2013.; Webster & Kruglanski, 1994a). A high NCC individual feels discomforted by ambiguity, and thus, has a tendency to hastily jump to conclusions in order to create an ostensibly coherent worldview. A high NC individual enjoys engaging in intellectual activities, and proactively searches for new information. Chapter 4 entails a survey study focusing on the relationship between these two cognitive predispositions and information seeking behavior related to the COVID-19 pandemic.

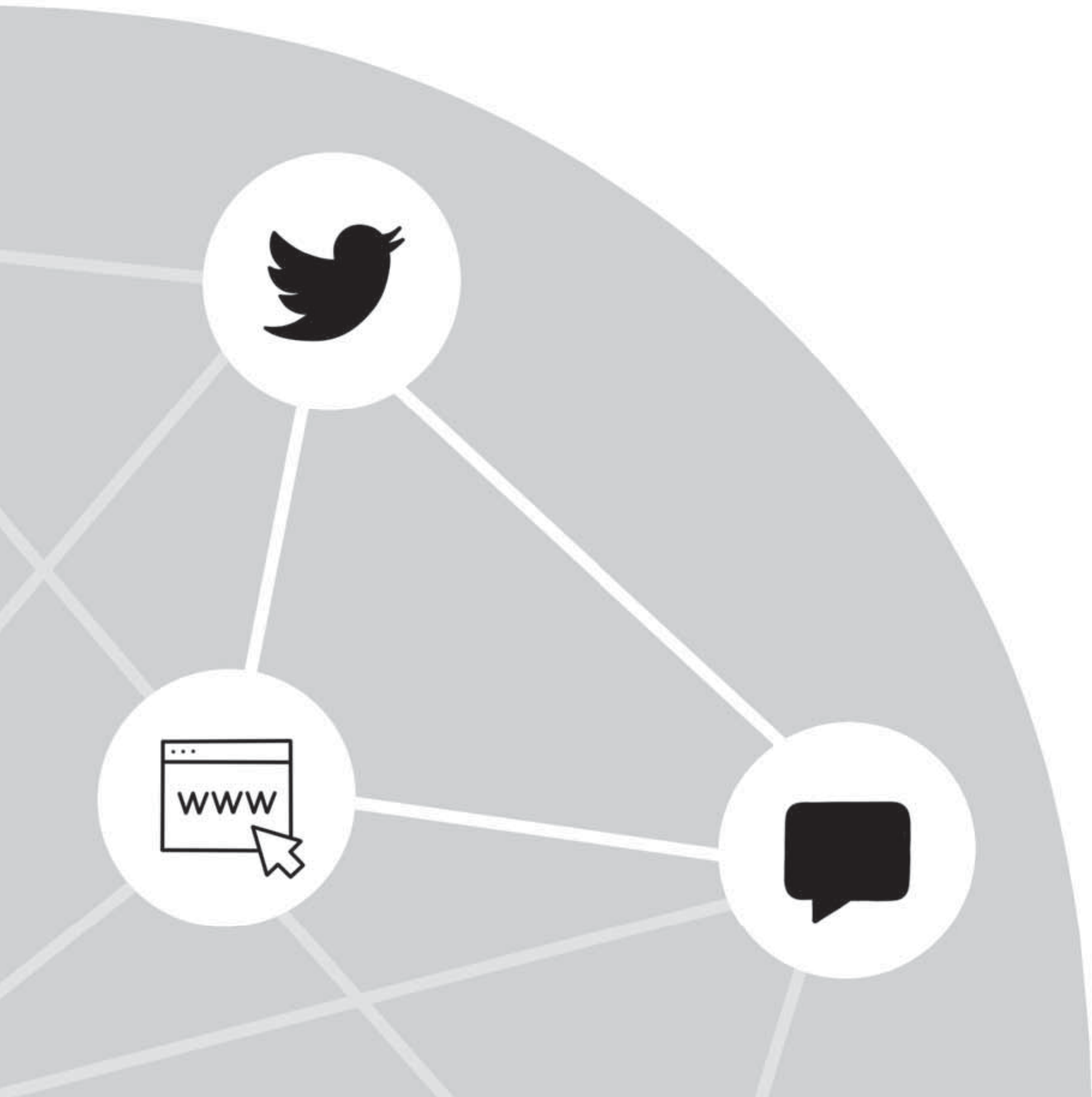
Conspiracy views on the Web

Major negative events such as a global pandemic can be misinterpreted as the result of deliberate covert actions of a group of people with malicious intentions, also referred to as conspiracy views. Such views can especially hinder public health efforts because they provoke feelings of distrust and undermine the credibility of well-established news outlets, government organizations, and scientific institutions. Therefore, it is paramount to understand the conditions under which these false conspiracy ideas arise.

Before the Internet, traditional media outlets were important gatekeepers of publicly available information, which minimized the spread of conspiracy views and other fringe beliefs to large audiences. The advent of the Internet has introduced a channel where individuals can freely and anonymously share personal views and opinions. This has led to the proliferation of alternative media sources, some of which promote conspiracy views. Conspiracy believers can easily connect and form online communities, creating a sense of validation and solidarity, which further reinforces their beliefs (Samory & Mitra, 2018). The false beliefs that are reciprocated within these fringe internet communities are not isolated from the rest of the Internet. On popular platforms such as X (formerly Twitter), misinformation spreads more rapidly and reaches more people compared to true news (Vosoughi et al., 2018). Thus, conspiratorial misinformation can potentially reach many people that are not (yet) engaged in conspiracy thinking, such as unfounded claims about election fraud. In **Chapter 5**, we performed an experiment in which we exposed Internet consumers to a website that promoted a conspiracy narrative. The aim was to establish the susceptibility of Internet consumers to adopt a novel conspiracy belief.

The four studies reported in this thesis regard unique facets of digital media usage. To summarize, we examine how message length constraints affect the language production of social media users. We also investigate how social cues on news websites influence how people process information. Moreover, we examined how cognitive traits predict the way people process and interpret facts and falsehoods. And finally, we examine how people respond to conspiracy ideas on the Web. Together, these studies form a comprehensive framework on behavioral, linguistic and cognitive aspects of digital media usage and display the dynamic relation between world-events and the affordance of digital media.

CHAPTER 2



How the character limit affects the language usage in tweets

Boot, A. B., Tjong Kim Sang, E., Dijkstra, K., & Zwaan, R. A. (2019). How character limit affects language usage in tweets. Palgrave Communications, 5, Article 76.
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Abstract

In November 2017 Twitter doubled the available character space from 140 to 280 characters. This provided an opportunity for researchers to investigate the linguistic effects of length constraints in online communication. We asked whether the *character limit change* (CLC) affected language usage in Dutch tweets and hypothesized that there would be a reduction in the need for character-conserving writing styles. Pre-CLC tweets were compared with post-CLC tweets. Three separate analyses were performed. (I) General analysis: the number of characters, words, and sentences per tweet, as well as the average word and sentence length. (II) Token analysis: the relative frequency of tokens and bigrams. (III) Part-of-speech analysis: the grammatical structure of the sentences in tweets (i.e., adjectives, adverbs, articles, conjunctives, interjections, nouns, prepositions, pronouns, and verbs). Pre-CLC tweets showed relatively more textisms, which are used to abbreviate and conserve character space. Consequently, they represent more informal language usage (e.g., internet slang); in turn, post-CLC tweets contained relatively more articles, conjunctions, and prepositions. The results show that online language producers adapt their texts to overcome limit constraints.

Keywords

social media, Twitter, character limit, text-mining, part-of-speech, tokenization, language usage, textisms

Spontaneous linguistic communication is typically unrestrained in terms of the length of utterances but in some situations there are constraints on utterance length. For example, there are word count limitations to newspaper headlines, advertisements, journalistic articles, student papers, and scholarly manuscripts. These limitations are sometimes so restrictive that they impact sentence structure and content and word forms. For instance, the advent of the telegraph, in which words were literally at a premium, necessitated an elliptic style that has become known as telegram style of *telegraphese*, which is viewed as a normal expressive form of language (Barton, 1998; Isserlin, 1985; Tesak & Dittmann, 1991). A more contemporary example of an elliptic style is *textese,* which is often used in modern text messages (Drouin & Driver, 2014).

Textese and telegraphese are both characterized by an imposed limit constraint (Barton, 1998; Drouin & Driver, 2014; Isserlin, 1985; Tesak & Dittmann, 1991). However, a crucial difference is the nature of the length restriction: In telegrams, the costs are related to the number of words and not the number of characters. In other words, a cost-effective telegram contains as few words as possible. In text messages, on the other hand, one is obliged to conserve character space, which results in a different practice of economy (Frehner, 2008). Character reduction as performed in textese can be achieved not only by minimizing the number of words but also by abbreviating words and using shorter synonyms and symbols. Textese has been called 'squeeze text', which well reflects its grammatical features (Carrington, 2004).

The character-reducing strategies inherent to textese are referred to as *textisms* (Carrington, 2004; Lyddy et al., 2014). They evolved not only to save character space but also to reduce typing efforts. Textisms reduce character use without compromising the conveyed meaning and even add meaning in some cases. This includes acronyms (e.g., *LOL* for 'laugh out loud'), emoticons (e.g. J instead of 'I am happy'), accent stylizations (e.g., slang terms such as *gonna*), nonconventional spellings (e.g., *gudnite*), homophones (e.g., *gr8* and *c u*), shortenings (e.g., *pic* as in 'picture'), contractions (e.g., *thx* for 'thanks'), and omission of punctuation (Carrington, 2004; De Jonge & Kemp, 2012; Ling & Baron, 2007; Plester et al., 2009; Tagliamonte & Denis, 2008; Thurlow & Brown, n.d.; Varnhagen et al., 2010).

Another strategy to reduce character usage is the omission of certain part-of-speech (POS) categories. The basic elements of a sentence are subject, verb, and object (SVO or SOV; Koster, 1975). The SVO structure comprises (pro)nouns and a verb. For example, '*Tom ate lunch*'. The main components of the SVO structure are unlikely to be omitted. In contrast, the POS categories that modify the basic structure and introduce additional information are more likely to be excluded. In textese and telegraphese, articles and conjunctions are often excluded (Carrington, 2004; Oosterhof & Rawoens, 2017). Consistent with this intuition, eye-tracking studies of reading have shown that function words such as articles and prepositions are often skipped in normal reading because these words are both short and highly predictable from context (Rayner et al., 2011). A reader can even fill in omitted articles and conjunctions. For example, '*car broke down stopped in middle of road*'. Although the overall readability is compromised, the message is still clear. Therefore, if words have to be omitted to reduce character usage, they are likely to be function words. However, other words can also be omitted, leaving out information. For example, '*the car broke down*' instead of '*the car broke down and stopped in the middle of the road*'. In this case, additional information is being withheld. Generally, this means limit constraints might also affect sentence structure.

An example of a contemporary platform that might necessitate elliptic writing strategies is Twitter, an online microblogging platform which imposes a message-length limit to its users. On November 8th 2017, Twitter doubled the character limit from 140 characters to 280 characters[1]; we will refer to this as the character limit change (CLC). After a trial period in September, Twitter observed that 9% of English tweets hit the previous limit of 140 characters, whereas only 1% of tweets reached the new 280-character limit (Rosen 2017). Doubling the character limit was thought to prevent a group of users from 'cramming their thoughts' (Rosen & Ihara 2017). Furthermore, only 2% of trial tweets surpassed 190 characters, indicating that many users used merely a few more characters than had previously been possible. When Twitter announced the upcoming CLC the community responded ambivalently. Some users appreciated the increased tweet length, having more space to express their thoughts, whereas others claimed it would harm the tweets' brevity and to-the-point characteristics (Watson, 2017).

The doubling of the maximum tweet length provides for an interesting opportunity to investigate the effects of a relaxation of length constraints on linguistic messaging. What happened to the average length of tweets? And more interestingly, how did CLC impact the structure and word usage in tweets?

The need for an economy of expression decreased post-CLC. Therefore, our first hypothesis states that post-CLC tweets contain relatively less textisms, such as abbreviations, contractions, symbols or other 'space-savers'. In addition, we hypothesize that the CLC affected the POS structure of the tweets, containing relatively more adjectives, adverbs, articles, conjunctions, and prepositions. These POS categories carry additional information about the situation being described,

1 Currently, there is much interest in algorithmic methods to define and recognize online human-behavior, such as consumer decisions, browsing activity, social-network structures, and personal interests. Twitter collects information to enhance the user experience; to show more relevant tweets, events, and people to follow, but also to enables targeted advertising (see Twitter's privacy policy; Twitter Inc 2018). From the user's perspective, the specific implementation of personal information is unclear. That is, many of the design decisions in Twitter's software are opaque to the user. In contrast, the CLC was a transparent design decision, which directly affected the way users could interact with the Twitter environment.

the referential situation; such as features of entities, the temporal order of events, locations of events or objects, and causal connections between events (Zwaan & Radvansky, 1998). This structural change also entails that sentences will be longer, with more words per sentence.

Gligorić, Anderson, and West (2018) compared pre and post-CLC tweets with a length of approximately 140 characters. They found that pre-CLC tweets in this character range comprise relatively more abbreviations and contractions, and fewer definite articles. In the current study, we used a different approach that adds complementary value to the previous findings: we performed a content analysis on a dataset of approximately 1.5 million Dutch tweets including all ranges (i.e., 1-140 and 1-280), instead of selecting tweets within a specific character range. The dataset comprises Dutch tweets that were created between October 25, 2017 and November 21, 2017, in other words two weeks prior to and two weeks after the CLC.

We performed a general analysis to investigate changes in the number of characters, words, sentences, emojis, punctuation marks, digits, and URLs. To test the first hypothesis, we performed token and bigram analyses to detect all changes in the relative frequencies of tokens (i.e., individual words, punctuation marks, numbers, special characters, and symbols) and bigrams (i.e., two-word sequences). These changes in relative frequencies could then be utilized to extract the tokens that were especially affected by the CLC. In addition, a POS analysis was performed to test the second hypothesis; that is, whether the CLC affected the POS structure of the sentences. An example of each investigated POS category is presented in Table 2.1.

Table 2.1 Part-of-Speech (POS) Categories of Interest

POS Category	Example	Function
Adjective	cold, happy, young, two, fun	Describes, modifies or gives more information about a noun or pronoun.
Adverb	slowly, very, always, well, too	Modifies a verb, an adjective or another adverb. It tells 'how' (often) and 'when'.
Article	it, a, an*	Defines a noun as definite or indefinite.
Conjunctive	and, or, but, because, yet, so	Joins two words, ideas, phrases together and shows how they are connected.
Interjection	haha, wow, hey, yes, oh	Expression of a strong emotion with a brief exclamation.
Noun	house, chair, dog, Mary, Tom	Name of a person, place, or any object.
Preposition	at, on, in, from, with, about	Shows the relationship of a noun or pronoun to another word.
Pronoun	I, you, it, we, them , those	Reference to a person or object.
Verb	are, is, go, speak, live, eat	Depicts an action or state of being.

Method

Apparatus

The data collection, pre-processing, quantitative analysis, figures, token analysis, bigram analysis, and POS analysis were performed using Rstudio (RStudio Team, 2016). The R packages that were used are: 'BSDA', 'dplyr', 'ggplot', 'grid', 'kableExtra', 'knitr', 'lubridate', 'NLP', 'openNLP', 'quanteda', 'R-basic', 'rtweet', 'stringr', 'tidytext', 'tm' (Arnholt & Evans, 2017; Benoit et al., 2018; Feinerer & Hornik, 2017; Grolemund & Wickham, 2011; Hornik, 2016, 2017; Kearney, 2017; Silge & Robinson, 2016; Wickham, 2016; Xie, 2018; Zhu, 2021).

Period of interest

The CLC occurred on November 8 2017 at 00:00 a.m. (UTC). The dataset comprises Dutch tweets that were created within two weeks pre-CLC and two weeks post-CLC (i.e., 10-25-2017 to 11-21-2017). This period is subdivided into *week 1, week 2, week 3*, and *week 4* (see Figure 2.1). To analyze the effect of the CLC we compared the language usage in 'week 1 and week 2' with the language usage in 'week 3 and week 4'. To distinguish the CLC effect from natural-event effects, a control comparison was devised: the difference in language usage between week 1 and week 2, referred to as *Baseline-split I*. Furthermore, the CLC could have initiated a trend in the language usage that evolved as more users became familiar with the new limit. This trend could be shown by comparing week 3 with week 4, referred to as *Baseline-split II*.

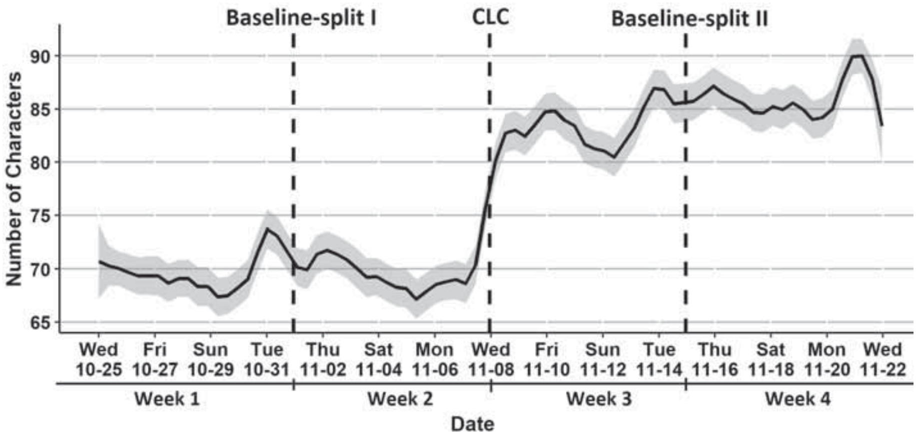


Figure 2.1. Moving average and standard error of the character usage over time, which shows an increase in character usage post-CLC and an additional increase between week 3 and 4. Each tick marks the absolute beginning of the day (i.e., 12:00 a.m.). The time frames indicate the comparative analyses: week 1 with week 2 (Baseline-split I), week 3 with week 4 (Baseline-split II), and week 1 and 2 with week 3 and 4 (CLC).

Data collection[2]

The website *twiqs.nl* was used as a means to collect tweet-ids[3], this website provides researchers with metadata from a (third-party-collected) corpus of Dutch tweets (Tjong Kim Sang & Van den Bosch, 2013). The tweet-ids allow for the collection of tweets from the Twitter API that are older than 9 days (i.e., the historical limit when requesting tweets based on a search query). The R-package 'rtweet' and complementary 'lookup_status' function were used to collect tweets in JSON format. The JSON file comprises a table with the tweets' information, such as the creation date, the tweet text, and the source (i.e., type of Twitter client).

Data cleaning and preprocessing[4]

The JSON files were converted into an R data frame object. Non-Dutch tweets, retweets, and automated tweets (e.g., forecast-, advertisement-, and traffic-related tweets) were removed. Additionally, we excluded tweets based on three user-related criteria: (1) we removed tweets that belonged to the top 0.5 percentile of user activity because we considered them non-representative of the normal user population, such as users who created more than 2000 tweets within four weeks. (2) Tweets from users with early access to the 280 limit were removed. (3) Tweets from users who were not represented in both pre and post-CLC datasets were removed, this procedure ensured a consistent user sample over time (within-group design, N_{users} = 109,661). All cleaning procedures and corresponding exclusion numbers are presented in Table 2.2.

2 OSF: "TCLC 1 Data Collection Pre-CLC.html" and "TCLC 2 Data Collection Post-CLC.html"
3 OSF: "tweet_ids_CLC_post.Rdata" and "tweet_ids_CLC_pre.Rdata"
4 OSF: "TCLC 3 Data Pre-Processing.html" and "TCLC 4 Data Pre-Processing 2.html"

Table 2.2 Dataset Exclusions and Inclusions

Tweet Type Excluded	Pre-CLC		Post-CLC	
	Number of Tweets	**Proportion**	**Number of Tweets**	**Proportion**
Non-representative Twitter clients (e.g., bots/automated tweets)	1,329,457	0.27	1,361,462	0.26
Upper 0.5% of user activity	928,627	0.19	1,095,653	0.21
URL/ad related	573,654	0.12	581,951	0.11
Non-Dutch	389,315	0.08	421,593	0.08
Retweets	660,791	0.14	740,885	0.14
Tweets without words (< 1%)	725	0	735	0
Users absent in pre or post-CLC dataset*	250,464	0.05	235,035	0.05
Included tweets (N)	744,673	0.15	764,642	0.15

Note. *Users not represented in both pre and post-CLC datasets (or users with early access to the 280 limit).

The tweet texts were converted to ASCII encoding. URLs, line breaks, tweet headers, screen names, and references to screen names were removed. URLs add to the character count when located within the tweet. However, URLs do not add to the character count when they are located at the end of a tweet. To prevent a misrepresentation of the actual character limit that users had to deal with, tweets with URLs (but not media URLs such as added pictures or videos) were excluded.

Token- and bigram analysis[5]

The R package 'quanteda' was used to tokenize the tweet texts into tokens (i.e., isolated words, punctuation marks, and numbers) and bigrams. Additionally, token-frequency-matrices were computed with: the frequency pre-CLC [$f(token\ pre)$], the relative frequency pre-CLC [$P(token\ pre)$], the frequency post-CLC [$f(token\ post)$], the relative frequency post-CLC and T-scores. The T-test is similar to a standard T-statistic and computes the statistical difference between means (i.e., the relative word frequencies). Negative T-scores indicate a relatively higher occurrence of a token pre- CLC, whereas positive T-scores indicate a relatively higher occurrence of a token post-CLC. The T-score equation used in the analysis is presented as equation (1) and equation (2). N is the total number of tokens per dataset (i.e., pre and post-CLC). This equation is based on the method for linguistic computations by Church, Gale, Hanks, and Hindle (1991; Tjong Kim Sang, 2011).

5 OSF: "TCLC 6 Token Analysis.html" and "TCLC 7 Bigram Analysis.html"

$$T = \frac{P(token\ post) - P(token\ pre)}{\sqrt{\sigma^2\left(P(token\ post)\right) + \sigma^2\left(P(token\ pre)\right)}} \quad (1)$$

$$\approx \frac{\frac{f(token\ post)}{N_{pre}} - \frac{f(token\ pre)}{N_{post}}}{\sqrt{\frac{f(token\ post)}{N^2{}_{post}} + \frac{f(token\ pre)}{N^2{}_{pre}}}} \quad (2)$$

Part-of-speech (POS) analysis[6]

The R package 'openNLP' was used to classify and count POS categories in the tweets (i.e., adjectives, adverbs, articles, conjunctives, interjections, nouns, numeral, prepositions, pronouns, punctuation, verbs, and miscellaneous). The POS tagger operates using a maximum entropy (maxent) probability model in order to predict the POS category based on contextual features (Ratnaparkhi, 1996). The Dutch maxent model used for the POS classification was trained on CoNLL-X Alpino Dutch Treebank data (Buchholz & Marsi, 2006; van der Beek et al., 2002). The openNLP POS model has been reported with an accuracy rating of 87.3% when used for English social media data (Horsmann et al., 2015). An ostensible limitation of the current study is the reliability of the POS tagger. However, similar analyses were performed for both pre- and post-CLC datasets, meaning the accuracy of the POS tagger should be consistent over both datasets. Therefore, we assume there are no systematic confounds.

Statistical interpretation

The large sample size (N = 1,516,425) is an approximation of the population size; this means that the standard errors are low and the confidence intervals (CI) are narrow. 99% CIs were implemented, as opposed to the commonly used 95% CI, to reduce the chance of type I errors.

Data Availability

Tweet-ids and the complete procedure are available to the reader at Open Science Framework. It is important to note that we are not permitted to share tweets. However, we are allowed to share tweet-ids on behalf of an academic institution and for the purpose of non-commercial research (see Developer Policy I.F.2.B. https://developer.twitter.com/en/developer-terms/policy).

6 OSF: "TCLC 8 Part-of-Speech Analysis.html"

Results

The results comprise three components: (1) General statistics – the CLC induced differences across multiple tweet features, (2) token (i.e., unigram) and bigram analyses to test the first hypothesis, and (3) POS analysis to test the second hypothesis.

General statistics

After the CLC, the average tweet length increased. Table 2.3 contains descriptive information about different tweet features such as character and word count. This table also provides the absolute and relative differences between pre and post-CLC tweets. All tweet features increased in frequency. Furthermore, the standard deviations of all length features increased, indicating an increase in variability. This suggests some users took advantage of the additional character space, whereas others continued to use fewer than 140 characters.

Figure 2.1 shows that the average character usage increased immediately after the CLC. Additionally, the character usage also increased from week 3 to week 4, suggesting that some users became familiar with the 280-limit in the week after the CLC. Figure 2.2 provides an overview of all observations and shows an increase in character usage from pre to post-CLC time frames. This figure also shows the day/night cycle in Twitter activity, a small proportion of users who were still limited to 140 characters after the CLC (due to outdated Twitter client versions), an initial increase in the amount of tweets near the 280-limit, and a decrease in the amount of tweets near the 280-limit as compared to the 140-limit. Figure 2.3 displays the character (2.3a), word (2.3b) and sentence (2.3c) usage over time, which show a similar increase in tweet length. Figure 2.4a displays the number of characters per word (i.e., word length) over time. The average word length remained unaffected by the CLC, except for a temporary increase the first day after the CLC. Figure 2.4b and Figure 2.4c present an increase in sentence length after the CLC, this suggests a syntactic change in sentence structure.

Table 2.3 Tweet Features Pre and Post-CLC

	Pre-CLC			Post-CLC			Difference	
Number of:*	**Mean**	**SD**	**99% CI**	**Mean**	**SD**	**99% CI**	**Absolute**	**Relative (%)**
Tweets per user	6.79	10.60	[6.71, 6.87]	6.97	10.63	[6.89, 7.06]	+ 0.18	+ 2.65
Characters	70.08	39.06	[69.96, 70.19]	84.82	60.63	[84.64, 84.99]	+ 14.74	+ 21.03
Words	11.89	6.64	[11.87, 11.91]	14.21	10.01	[14.18, 14.24]	+ 2.32	+ 19.51
Sentences	1.55	0.80	[1.55, 1.56]	1.70	1.02	[1.70, 1.70]	+ 0.15	+ 9.68
Characters per word	4.77	1.27	[4.77, 4.77]	4.81	1.48	[4.80, 4.81]	+ 0.04	+ 0.84
Characters per sentence	49.51	30.32	[49.42, 49.6]	53.42	36.32	[53.31, 53.53]	+ 3.91	+ 7.90
Words per sentence	8.49	5.27	[8.47, 8.50]	9.07	6.17	[9.05, 9.09]	+ 0.58	+ 6.83
Emojis	0.27	0.93	[0.27, 0.27]	0.28	1.12	[0.28, 0.28]	+ 0.01	+ 3.70
Digit characters	0.45	1.41	[0.45, 0.45]	0.53	1.84	[0.53, 0.54]	+ 0.08	+ 17.78
Numbers	0.27	0.77	[0.27, 0.27]	0.29	0.90	[0.29, 0.30]	+ 0.02	+ 7.41
Punctuation marks	2.41	2.30	[2.40, 2.42]	2.85	3.21	[2.84, 2.86]	+ 0.44	+ 18.26
URLs	0.11	0.31	[0.11, 0.11]	0.13	0.34	[0.13, 0.13]	+ 0.02	+ 18.18

Note. 99% CIs were implemented, as opposed to the traditional 95% CI, to reduce the chance of type I errors. The CIs are narrow because the sample size is very large.
*All feature means were computed per tweet, except for the number of tweets, which was computed per user.

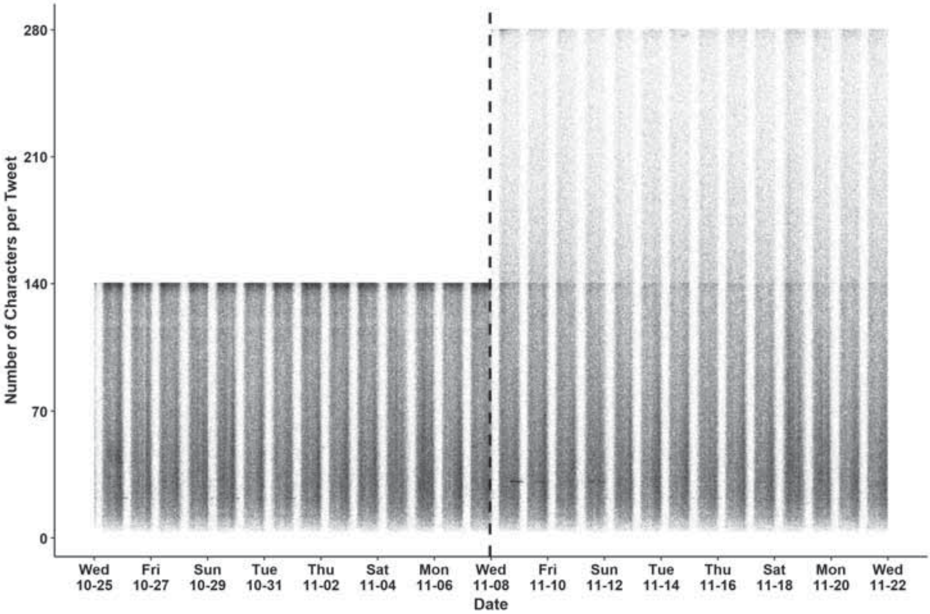


Figure 2.2. Character usage over time. This scatterplot displays the number of characters in each tweet (n = 1,509,315) over time. The reference line indicates the CLC. The observations show an increase in character usage post-CLC, fewer tweets accumulating near 140 characters post-CLC, the day/night cycle of tweet behavior, and a small proportion of tweets that were still limited by the 140-limit post-CLC (outdated Twitter client versions).

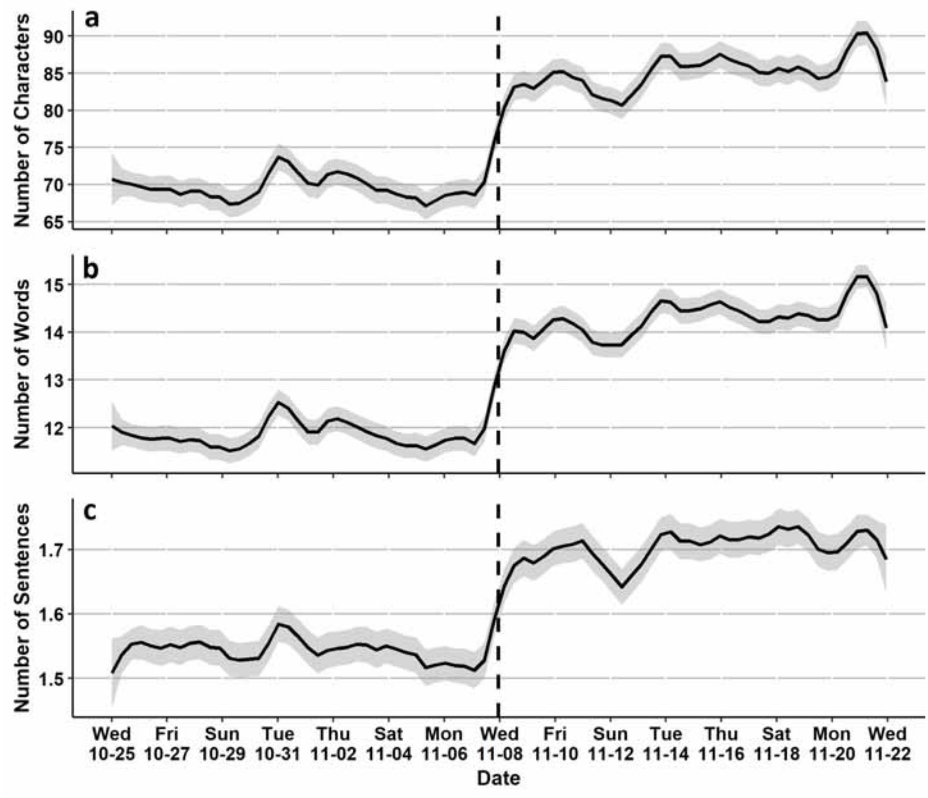


Figure 2.3. Moving averages for the number of characters (a), words (b), and sentences (c), including standard errors. The reference line indicates the CLC. Each tick marks the absolute beginning of the day (i.e., 12:00 a.m.). The moving averages show an increase in tweet length post-CLC. Character, word, and sentence usage display a similar increase post-CLC.

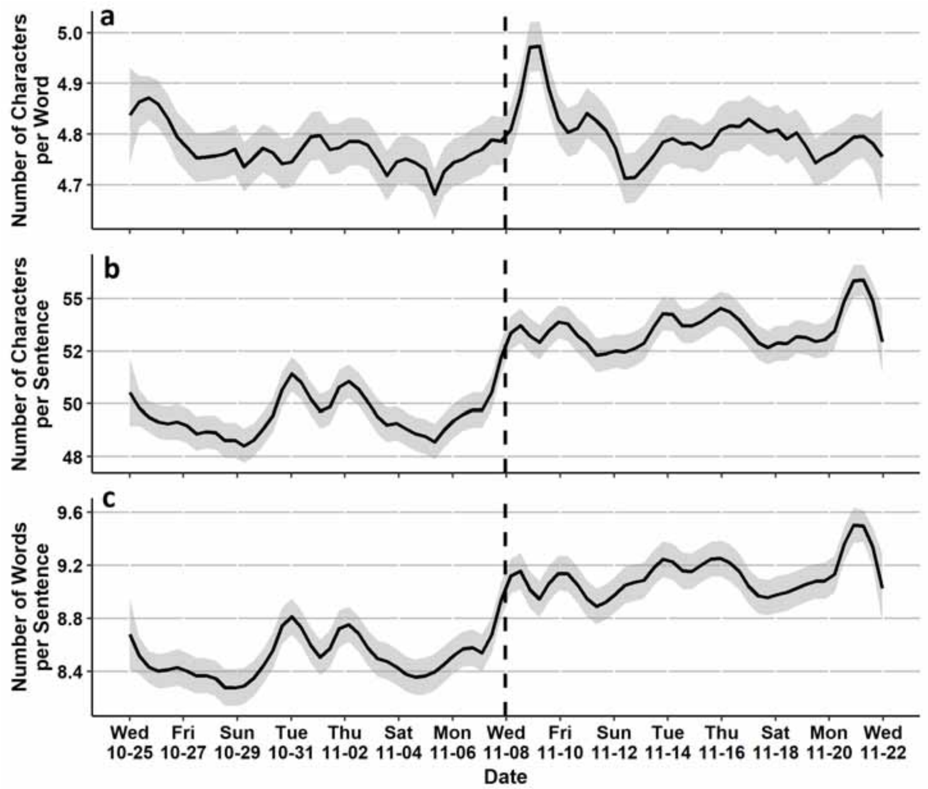


Figure 2.4. Moving averages for the number of characters per word (a), characters per sentence (b), and words per sentence (c), including standard errors. The reference line indicates the CLC. Each tick marks the absolute beginning of the day (i.e., 12:00 a.m.). Word length increased temporarily post-CLC but then decreased to the previous level. Sentences contained more characters and words post-CLC.

Figure 2.5 shows a large amount of pre-CLC tweets (15.48%) within the upper range of 121-140 characters. In comparison, a much smaller proportion of post-CLC tweets (1.73%) are within the upper range of 261-280 characters. Alternatively, the percentage of pre-CLC tweets near the pre-CLC limit (i.e., 138-140 characters) is 4.73%, whereas the post-CLC limit (i.e., 278-280 characters) comprises just 0.48% of post-CLC tweets. In other words, doubling the character limit appears to have decreased the hindrance by a factor of ten. Figure 2.6 shows the distribution of word usage in tweets pre and post-CLC. Again, it is shown that with the 140-characters limit, a group of users were constrained. This group was forced to use about 15 to 25 words, indicated by the relative increase of pre-CLC tweets around 20 words. Interestingly, the distribution of the number of words in post-CLC tweets is more right skewed and displays a gradually decreasing distribution. In contrast, the post-CLC character usage in Figure 2.5 shows small increase at the 280-characters limit.

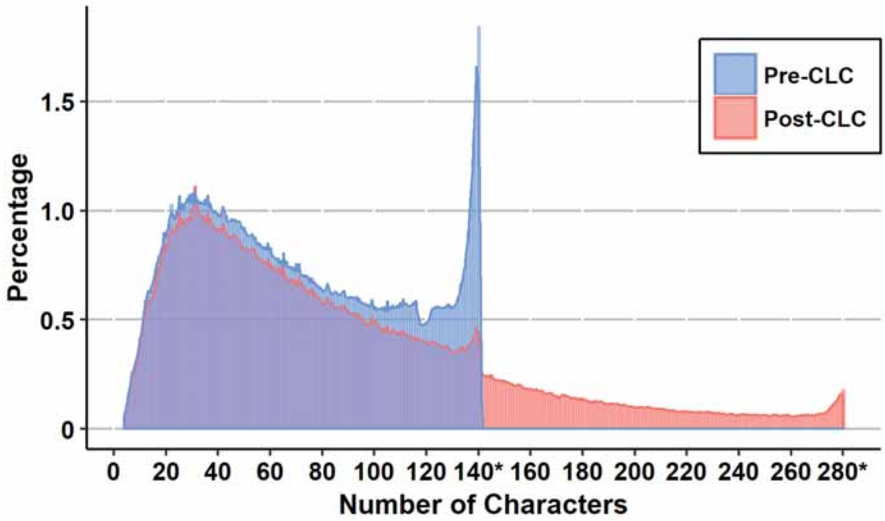


Figure 2.5. Character-usage distribution; pre and post-CLC. This density distribution shows a large proportion of pre-CLC tweets within the upper range of 120-140 characters, whereas the proportion of post-CLC tweets within the upper range of 260-280 characters was reduced by a factor of ten.

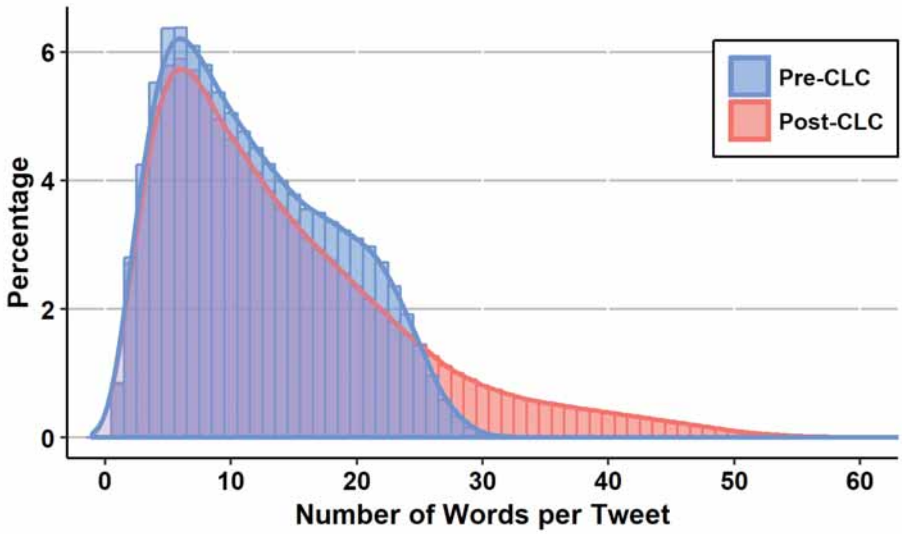


Figure 2.6. Word-usage distribution; pre and post-CLC. This density distribution shows that in pre-CLC tweets there were relatively more tweets within the range of 15-25 words, whereas post-CLC tweets shows a gradually decreasing distribution and double the maximum word usage.

Token and bigram analyses

To test our first hypothesis, which states that the CLC reduced the use of textisms or other character-saving strategies in tweets, we performed token and bigram analyses. Firstly, the tweet texts were separated into tokens (i.e., words, symbols, numbers and punctuation marks). For each token the relative frequency pre-CLC was compared to the relative frequency post-CLC, thus revealing any effects of the CLC on the use of any token. This comparison of pre and post-CLC percentage was revealed in the form of a T-score, see equation (1) and equation (2) in the method section. Negative T-scores indicate a relatively higher frequency pre-CLC, whereas positive T-scores indicate a relatively higher frequency post-CLC. The total number of tokens in the pre-CLC tweets is 10,596,787 including 321,165 unique tokens. The total number of tokens in the post-CLC tweets is 12,976,118 which comprises 367,896 unique tokens. For each unique token three T-scores were computed, which indicates to what extent the relative frequency was affected by Baseline-split I, Baseline-split II and the CLC, respectively (see Figure 2.1).

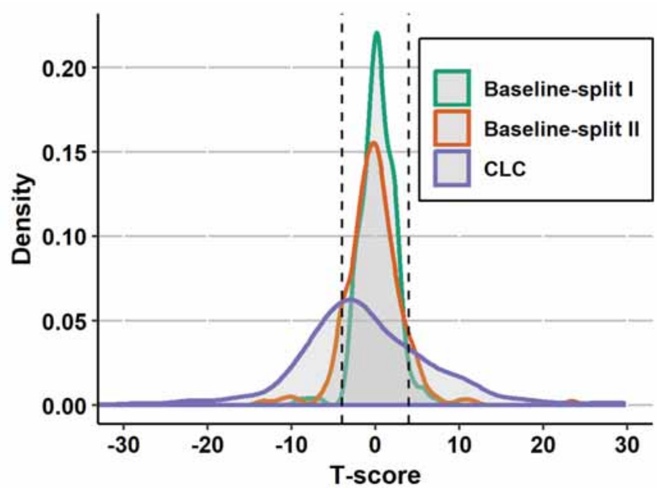


Figure 2.7. T-score distribution of high-frequency tokens (> 0.05%). The T-score indicates the variance in word usage; that is, the further away from zero, the greater the variance in word usage. This density distribution shows the CLC induced a larger proportion of tokens with a T-score lower than -4 and higher than 4, indicated by the vertical reference lines. In addition, the Baseline-split II shows an intermediate distribution between Baseline-split I and the CLC (for time-frame specifications see Figure 2.1).

Figure 2.7 presents the distribution of the T-scores after removal of low frequency tokens, which shows the CLC had an independent effect on the language usage as compared to the baseline variance. Particularly, the CLC effect induced more T-scores < -4 and > 4, as indicated by the reference lines. In addition, the T-score distribution of the Baseline-split II comparison shows an intermediate position between Baseline-split I and the CLC. That is, more variance in token usage as compared to Baseline-split

I, but less variance in token usage as compared to the CLC. Therefore, Baseline-split II (i.e., comparison between week 3 and week 4) could suggests a subsequent trend of the CLC. In other words, a gradual change in the language usage as more users became familiar with the new limit.

To minimize natural-event-related confounds the T-score range, indicated by the reference lines in Figure 2.7, was utilized as a cutoff rule. That is, tokens within the range of -4 to 4 were excluded, because this range of T-scores can be ascribed to baseline variance, as opposed to CLC-dependent variance. Furthermore, we removed tokens that showed greater variance for Baseline-split I as compared to the CLC. A similar procedure was performed with bigrams, resulting in a T-score cutoff-rule of -2 to 2, see Figure 2.8. Tables 4-7 present a subset of tokens and bigrams of which occurrences were the most affected by the CLC. Each individual token or bigram in these tables are accompanied by three related T-scores: Baseline-split I, Baseline-split II, and CLC. These T-scores can be used to compare the CLC effect with Baseline-split I and Baseline-split II, for each individual token or bigram.

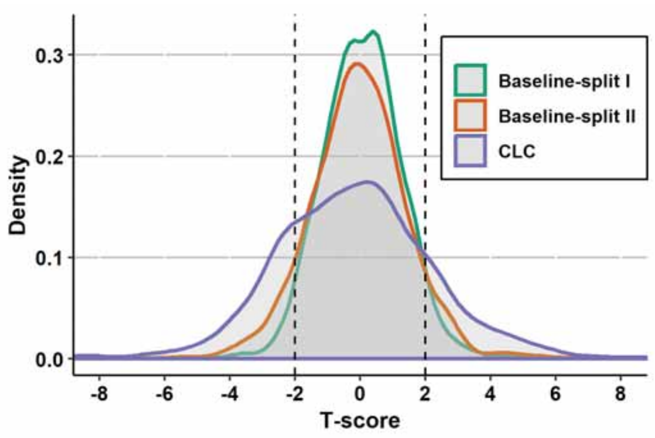


Figure 2.8. T-score distribution of high-frequency bigrams (> 0.05%). The CLC induced a larger proportion of bigrams with a T-score lower than -2 and higher than 2, indicated by the vertical reference lines.

The tokens that occurred relatively less frequently post-CLC are presented in Table 2.4. These tokens comprise: symbols (e.g., *&* , *>,* **/ , +, ^, =**), numerals (e.g., *1,2,3*) acronyms, shortenings and contractions (e.g., *t, k, ff, ni, mn, nie, jy, gwn, s, lol*; which refer to: *het, dat, ok/ik, even, niet, hem, niet, jij, gewoon, is, laugh out loud*; translations: *it, that, ok/I, for a bit*[7], *not, my, not, you, just, is*), punctuation marks (e.g., ***! ? : ;*** but not the period and comma), pronouns (e.g., *ik, jij, hem, hij, me, je, jou*; translations: *I, you,*

7 The Dutch word 'even', which can be translated to 'for a bit' or 'just for a moment', is a commonly used filler and is often abbreviated to 'ff', which is short for "effe," a colloquial version of "even."

him, he, me, you/your), opinion-related adjectives/adverbs (e.g., echt, *lekker, mooi, goed, nieuwe, niks, leuk, zeker, mooie, super*; translations: *really, nice/tasty, nice/beautiful, good, new, nothing, nice/beautiful, nice/nicely, sure, nice, super*), and interjection words (e.g., *ja, haha, nee, man, hoor, nou, hahaha, he, jaa, wow, jaaa, ok, fuck, shit, wtf*; translations: *yes, haha, no, man, you know, well, hahaha, hey/huh, yeah, wow, okay*). In summary, the words that occurred relatively more frequently pre-CLC represent mainly informal language use, such as contractions, unconventional spellings, symbols and profanity.

Table 2.4 Tokens that Occurred Relatively Less Frequently Post-CLC and Related T-scores (Baseline-split I; Baseline-split II; CLC)

2 (-3; -2; -36)	ff (0; -4; -9)	zeg (0; 0; -6)	omg (0; -6; -5)	ok (-1; -4; -4)
! (-1; -3; -28)	k (3; -3; -9)	& (2; -1; -6)	goeie (1; -1; -5)	ging (0; -2; -4)
? (-1; -9; -23)	hoor (0; -1; -8)	nie (-1; -7; -6)	sterkte (-2; -2; -5)	klopt (0; -3; -4)
ik (5; -13; -22)	nieuwe (0; -4; -8)	h (-2; -4; -6)	oke (1; -2; -5)	vond (-3; -1; -4)
1 (-2; -4; -21)	niks (0; 0; -8)	super (-1; -2; -6)	raar (-1; -2; -5)	s (0; 0; -4)
ja (1; -4; -17)	mn (4; -6; -8)	m (-1; -3; -6)	kapot (-1; -1; -5)	valt (-1; 1; -4)
/ (-2; -4; -16)	dacht (-1; -3; -8)	lol (2; -1; -6)	wow (0; -2; -5)	z'n (-1; 1; -4)
t (2; -3; -16)	hahaha (3; -3; -8)	kut (3; -4; -6)	jy (-3; -4; -5)	ofzo (2; -1; -4)
echt (6; -6; -15)	ie (-1; 0; -8)	ma (3; -3; -6)	1e (2; 2; -5)	lief (2; 0; -4)
v (-2; -2; -13)	plezier (-1; 0; -8)	gwn (3; -1; -6)	verjaardag (-1; -1; -5)	dood (2; 2; -4)
> (1; 1; -13)	je (-1; 0; -7)	xd (2; -3; -6)	wou (0; -1; -5)	moeder (-2; -1; -4)
heb (3; -10; -12)	al (2; -4; -7)	tis (3; -2; -6)	pfff (0; 0; -5)	ah (0; -2; -4)
3 (1; 2; -12)	me (3; -5; -7)	knap (1; 0; -6)	las (1; 0; -5)	^ (0; 0; -4)
wel (-1; -2; -11)	hij (0; -5; -7)	jaa (3; -3; -6)	oei (0; 1; -5)	p (0; -2; -4)
haha (2; -3; -11)	leuk (-1; -1; -7)	mooie (2; 3; -5)	hi (3; -1; -5)	shit (1; -1; -4)
ben (3; -4; -10)	nou (-2; 2; -7)	kijk (2; 2; -5)	eng (-1; 2; -5)	ding (1; -4; -4)
weer (3; 2; -10)	zeker (0; -2; -7)	oh (-1; -4; -5)	nr (-1; 1; -5)	wtf (5; -3; -4)
lekker (0; 0; -10)	hem (-1; -6; -7)	snap (3; 1; -5)	xx (1; -4; -5)	ha (1; 1; -4)
nee (0; -4; -10)	jou (0; -3; -7)	hou (0; -1; -5)	drama (2; 2; -5)	zn (1; -3; -4)
succes (-1; 0; -10)	kom (2; -1; -7)	top (-1; 2; -5)	jaaa (0; -2; -5)	fuck (2; -1; -4)
x (5; -4; -10)	he (3; -2; -7)	slecht (1; 3; -5)	same (2; -2; -5)	zon (3; 4; -4)
nog (1; -4; -9)	gefeliciteerd (-6; 1; -7)	idd (-2; -2; -5)	mij (4; -2; -4)	hoezo (-1; -1; -4)
zo (3; -2; -9)	+ (1; -3; -7)	heerlijk (3; -2; -5)	; (-1; 0; -4)	vet (-1; -2; -4)
was (-3; -1; -9)	ni (3; -5; -7)	gij (3; -5; -5)	n (0; -4; -4)	nice (1; -1; -4)
goed (1; 1; -9)	: (0; -4; -6)	d (-3; -1; -5)	beter (0; 1; -4)	hahah (1; -1; -4)
jij (1; 0; -9)	kan (0; -4; -6)	= (1; -4; -5)	dank (0; -1; -4)	btw (0; -2; -4)
ga (3; -2; -9)	toch (-1; -2; -6)	das (0; -2; -5)	* (3; 2; -4)	pff (0; -1; -4)
mooi (2; 1; -9)	gaat (-3; -1; -6)	7 (2; 0; -5)	m'n (2; -3; -4)	xxx (-1; -3; -4)
man (1; -1; -9)	wil (4; -1; -6)	hopelijk (-3; 0; -5)	beste (0; -1; -4)	boys (-2; 4; -4)
4 (0; 0; -9)	waarom (1; -2; -6)	ek (0; -8; -5)	leuke (0; -1; -4)	oma (-3; -1; -4)

Note. Subset of the total 321,165 unique tokens (frequency > 0.005%). The three T-scores represent Baseline-split I, Baseline-split II, and the CLC, respectively (see Figure 2.2). Negative T-scores indicate a decrease in token usage and positive T-scores indicate an increase in token usage.

Table 2.5 presents tokens that occurred relatively more frequently *post*-CLC, these tokens comprise: articles (i.e., *de, het, een*; translations: feminine/masculine *the,* neuter *the*, *a(n)*), conjunctions (e.g., *en, of, omdat, want, zodat*; translations: *and, or, because, because, so that*), prepositions (e.g., *door, in, om, met, over, tijdens, aan, tot*; translations: *through/by, in, for/at, with, about/over, during, to/on, until*), auxiliary and linking verbs (e.g., worden, *hebben, zijn, moeten, kunnen, maken, willen*; translations: *become, have, are, must, can, make, want*). Overall, the tokens that occurred relatively more frequently post-CLC represent more formal language usage as compared to the pre-CLC tokens in Table 2.4.

Table 2.5 Tokens that Occurred Relatively More Frequently Post-CLC and Related T-scores (Baseline-split I; Baseline-split II; CLC)

de (0; 10; 30)	over (2; 1; 9)	blijven (1; 0; 6)	echter (-1; 0; 5)	anderen (-1; 3; 4)
en (2; 5; 27)	onze (-3; -4; 9)	zullen (-1; -1; 6)	er (0; 1; 4)	gekregen (0; -1; 4)
van (0; 7; 22)	alle (0; 2; 9)	o.a (1; -3; 6)	daar (2; 4; 4)	zorgen (1; 1; 4)
hun (2; 7; 18)	mensen (5; 5; 8)	werden (1; 0; 6)	zelf (1; 1; 4)	ten (0; 1; 4)
het (1; 3; 17)	andere (1; 2; 8)	we (2; 2; 5)	allemaal (2; -1; 4)	enkele (-1; 3; 4)
te (0; 0; 16)	omdat (2; 1; 8)	tot (0; -2; 5)	onder (0; 1; 4)	brengen (-1; 1; 4)
, (-1; 0; 15)	bijvoorbeeld (0; 2; 8)	ons (0; 1; 5)	uw (1; -1; 4)	kort (1; -3; 4)
in (1; 3; 13)	dat (-3; 2; 7)	wij (2; 3; 5)	elkaar (-1; 2; 4)	feit (1; 2; 4)
door (2; 4; 13)	deze (1; 3; 7)	laten (0; 2; 5)	zelfs (2; -4; 4)	gebeurd (-1; -1; 4)
om (0; 1; 12)	moeten (0; 4; 7)	willen (2; 5; 5)	waren (1; 1; 4)	namelijk (1; 3; 4)
‘ **(** ' (-2; 0; 12)	zoals (0; 2; 7)	eigen (0; 4; 5)	vooral (-1; 0; 4)	betreft (-2; 2; 4)
worden (2; 3; 12)	tijdens (1; -1; 7)	krijgen (2; 2; 5)	gemaakt (1; -1; 4)	voorbeeld (0; 1; 4)
met (2; 3; 11)	overigens (-2; 2; 7)	houden (-2; 6; 5)	men (0; 0; 4)	blijkt (1; -2; 4)
ze (-1; 2; 11)	hen (0; 1; 7)	mogen (1; 2; 5)	terwijl (1; -1; 4)	veranderen (1; 3; 4)
een (-3; 6; 10)	als (-1; 2; 6)	zouden (1; -1; 5)	mogelijk (-2; 1; 4)	ondanks (0; 3; 4)
die (0; 4; 10)	aan (2; -1; 6)	kleine (-1; 0; 5)	enkel (0; 0; 4)	daarmee (-1; 2; 4)
zijn (2; 3; 10)	kunnen (0; 0; 6)	plaats (-1; 1; 5)	manier (0; 1; 4)	groter (0; 0; 4)
hebben (-1; 0; 10)	maken (2; 2; 6)	zodat (1; 1; 5)	vroeger (1; 2; 4)	bepaalde (-1; 2; 4)
zich (-2; 3; 10)	want (0; -2; 6)	ter (0; 2; 5)	etc (1; 0; 4)	voldoende (-1; -2; 4)
zij (-1; -1; 10)	grote (0; 0; 6)	vervolgens (1; 1; 5)	gesprek (1; 0; 4)	waardoor (-1; 0; 4)
of (-2; -2; 9)	tussen (0; 2; 6)	waarin (0; -1; 5)	persoon (0; -1; 4)	

Note. Subset of the total 367,896 unique tokens (frequency > 0.005%). The three T-scores represent Baseline-split I, Baseline-split II, and the CLC, respectively (see Figure 2.2). Negative T-scores indicate a decrease in token usage and positive T-scores indicate an increase in token usage.

Table 2.6 presents bigrams that occurred relatively more frequently pre-CLC. These bigrams mainly comprise *personal pronoun* + *verb* combinations (i.e., *ik ga, ik heb, ik ben, ik wil, ik dacht, heb je, ik moet, denk ik, ik kan, ik kom, ik had, ik was*; translations: *I am going, I have, I am, I want, I thought, have you, I must, I think, I can, I come, I had, I was*). Again, the results suggest that there was relatively more informal language usage, that is, relatively more frequent occurrences of self-referential language, which implies a more personal and subjective language usage.

Table 2.6 Bigrams that Occurred Relatively Less Frequently Post-CLC and Related T-scores (Baseline-split I; Baseline-split II; CLC)

wat een (-2; 6; -10)	ook wel (0; 1; -4)	kan je (3; 0; -3)	zie ik (1; 0; -3)
ik ga (1; -4; -10)	het was (0; -2; -4)	al een (-1; -1; -3)	de enige (0; -2; -3)
ik heb (3; -7; -9)	ik had (0; -2; -4)	een mooie (0; 1; -3)	zo goed (1; 0; -3)
veel plezier (-1; -1; -9)	is toch (0; -1; -4)	nog wel (-1; -2; -3)	en dan (0; 0; -2)
ik ben (1; -3; -8)	echt een (0; -1; -4)	ik wel (0; -1; -3)	heb ik (1; -4; -2)
ik ook (2; -4; -8)	toch niet (0; -1; -4)	ga je (0; 0; -3)	en ik (0; -2; -2)
nu al (0; -4; -8)	hij is (-2; -2; -4)	de nieuwe (1; -1; -3)	ook niet (2; 0; -2)
zin in (2; -3; -8)	ik was (-2; -1; -4)	wil je (-1; 0; -3)	is niet (-1; -1; -2)
ik wil (6; -3; -7)	is nog (-1; -2; -4)	dat was (-1; 1; -3)	ook een (0; 0; -2)
heb je (0; -2; -6)	is zo (0; -2; -4)	gaan we (2; -1; -3)	ik vind (-2; 1; -2)
is echt (2; -1; -6)	op je (-2; -2; -4)	ja dat (-1; 0; -3)	vind ik (-2; -1; -2)
ik moet (1; -3; -6)	je kan (1; 0; -4)	is al (1; 0; -3)	dat hij (0; -2; -2)
dank je (0; -4; -6)	niet goed (1; 1; -4)	van mij (2; 1; -3)	ik zie (1; 1; -2)
ik dacht (-1; -1; -6)	heb een (0; -1; -4)	na een (0; 1; -3)	en nu (0; -1; -2)
jij ook (0; -1; -6)	tijd voor (2; 0; -4)	ik je (-1; -1; -3)	heel veel (2; -2; -2)
ik kan (0; -4; -5)	ja maar (-1; -2; -4)	toch wel (-2; 1; -3)	echt niet (1; 0; -2)
denk ik (1; -2; -5)	wil ik (1; 3; -4)	nog even (0; 2; -3)	moet ik (1; -3; -2)
je bent (1; 0; -5)	nog geen (2; 1; -4)	heb het (0; -1; -3)	een keer (-2; 0; -2)
is wel (-1; -1; -5)	is het (0; 0; -3)	mag ik (-1; -1; -3)	ik hoop (-2; 0; -2)
kan niet (-1; -2; -5)	dat ik (2; -6; -3)	maar wel (0; 1; -3)	maar niet (1; 1; -2)
ja ik (0; -1; -5)	als ik (1; -3; -3)	ik al (3; -1; -3)	een nieuwe (1; -1; -2)
we gaan (-1; 1; -5)	ben ik (1; -3; -3)	een goede (-1; 0; -3)	zou ik (-2; 0; -2)
ziet er (1; -1; -5)	nog niet (-1; -1; -3)	niet echt (-1; 0; -3)	had ik (2; -3; -2)
wat is (1; 1; -4)	nog een (-1; -1; -3)	ik zit (0; -2; -3)	was een (-1; 0; -2)
ben je (0; 1; -4)	ik niet (-1; -2; -3)	ik in (1; 0; -3)	een hele (-2; 0; -2)
je wel (2; -1; -4)	ook nog (-2; 0; -3)	de beste (-2; -1; -3)	die van (0; 0; -2)
ga ik (2; -1; -4)	weer een (-1; 0; -3)	volgende week (-2; 0; -3)	fijne dag (0; 0; -2)

Note. Subset of the total 2,512,430 unique bigrams (frequency > 0.015%). The three T-scores represent Baseline-split I, Baseline-split II, and the CLC, respectively (see Figure 2.2). Negative T-scores indicate a decrease in relative occurrence and positive T-scores indicate an increase in relative occurrence.

The bigrams that occurred relatively more frequently post-CLC, in Table 2.7, comprise mainly prepositional phrases or preposition + article combinations (e.g., *van de, van het, door de, naar het, van een, om de, over de, aan de, over het, in het, met het, met de, om het, bij het, om een, voor het*; translations: *from the, from the, by the, to the, from a, about the, over the, in the, with the, about/over the, by the, around the, for the*), suggesting more detailed descriptions of the situation that is referred to in the tweets. Importantly, the introduction of extra prepositions can also explain the increase in sentence length after the CLC.

Table 2.7 Bigrams that Occurred Relatively More Frequently Post-CLC and Related T-scores (Baseline-split I; Baseline-split II; CLC)

van de (0; 5; 17)	met het (1; 1; 5)	van deze (-1; 0; 4)	is de (1; -1; 2)
dat de (-2; 3; 12)	is en (0; 1; 5)	bij de (1; 2; 3)	en een (1; -1; 2)
van het (1; 2; 11)	over het (-1; 2; 5)	dat het (-2; 1; 3)	in mijn (0; -1; 2)
en de (-1; 2; 11)	aan te (1; 0; 5)	om te (0; 0; 3)	uit de (0; 0; 2)
door de (0; 2; 10)	in een (0; 1; 4)	op het (0; 0; 3)	en niet (0; 1; 2)
van een (-1; 2; 8)	voor het (2; 0; 4)	op een (0; 3; 3)	al die (0; -2; 2)
naar het (-2; -5; 8)	dat ze (0; 3; 4)	en die (-1; 0; 3)	wat je (0; 1; 2)
dat er (0; 1; 7)	te maken (0; 3; 4)	is voor (1; 2; 3)	naar een (0; 1; 2)
om de (2; 2; 7)	dan ook (-1; -1; 4)	bij een (-1; 2; 3)	en wat (0; 2; 2)
aan de (0; 1; 6)	als de (0; 1; 4)	ze niet (0; 0; 3)	dat een (-1; 2; 2)
met een (0; 1; 6)	alleen maar (1; 1; 4)	en als (0; 1; 3)	nog eens (0; 0; 2)
over de (1; 2; 6)	er zijn (0; -1; 4)	aan een (0; -1; 3)	een andere (0; 3; 2)
en het (0; 1; 6)	meer dan (0; -3; 4)	over een (-1; 0; 3)	samen met (-1; 0; 2)
mensen die (4; 3; 6)	bij het (1; -1; 4)	uit te (-1; 0; 3)	is dan (1; 0; 2)
in het (0; 3; 5)	om een (2; 0; 4)	door een (1; 2; 3)	
met de (-1; 2; 5)	op te (0; 3; 4)	in de (1; 1; 2)	
en dat (3; 3; 5)	om het (1; 1; 4)	voor de (-1; 3; 2)	

Note. Subset of the total 2,974,471 unique bigrams (frequency > 0.015%). The three T-scores represent Baseline-split I, Baseline-split II, and the CLC, respectively (see Figure 2.2). Negative T-scores indicate a decrease in relative occurrence and positive T-scores indicate an increase in relative occurrence.

POS analysis

The second hypothesis about a potential increase in the use of adjectives, adverbs, articles, conjunctions, and prepositions, was tested using a POS analysis. Table 2.8 displays the relative frequencies of POS categories. Figure 2.9 presents the relative differences in POS usage after the CLC, compared with Baseline-split I and II. The CLC had a greater effect on POS usage as compared to baseline differences. Particularly, the CLC induced an increase in the usage of articles, conjunctives, and prepositions as compared to other POS categories. This increase means that the CLC changed the syntactic structures of tweets, which is also supported by the finding that sentence length increased. Unexpectedly, the relative frequency of adverbs and adjectives did not increase after the CLC. In addition, the difference between Baseline-split I and Baseline-split II shows more variation between week 3 and week 4 as compared to week 1 and week 2. This suggests a trend in the language usage initiated by the CLC.

Table 2.8 Part-of-Speech (POS) Distribution

	Pre-CLC		Post-CLC		Difference	
Part-of-Speech Category	**Percentage**	**CI 99%**	**Percentage**	**CI 99%**	**Post - Pre**	**Relative (%)**
Adjectives	8.68	[8.65, 8.71]	8.55	[8.52, 8.57]	0.13	-1.56
Adverbs	13.3	[13.27, 13.34]	12.94	[12.90, 12.98]	0.36	-2.71
Articles	6.21	[6.18, 6.23]	6.57	[6.54, 6.59]	-0.36	5.86
Conjunctives	5.42	[5.41, 5.45]	5.68	[5.66, 5.71]	-0.26	4.72
Interjections	0.44	[0.44, 0.45]	0.38	[0.38, 0.39]	0.06	-13.32
Nouns	23.68	[23.63, 23.74]	23.64	[23.58, 23.70]	0.04	-0.19
Prepositions	9.73	[9.70, 9.76]	10.11	[10.07, 10.14]	-0.38	3.85
Pronouns	12.99	[12.96, 13.03]	12.87	[12.83, 12.90]	0.12	-0.99
Verbs	19.54	[19.49, 19.58]	19.27	[19.23, 19.32]	0.27	-1.36

Note. All POS categories show no overlap in the 99% CI, except for nouns.

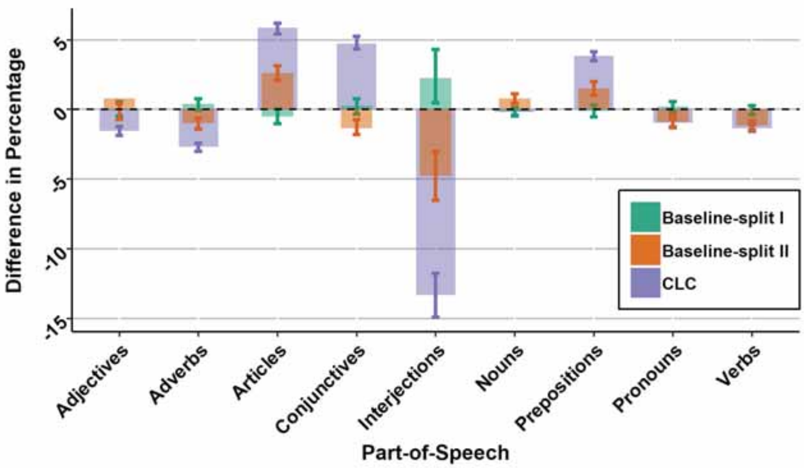


Figure 2.9. Relative difference in part-of-speech usage, error bars represent 99% CIs. This bar chart shows the effect of the CLC on the part-of-speech structure of sentences as compared to Baseline-split I and Baseline-split II (for time-frame specifications see Figure 2.1). The CLC induced an increase in the relative usage of articles, conjunctions, and prepositions. The relative usage of interjections decreased more than other categories and shows the highest baseline variance due to the relatively low frequency.

Conclusion and discussion

We investigated the effect of the character limit change (CLC) on the language usage in tweets. The results indicate that the CLC has, in fact, affected the language usage in tweets. The first hypothesis was supported; the pre-CLC tweets comprise relatively more textisms, such as shortenings, contractions, unconventional spellings, symbols and numerals. The second hypothesis was partially supported. As expected, the grammatical structure was affected by the CLC: post-CLC sentences are longer and comprise more articles, conjunctives, and prepositions than pre-CLC sentences. However, adjectives and adverbs did not increase in relative frequency. To discuss the results and implications, this section is structured as follows: first, we discuss an important insight about the results, that is, a change in the formality of language usage. After this, each of the investigated POS components are discussed separately. We conclude with possible interpretations of the results with regard to user behavior and limitations of our study.

Formality of language

The CLC seems to have brought about a qualitative change in language usage in tweets. Pre-CLC tweets contain relatively more informal language (i.e. textisms, self-referential pronouns, and interjection words), whereas post-CLC tweets show relatively more formal language usage. This change in formality is specifically evident in the relative frequencies of the personal pronoun *ik* (*I*) and the article word *de* (*the*), which decreased and increased respectively. Previous n-gram research has shown that the frequencies for *ik* and *de* are indicators of informal and formal language usage (Bouma, 2015). Particularly, *ik* is used very frequently in self-referential and subjective texts such as personal social-media messages. On the other hand, *de* is used relatively more frequently in neutral and objective texts such as news articles and books. The results suggest that the CLC has led to a general change in the formality of language usage on Twitter.

POS structure

Articles indicate whether a noun refers to a specific entity or to an unspecified entity or class of entities (e.g., ‘the house’ vs, ‘a house’). This information is not always essential, hence, articles can be excluded to save space or reduce the number of words, a strategy that characterizes both telegraphese and textese, (Carrington, 2004; Oosterhof & Rawoens, 2017). Articles occurred relatively more frequently after the CLC. With sufficient space, apparently, users prefer to include articles.

Conjunctions are used to link words, phrases, or clauses. The increase in conjunctions after the CLC may have multiple causes. Firstly, the relaxation of the previous restraining character limit means conjunctions are no longer ‘wasting’ character space, conjunctions do not necessarily have to be excluded anymore. Secondly, more available space also means there is more room for summations and subordinate clauses, thus, increasing the need for conjunctions. Another explanation for the increase in conjunctions is the pre-CLC usage of conjunctive symbols instead of words (e.g., '/', '+', '&' as compared to '*or*', 'and').

Prepositions indicate 'where' or 'when 'an object or an individual is in relation to something else. Prepositions can describe the spatial arrangement of entities (e.g., '*The tree is* ***in front of*** *the house.*'). However, they are also routinely extended to depict the relations between abstract ideas, such as intentions and contrasts (e.g., *'I wear overly casual clothing to work* ***despite*** *the criticism* ***from*** *my coworkers.*'). As opposed to articles and conjunctions, most prepositions cannot be excluded without changing the conveyed meaning (e.g., '*The three is [ ] the house')*. Remarkably, the CLC increased preposition usage, which suggests that the prepositional information was being withheld prior to the CLC, in order to save character space. This restraint results in a truncated version of the originally intended sentence.

Example (I):

Pre-CLC: *'It was a sunny beach day.'*

Post-CLC: *'It was a sunny day* ***on*** *the beach,* ***despite*** *some rain* ***in*** *the morning'.*

In contrast, some prepositions are omissible without changing the conveyed meaning (Rohdenburg 2002).

Example (II):

'They had difficulty [in] getting there in time.'

Both example (I) and (II) show how the relative frequency of prepositions may have increased post-CLC. However, only example (I) suggests that information was being withheld. Interestingly, the bigram analysis showed that the CLC especially increased the usage of preposition and article combinations (e.g., *by the, from the, to a),* which appear to add non-omissible prepositional information. This finding supports the notion that information was being withheld and some sentences were obligatory truncated pre-CLC, much like example (I).

As opposed to prepositions, there was no increased usage of *adjectives* and *adverbs*. In fact, the relative usage of adjectives and adverbs *decreased* somewhat post-CLC. Adjectives and adverbs modify nouns and verbs and describe features of entities, actions, and events. For example: *'These shoes are* ***too*** (i.e., adverb) ***small*** (i.e., adjective).' This featural information is, perhaps, too important to be excluded from a message. When a user has to decrease word usage to remain with the character limit, it appears prepositional information is considered as expendable, whereas information related by adjectives and adverbs is regarded as indispensable. Consider the following example:

1. ‘It was so nice to see my old friends and teachers from high school at the reunion.’ (i.e., the original message).
2. ‘Great reunion: nice to see my old high-school friends/teachers again.’ (excluding prepositions, articles, and conjunctions)
3. ‘My friends and teachers from high school were at the reunion.’ (excluding adjectives and adverbs)

Example 2 is clearly a more faithful rendition of the original message than example 3. Adjectives and adverbs are mainly used to describe feelings and/or opinions, which better represents the crux of a message than prepositional information. This could explain why adjective and adverb usage did not increase after the CLC.

Interjections show the largest decrease in relative frequency, see Figure 2.8. The term ‘interjection’ is a descendent from the Latin words ‘inter’ and ‘jacĕre’ (i.e., ‘to throw’). An interjection is ‘thrown’ between sentences and represents a sudden expression of feelings (e.g., ‘Oh my!’, ‘Wow!’, ‘Haha’). Short replies mainly comprise interjections, and importantly, these interjections require very little character space. This means that the previous limit of 140 characters was already sufficient for the use of interjections. Any additional character space would therefore not be likely to affect interjection usage. This explains the relative decrease in interjection frequency compared to the other POS categories. Furthermore, the relatively low frequency of interjections also explains the higher baseline error variance as compared to the other categories.

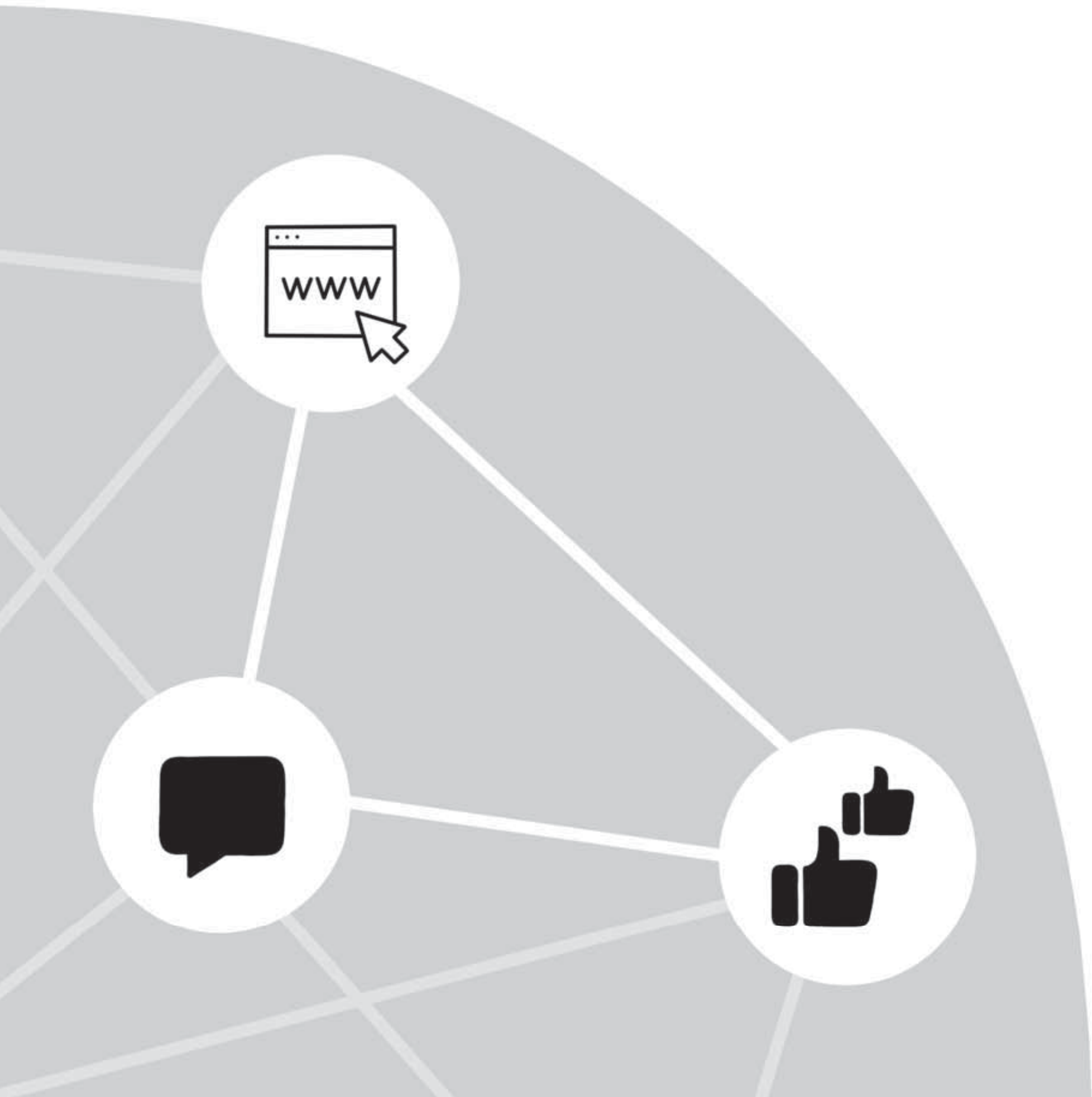
In conclusion, the character limit change has affected language use in tweets in our sample. Tweets contained more articles, conjunctions, and prepositions, as well as relatively more formal language and relatively less informal language (i.e., textisms and interjections) after the limit change. Before the CLC, a group of users were being constrained in the conveyance of their message; post-CLC, these users obtained the character space they need. As our results show, doubling the character limit reduced the observed hindrance by a factor of ten. Therefore, the 280 characters limit appears to be much more sufficient than 140 characters to convey messages on Twitter. The new limit might appear to be a gold standard for Twitter. However, it is conceivable that, as users become more familiar with the new limit, the number of characters will increase over time. As suggested by the Baseline-split II analysis, the language usage evolves as subsequent trend of the CLC. Future research could show whether the character and language usage remains consistent or not.

Future research may also address whether the effects of the CLC in Dutch tweets are observable in other languages as well. That is, a decrease in the usage of textisms and an increase in the usage of articles, conjunctions, and prepositions. The underlying rationale being that the CLC effects are likely to be related to the function of these words and the type of information they convey, rather than the language itself. That being said, the character efficiency of the language could potentially moderate the CLC effects. Particularly, a language that is more character-efficient would be less constrained by a length limit as compared to a less character-efficient language.

An inevitable limitation of the current design is the confounding effect of natural events on the public language usage. The use of certain words can be event related. To assuage the potential impact of these confounds we removed tokens and bigrams that showed higher baseline variance as compared to the CLC-effect. However, to fully eliminate issues related to natural events, one may devise an experimental study to investigate the effect of a CLC on language usage. A CLC-dependent effect on language usage could be tested while controlling for any natural confounds (i.e., topic and event-related effects), that are bound to occur in observational studies. However, an experimental setting would reduce the ecological validity of the study. Therefore, the current study would be complementary to an experimental study.

Text-limit constraints in Tweets affect language usage, as we found in the current study. The relaxation of the character limit constraint means that writers are less likely to adapt their intended message by using strategies to compress it. Without constraints there is less need for economy of expression. The doubling of the character limit in Twitter has considerably decreased the need to compress messages. With the new limit of 280 characters, more users finally have the character space to express their thoughts. Our findings show that online language production can be affected by the character limit constraints of the medium. If necessary, language producers adapt their texts to overcome these constraints.

CHAPTER 3



The processing and evaluation of news content on social media is influenced by peer user commentary

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Abstract

Contemporary news often spreads via social media. This study investigated whether the processing and evaluation of online news content can be influenced by *Likes* and *peer-user comments*. An online experiment was designed, using a custom-built website that resembled Facebook, to explore how Likes, positive comments, negative comments, or a combination of positive and negative comments would affect the reader's processing of news content. The results showed that especially negative comments affected the readers' personal opinions about the news content, even in combination with other positive comments: They (1) induced more negative attitudes, (2) lowered intent to share it, (3) reduced agreement with conveyed ideas, (4) lowered perceived attitude of the general public, and (5) decreased the credibility of the content. Against expectations, the presence of Likes did not affect the readers, irrespective of the news content. An important consideration is that, while the negative comments were persuasive, they comprised subjective, emotive, and fallacious rhetoric. Finally, negativity bias, the perception of expert authority, and cognitive heuristics are discussed as potential explanations for the persuasive effect of negative comments.

The rise of social media has introduced virtually unlimited communication and unprecedented access to information. Information conveyed via social media is complemented with several social cues reflecting a variety of user interactions. Some examples are peer-user comments, Likes, favourites, recommendations, number of views, user-created content, user profiles, personal playlists, consumer reviews, and user ratings. Likes (i.e., favourites) and user comments are perhaps the most ubiquitous and universally implemented features across different social media platforms (e.g., Facebook, Twitter, Instagram). The current experimental study investigated how social media users are being affected by Likes and user comments when they process social media content. We used five distinct outcome variables: attitude, share intent, ideological congruence (i.e., level of agreement with the content), perceived public attitude, and credibility. These variables were partially adapted from previous studies (Appelman & Sundar, 2015; Winter et al., 2015; Xu, 2013).

Conformity behaviour in groups has been a key research topic in psychology. The early Asch paradigm studies have shown that individuals tend to change their judgements to conform to the majority group (Asch, 1951, 1955, 1956). In literature about opinion formation processes, conformity to public opinions has been referred to as the *bandwagon effect* (Nadeau et al., 1993). The bandwagon is a metaphor for a popular activity. This metaphor originates from nineteenth century American parades, in which a wagon would carry a band playing music to attract followers (Schmitt-Beck, 2015). The bandwagon effect describes how individuals adapt their own opinions to conform to the public's opinions. This phenomenon has been referred to as a cognitive bias known as the bandwagon heuristic (Sundar, 2008), and has also been related to the consensus heuristic, the cognitive bias to perceive the majority's opinion as the correct one (Mutz, 1998). On social media, Likes and user comments can be perceived as the metaphorical 'bandwagon', reflecting the popular attitudes and opinions among peer social media users. In turn, these social cues have been shown to persuade other users that observe these posts, an evident bandwagon effect. For example, Likes have previously been shown to increase the likeability of the content and the probability that the observer will also hit the Like button (Bak & Kessler, 2012; Sherman et al., 2016). The bandwagon effect predicts that social media users adapt their own beliefs, attitudes, and opinions to match that of their peers (Kim, 2018; Lowe-Calverley & Grieve, 2018; Sundar, 2008; Waddell, 2017b). In the current study, we investigated whether Likes and comments can cause a bandwagon effect on the processing and evaluation of news content on a social networking site.

Likes

The Like button and similar social-media features (e.g., *Favourite, Upvote, +1*) have been conceptualized as paralinguistic digital affordances (PDAs); communicative cues within social media without a specific predefined meaning (Hayes et al., 2016). The Like button reflects a leading aspect of user engagement: a single-click social tool that, at the surface level, enables users to express enjoyment or share their interest for specific content. However, its affordance and meaning have been shown to extend its phatic design. For example, the Like button is also used for social support, to maintain social ties, and as a tool for impression management (Carr et al., 2016; Eranti & Lonkila, 2016; Hayes et al., 2016; Ozanne et al., 2017). Altogether, the Like button is a central feature of the social-media environment. Likes are utilized and observed by billions of social media users, which emphasizes the importance of investigating its influence.

In contrast to previous studies, we compared the presence with the omission of Likes. Previous experimental studies have compared the effects of "low" and "high" number of Likes (e.g. Winter et al., 2015). However, the effects of inclusion and omission of Likes on user cognition have rarely been examined. In April of 2019, Instagram announced that the company was planning to hide the number of Likes from its users because it did not want Instagram "to feel like a competition" (Rodriguez, 2019). Facebook (owned by the same company) also started a trial of selectively omitting Likes to reduce the negative impact of social comparison ("Facebook to hide number of likes", 2019). Considering these recent developments, we considered it especially relevant to investigate the cognitive implications of the omission compared to the presence of Likes. We hypothesized that Likes affect the observer's content processing and evaluation by creating a bandwagon effect. More specifically, we expected Likes to improve (a) attitude towards the content, (b) the likelihood that the reader will share or recommend the content, (c) agreement with ideas conveyed in the content, (d) the perceived public attitude, and (e) the credibility of the content (**H1**).

Peer-user comments

A second variable that we manipulated in our experiment was the presentation of user comments. Previous studies have shown that the presence of comments affect the perception and evaluation of online news articles. They can increase or decrease the acceptance and attitudes of the reader (Kim, 2018; Waddell, 2017b, 2017a; Winter et al., 2015). As with Likes, the psychological mechanism for the effect of comments has been framed in terms of the bandwagon heuristic (Sundar, 2008; Waddell, 2017a). Online news readers use peer comments as cues that are representative of the general public's opinion, which influences their own attitude towards the content (Kim, 2018).

Furthermore, comments can lower the perceived credibility when they are used as a quote or a source of evidence within a news article (Waddell, 2017b). However, if comment sections include uncivil language, they can increase the perceived credibility of the main article due to a contrast effect (Thorson et al., 2010).
Peer comments provide additional information to the reader, which can consist of objective or subjective content. An objective comment is factual, based on evidence and logic, or verifiably true or false. An example:

> *"Greta Thunberg is a young environmental activist because, as a teenager, she has approached and challenged multiple world leaders to mitigate climate change". (Example 1)*

A subjective comment, on the other hand, is based on opinions or personal anecdotes, which cannot be independently verified or refuted. Hence, subjective comments are not necessarily grounded in reality. An example:

> *"Greta Thunberg is a hero. She's brave enough to do what many people are thinking but are too afraid to act on. I hope more world leaders take her message seriously." (Example 2)*

Hinnant, Subramanian, and Young (2016) investigated the effects of anecdotal versus scientific evidence in comments on an article about climate change. As might be expected, comments that invoked scientific evidence had a greater influence on the readers' attitude than comments that invoked anecdotal evidence. However, for conservative readers with low need for cognition (a construct that represents the joy of engaging in one's own thought processes), even anecdotal rhetoric was found to influence the perceived credibility and disrupt the intended message of the story (Cacioppo & Petty, 1982). Further examination of this susceptibility to subjective comments is crucial to understanding online behaviour and cognition in an era of mounting 'fake news', misinformation, and disinformation, where anyone can join online debates or add commentary to websites' comment sections (Lazer et al., 2018). Therefore, in addition to Likes, we investigated the effect of different comment types on the observer.

In this study, participants encountered either positive, negative, no comments or a combination of positive and negative comments. These comments comprised subjective statements (as shown in Example 2), emotive language and/or fallacious rhetoric. We hypothesized that the reader's content processing and evaluation would be affected by the presence of these comment sections. Based on a bandwagon effect, we expected positive comments would improve whereas negative comments would impair (a) attitude towards the content, (b) the likelihood the reader will share or recommend the content, (c) agreement with ideas conveyed in the content, (d) the perceived public attitude, and (e) the credibility of the content (**H2**).

Similar to the current study, Winter and colleagues (2015) investigated the effects of peer comments and Likes on Facebook news channels and the related psychological mechanisms of information processing. In their online experiment, participants saw a summary of an online news story on a Facebook page including comments and Likes. The type of comments and the number of Likes were manipulated in a 5 x 2 between-subjects design. The comment types were either positive or negative and either subjective or argumentative (i.e., objectively and independently verifiable or refutable arguments), which rendered four different comment conditions including a fifth condition without comments. The number of Likes was either "low" (around 40) or "high" (around 500). Subsequently, participants read the original article after which they answered questions about their attitude toward the topic, perceived public opinion, evaluation of the article (i.e., writing style, usefulness, and likeability), and credibility of the text.

Against the authors' expectation of bandwagon heuristics, no conformity effects of Likes were found. In other words, the number of Likes did not influence the readers' evaluation of the news article. Negative comments were found to be more persuasive than Likes and positive comments. The authors explained this based on a ceiling effect; readers had a high level of agreement with the ideas conveyed in the article. Therefore, information of negative valence aroused more attention (Winter et al., 2015). Thus, positive comments as well as Likes (i.e., a positive expression) did not show further strengthening effects. The authors suggested that this interpretation could be tested with a variation of the slant of the article (i.e., ideas conveyed in the article), without making further suggestions for the kind of content. In their experiment, the article that was presented to the readers described arguments from a professor in economics against the prohibition of marijuana, proposing that legalization of the drug would lead to more control. The slant of the content was ideologically progressive and liberal. Therefore, the content may have caused for high levels of agreement in participants, comprising mainly European academic students.

Hypothetically, if high agreement with the content decreases the influence of Likes and positive comments due to a positive ceiling effect, then initial disagreement with the content could potentially prevent a positive ceiling effect and increase the influence of Likes and positive comments. Therefore, we expected that Likes and positive comments would have a greater influence on the reader's attitude towards social-media content if the reader has a negative predisposition as compared to a positive predisposition towards the content (**H3**).

The relatively small effects of positive comments and likes as compared to negative comments in the study of Winter and colleagues could also be ascribed to a negativity bias. Previous studies have shown the prevalence of negativity bias; generally, negative information induces stronger psychological effects than neutral and positive information (Baumeister et al., 2001; Ito et al., 1998; Norris, 2019; Rozin & Royzman, 2001). Therefore, we expected that negative comments in the current experiment should have greater influence on the reader than positive and neutral comments. Furthermore, we expected that this negativity bias would persistent across different ideological dispositions towards the article. More specifically, negative comments should have a greater influence on the reader's attitude towards social-media content than positive comments, irrespective of the reader's personal disposition towards the content (**H4**).

Another explanation for the lack of strengthening effects of Likes in the study by Winter and colleagues might be related to the experiment's ecological validity. Participants viewed a static and non-interactive screenshot of a Facebook page. Arguably, the social cues on this static image were less meaningful to the user than social cues in an interactive social-media interface. In addition, a static image of a Facebook page may induce unnatural behaviour. For instance, participants are more likely to second-guess the experimental manipulation and the experimenter's hypothesis. To ensure the ecological validity of the current experiment, participants performed the task using an ostensibly real and interactive social-media interface.

Content types

In the current study we compared the effects of Likes and comments between different content types. Specifically, the article contents would engender a variety of attitudes in the readers: either agreeing, disagreeing, or neutral dispositions. Considering the cohort and background of the subject pool for the current study (psychology students at Erasmus University Rotterdam) it was assumed that they tend to have more liberal than conservative ideologies (Inbar & Lammers, 2012; Pohl et al., 2021). This assumption has led to the selection of three news reports, each assumed to induce a certain attitude in the participant:

1. *Ideologically congruent* – A news article about a meeting between climate activist Greta Thunberg and Canadian president Justin Trudeau. We assumed that most participants would agree with Greta Thunberg's climate activism. Therefore, participants would predominantly have a positive predisposition towards the content of this article.
2. *Ideologically incongruent* – A news article about a study reporting a relationship between violent video games and aggressive behaviour. Considering the cohort and age of the participants, they were assumed to have more progressive ideas and to be likely to have a personal affinity for video games (e.g., 92% of people between the ages 16 and 24 years play video games in the UK; Statista, 2021). Thus, participants were assumed to have a more negative predisposition towards the content of this article.
3. *Ideologically neutral* – A news article about an upcoming tropical storm near the coast of Ireland. This article described a mere weather phenomenon, which did not convey an explicit ideology.

Comparing the effect of Likes and peer comments between different types of content would yield comprehensive findings. Specifically, it would show how Likes and peer comments affect information processing under different reader dispositions. Accordingly, we hypothesized that if the article content is ideologically neutral, then the reader would neither agree nor disagree with the content. Therefore, likes and comments should have a greater influence (i.e., bandwagon effect) on the reader's attitude than if the article content conveys an ideology. Thus, Likes and comments should have a greater influence on the reader's attitude towards ideologically neutral content as compared to content with an ideological slant (**H5**).

The experiment

A custom website, using a similar interface as Facebook, was designed for this study. This site contained news articles and complementary social cues. A copy of the original website can be viewed online (https://online-task-anonymous-example.netlify.app/). We highlight five key features of the current design: (1) The experiment compared the presence of Likes with the omission of Likes, investigating the effect of the contemporary trend of omitting Likes in social media platforms. (2) The Likes were added to the original article, but they were also added to the comments, as often seen in social media formats. (3) The comments only comprised subjective rhetoric (see Example 2 and Figure 3.1), no objective comments such as Example 1 were presented. (4) To investigate the effect of the overall valence or sentiment of the comments, four conditions were compared: positive comments, negative comments, positive and negative (mixed) comments, and no comments (control). (5) To examine the interaction between comments and the reader's ideological disposition, three different news articles were used: an ideologically congruent article, an ideologically incongruent article, and an ideologically neutral article.

Figure 3.1. Example of mixed comment section and Likes manipulations. This comments section manipulation was presented to participants in group 5 (see Table 3.1). These comments and Likes (both under the article and under the comments) were presented below a news article about Greta Thunberg. The comments only comprised subjective rhetoric.

The current experiment resembles the research design by Winter et al. (2015), however there are some key methodological differences and extensions. Firstly, we used an interactive html-based website that participants could browse on their personal computer, simulating a more personal online experience. The website contained more realistic interactive elements such as selectable texts, navigation bars, buttons, and cover image slideshows. Secondly, multiple news contents were presented as opposed to one news article, which were assumed to create a variety of predispositions within the readers, that in turn, could interact differently with the complementary Likes and comments. Furthermore, the comment manipulation in the current experiment also included an additional condition that was not included by Winter at al., a mixed comments condition including both positive and negative comments. The Likes manipulation was different on two aspects: (1) comparing the presence of Likes with the omission of Likes rather than comparing a high and a low number of Likes, and (2) the Likes were presented under the main news article as well as under each individual comment. Finally, in addition to the outcome measures *ideological congruence*, *perceived public attitude*, and *credibility*, that are comparable to the measures used by Winter et al., we also added *share intent* and general *attitude.*

Outcome variables

After reading each article, participants rated a set of statements reflecting five different categories: attitude, share intent, ideological congruence, perceived public attitude, and credibility (see Table 3.2 for an overview of the items). These variables were partially adapted from previous studies (Appelman & Sundar, 2015; Winter et al., 2015; Xu, 2013): (a) *attitude* – the reader's personal disposition towards the content, (b) *share intent* – the reader's intension to share or recommend the content, (c) *ideological congruence* – the extent to which the reader agrees with content-conveyed ideas, (d) *perceived public attitude* – the reader's perception of the general public's attitude towards the content, and (e) *credibility* – the reader's perception of the credibility of the content. In this study, these categories were considered to adequately reflect content processing and evaluation.

Methods

Preregistration

This study was preregistered on Open Science Framework. We preregistered our hypotheses, study design, sample size, analysis type, exclusion criteria, and statistical inference criteria [https://osf.io/d37f5].

Participants

This study was approved by the Ethics review Committee DPECS at Erasmus University Rotterdam (application reference 19-043). All participants provided their informed consent before participating in this study. A total of 560 students, first and second year bachelor Psychology students from Erasmus University Rotterdam, participated in the experiment. Participants were excluded from the analysis if their time spent on the reading task was shorter than two minutes, which ensured all participants in the analysis carefully read the article. Moreover, participants were excluded if they did not complete the questionnaire. In addition, data from four participants were removed because they used a mobile operating system to perform the task. The final sample size comprised 412 participants (330 females, $Mean_{age}$ = 20.52, SD = 2.85). Demographic details of the sample can be found in Supplementary Table S3.1 (Appendix B).

Design and materials

The experiment was an online task that participants could perform on their own computer. We designed and built a website that was ostensibly similar to the graphical user interface of Facebook and other social networking sites (for an interactive example see the link in Table 3.1). Three news articles were presented on this website: an article about climate activist Greta Thunberg, an article about a tropical storm near the coast of Ireland, and an article about a study that found a relation between violent video games and behaviour. The latter article was slightly altered so that it more strongly conveyed the idea that this relation was true, leaving out subtle nuances that were in the original article. The three news articles were adapted from the English newspaper the Guardian and showed consistent writing style and structure. Each article reflected a different content type (within-subject variable): ideologically congruent, neutral, and incongruent. The articles were complemented with two types of social cues: Likes and user comments, which were manipulated to one of eight between-subject conditions (see Table 3.1). The mixed comments condition, presented in Figure 3.1, comprised a combination of two positive and two negative comments, which were identical to half of the comments in the positive and negative comments conditions. An interactive example of the experiment, containing all Web elements, can be viewed at https://online-task-anonymous-example.netlify.app/. Each experimental condition can also be viewed in Supplementary Materials (non-interactive pdf format) https://osf.io/mq2g8/?view_only=e39096a2e93842e193d8518771985272. The Likes were presented both below the news article and under each comment as shown in Figure 3.1.

Table 3.1 Between-subject Conditions in the Online Experiment

Between-subject conditions	Likes presented	Likes omitted
Positive comments	Group 1 (dprz)*	Group 2 (wgdy)
Negative comments	Group 3 (fspc)	Group 4 (pdrt)
Mixed (positive and negative comments)	Group 5 (rdts)	Group 6 (wphj)
No comments	Group 7 (ypdt)	Group 8 (cnfp)

Note. This is an overview of the eight between-subject conditions. *Each condition can be viewed using the unique code on the example website https://online-task-anonymous-example.netlify.app/ or they can be viewed as non-interactive examples in Supplementary Materials on OSF (https://osf.io/mq2g8/?view_only=e39096a2e93842e193d8518771985272). Each participant browsed three different news articles.

Procedure

Participants were randomly assigned to one of eight conditions and were instructed to use a computer and minimize potential distractions and disturbances. They received a link to the experiment and a complementary code to start the task. To start the task, participants provided their informed consent and entered a specific four-letter code. After an introductory page, participants read three news articles, each followed by an embedded Qualtrics software survey. The order of within-subject conditions (i.e., article-content type) was based on block randomization, beginning with either congruent or incongruent content types, followed by the neutral content type, and ending with either the congruent or incongruent content type. Subsequently, the participants filled out a questionnaire regarding personal social-media usage and demographic traits. Finally, a debriefing page was used to inform participants about the diminished veracity of the altered article about violent video games and aggression.

Measures

Five outcome variables, reflecting content processing and evaluation, were assessed using seven-point scale ratings, see Table 3.2 for an overview of the items.

Table 3.2 Outcome Variables with Internal Consistencies, Descriptions, and Items

Variable; Internal consistency	Description	Items (i.e., statements)
Personal attitude; Cronbach's alpha= .81	Disposition of the reader towards the article	*"I feel positive about the article"* *"I consider this news to be valuable"* *"I like this article"*
Share intent Cronbach's alpha= .86	Expected behavioural/social response	*"I would recommend this article to my friends"* *"I would hit the Like button"* *"I would share this article with my friends"*
Ideological congruence (ideologically congruent article); Cronbach's alpha= .77*	The extent to which the reader agrees with ideas conveyed in the article about climate activist Greta Thunberg	*"Greta Thunberg is doing great work as an environmental activist"* *"Greta Thunberg's meeting with Canadian prime minister, Justin Trudeau, was a success"* *"Justin Trudeau will act on climate and support Great Thunberg's cause"*
Ideological congruence (ideologically neutral article); Cronbach's alpha= .77*	The extent to which the reader agrees with ideas conveyed in the article about a tropical storm	*"Hurricane Lorenzo is dangerous"* *"People should prepare for Hurricane Lorenzo"* *"People should be concerned about the potential impact of Hurricane Lorenzo"*
Ideological congruence (ideologically incongruent); Cronbach's alpha= .77*	The extent to which the reader agrees with ideas conveyed in the article about violent videogames and aggression	*"Violent video games induce aggressive behaviour"* *"Kids who play violent video games think violence is acceptable in real life"* *"Parents should limit their kids' exposure to violent video games"*
Perceived public attitude (i.e., bandwagon perception); Cronbach's alpha= .85	The readers perception of the general public's opinion about the article	*"The general public feels positive about this article"* *"The general public considers this news to be valuable"* *"The general public likes this article"*
Credibility; Cronbach's alpha= .81	The readers perception of the credibility of the article's content	*"How well do the following words describe the article's content?" – "Accurate" – "Authentic" – "Believable"* (Three separate items)

Note. Seven-point-scale ratings were used for the items. Each of the five categories was measured separately for each article; the items were identical across articles, except for the category ideological congruence.

Analysis

We used a sequential-analyses design (Lakens, 2014). This means we performed an interim analysis using a predetermined sample size and decided to end data collection based on the predetermined inference criteria (see preregistration on OSF). We corrected for alpha inflation using the O'Brien-Fleming procedure, alpha = .011. Mixed factorial ANOVAs (2x4x3) were performed for each outcome variable, testing main effects and interaction effects of Likes (between-subjects; 2 levels; omitted vs. presented), comments (between-subjects; 4 levels; positive, negative, mixed, and no comments), and article-content type (within-subjects; 3 levels; congruent, incongruent, and neutral). Mauchly's test was used to determine whether the assumption of sphericity was violated. Greenhouse-Geisser estimates of sphericity were used to correct the degrees of freedom. Article-content type was a within-subjects variable that violated the sphericity assumption across all five outcome variables (attitude, W = .977, p = .009, ε = .98; share intent, W = .977, p = .008, ε = .98; ideological congruence, W = .935, p < .001, ε = .94; perceived public attitude, W = .983, p < .001, ε = .98; credibility, W = .896 p < .001, ε = .91). Bonferroni corrections were used to adjust p-values for multiple comparisons.

Results

We report five mixed factorial ANOVAs post-hoc analyses for each of the outcome variables *attitude*, *share intent, ideological congruence, perceived public attitude,* and *credibility*.

Attitude

We found a significant main effect of comment sentiment on attitude, $F(3, 404) = 4.19$, $p = .006$, generalized $\eta2 = .013$. Pairwise comparisons revealed a significant difference between *positive* and *mixed* comments, $p = .002$, and a significant difference between *positive* and *negative* comments, $p = .008$. Figure 3.2 shows that negative and mixed comment sentiments (i.e., negative and positive comments) induced more negative attitudes towards the article content as compared to positive comments. Moreover, we found an interaction effect (although above the alpha level of .011) between article-content type and comments, $F(6.14, 826.70) = 2.39$, $p = .028$, generalized $\eta2 = .010$. This interaction effect can be seen in Figure 3.3: without comments, participants were relatively more positive about the congruent article and relatively more negative about the neutral article. Finally, we found a significant main effect of article-content type on attitude, $F(2.05, 826.70) = 13.21$, $p < .001$, generalized $\eta2 = .018$ (see Supplementary Figure S3.1 in Appendix B), but there was no effect of the Likes condition on attitude, $F(1,404) = 0.83$, $p = .362$.

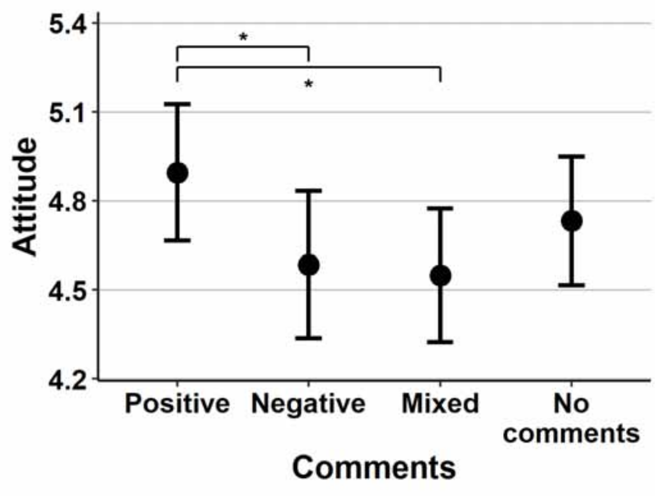


Figure 3.2. Main effect of comment sentiment on attitude. Participants viewed news content on a manipulated but ostensibly real social networking site. We manipulated the sentiment of user comments to be either positive, negative, both (i.e., 'mixed'), or no comments. Error bars represent 95% CIs, significant differences (p < .011) are indicated with asterisks.

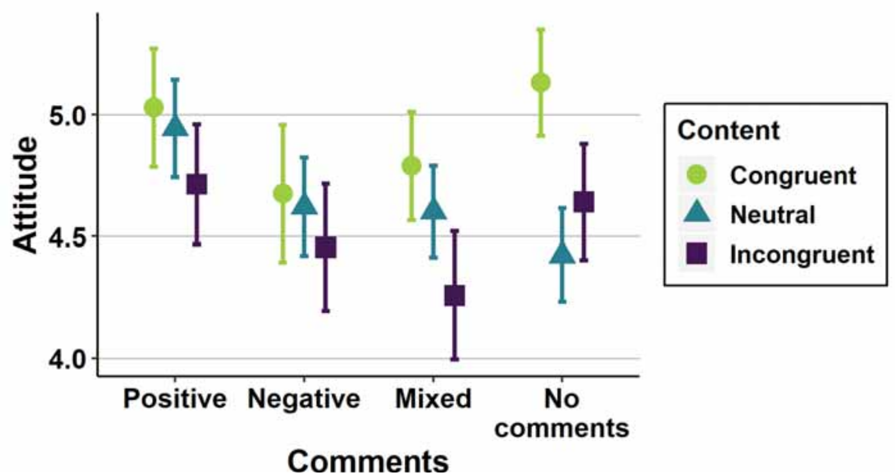


Figure 3.3. Interaction effect of comment sentiment and article-content type on attitude. Participants viewed three news articles on a manipulated but ostensibly real social networking site. The ideas conveyed by the article contents were assumed to be congruent, neutral, and incongruent with the participants' ideological dispositions. Error bars represent 95% CIs.

Share intent

There was a significant main effect of comments on share intent, $F(3, 404) = 4.52$, $p = .006$, generalized $\eta 2 = .004$. Pairwise comparisons revealed a significant difference between *positive* and *mixed* comments, $p = .002$, and a significant difference between *positive* and *negative* comments, $p = .003$. However, the difference between *no comments* and *mixed* was nonsignificant, $p = .013$ (pre-determined alpha level was .011). Similarly, *no comments* and *negative comments* were not significantly different either, $p = .019$. Figure 3.4 shows that readers were considerably less likely to share the article if it was complemented with negative or mixed comments as compared to positive comments. Furthermore, we found an interaction effect (above the alpha level of .011) between article-content type and comments, $F(6.14, 826.91) = 2.16$, $p = .045$, generalized $\eta 2 = .007$. Figure 3.5 shows that the overall presence of comments decreased the willingness to share the congruent article-content compared to no comments. Finally, we found a significant main effect of article-content type on share intent, $F(2.05, 826.91) = 11.60$, $p < .001$, generalized $\eta 2 = .013$ (see Supplementary Figure S3.1 in Appendix B), but there was no effect of the Likes condition on share intent, $F(1,404) = 0.09$, $p = .761$.

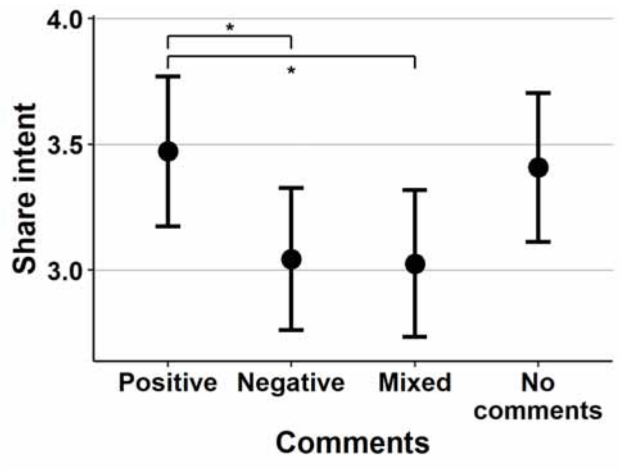


Figure 3.4. Main effect of comment sentiment on share intent. Error bars represent 95% CIs, significant differences (p < .011) are indicated with asterisks.

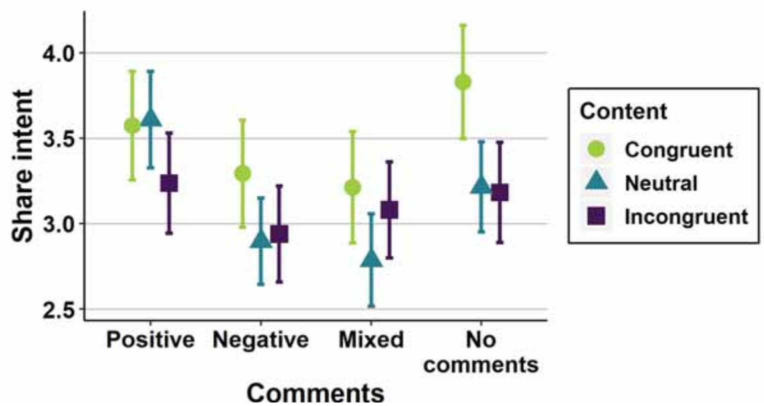


Figure 3.5. Interaction effect of comment sentiment and article-content type on share intent. Error bars represent 95% CIs.

Ideological congruence

There was a significant main effect of comments on ideological congruence, $F(3, 404) = 12.15$, $p < .001$, generalized $\eta 2 = .039$. Pairwise comparisons showed significant differences between all comment types, $p < .001$, except for positive and no comments, and negative and mixed comments. In Figure 3.6 can be seen that for both negative and mixed comments the readers showed less agreement with ideas conveyed in the article as compared to positive comments or no comments. Moreover, we found a significant main effect of article-content type on ideological congruence, $F(2.13, 860.51) = 103.07$, $p < .001$, generalized $\eta 2 = .123$ (see Supplementary Figure S3.1 in Appendix B). However, we did not find a significant interaction effect between article-content type and comments, $F(6.39, 860.51) = 1.89$, $p = .079$, and there was no significant main effect of Likes on ideological congruence, $F(1,404) < 0.01$, $p = .995$.

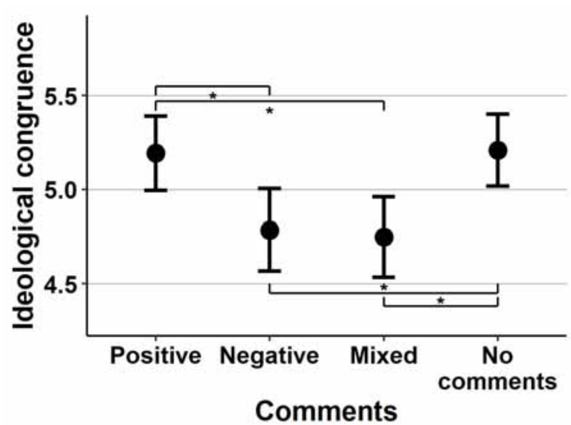


Figure 3.6. Main effect of comment sentiment on ideological congruence. Error bars represent 95% CIs, significant differences (p < .011) are indicated with asterisks.

Perceived public attitude

We found a significant main effect of comments on perceived public attitude, $F(3, 404) = 87.22$, $p < .001$, generalized $\eta 2 = .248$, and a significant interaction effect between article-content type and comments, $F(6.10, 821.93) = 3.07$, $p = .006$. Figure 3.7 shows that comment sentiment had a greater effect when complementing the neutral article-content. Furthermore, pairwise comparisons of the comment conditions revealed significant differences between all comment types, $p \leqslant .007$. Figure 3.7 shows that the perceived public attitude was highly affected by comment sentiment. Positive comments induced the most positive perceived public attitude and negative comments induced the most negative perceived public attitude. Finally, we found a significant main effect of article-content type on the perceived public attitude, $F(2.03, 821.93) = 10.01$, $p < .001$, generalized $\eta 2 = .012$, but there was no effect of the Likes condition, $F(1,404) = 0.21$, $p = .644$.

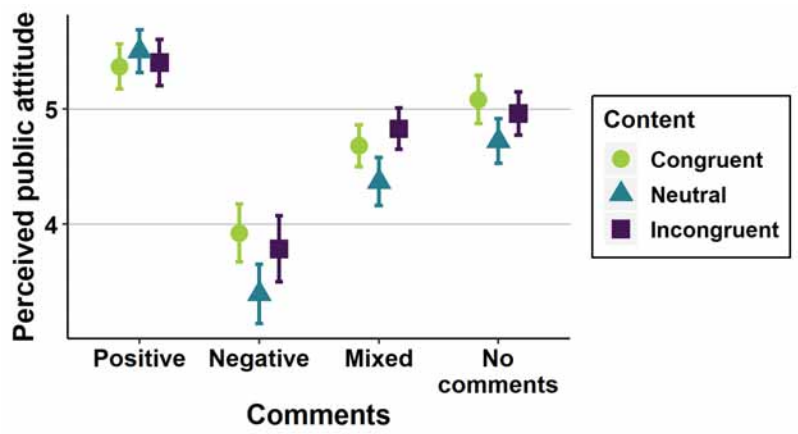


Figure 3.7. Interaction effect of comment sentiment and article-content type on perceived public attitude. Error bars represent 95% CIs.

Credibility

We found a significant main effect of comments on credibility, $F(3, 404) = 8.68$, $p < .001$, generalized $\eta 2 = .030$. Pairwise comparisons of the comments showed significant differences between all comment types, $p \leqslant .001$, except for positive and no comments, and negative and mixed comments. Figure 3.8 illustrates how the credibility of the article was affected by presence of a comment section: both negative and mixed comments decreased the credibility as compared to positive comments or no comments. Moreover, we found a significant main effect of article-content type on the credibility, $F(2.21, 891.72) = 77.97$, $p < .001$, generalized $\eta 2 = .092$ (see Supplementary Figure S3.1 in Appendix B). However, we did not find a significant interaction effect between article-content type and comments, $F(6.62, 891.72) = 1.55$, $p = .159$, and there was no significant main effect of Likes, $F(1,404) = 1.41$, $p = .236$.

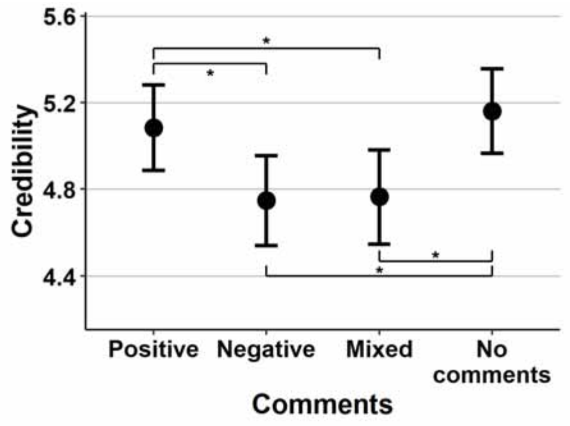


Figure 3.8. Main effect of comment sentiment on credibility. Error bars represent 95% CIs, significant differences (p < .011) are indicated with asterisks.

Discussion

We investigated how Likes and user comments influenced the readers' processing and evaluation of news articles on social media. The comment sections, manipulated in our online experiment, affected the readers' content processing and evaluation. Particularly, the presence of negative comments (1) negatively affected the readers' attitude towards the news article, (2) reduced the likelihood the reader would share or recommend it, (3) reduced agreement with ideas conveyed in the article, (4) engendered the perceived public attitude more negatively, and (5) even reduced the credibility of the article. Importantly, participants were not instructed to read or utilize the comment sections to form their opinions. Nevertheless, their opinions were, in fact, influenced by comments comprising subjective, emotive, and even fallacious rhetoric.

In the current study, the presence of Likes had no effect on the readers' content evaluation. Thus, we found no evidence to support our first hypothesis (H1). This means we did not observe a bandwagon effect of the Likes. However, in line with our second hypothesis (H2), we found that negative comments had a negative effect on the readers' content evaluation. Analyses of main effects of comment sentiment showed positive comments did not affect the reader as much as negative comments did (see Figure 3.2). However, analyses of interaction effects between article-content type and comment sentiment revealed positive comments had different effects based on the predisposition towards the article (see Figure 3.3 and Figure 3.5). Particularly, the group that was presented with positive comments below the ideologically *congruent* article (i.e., news article about Greta Thunberg) showed relatively more negative attitudes and less intention to share the content compared to the group that was not presented with comments. However, when the ideologically *incongruent* article (i.e., news article about a relation between videogames and aggression) was presented with positive comments the effects were much smaller. Hence, our third hypothesis (H3), that a negative predisposition would increase the effect of positive comments compared to a positive predisposition, was not directly supported. That said, we did find a weak interaction between article-content type and comment sentiment. That is, positive comments induced larger positive effects in combination with the ideologically *neutral* article (i.e., news article about a tropical storm). This suggests that if the content does not convey a specific ideology, readers tend to rely more on the positive sentiment of the comments to form their opinions. Thus, peer comments can induce a bandwagon effect in readers who lack a strong predisposition. In that case, readers employ a consensus heuristic, and use the majority opinion as a proxy for their own opinion (Mutz, 1998; Schmitt-Beck, 2015).

The results show a pattern of negativity bias (Baumeister et al., 2001; Ito et al., 1998; Norris, 2019; Rozin & Royzman, 2001); even when readers were exposed to both positive and negative comments, they were more influenced by the negative comments, showing similar results as readers who were only exposed to negative comments. Therefore, we can conclude negative comments have a greater effect on the readers' attitude as compared to positive comments (H4). An important consideration is that the sample consisted of young adults; this age group has been shown to be more likely to have a negativity bias. Older adults, on the other hand, are likely to have a positivity bias (Carstensen & DeLiema, 2018). Future research could investigate whether older adults are less influenced by negative comments when they process social media content, and whether they are more influenced by positive comments.

The mixed comments condition results provide unique implications; readers were exposed to two positive and two negative comments (i.e., two comments from the positive comments condition and two comments from the negative comments condition). The mixed comment section was qualitatively distinct from the purely negative and purely positive comment sections because it provided more contrasting peer opinions. This distinction explains the differentiation in the *perceived public* attitude, which was intermediate compared to the other conditions (see Figure 3.7). However, the other outcome variables reflecting *personal* opinions (i.e., attitude, share intent, agreement with ideas, and credibility) were negatively biased, resembling the negative comments condition (see Figure 3.2, Figure 3.4, Figure 3.6, and Figure 3.8). This finding provides a unique dissociation of potential cognitive processes underlying the influence of comments. That is, the bandwagon heuristic is not an appropriate underlying cognitive process because there was no straightforward majority opinion in the mixed comments condition. A negativity bias, on the other hand, is a more appropriate cognitive mechanism for the finding that readers' *personal* opinions were relatively negative, even when half of the comments were positive. The results suggest that the evaluation and influence of the comments in the mixed condition was similar to how those same comments were evaluated in the other conditions; positive comments had little influence whereas negative comments greatly influenced the readers.

Based on our findings, we can conclude that especially comments with a negative sentiment can influence how readers evaluate the alluded content. A negativity bias explains how negative comments either aroused more attention and/or how negative comments received more conscious processing than positive comments (Baumeister, et al., 2001). However, a negativity bias offers an evolutionary-based explanation for this finding. In theory, a negativity bias would increase a species' chance for survival, as a bias towards negative stimuli would improve the species' ability to avoid harmful situations (Norris, 2019). In addition to the evolutionary-based negativity bias, we present a more proximal explanation as well. Specifically, a negative sentiment may be more interesting to the reader. Perhaps, encountering a criticism invokes a different, more contrasting, perspective on the content as compared to a mere endorsement. A criticism counters a previous idea, so it may appear as more novel and distinct (e.g., novel popout effect see Johnston et al., 1990), and thus, is perhaps more likely to be influential than a positive comment.

An unexpected finding was that the negative comments did not have a larger effect on the readers' attitude in combination with the neutral article as compared to the incongruent and congruent articles (H5). Interestingly, the presence of comments appeared to decrease the range of attitudes for the different articles and even decreased the readers' willingness to share or recommend the ideologically congruent article. This may be rooted in the possibility that, when readers are willing to share the original news content, they are more reluctant to share it if they associate the content with the subjective comment section.

Participants were asked to estimate the general public's attitude towards the articles. Not surprisingly, the comment sentiments were congruent with the perceived public attitudes, because the comment sections could be utilized as cues representing the general public's opinions. An important finding here is that participants were, in fact, aware of the positive comments in the mixed condition, showing more positive perceived public attitudes as compared to the negative sentiment condition (see Figure 3.7). It is remarkable that the negativity bias was evident in reports of personal attitude but not in reports of the perceived public attitude. This difference suggests that while readers are more influenced by negative comments than positive comments, this is likely not due to an attentional bias towards negative cues. Otherwise, the perceived public attitude would also have shown a negativity bias. Instead, the negativity bias was probably caused by a distinction in the way negative and positive comments are processed.

The ostensible significance of a peer comment, and therefore its influence, may be based on the way the reader perceives this peer. For example, critical peer commenters may be perceived as more knowledgeable, more experienced, or more rational as compared to commenters who merely endorse content. Therefore, criticisms or negative comments may be more persuasive than positive comments. The notion that readers attribute characteristics to the creators of the comments remains speculative. However, there is evidence that messages with a negative sentiment are more convincing than those with a positive sentiment; Habernal and Gurevych (2016) created and tested a computational deep learning method to predict the convincingness of arguments on the Web. They found that in some cases arguments with a strong negative sentiment were more convincing than other arguments. Another study, performed by Kluck, Schaewitz, and Krämer (2019), showed that negative comments that expressed concerns about the veracity of a news story, diminished the perceived credibility of this news story. A negative comment is likely to convey criticism. Criticism might induce the perception of either intellectual or experience-based authority. In turn, the reader might engage in the heuristic cognition known as authority bias (Milgram, 1963), attributing greater accuracy or value to this comment than more positive comments. The notion that negative comments are more convincing or persuasive due to perceived authority by the reader should be investigated in future research.

We did not find evidence to support our first hypothesis, the presence of Likes did not affect the readers' content processing and evaluation. A possible explanation is that Likes are not as meaningful to an observer as they would be to the sender or the recipient. Furthermore, Likes could become more meaningful to the reader when they reflect user interactions within a familiar group such as friends on Facebook. In the current experiment, the Likes reflected aggregated feedback from unknown users, which is possibly less meaningful than observing Likes from friends, acquaintances, or well-known persons. However, an alternative explanation is that the Likes were not perceived and processed as social cues in the first place. In other words, the numbers indicating the quantity of Likes were not processed as cues for positive affectivity; instead, they were processed as mere numbers without a specific meaning.

The study by Winter and colleagues (2015) also did not yield a significant effect of Likes when comparing high and low number of Likes (instead of presence and omission of Likes in the current study). In their discussion, they speculate that due to a negativity bias Likes do not arouse attention, because they are limited to positivity.

Secondly, they speculate that Likes have less influence on the readers, as they are less concrete than comments. Kluck and colleagues (2019) made a similar observation. They investigated the influence of a bandwagon credibility rating (i.e., a cue of the average credibility score from a large group of users), which also failed to influence the readers. Their explanation was, just as Winter et al., that the aggregated user feedback is more ambiguous than comments. Both studies refer to the *exemplification theory* by Zillmann (2009) and stipulate that comments, which are more concrete, are better *exemplars* of peer-user attitudes than the aggregated user feedback. Therefore, comments are supposedly processed with less cognitive effort than Likes.

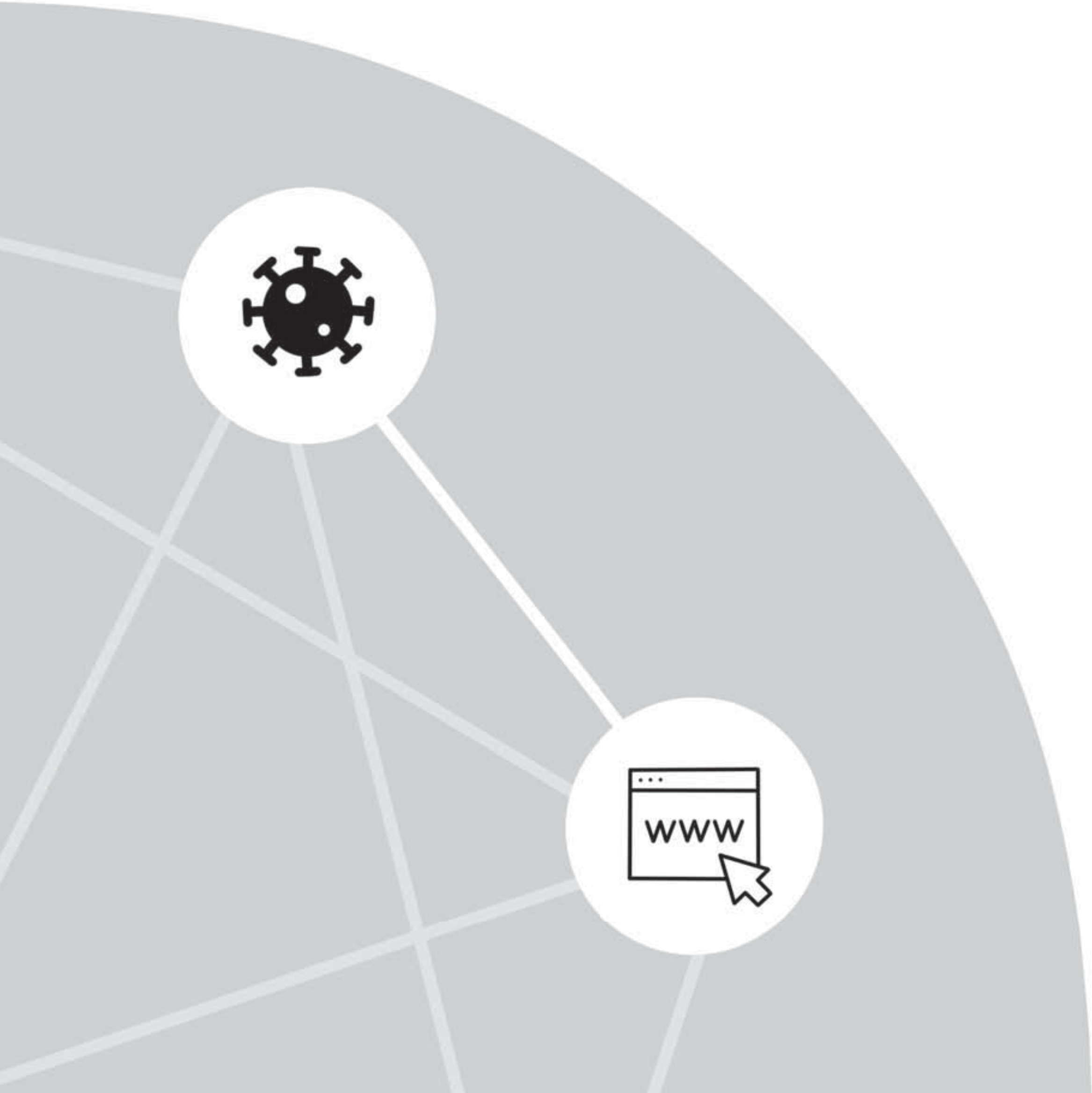
Thus, as Winter et al. and Kluck et al. have previously proposed, Likes are probably interpreted and processed differently than the comments. Likes indicate popularity in a quantitative measure. A quantity or number is possibly not processed as intuitively as the rhetoric in the comment section. In other words, numbers are possibly less meaningful to the reader, because they do not convey explicit semantics or ideologies. In line with this notion, Likes have been conceptualized as paralinguistic digital affordances, which allegedly do not convey a specific predefined meaning (Hayes et al., 2016). Moreover, studies have shown that numbers are sometimes not intuitively processed as meaningful affective cues. For example, when a data display presents a large number of human casualties to an audience, this number does not engender equally representative feelings of empathy in this audience (Slovic et al., 2011). Campbell and Offenhuber (2019) have stated “numbers representing lives do not convey the importance of those lives – numbers numb”. Perhaps, social media users do not implicitly attribute meaning to the number of Likes just as human casualty numbers fail to induce an appropriate emotional response in readers. Comments, on the other hand, are more concrete exemplars of peer-user attitudes and therefore are more influential (Kluck et al., 2019; Winter et al., 2015).

In addition to exemplification theory, dual processing system theories may provide a useful framework for the processing of Likes and comments (Barret, Tugade, & Engle, 2004; Epstein, 1994). If social media users employ an analytic, slow, and reflective information processing system (i.e., system 2), then the underlying meaning of the number of Likes, which is the positive affectivity of other users, can be inferred. However, if social media users employ a fast, intuitive, emotionally driven system, that uses fewer cognitive resources (i.e., system 1), they are less likely to ascribe explicit meaning to the number of Likes. In that case, social media users are less likely to utilize the Likes to form their personal opinions. Comments, on the other hand, are more concrete exemplars of peer opinions, which are comprehended without the need for analytic and inferential information processes. Future research should investigate which underlying mechanisms are involved in the perception, interpretation, and utilization of Likes.

A limitation of our experiment was that the assumed ideological disposition of the readers or their attitude towards the article-content was different than initially expected. That is, participants were less negative about the ideologically incongruent article-content (i.e., an article about the relationship between video games and aggressive behaviour) than initially assumed. Ideally, participants would show a more negative attitude toward the incongruent article-content than the neutral article-content, in order to examine the interaction of personal disposition and comment sentiment. That said, we do not think this limitation has drastically confounded our general findings; positive comments appeared to have little effect on the readers' attitude, which makes an interaction effect between a negative disposition and positive comments unlikely.

In conclusion, beliefs and opinions about news presented on social media can easily be affected by negative peer-user comments. Most strikingly, the evaluation of ostensibly objective information can be distorted by subjective, emotive, and fallacious rhetoric. Likes, on the other hand, do not appear to influence the readers as much. The current findings contribute to the psychology of online media behaviour and may have some important implications. If a news platform aims to objectively inform its audience, the findings of this study may serve as an important consideration on to whether comment sections should be included on the platform's news pages. In addition, social media users may benefit by being more aware of the potential influence of peer-user comments on their personal beliefs and attitudes. One should ask: 'does the internet stranger who wrote this comment actually have authoritative experience or knowledge on this topic?' While critical and negative comments may appear convincing, it is wise to be sceptical about the criticisms.

CHAPTER 4



Gathering, processing, and interpreting information about COVID-19

Boot, A. B., Eerland, A., Jongerling, J., Verkoeijen, P. P. J. L., & Zwaan, R. A. (2021). Gathering, processing, and interpreting information about COVID-19. Scientific Reports, 11, Article 6569. https://doi.org/10.1038/s41598-021-86088-3

Abstract

Does cognitive motivation influence how people gather and interpret information about COVID-19 and their adherence to measures? To address these questions, we conducted a longitudinal survey among European and American respondents. Wave 1 (*N*=501) was conducted on March 27, 2020 and Wave 2 (*N*=326) on July 1, 2020. We assessed COVID-19 knowledge, endorsement of COVID-19 conspiracy theories, media use, Need for Cognition (NC), Need for Cognitive Closure (NCC), and self-reported adherence to governmental measures taken.

Results showed that nearly three-quarters of our respondents actively searched for information about COVID-19. Most at least once a day. Information seeking behaviour was not influenced by cognitive motivation (i.e., NC and NCC). However, cognitive motivation was related to (1) knowledge about COVID-19, (2) conspiracy rejection, and (3) change in knowledge over time. Respondents with more knowledge on COVID-19 also indicated to adhere more often to measures taken by their government. Self-reported adherence to measures was not influenced by cognitive motivation. Implications of these findings will be discussed.

Keywords

COVID-19, information processing, cognitive motivation, conspiracy theories, media use

A world-altering event provides a shock to the systems by which we, and others around us, try to make sense of our environment. Since the advent of the digital media, major events are typically followed by a daily barrage of information, misinformation, and disinformation. In this study, we investigated whether people's cognitive motivation to understand the world could predict how people acquire, interpret, and process information about COVID-19. Specifically, what is the extent of factual knowledge people have about COVID-19? How stable across time is this knowledge? How frequently do they search for new information? Which information sources do they rely on? How confident are they about what they know? How do they evaluate false conspiracy theories? And how is their knowledge related to their behaviour? We investigated these questions in a survey that examined people's responses to COVID-19, by many seen as the most impactful global event since World War II.

COVID-19, the infectious disease caused by severe acute respiratory syndrome coronavirus 2, has resulted in a worldwide pandemic (declared by the World Health Organization on March 11, 2020). As individuals in many countries were practicing social distancing in the early spring of 2020, they were largely reliant on the (digital) media to gather information and develop an understanding of developments related to COVID-19. As of April 7, 2020, fact checkers have identified 225 pieces of misinformation about COVID-19 (Brennen et al., 2020). The most common claims within pieces of misinformation concerned the actions or policies that public authorities were taking to address COVID-19.

To examine people's gathering and comprehension of information related to the COVID-10 pandemic, we conducted an online survey in two waves. The first wave was conducted on March 27 of 2020 among 501 adults who are fluent in English while the second wave was conducted on July 1 of 2020 among 326 adults that also participated in Wave 1. We asked about people's (digital) media use and their knowledge and beliefs about COVID-19. In Wave 1 we administered two standardized tests of cognitive motivation, Need for Cognition (Cacioppo et al., 2013; Cohen et al., 1955; Petty et al., 2009), and Need for Cognitive Closure (Webster & Kruglanski, 1994a). We used these measures to assess responses in Wave 1 as well as any changes on the COVID-19 Knowledge Test responses in Wave 2. As will be detailed below, each wave was preregistered separately.

Need for Cognition

To presuppose specific COVID-19 information processes we considered two distinct types of cognitive motivations. Our first hypothesis was based on the Need for Cognition (NC), a scale that reflects the pleasure one experiences in one's own thought processes (Cacioppo et al., 2013; Petty et al., 2009). People who are high in NC experience pleasure from engaging in effortful cognitive processes, whereas people low in NC people are less likely to enjoy these processes (Petty et al., 2009). High NC people also tend to be more resistant to persuasive messages by performing a more effortful analysis and cognitive reflection on the quality of the information (Cacioppo et al., 1983). Based on these previous findings, we expected that a person high in NC would be likely to seek out a great deal of information about COVID-19, consider all the pertinent information by consulting a broad variety of resources, and would think deeply and critically about the topic. Therefore, we also expected people high in NC to acquire a substantial amount of factual knowledge about the virus.

Furthermore, we assumed that it is more probable that conventional media (newspapers, radio, TV) can endure close scrutiny than social media. For example, conventional media are often based on traditional journalism and (arguably) more objective news reports, whereas social media often comprise tabloid journalism and unofficial sources, which tend to convey more sensation-driven news stories and subjective discourse, respectively (Bastos, 2016). Additionally, social media users have been shown to spread false news more quickly and more broadly than true news (Vosoughi et al., 2018). Thus, we hypothesized that if a person high in NC is more likely to focus on objective and factual news about COVID-19 than on subjective discourse on this topic, this person would be more likely to use conventional media.

Hypothesis 1: (a) People who have relatively low NC (vs. high NC) have less factual knowledge about COVID-19 – (b) they show a lower frequency of COVID-19 information updates – (c) and they rely more on new media and informal sources (e.g., social media, colloquial conversations) to acquire new information about COVID-19.

Need for Cognitive Closure

We based our second hypothesis about cognitive motivation and COVID-19 information processing on the Need for Cognitive Closure (NCC). Where NC focuses on the process of thinking, NCC focuses on the outcome of the thought process. Individuals who are high in NCC are motivated to quickly arrive at an interpretation of a state of affairs and then preserve this interpretation in the face of incoming information. These two intellectual moves are known as *seizing* and *freezing*, respectively (Kruglanski & Webster, 1996a; Pierro & Kruglanski, 2008). NCC is both situational (i.e., people experience it to a greater degree in urgent situations than in less urgent situations) and dispositional (i.e., some people experience it more than others). We focus on the dispositional component of NCC in the current study, given that we are primarily interested in individual differences. Also, we expected people to experience a great deal of NCC during the early phase of a pandemic. Individuals low in NCC are thought to be less eager to arrive at and hold on to an interpretation of a state of affairs.

Presumably, this means people low in NCC are more likely to hedge their answers when their knowledge is being tested. For example, a person low in NCC could be more likely to judge a true statement with ‘I think this is true’, whereas a person high in NCC could be more likely to answer with ‘I am sure this is true’.

Hypothesis 2: People high in NCC have more confidence in their acquired knowledge than people low in NCC.

Proneness to conspiracy beliefs

We are also interested in the degree to which individuals are willing to endorse one or more conspiracy-related assumptions about COVID-19. Conspiracy theories provide readily available answers to convoluted issues such as the pandemic, and can therefore mitigate feelings of uncertainty (Marchlewska et al., 2018a). Thus, one might expect that high NCC individuals, who wish to diminish uncertainties (i.e., cognitive closure), would be more likely to endorse conspiracy theories about the pandemic. Still, several studies report at best weak correlations between the two (Imhoff & Bruder, 2014; Leman & Cinnirella, 2013; Moulding et al., 2016). However, it has been observed that these studies examined the link between NCC and conspiracy beliefs in contexts in which conspiracy theories would be particularly inaccessible to the individual (Leman & Cinnirella, 2013; Marchlewska et al., 2018a). Indeed, when conspiracy theories were made more accessible to respondents, a correlation between NCC and conspiracy thinking emerged. Moreover, when conspiracy theories are situationally accessible explanations for real events, people high in NCC are more likely to accept these conspiracy theories as truths (Marchlewska et al., 2018a). Considering the COVID-19 infodemic, it is very likely that social media users have been exposed to conspiratorial explanations for the pandemic at least occasionally. For example, it is been shown that Twitter posts related to COVID-19 have a questionable to reliable source ratio of .11, which means there are approximately 11 unreliable posts for every 100 reliable posts on Twitter (Cinelli et al., 2020). Likewise, YouTube suffers a ratio of .07, meaning there are 7 questionable videos posted about COVID-19 for every 100 reliable videos (Cinelli et al., 2020). Thus, if high NCC can predict a higher proneness to conspiracy beliefs under the prerequisite that these theories are situationally accessible, then we expect high NCC individuals who use less reliable sources such as social media (which is presumably predicted by low NC) to be particularly susceptible to adopt conspiracy beliefs. Therefore, our third hypothesis derives from a potential interaction between NC and NCC. All hypotheses of this study are summarized in Table 4.1.

Hypothesis 3: People who are high in NCC but low in NC are less likely to reject conspiracy theories about COVID-19 than high NCC & high NC people, low NCC & high NC people, and low NCC & low NC people.

Table 4.1 Hypotheses Regarding COVID-19 Knowledge, Conspiracy Rejection, and Media Use Based on Need for Cognition and Need for Cognitive Closure

		Need for Cognition (NC)		**Hypotheses**
		Low*	**High***	**
Need for Cognitive Closure (NCC)				
	Low*	Low COVID-19 knowledge	High COVID-19 knowledge	1a
		Low searching	High searching	1b
		Low quality of sources	High quality of sources	1c
		Low certainty	Low certainty	2
		High rejection of conspiracy theories***	High rejection of conspiracy theories	3
	High*	Low COVID-19 knowledge	High COVID-19 knowledge	1a
		Low searching	High searching	1b
		Low quality of sources	High quality of sources	1c
		High certainty	High certainty	2
		Low rejection of conspiracy theories	High rejection of conspiracy theories	3

Note. * Previous studies have categorized NC and NCC scales in 'high' and 'low' groups, thus dichotomizing continuous scores in statistical analysis 7,13–16. However, categorization is unnecessary for statistical analysis and even has methodological weaknesses 17. That said, labelling participants as high or low groups does allow for a convenient comparison of the outcome variables. To achieve the middle ground, we have chosen to use continuous variables in our statistical analyses, whereas in our descriptive statistics we have added comparisons based on high and low NC - NCC categories. ** Hypotheses 1a-c are based on NC, Hypothesis 2 is based on NCC, and hypothesis 3 is based on an interaction between NC and NCC. *** In our preregistration hypothesis 3 was formulated in terms of 'endorsement' instead of 'rejection'.

Behaviour in the pandemic and temporal changes in knowledge

In addition to factual knowledge about COVID-19, another important aspect of the pandemic is behaviour. Particularly, the effectiveness of health-regulations and guidelines against the coronavirus is dependent on the level of compliance and adherence amongst the population. To examine this idea, we added two additional questions in Wave 2 about adherence behaviour and the perceived importance of different organizations such as one's government or the World Health Organization (WHO). Furthermore, we considered it valuable to perform a second iteration of the knowledge measures to study temporal differences. Thus, complementary to the Wave 1 analysis, we used an exploratory approach to analyse Wave 2 data and asked whether cognitive motivation (NC and NCC), the guiding principle in this study, could predict adherence behaviour as well as temporal changes in COVID-19 knowledge between Wave 1 (March 27) and Wave 2 (July 1).

WAVE 1

Method

We administered two surveys: the first survey (Wave 1) was administered on March 27 of 2020, and on July 1 of 2020 we sent out a second survey (Wave 2). The first survey was designed to assess the level of knowledge about COVID-19, the ability to reject COVID-19-related conspiracy theories, cognitive motivations, media use related to COVID-19, general media use, and demographic traits (see Table 4.2 for more detailed descriptions). Wave 2 was intended to gather additional data about potential temporal changes in COVID-19 Knowledge, Conspiracy Rejection, as well as additional information about adherence to government-imposed measures (described in more detail in the Wave 2 section). Wave 1 and Wave 2 data were analysed separately. The current section (i.e., Wave 1) proceeds with Wave 1 methods and analyses.

Respondents

Five hundred and twenty-six respondents completed the Wave 1 survey via the Prolific.com platform. Sixteen respondents were excluded for spending too much time on the survey. Another nine respondents were excluded for failing the catch question. In our preregistration we included an additional exclusion criterion based on the lie-score of the respondents on the NCC (Kruglanski et al., 2013). In hindsight, however, this criterion proved to be undesirable: the data strongly suggested that the lie score was not a valid measurement for respondents' mischief. That is, respondents with a lie score >15 still passed the catch-question and commented on the survey in an ostensibly proactive and honest manner. Moreover, we believe that the answers in the "lie" questions were partially influenced by a social-desirability bias and were prone to idiosyncratic interpretations of the adverbs in the response options. For example, the item *"I have never been late for an appointment or work."* was answered with "*slightly agree*", "*moderately agree*", and "*strongly agree*" by 10.2, 20.0, and 12.8 percent of the respondents, respectively. According to the initial lie-item exclusion criterion, 43 percent of respondents gave a response that would indicate lying, which appears highly unlikely. A final reason for the decision to remove the lie-score criterion was the questionable Cronbach's α of .62.

The final sample included 501 respondents (238 females). Respondents' ages ranged from 18 to 77 (M = 31.25, SD = 11.33). See Supplementary Tables S4.1-S4.5 in Appendix A for descriptive statistics regarding the career fields, level of education, nationality, native language, and gender identity of our Prolific sample. On average, the survey took 22 minutes to complete. Respondents were paid £2.75, amounting to an average hourly fee of £7.50. All respondents were fluent in English according to the Prolific database.

Table 4.2 Overview and Descriptions of the Measures in Wave 1

Category	Measure	Items	Description
Information processing	COVID-19 Knowledge	24	*Knowledge about COVID-19* in terms of accuracy and confidence.
	Conspiracy Rejection	8	*COVID-19-related conspiracy rejections* in terms of accuracy and confidence.
Cognitive motivation	Need for Cognition Scale (NC) (Cacioppo et al., 2013)	18	The desire to engage in cognitive activities (e.g., critical thinking, acquiring a deeper understanding of certain topics).
	Need for Cognitive Closure Scale (NCC) (Kruglanski et al., 2013)	47	The desire for coherence in personal thought processes. High NCC predicts a higher likelihood to arrive more quickly at interpretations and more definitive inferences about the situation (i.e., ideationally crystalized worldview). Low NCC predicts more cognitive flexibility and higher acceptance to uncertainties (i.e., ideationally fluid worldview).
COVID-19 media use	Sources	10	The extent to which different types of sources are used to acquire information about COVID-19 (e.g., news sites, social networking sites, friends/family).
	Conditions	4	The conditions of COVID-19 news encounters (i.e., active searching, coincidentally, colloquially, and avoidance behaviour).
	Frequency	1	The frequency of COVID-19 information updates.
	Motivations	5	The underlying motivations to acquire information about COVID-19 (i.e., need to be informed, need to educate others, concerns about personal health, relatives, and the general public)
General media use	Platforms used	1	The online platforms that are used by the participant (i.e., online media environment).
	Daily time spent	1	The average daily time spent on the online platforms.
Demographic traits	Various measures	7	Age, gender identity, career field, nationality, native language, and level of education.

Note. The measures of Wave 1 reflect cognitive motivations (NC and NCC), information processing and interpretation (COVID-19 Knowledge and Conspiracy Rejection) and information seeking behaviour (sources, conditions of news encounters, frequency, and motivations).

Materials and procedure

Respondents first filled out the COVID-19 Knowledge Test that we developed for this survey. This test consists of 32 statements regarding the state of knowledge about COVID-19 as it was in March 2020. Twelve statements were thought to be correct (e.g., *Fever is a symptom of the coronavirus*), twelve were thought to be incorrect (e.g., *Flu vaccine protects you against the coronavirus*), and eight concerned inferred motives (e.g., *The coronavirus was released by the Chinese government to prevent overpopulation*).

We expected the twelve correct and incorrect statements to measure individuals' knowledge of COVID-19, while the eight items on inferred motives were thought to measure individuals' belief in conspiracy theories regarding the virus. Respondents indicated whether or not they thought these statements were true, and how confident they felt about their judgment (1 = *I am sure this is not true*, 2 = *I think this is not true*, 3 = *I don't know*, 4 = *I think this is true*, 5 = *I am sure this is true*). In the current study, 'COVID-19 Knowledge' was defined as 'scientifically justified belief on an ordinal spectrum of accuracy weighted by confidence level'. After reverse-coding the false statements we interpreted the five-point scale accordingly (1 = *highly inaccurate*, 2 = *inaccurate*, 3 = *neutral*, 4 = *accurate*, 5 = *highly accurate*). In addition, respondents filled out questions about media use related to COVID-19, general media use, and demographic traits (see Table 4.2).

Availability of materials and data

The data, preregistration, and materials from this study are available here https://osf.io/38b65/files/. The data can be converted to other file types (currently R format) and the R syntax used in this study can be made available upon request.

Results

The results are presented in two parts. First, we present our confirmatory factor, regression, and cluster analyses. Next, we present descriptive statistics regarding the COVID-19 Knowledge and Conspiracy items and COVID-19-related media use.

Confirmatory analyses

We tested whether the COVID-19 Knowledge Test consisted of two different factors (COVID-19 *Knowledge* and *Conspiracy Rejection*). To this end, we ran a confirmatory factor analysis in the R-package *lavaan* (Rosseel, 2012). Specifically, we fitted a two factor model using robust weighted least square estimation. The first factor, *Knowledge*, was the accuracy score for the first 24 items of the COVID-19 Knowledge test. The second factor, *Conspiracy Rejection*, was the accuracy score on the last eight items of the COVID-19 Knowledge test. This factor-structure was fit to a random subsample of 200 individuals, and validated on the remaining respondents in our sample.

We removed items 4, 5, 17, 29, and 31 from our analyses, because some answer options for these ordinal variables were not present in our subsample. After removing these items, the two-factor model showed sufficient fit to the data ($\chi^2(323) = 399.52$, $p = .002$; CFI = .988; RMSEA = .035; SRMR = .086). When validating the model on the remaining 301 respondents, we removed item 16 and 25 due to unused answer options. In our validation sample items 4, 5, 17, 29, and 31 were not removed. Model fit for the 2-factor model was again sufficient ($\chi^2(404) = 637.80$, $p < .001$; CFI= .977; RMSEA = .046; SRMR = .085). When fitted to the whole sample, no items needed to be removed and the model showed good fit ($\chi^2(433) = 781.06$, $p < .001$; CFI= .985; RMSEA = .041; SRMR = .071). These results indicate that COVID-19 *Knowledge* and *Conspiracy Rejection* can be distinguished as factors in the COVID-19 Knowledge Test.

Test of NC and NCC as predictors

We were interested in whether NC and NCC predict the COVID-19 Knowledge Test results and COVID-19-related information searching frequency. Therefore, we chose to perform a regression analysis. Adding NC, NCC, and their interaction as predictors for the *COVID-19 Knowledge* and *Conspiracy Rejection* factors lead to a model that also has sufficient fit to the data ($\chi^2(553) = 979.06$, $p < .001$; CFI= .981; RMSEA = .041; SRMR = .073). Results show that NC was positively related to *COVID-19 Knowledge* (b(se) = .254 (.062), beta=.242, p <.001), which supported **hypothesis 1a** (i.e., *low NC is associated with less factual knowledge about COVID-19*). NC was also positively related to *Conspiracy Rejection* (b(se) = .136 (.057), beta=.134, $p < .001$), high NC participants were more likely to reject false conspiracy theories about COVID-19. However, there were no significant relations between NC and media use at Wave 1 (NC: b(se) = .070 (.052), beta=.070, $p = .180$; NCC: b(se) = .062 (.053), beta=.062, $p = .242$). Therefore, there was no support for **hypothesis 1b** (i.e., *people who have relatively low NC show a lower frequency of COVID-19 information updates)*.

NCC, the other measure of cognitive motivation, was positively related to *COVID-19 Knowledge* (b(se) = .252 (.061), beta=.240, p <.001), and was positively related to *Conspiracy Rejection* (b(se) = .143 (.054), beta=.141, $p = .008$). This means high NCC predicted higher scores on the COVID-19 Knowledge Test. However, descriptive analyses of the data had to be used to examine whether scores could be caused by higher confidence. Thus, the results from the inferential analysis could not conclusively support or disconfirm **hypothesis 2** (i.e., *people high in NCC have more confidence in their acquired knowledge than people low in NCC*). This limitation will be further discussed.

Test

In addition, there was a significant interaction of NC and NCC on *COVID-19 Knowledge* (b(se) = -.109 (.051), beta=-.104, $p = .032$). Participants who were both high in NC and NCC showed higher levels of *COVID-19 Knowledge*. However, there was no significant NC x NCC interaction effect on *Conspiracy Rejection*. Therefore, the results did not support **hypothesis 3** (i.e., *people who are high in NCC but low in NC are less likely to reject conspiracy theories about COVID-19 than high NCC & high NC people, low NCC & high NC people, and low NCC & low NC people*).

To further test whether there were different types of respondents as proposed in Table 4.1, we performed a principal component analysis. This cluster analysis did not accurately summarize the data to support the notion of distinct types of respondents based on NC, NCC, COVID-19 Knowledge, Conspiracy Rejection, and media use (see Supplementary Figure S4.1 in Appendix B). Therefore, the current results also did not support **hypothesis 1c** (i.e., *people who have relatively low NC rely more on new media and informal sources to acquire new information about COVID-19*).

Descriptive statistics

COVID-19 knowledge

Respondents' knowledge of COVID-19 was approximated based on their personal evaluation of 24 correct and incorrect COVID-19-related statements (see Figure 4.1; internal-consistency factor: ωh = .71). The highest consensus amongst respondents was yielded by the statement "*Social distancing helps slow down the spread of the coronavirus*" that was endorsed by about 99% of the respondents (three respondents rejected this claim and three respondents indicated not to know whether this statement was true or not). The statement that yielded the highest level of uncertainty (36.0%) was *"It is possible to become immune to the coronavirus after recovery."* On average, respondents were better at judging true statements to be true (83.3%) than at rejecting false statements (66.7%; see Table 4.3). Respondents were also more likely to respond with "I don't know" when evaluating false statements compared to true statements, showing more ignorance. These results indicate that the average level of COVID-19 knowledge in our sample was fairly high in this early phase of the pandemic.

Table 4.3 Descriptive Statistics COVID-19 Knowledge Test (N = 501)

Item veracity	Knowledge Test answers	Mean percentage	SD	95% CI		Min	Max
True statements (12 items)	*"I am sure this is true"*	56.1	22.0	[54.2,	58.1]	0	12/12 items
	"I think this is true"	29.4	19.0	[27.7,	31.1]	0	12/12 items
	"I don't know"	8.2	10.3	[7.3,	9.1]	0	10/12 items
	*"I think this is **not** true"*	4.4	6.1	[3.9,	4.9]	0	4/12 items
	*"I am sure is **not** true"*	1.9	4.1	[1.5,	2.2]	0	3/12 items
False statements (12 items)	*"I am sure this is true"*	4.5	7.2	[3.8,	5.1]	0	5/12 items
	"I think this is true"	13.5	10.7	[12.5,	14.4]	0	7/12 items
	"I don't know"	14.4	13.4	[13.2,	15.5]	0	11/12 items
	*"I think this is **not** true"*	25.0	16.2	[23.5,	26.4]	0	10/12 items
	*"I am sure is **not** true"*	42.7	20.5	[40.9,	44.5]	0	11/12 items
Conspiracy statements (7 items)	*"I am sure this is true"*	0.3	2.5	[0.1,	0.5]	0	2/7 items
	"I think this is true"	2.4	7.9	[1.7,	3.1]	0	5/7 items
	"I don't know"	13.1	24.7	[11.0,	15.3]	0	7/7 items
	*"I think this is **not** true"*	20.5	28.1	[18.1,	23.0]	0	7/7 items
	*"I am sure is **not** true"*	63.6	37.7	[60.3,	66.9]	0	7/7 items
Negated conspiracy statement (1 item)	*"I am sure this is true"*	28.7	45.3	[24.8,	32.7]	Not applicable for a single item	
	"I think this is true"	29.1	45.5	[25.2,	33.1]		
	"I don't know"	23.0	42.1	[19.3,	26.6]		
	*"I think this is **not** true"*	11.8	32.3	[9.0,	14.6]		
	*"I am sure is **not** true"*	7.4	26.2	[5.1,	9.7]		

COVID-19 conspiracy evaluation

We examined respondents' evaluation of conspiracy theories by presenting eight COVID-19-related statements containing nefarious motives by groups of powerful agents. Respondents showed high rejection of the eight conspiracy statements (internal-consistency factor: ωh = .89): 373 respondents (74.5%) categorically rejected all conspiracy statements, 91 respondents (18.2%) endorsed one conspiracy statement, 21 respondents (4.2%) endorsed two conspiracy statements, and only 16 respondents (3.2%) endorsed three or more conspiracy statements. Interestingly, the level of uncertainty was much higher than the level of endorsement: 78 respondents (15.6%) were unsure about the veracity of one conspiracy statement and 120 respondents (24.0%) were unsure about two or more conspiracy statements. However, the statement that explicitly denied human motives, "*The coronavirus was not created by humans,*" was rejected by 96 respondents (19.2%) and 115 respondents did not know the answer (23.0%). This means that 19.2% of our respondents thought the coronavirus was created by humans. In comparison, each more specific statement implying human motives was endorsed on average by 14 respondents (2.7%) and 65 respondents (13.1%) did not know the answer. Table 4.3 shows the descriptive statistics of the COVID-19 Knowledge Test.

Supplementary Tables S4.8-S4.11 present comparative statistics of the COVID-19 Knowledge Test between the four NC and NCC groups. The most striking contrasts can be observed between respondents high and low in NCC, showing systematic differences in the use of "*I am sure*", "*I think*", and "*I don't know*" answers, for the knowledge statements as well as the conspiracy statements. Particularly, respondents high in NCC more often respond with "*I am sure*", whereas respondents low in NCC tend to respond with "*I think*" and "*I don't know*" relatively more often. For example, low NC/high NCC-respondents evaluated an average of 64.2% (95% CI[59.9, 68.5] of true statements with "*I am sure this is true*", whereas low NC/low NCC-respondents evaluated an average of 47.8% (95% CI[40.5, 55.0]) of true statements with "*I am sure this is true*" (see Supplementary Table S4.8 in Appendix A). In contrast, low NC/high NCC-respondents evaluated 23.2% (95% CI[19.0, 27.4] of true statements with "*I think this is true*", whereas low NC/low NCC-respondents evaluated 32.5% (95% CI[26.7, 38.3]) of true statements with "*I think this is true*". Additionally, low NC/low NCC-respondents more often used the "*I don't know*" response: 12.5% (95% CI[8.5, 16.5]) compared to 4.6% (95% CI[3.2, 6.1]) by the low NC, high NCC group. Similar trends are evident in the false statement category in Supplementary Table S4.9 in Appendix A.

Figure 4.1. COVID-19 Knowledge Test. Proportions of respondents (N = 501) per answer option per item of the COVID-19 Knowledge Test. (a) = true statement, (b) = false statement, * conspiracy statement. See Appendix C for comparisons between groups based on NC and NCC scores Cognitive motivation. To compare the results of the COVID-19 Knowledge Test between different NC and NCC combinations we extracted four subsets from our sample. We used a median split to determine whether a respondent was high or low in NC. Whether respondents were high or low in NCC was based on the top and bottom quartiles of the NCC scores, a procedure suggested by the authors of the NCC test (Kruglanski et al., 2013). The discrepancy in categorization methods of NC and NCC groups (i.e., median split and outer quartiles) was chosen for pragmatic reasons. That is, excluding the data of two independent measures' interquartile ranges would vastly diminish the number of observations per cell. Group sizes were 61 (Hi-NC, Hi-NCC), 78 (Hi-NC,Lo-NCC), 61 (Lo-NC, Hi-NCC), and 52 (Lo-NC, Lo-NCC). An important consideration here is that these groups were solely categorized

for descriptive purposes and were not used in the inferential analyses. The descriptive results of the NC and NCC scales and subscales can be found in Supplementary Table S4.6 in Appendix A.

Conspiracy endorsement across the four NC and NCC types was low (i.e., close to 0%, see Supplementary Table S4.10 in Appendix A). That said, there was a large difference in the use of the answer "*I am sure this is not true*" with regard to conspiracy statements between high NC/high NCC-respondents and low NC/low NCC-respondents: 80.6% (95% CI[72.7, 88.5]) chance and 50.8% (95% CI [40.2, 61.5]) chance, respectively. Moreover, low NC/low NCC-respondents also showed a greater tendency to answer "*I don't know*" with 17.9% (95% CI[10.1, 25.6]) as compared to high NC/high NCC-respondents with 4.4% (95% CI[-0.2, 9.1]) chance to answer "*I don't know*". This suggests respondents low in NC and low in NCC were less likely to make explicit truth claims, and therefore, less likely to reject conspiracy statements.

Media use related to COVID-19

Use of sources

News sites, social networking sites, and television broadcasts are the primary sources of COVID-19 information in our sample (see Figure 4.2). Traditional media, such as printed newspapers and radio broadcasts, are scarcely utilized. Almost all respondents (93%) indicated to rely on friends and family as sources of information. Yet this source type was not consulted frequently. Only 34% of the respondents indicated to rely on friends and family 'a lot' or 'to a great deal'. This suggests that friends and family were more important as secondary rather than primary source of COVID-19 information, despite being the most used source.

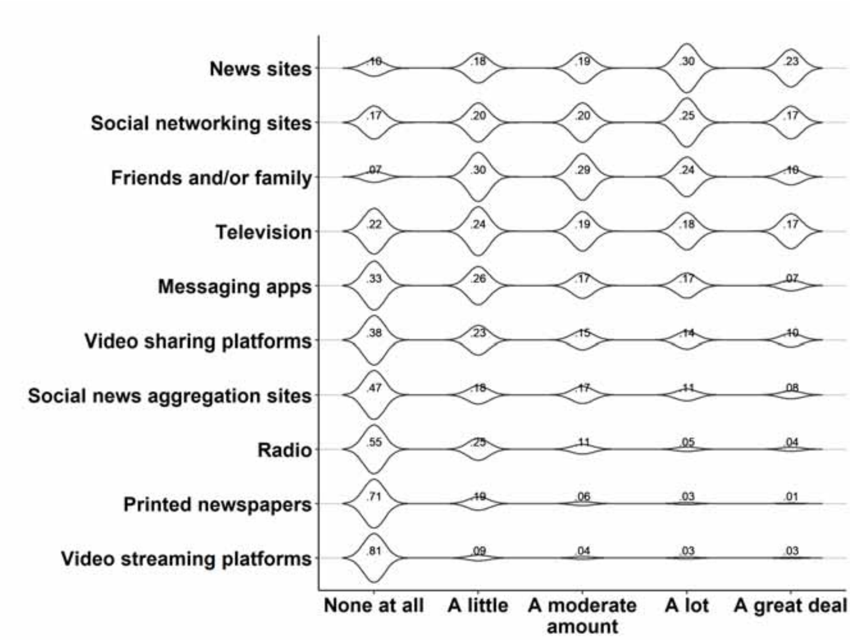


Figure 4.2. Media Use Wave 1. Proportion of respondents (N = 501) that made use of a particular source to acquire COVID-19 information.

Search for information

Many respondents (73.8%) actively searched for updates on COVID-19 (see Table 4.4). Interestingly, a large majority of respondents also coincidentally encountered COVID-19 news (79.4%) and was updated on COVID-19 by friends, family, or co-workers (78.4%). This implies that active and passive consumption of information are not mutually exclusive. Moreover, it suggests that not all COVID-19 news was necessarily desired. This is supported by the finding that 37.6% of the respondents ignored COVID-19 news at least occasionally.

Most respondents actively searched for updates on COVID-19 once a day (53.7%), followed by once per hour (23.4%), once every few days (14.8%), multiple times per hour (5.4%), and never (2.8%). Thus, a large majority of respondents (82.5%) was engaged in COVID-19 information seeking behaviour on a daily basis or more frequently. Search frequencies seem to be relatively similar across NC and NCC groups (see Figure 4.3).

Nearly all respondents (96%) actively searched for COVID-19 related information due to a desire to be informed, whereas half of the respondents (51.7%) also expressed a desire to educate others about COVID-19 (see Table 4.5). Searching behaviour was more driven by concerns about the health of close friends or relatives (92.4%), than by concerns regarding the health of the general public (84.4%) or respondents' own health (66.8%).

Table 4.4 Conditions of COVID-19 News Encounters

Item	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I actively search for updates about the coronavirus.	9.2	10.4	6.6	40.5	33.3
I coincidentally read news about the coronavirus when I`m browsing online.	4.4	6.0	10.2	51.1	28.3
I get updates about the coronavirus from other people (friends, family, coworkers).	3.0	8.0	10.6	48.9	29.5
I ignore news about the coronavirus.	62.5	24.8	7.6	4.6	0.6

Note. Values represent percentages. N = 501

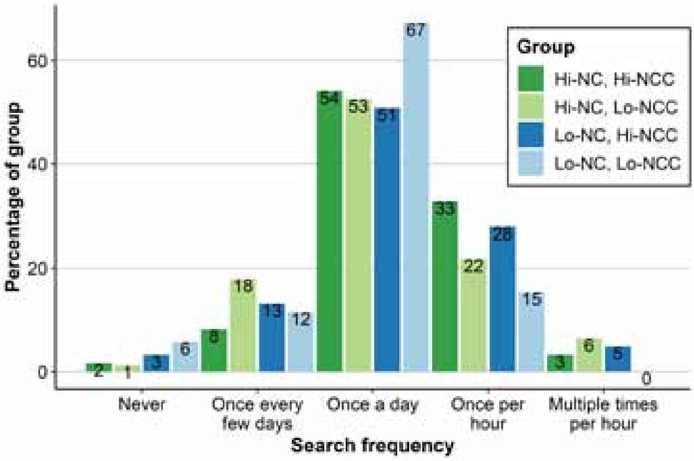


Figure 4.3. Media Use Frequency. COVID-19 Information Search Frequency Compared Across NC and NCC Types.

Table 4.5 Motivations for COVID-19-related Information Acquisition

Item	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I want to be informed about the coronavirus.	1.2	1.2	1.6	30.1	65.9
I want to educate others.	7.0	14.2	27.1	28.3	23.4
I worry about my own health.	5.2	16.0	12.0	38.5	28.3
I worry about the health of people close to me.	1.6	3.4	2.6	26.9	65.5
I worry about the health of the general public.	3.0	4.0	8.2	39.9	44.9

Note. Values represent percentages. N = 501

Discussion

Acquisition of information about COVID-19

We tested preregistered hypotheses about the cognitive antecedents of COVID-19 information acquisition and processing. Specifically, we hypothesized that respondents would engage in certain information seeking behaviour based on their NC and NCC scores. Contrary to our hypothesis, cognitive motivation, as measured by NC and NCC, was not related to the frequency or type of media use related to COVID-19 information (i.e, hypotheses 1b and 1c).

Descriptive analyses showed that a large majority actively searched for COVID-19 related news while also encountering this news accidentally. The frequency of searching for COVID-19 news updates was daily for the majority of information seekers. Also interesting was that some respondents actively ignored information about the virus, even early in the pandemic.

We also investigated the underlying circumstances and motivations for COVID-19 information acquisition and general media use. The main motivations to acquire new information were the personal desire to be informed and, to a lesser extent, to be able to educate others. Moreover, health concerns related to the risks of COVID-19 were mainly directed at close friends or relatives, and more altruistically, the general public's health instead of personal health. It is important to recall once more that this information seeking behaviour was measured on March 27, in a relatively early phase of the pandemic in the countries from which our sample originates.

Interpretation of information

As for the acquisition of COVID-19 related information, we also expected NC and NCC to influence the interpretation of information. More specifically, we hypothesized that people high in NC have more factual knowledge about COVID-19 than people low in NC (i.e., hypothesis 1a), people high in NCC feel more certain about their knowledge than people low in NCC (i.e., hypothesis 2), and we expected weaker rejection of conspiracy theories in people low in NC and high in NCC (i.e., hypothesis 3). Before testing these hypotheses, a confirmatory factor analysis indicated that the COVID-19 Knowledge Test can be used to measure factual knowledge on COVID-19 as well as belief in conspiracies about the virus.

COVID-19 knowledge and confidence

Congruent with hypothesis 1a, a regression analysis showed that NC was positively related to COVID-19 knowledge. People high in NC appeared to be more knowledgeable about the virus and the situation. NCC was also positively related to COVID-19 knowledge and we found an interaction effect of NC and NCC on COVID-19 knowledge. Participants who were both high in NC and NCC showed higher levels of COVID-19 knowledge (i.e., accurate answers with higher confidence). Descriptive analyses suggest that, in line with hypothesis 2, people high in NCC are more certain about their responses to knowledge statements than people low in NCC. This pattern was found for true as well as false statements.

The descriptive statistics showed a clear distinction in the processing of true versus false statements in the COVID-19 Knowledge Test. Respondents showed higher accuracy in their evaluations of true statements. These results suggest COVID-19 information seekers tend to be less eager to make an explicit judgement about the veracity of false information. This may be rooted in the idea that false statements are more likely to be unrecognized or unknown. From an intellectually honest standpoint, it is fair to say "I do not know whether this is true." Interestingly, this introduces an epistemological bias: false information is less likely to be refuted than correct information is to be endorsed.

COVID-19 conspiracy rejection

We hypothesized that conspiracy beliefs could be predicted by an interaction of low NC and high NCC (i.e., Hypothesis 3). That is, a combination of high confidence in personal knowledge (i.e., high NCC) without a need for intellectual activities and acquisition of new information (i.e., low NC) would, hypothetically, render a person more likely to engage in conspiracy thinking. However, we did not find this interaction effect. It might have been difficult to uncover the true relationship between NC, NCC, and conspiracy beliefs due to the very low number of respondents endorsing the conspiracy items in our sample (i.e., 4.8% average chance to endorse conspiracy statements; 2.7% chance after exclusion of item "The coronavirus was (not) created by humans."). The ability to successfully reject conspiracy theories (with high confidence) was associated with a high level of COVID-19 knowledge as evidenced by a positive correlation between COVID-19 knowledge and rejection of conspiracy theories, which is consistent with the findings from previous studies (Bolsen et al., 2015).

An alternative way to assess support for conspiracy thinking is to assess how many respondents endorsed at least one of the conspiracy statements. On this measure, 91 respondents (18.2%) endorsed one of eight conspiracy statements and 37 respondents (7.4%) endorsed two or more conspiracy statements. Another aspect of the conspiracy evaluations that grasped our interest was the relatively high level of uncertainty: 78 respondents (15.6%) were unsure (i.e., they answered 'I don't know' when asked to indicate whether the items were true) about one conspiracy statement and 120 respondents (24.0%) were unsure about two or more conspiracy statements. Thus, a large percentage of respondents (about 40%) were not able to make an explicit truth claim about at least one of the conspiracy statements (i.e., 'I am sure this is true/not true', 'I think this is true/not true'). Perhaps, respondents who evaluate conspiracy statements with 'I don't know' are more susceptible to adopt novel conspiracy beliefs, considering they do not reject conspiracy ideas at face value. Alternatively, respondents may feel more comfortable to withhold beliefs about novel ideas. Therefore, they are possibly more reluctant to make explicit judgements about surreal conspiracy claims, which tend to be more novel and yield less recognition.

Considering the timeline of the COVID-19 situation, we reckoned it was important to perform a follow-up survey. Three months after the first wave, we launched a second wave of the survey among the original sample. We addressed the following research questions: How do COVID-19 knowledge and endorsement of conspiracy theories change over time? What is the relation between these changes, NC, and NCC? How are NC and NCC associated with adherence to governmental measures regarding COVID-19? And finally, what are the most respected organizations and sources for obtaining information and guidelines about COVID-19 and how is this related to NC and NCC?

WAVE 2

Method

Respondents

On July 1 of 2020, we sent out a Wave 2 survey to those individuals who had participated in Wave 1. Three-hundred-and-fifty-two respondents from Wave 1 participated in Wave 2. The data for ten respondents were removed from the analysis because they spent too much time on the COVID-19 Knowledge Test (z-score > 3.29) or failed the catch question. Sixteen respondents did not meet the inclusion criteria for Wave 1 and were therefore also excluded from the Wave 2 analyses. The final sample size was 326 (65% of the original sample, 154 females). Respondents' ages ranged from 18 to 70 (M = 32.44, SD = 12.06). See Supplementary Tables S12-S16 in Appendix A for descriptive statistics regarding the career fields, level of education, nationality, native language, and gender identity of our Prolific sample. On average, the survey took 15 minutes to complete. Respondents were paid £1.88, amounting to an average hourly fee of £7.50. All respondents were fluent in English according to the Prolific database.

Materials and procedure

Wave 2 comprised (1) an updated version of the COVID-19 Knowledge Test, (2) open-ended questions about the origin, symptoms, measures, and societal impact of COVID-19, (3) questions regarding the frequency of media use related to COVID-19 news,

(4) questions regarding the importance of a range of sources for acquiring COVID-19 knowledge, and (5) adherence to government-imposed measures.

The COVID-19 Knowledge Test was updated. One item was moved from the false to the true statement category, because new scientific insight proved this statement to be true rather than false, and eight new items were added. As a result, the updated COVID-19 Knowledge Test consisted of 16 true statements and 16 false statements. We made no changes to the conspiracy statements. To assess media use, respondents indicated how frequently they made use of 18 (categories of) sources to acquire COVID-19 knowledge on a 7-point scale (1 = *I don't use this source*, 7 = *multiple times per day*). The complete survey (https://osf.io/vrbpw/) as well as our preregistration (https://osf.io/mp2ua/) can be viewed online on OSF. All the measures (except the open-ended questions) from the second survey are displayed in Table 4.6. The data from the open-ended questions about the origin, symptoms, measures, and societal impact of COVID-19 are reported in a supplementary online appendix (https://osf.io/38b65/).

Table 4.6 Overview and Descriptions of the Measures in Wave 2

Category	Measure	Items	Description
Information processing	COVID-19 Knowledge	32	*Knowledge about COVID-19* in terms of accuracy and confidence.
	Conspiracy Rejection	8	*COVID-19-related conspiracy rejections* in terms of accuracy and confidence.
Media use	Frequency per source	18	The extent to which different types of sources are used to acquire information about COVID-19 (e.g., news sites, social networking sites, friends/family).
Behaviour	Adherence to measures	1	The degree of adherence to government-imposed measures against COVID-19.
	Perceived importance of sources	8	The perceived importance of different sources and organizations with respect to acquiring new information and guidelines.

The measures of Wave 2 were complementary to the Wave 1 measures. Again, we measured COVID-19 information processing and interpretation (COVID-19 Knowledge and Conspiracy Rejection), which allowed us to investigate temporal changes between Wave 1 and Wave 2. In addition, we added a more comprehensive media question to assess usage frequency per distinct media source. We also added two behaviorally focused questions about adherence to government-imposed measures and the perceived importance of different organizations that publish health regulations or guidelines to counter COVID-19. We used measures on cognitive motivation and demographic traits from Wave 1, because our Wave 2 sample 1 (N =326) comprised a subset of our Wave 1 participants (N=501).

Results

Similar to the Wave 1 results, we will start with the report of our inferential analyses followed by descriptive analyses.

Wave 1 and Wave 2 overall comparison

Did knowledge of COVID-19 and belief in conspiracy theories change between March and July 2020? To determine whether we could accurately quantify change in COVID19-Knowledge and Conspiracy Rejection factors, we used the longitudinal measurement invariance of the COVID19-Knowledge Test using data from all 326 individuals that participated in both waves. Because all items are categorical, however, not all default measurement invariance analysis steps could be undertaken. A model for configural invariance for example, would have to estimate 62 factor loadings, 248 thresholds, 62 residual variances, 2 latent factor variances, 2 latent factor means, and a covariance between the latent factors. If we allowed for correlated residual across measurement occasion, we would also estimate 62 such correlations. This number of parameters is too high to obtain stable estimates given our sample size. We therefore chose to fit an invariance 2-wave model of the COVID-19 Knowledge Test in which all factor loadings and thresholds were constrained to be equal, and in which residuals were freely estimated and allowed to correlate over time. All analyses were run using the R-package lavaan (Rosseel, 2012). In addition, all models were fitted using the diagonally weighted least squares (DWLS) estimator, robust standard errors, and a mean- and variance-adjusted chi-square test. The invariance 2-wave model showed sufficient fit to the data (χ^2 (1939) = 2978.44, p < .001; CFI = .925; RMSEA =.041) which allowed an investigation of change in COVID-19 Knowledge and Conspiracy Rejection between waves using Latent Difference Scores (McArdle, 2009). Note that we did not pre-register the use of latent difference scores. We proposed regressing the factor-scores obtained on the Wave 2 data on the factor scores from Wave 1. However, the latent difference scores gave us a more precise estimate of change in the factors and the variance in this change. As we used latent difference scores, the relation between NC and NCC on the one hand and change in COVID19-Knowledge and Conspiracy Rejection on the other was investigated by regressing the latent difference scores for these two factors on the total NC and NCC scores. This Latent Difference Score model is an equivalent model to the 2-wave model and therefore has identical fit (χ^2(1939) = 2978.44, p < .001; CFI = .925; RMSEA =.041). The results showed that there was no significant mean increase in either COVID-Knowledge (-.029 (.050), p =.559) or Conspiracy Rejection (-.011 (.053), p =.833). There was significant variance in both latent change factors (Knowledge: s2(se) = .447 (.070), χ^2(1) = 54.48, p < .001; Conspiracy: s2(se) = .520 (.058), χ^2(1) = 83.02, p < .001).

Wave 1 and Wave 2 comparison based on NC and NCC

In addition to overall changes in *COVID-19 Knowledge* and *Conspiracy Rejection* from Wave 1 to Wave 2, we asked whether any changes could be associated with NC and NCC. Adding NC, NCC, and their interaction as predictors for the latent change scores of *COVID19-Knowledge* and *Conspiracy Rejection* showed that NC and NCC were both positively related to change in *COVID19-Knowledge* (NC: b(se) = .196 (.076), beta=.253, p = .010; NCC: b(se) = .283 (.076), beta=.366, p < .001), while NCC was also positively related to change in *Conspiracy Rejection* (b(se) = .188 (.071), beta=.246, p = .008). Need for Cognition was not significantly related to change in *Conspiracy Rejection* (b(se) = .122 (.066), beta=.160, p = .063). There was no significant interaction effect on change in either *COVID19-Knowledge* (b(se) = -.113 (.062), beta=-.198, p = .068) or *Conspiracy Rejection* (b(se) = -.061(.054), beta=-.108, p = .266). In summary, both NC and NCC were associated with an increase in COVID-19 Knowledge from Wave 1 to Wave 2. NCC was also a predictor of an increase in rejectance of conspiracy statements from Wave 1 to Wave 2.

COVID-19 knowledge and compliance behaviour

The relation between COVID19-Knowledge and Conspiracy Rejection at Wave 2 and (1) adherence to government-imposed measures and (2) the perceived importance of each information source was investigated using a path model. In this model, the eight items on different news sources, and adherence to measures were endogenous or dependent variables, while the Wave 2 factor scores were exogenous or independent variables. *COVID-19 Knowledge* and *Conspiracy Rejection* were added to this model as predictors. Results show that this path model sufficiently fitted the data (χ^2(694) = 1071.78, p < .001; CFI = .943; RMSEA =.045). In addition, we found that COVID19-Knowledge at Wave 2 was significantly positively related to adherence behaviour at Wave 2 (b(se) = .225 (.065), beta = .271, p = .001). All other relations were non-significant.

To investigate the relationships of NC and NCC with adherence to government-imposed measures, the perceived importance of respected sources, participant age (as covariate factor) and media use, we computed an additional network model (see Supplementary Figure S4.6 in Appendix B). The R package ‘bootnet’ and the complementary function ‘estimateNetwork()’ with the “EBICglasso” method (i.e., a Gaussian Markov random field estimation based on graphical LASSO and an extended Bayesian information criterion to select parameters) were used (Epskamp et al., 2018). Both NC and NCC were not related to the perceived importance of respected sources, adherence to measures, or media use. However, NC and NCC were weakly negatively correlated and NCC was positively correlated to participant age.

Descriptive analyses

COVID-19 knowledge

On average, 73.3% of the true statements were correctly endorsed, whereas 67.9% of the false statements were correctly rejected (see Supplementary Table S4.17 in Appendix A; internal-consistency factor: ωh = 0.80). The largest difference in responses was yielded by the item “*Face masks can protect you against the coronavirus*.” That is, this statement was endorsed by more respondents in Wave 2 (30.7%) than in Wave 1 (10.1%). This specific item also explains the overall increase of “*I am sure this is true*” judgements in the false statement category (see Table 4.7). The overall evaluations of the COVID-19 Knowledge Test statements for Wave 2 are presented in Supplementary Figure S4.2 in Appendix B, and the latent difference scores between Wave 1 and Wave 2 per item are presented in Supplementary Figure S4.3 in Appendix B.

COVID-19 conspiracy evaluation

More than half of the respondents (57.4%) either rejected all eight conspiracy theories or gave neutral answers both at Wave 1 and Wave 2 (internal-consistency factor Wave 2: ωh = 0.89). A far smaller group of 46 respondents (14.1%) accepted at least one conspiracy theory both at Wave 1 and Wave 2. This means that belief in conspiracy theories changed between Wave 1 and Wave 2 for 28.5% of the respondents. This change contained either a shift from rejection of all conspiracy theories at Wave 1 to endorsement of at least one conspiracy item at Wave 2 (16.3%), or the other way around (12.3%). Moreover, 39.3% of respondents could not explicitly reject all of the conspiracy statements both at Wave 1 and Wave 2, whereas 35.2% did reject all conspiracy statements at Wave 1 and Wave 2. The remaining group showed changes on this measure: 12.6% of respondents could not reject all conspiracy statements at Wave 1, and 12.9% could not reject all conspiracy statements at Wave 2.

Table 4.7 Comparison of COVID-19 Knowledge Test Answers Between Wave 1 and Wave 2 (Within-group and Identical Items Only; N = 326)

		Wave 1			Wave 2			
Item veracity	**Knowledge Test answers**	**Mean percentage**	**95% CI**		**Mean percentage**	**95% CI**		**Diff.**
True statements (12 items)*	*"I am sure this is true"*	57.0	[54.6,	59.4]	53.2	[50.6,	55.9]	-3.8
	"I think this is true"	28.6	[26.5,	30.6]	31.2	[28.9,	33.5]	+2.6
	"I don't know"	8.4	[7.3,	9.5]	8.6	[7.5,	9.6]	+0.2
	*"I think this is **not** true"*	4.3	[3.6,	4.9]	5.1	[4.2,	5.9]	+0.8
	*"I am sure this is **not** true"*	1.7	[1.3,	2.2]	1.9	[1.1,	2.8]	+0.2
False statements (11 items)*	*"I am sure this is true"*	4.7	[3.9,	5.6]	6.6	[5.7,	7.5]	+1.9
	"I think this is true"	13.4	[12.2,	14.7]	14.9	[13.8,	16.1]	+1.5
	"I don't know"	13.9	[12.5,	15.4]	13.5	[12.0,	15.0]	-0.4
	*"I think this is **not** true"*	23.8	[22.0,	25.6]	22.1	[20.2,	23.9]	-1.7
	*"I am sure this is **not** true"*	44.1	[41.7,	46.5]	42.9	[40.5,	45.3]	-1.2
Conspiracy statements (7 items)	*"I am sure this is true"*	0.3	[0.0,	0.6]	0.9	[0.4,	1.4]	+0.6
	"I think this is true"	2.5	[1.6,	3.3]	3.2	[2.1,	4.4]	+0.8
	"I don't know"	14.2	[11.4,	17.0]	11.3	[8.8,	13.7]	-2.9
	*"I think this is **not** true"*	19.6	[16.6,	22.6]	19.4	[16.5,	22.3]	-0.2
	*"I am sure this is **not** true"*	63.5	[59.3,	67.6]	65.2	[61.1,	69.2]	+1.7
Negated conspiracy statement (1 item)	*"I am sure this is true"*	28.5	[23.6,	33.4]	26.7	[21.9,	31.5]	-1.8
	"I think this is true"	27.9	[23.0,	32.8]	26.7	[21.9,	31.5]	-1.2
	"I don't know"	23.0	[18.4,	27.6]	22.7	[18.1,	27.3]	-0.3
	*"I think this is **not** true"*	13.2	[9.5,	16.9]	12.9	[9.2,	16.5]	-0.3
	*"I am sure this is **not** true"*	7.4	[4.5,	10.2]	11.0	[7.6,	14.5]	+3.7

Note. This table shows comparative descriptives of the COVID-19 Knowledge Test of Wave 1 (March 27, 2020) and Wave 2 (July 1, 2020). The percentages are based on a subset of participants that participated in both surveys. The items that were not presented to participants in Wave 1 were removed. One item of the false items was moved to the correct statement category in Wave 2, and therefore also removed from this comparison. Differences in percentages that show overlap between CIs are presented in grey font colour.

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Media use

Supplementary Figure S4.4 in Appendix B shows the frequencies with which different sources are consulted for COVID-19 information. Evidentially, the nature and frequency of COVID-19 information acquisition is highly variable across respondents in our sample. That said, the source ‘friends, relatives, and co-workers’ yielded the highest proportion of respondents who reported to use it ‘multiple times per day’. This suggests that colloquial conversations play a prominent role in the exchange of COVID-19 information. On a daily basis, the most widely used sources of COVID-19 information are news broadcasts (e.g., “BBC”, “CNN”), television/radio, and newspapers (incl. digital). Furthermore, Google and real-time statics sites are also frequently used to obtain or encounter COVID-19 news. Within the category of social media, Facebook and Twitter are the most popular sources of COVID-19 news. Overall, respondents in our sample mainly rely on conventional media to obtain information about COVID-19. However, they also encounter information colloquially and when they use social media.

Perceived importance of sources

Supplementary Figure S4.5 in Appendix B presents the perceived importance of different sources and organizations with respect to acquiring COVID-19 information and guidelines. The majority of respondents reported the World Health Organization (WHO) to be either important or very important (69%), whereas 10% of respondents perceived the WHO as unimportant. Furthermore, national health organizations were also reported as important or very important by the majority of respondents (78%), whereas only 4% perceive their national health organization as unimportant. After health organizations, governments (58%), heads of governments (51%), general practitioners (51%), (former) COVID-19 patients (47%), and relatives/family (40%) are perceived as important or very important by approximately half of the respondents. Moreover, leaders of respondents’ chosen political parties are perceived as unimportant by 40%, whereas only 26% perceive their party leaders as important or very important. Altogether, the WHO and national health organizations are highly valued in our sample, whereas political party leaders are perceived as less important.

Adherence behaviour

We also investigated the respondents’ adherence to government-imposed measures. Most respondents (48.5%) reported to ‘always’ follow the measures. The second largest group (37.1%) reported to ‘often’ follow the measures. A smaller group (9.8%) reported to ‘sometimes’ follow the news. The smallest group reported to either ‘rarely’ (2.8%) or to never (1.8%) follow the measures. Only four respondents (1.2%) appeared to be noncompliant for other reasons than inadequacy of their government. Overall, the provided explanations indicated that low adherence to measures can mainly be attributed to a lack of governmental guidance or actions. See the Supplementary Examples and responses to the open-ended question about adherence in online Appendix D (https://osf.io/xcu2k/).

Discussion

The second wave enabled us to address potential temporal-induced changes in the evaluation of the COVID-19 Knowledge Test statements. We found no considerable changes in COVID-19 knowledge and conspiracy beliefs from March 27 to July 1. However, one of the statements was a remarkable exception: *"Face masks can protect you against the coronavirus."* respondents judged this statement to be true more often in the second wave. Possibly, this change in opinions reflects a behavioral shift on a societal level. That is, while governments have endorsed or imposed the use of face masks to mitigate the spread of the virus, citizens may have adopted a more positive sentiment towards the use of face masks. Perhaps, citizens tend to believe that face masks are used for self-protection rather than for altruistic purposes. In addition, governmental ads and guideline updates on wearing face masks may have increased explicit recognition of this statement, which likely has induced a more positive affect. Thus, increasing the likelihood that respondents evaluate this statement to be true in Wave 2. Indeed, previous studies have shown that explicit recognition increases positive affect towards priorly exposed stimuli (Brooks & Watkins, 1989; Fang et al., 2007; Newell & Shanks, 2007; Stafford & Grimes, 2012).

Despite overall factual knowledge about COVID-19 remaining relatively unaffected, both NC and NCC (assessed in Wave 1) were positively associated with latent difference scores on the items between Wave 1 and Wave 2. This suggests that respondents high in NC or NCC were more likely to increase their knowledge about COVID-19 from Wave 1 to Wave 2. Considering that respondents high in NC are more likely to engage in information-acquiring activities, it is not surprising that they were more likely to change their views over time. However, the positive relation we found between the difference scores and NCC appears less intuitive. Theoretically speaking, high NCC individuals would be more likely to remain unswayed by new information and be more prone to hold on to initial beliefs. As discussed in the introduction, NCC consists of two processes, *seizing* and *freezing*. As long as people are in the seizing phase, they will continue to collect information and compare it to the interpretation they already have to achieve closure. Once they are confident in their interpretation, they are in the freezing phase and the interpretation process will be terminated. It is quite possible, given the volatile nature of the pandemic, that many of our respondents had not yet reached the freezing phase and were still comparing their

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initial interpretation to alternatives. We note, however, that without explicit measures of seizing and freezing, the hypothesis becomes unfalsifiable.

Another potential explanation for the positive relation of NCC on our measure of *Conspiracy Rejection* over time might be rooted in the high confidence level of high NCC participants. That is, if both high and low NCC groups would gain news insight between Wave 1 and Wave 2 about the origin and motives related to COVID-19, high NCC participants would be relatively more likely to answer with “I am sure this is not true” at Wave 2, whereas low NCC participants would be relatively more likely to answer with “I think this is not true” at Wave 2. Therefore, the latent difference scores for high NCC participants would be higher (i.e., +2) as compared to low NCC participants (i.e., +1.) In addition, doubts about the reprehensibility of the conspiracy statements at Wave 1 may have been mitigated at Wave 2, because participants were debriefed about the reprehensibility of some of the statements (without mentioning which particular statements were false) after the first survey. Thus, during the first survey participants were probably more oblivious to the presence of the implemented false conspiracy statements and more prone to answer neutrally, whereas in the second survey participants were more cognizant of the potential presence of these false statements.

Compared to Wave 1, this second wave included three additional measures: (1) a more in-depth inquiry on the media use with respect to COVID-19, (2) an indication of perceived importance of different sources, and (3) an indication of adherence to government-imposed measures against COVID-19. We did not find relations of these variables with either NC or NCC.

General discussion

We were interested in how cognitive motivation impacts the acquisition, processing, interpretation of information in a situation of great uncertainty, namely during early phases of the COVID-19 pandemic. In addition, we were interested in how cognitive motivation is associated with the updating of mental representations after a three-month interval. We will discuss our main findings regarding the relations, or absence thereof, we observed between our measures of cognitive motivation, NC and NCC, and COVID-19 knowledge, conspiracy rejection, media use, and behavioural measures. We will also highlight several additional noteworthy findings.

Cognitive motivation

People differ with respect to the amount of pleasure they derive from their own thought processes and with respect to how motivated they are to quickly arrive at an interpretation of a state of affairs. The former is called the Need for Cognition, the latter the Need for Cognitive Closure (Cacioppo & Petty, 1982; Cohen et al., 1955;

Kruglanski & Webster, 1996a; Petty et al., 2009). We reasoned that people would engage in different behaviours regarding the gathering, processing, and interpretation of information based on their need for cognition and need for cognitive closure. We thought of NC and NCC as largely unrelated factors. Consistent with this, we found that NC and NCC exhibit a slightly negative correlation. This finding is in line with previous research (Webster & Kruglanski, 1994a).

COVID-19 Knowledge

In line with our first hypothesis (see **H1a**), the regression analysis of Wave 1 and Wave 2 data showed a relationship between NC and COVID-19 Knowledge, in which higher NC predicts increased knowledge. Unexpectedly however, NCC was also associated with increased COVID-19 Knowledge. Therefore, people who are high in NC and/or NCC have more COVID-19 Knowledge (based on our measure of COVID-19). Confirmatory analysis of the differences between Wave 1 and Wave 2 scores also showed positive effects of both NC and NCC on COVID-19 Knowledge over time. People high in NC as well as people high in NCC showed an increase of knowledge (i.e., an increase of confidence and/or accurate knowledge). Thus, as might be expected, people who enjoy cognitive activities more (i.e., people high in NC), are more likely to increase their knowledge, as are people who are looking for a coherent interpretation of a state of affairs (i.e., people high in NCC).

The statement "It is possible to become immune to the coronavirus after recovery" was regarded as a true statement in the COVID-19 Knowledge Test. We are aware that this notion has been quite controversial during the beginning of the pandemic. Therefore, we provide additional rational for classifying the statement as true. At the time of the survey there was no scientific consensus on whether people could develop long-term immunity to the SARS-CoV-2 virus (i.e., the cause of COVID-19). For example, there were known cases of recovered patients who remained viral positive or even relapsed (Shi et al., 2020). However, research also showed that that a primary SARS-CoV-2 infection in rhesus macaques could protect from reinfection, and there was evidence of SARS-CoV-2 specific antibodies in humans as well (Bao et al., 2020; Ju et al., 2020). Evidently, there was *a possibility* to become immune after recovery (at least temporarily). Moreover, governments such as in the UK and the Netherlands mentioned 'herd immunity' as a natural by-product of the pandemic (which was a controversial sentiment because achieving herd immunity without vaccinations would, contrary to the goal, cost many lives) (Boseley, 2020). Thus, there was both evidence and (in some countries) governmental acknowledgment of the possibility of immunity.

Conspiracy theories

We hypothesized that people low in NC but high in NCC are more likely to engage in conspiracy beliefs (see **H3**). However, we did not find this interaction effect. Instead, both NC and NCC are positively related to the rejection of conspiracy theories. NCC also proved to be associated with an increase in rejection of conspiracy theories over time, from Wave 1 to Wave 2. The ability to successfully reject conspiracy theories is associated with more knowledge about COVID-19 as well. The average chance of endorsing a conspiracy theory was about 2.7% at Wave 1 and Wave 2 (excluding the item "The coronavirus was not created by humans"). Thus, the endorsement of conspiracy theories is marginal in our sample. Alternatively, we found that about a quarter of participants endorsed at least one of eight conspiracy theories. However, we have to consider this would also inflate the potential influence of response biases such as the acquiescence bias (i.e., 'yea-saying') with a factor of eight (i.e., the number of conspiracy items). Obviously, not all conspiracy theories are wrong. Watergate, for example, was an actual conspiracy. In this sense, it is perhaps not surprising that a sizable portion of respondents were unable to refute all conspiracy statements. That said, considering results of both Wave 1 and Wave 2, only 14.1% of participants endorsed at least one conspiracy theory at both waves, which is still considerably lower than conspiracy endorsement found in other studies (Douglas et al., 2017). For example, Oliver and Wood (2014) found that 55% of their participants endorsed at least one conspiracy theory, in a study by Gombin (2013) this was 50.3% (Gombin, 2013; Oliver & Wood, 2014). However, we have to be careful making direct comparisons considering the differences in specific ideologies and content conveyed by conspiracy statements between studies, as well as differences in the demographic traits (e.g., nationality, political affiliation) of the samples.

Media use

We expected to observe different types of information seeking behaviours based on variations in NC and NCC. First, we expected NC to predict the frequency of information gathering activities. Specifically, people high in NC would seek out new information more frequently than people low in NC (see **H1b**). However, regression analyses of Wave 1 data did not show relations of NC with COVID-19-related information searching frequency. Moreover, we expected that NC would predict the type of sources used as well (see **H1c**). However, none of the usage frequencies of the sources listed in our Wave 2 survey were related to NC. This means that, in our sample, NC did not predict the type or quality of sources used to acquire COVID-19.

Clusters

Our confirmatory cluster analyses of the Wave 1 data failed to support the notion of four different groups of people based on the two measures of cognitive motivation, and our measures of COVID-1- knowledge, conspiracy thinking, and media use, as hypothesized in Table 4.1. This will be further discussed below.

Self-reported behavioural measures

In our Wave 2 survey we added additional questions regarding the perceived importance of different sources and adherence to government-imposed measures, which did not show relationships with either NC or NCC. However, we did find that people with higher COVID-19 Knowledge (i.e., participants who performed better on the COVID-19 Knowledge Test) report more faithful adherence to measures.

Limitations

The present study has several limitations. The outcome variable *COVID-19 Knowledge* can be seen as a combination of two conceptually independent constructs: the accuracy of the judgments (i.e., correct or incorrect) and the level of confidence in personal knowledge (i.e., “I am sure”, “I think”, “I don’t know”). From the participants perspective however, these constructs were not independent as they used a single ordinal five-point scale (i.e., 1 = “I am sure this is not true”, 2 = “ I think this is not true”, 3 = “I don’t know”, 4 = “I think this is true”, 5 = “ I am sure this is true”). We chose to use the original five-point scale in our inferential analyses and found main effects and interaction effects of NC and NCC on our measure of *COVID-19 Knowledge*. An important consideration here is that, based on our inferential analyses, we cannot conclude whether this effect is mainly caused by differences in judgement accuracy, judgement confidence, or both.

With that caveat, the comparative descriptive statistics of the COVID-19 Knowledge Test of Wave 1 data in Supplementary Tables S4.8-S4.10 in Appendix A do suggest that NCC is a predictor of the level of confidence in people’s views about COVID-19. Respondents low in NCC showed lower levels of certainty compared to respondents who are high in NCC. More specifically, respondents who are low in NCC were relatively more likely to use the “I don’t know” and “I think” responses, whereas respondents high in NCC were relatively more likely to use the “I am sure” response. This suggests that high NCC individuals had more confidence in personal knowledge irrespective of the veracity of this knowledge. Either way, with the current design and analyses we cannot justify whether Hypothesis 2 (i.e., higher NCC predicts higher certainty) should be accepted or rejected. To properly analyse the relationship of NCC on confidence it is necessary to isolate the constructs of confidence and accuracy.

Future research could introduce an experimental design that would allow for an appropriate separation of the two constructs.

Our cluster analysis showed no distinct groups based on *COVID-19 Knowledge*, *Conspiracy Rejection*, media use, and motivations to acquire news. A possible explanation might be that the data was not suited for the current cluster analysis method. More specifically, we used k-means clustering algorithms to compute principal components, which is based on two assumptions: the data should be spherical, and the clusters should be roughly equal in size. Perhaps, the current data did not meet these criteria. For example, if confidence levels are (partially) independent from the level of accuracy of knowledge this may result in non-spherical data; that is, one group would show more extreme scores with incorrect high confidence (i.e., 1) and correct high confidence scores (i.e., 5), whereas another group may have shown more centered scores (i.e., 2,3,4). In addition, the four hypothesized groups may be unequally represented in our sample. It is likely that a potential group of conspiracy endorsers would be relatively small compared to conspiracy rejecters. Thus, k-means clusters would show overlap, because this method does not account for large differences in group sizes.

Moreover, our sample might not have been representative. Our respondents displayed much factual knowledge about COVID-19, were eager to gather information about the virus as well as to educate others about it (>50% of the respondents in Wave 1), and showed little endorsement for conspiracy theories regarding COVID-19. One could argue that perhaps our sample's scores for NC and NCC are not comparable to the scores found in other studies. However, the NC and NCC scores found in our study correspond with previous research on NC (see Supplementary Table 4.7 in Appendix A for comparisons of the means and standard deviations) (Djikic et al., 2013; Furlong, 1993; Kernis et al., 1992; Miller et al., 1991; Peltier & Schibrowsky, 1994; Roets & Van Hiel, 2011).

A final limitation that should be discussed here is that the measure of adherence to government-imposed measures depended on the activities of one's government. While we were mainly interested in the range of compliance to governmental guidelines and its relationship with NC and NCC, we are aware that this measure is likely confounded by the different political environments of the respondents. As shown in online Appendix D (https://osf.io/xcu2k/), respondents who reported to rarely or never follow government-imposed guidelines predominantly explained that their governments were either inactive or inadequate with respect to countering the coronavirus.

Conclusion

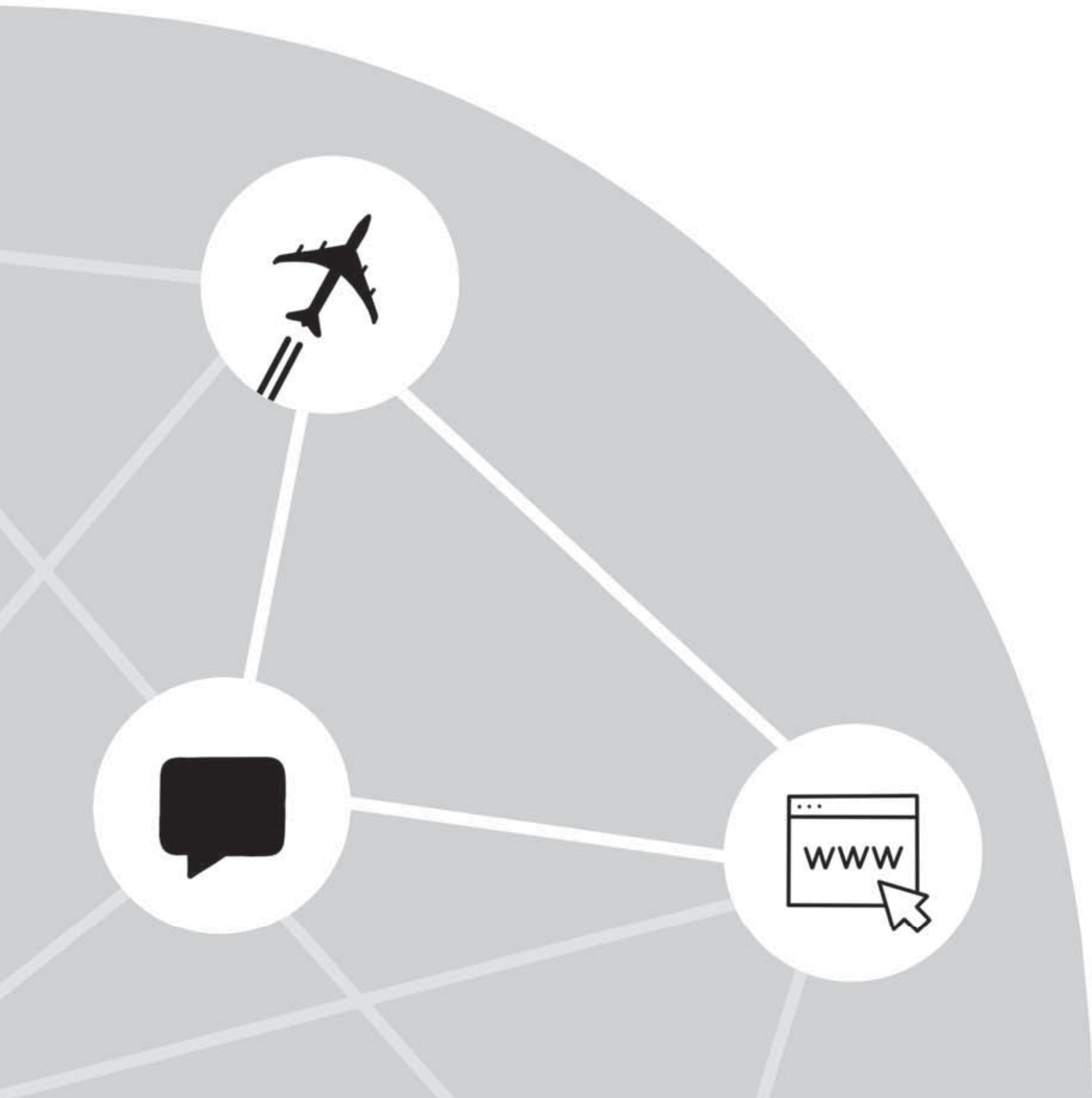
As might be expected in a state of high epistemic uncertainty, nearly three-quarters of our respondents actively searched for information about COVID-19. A large majority of the respondents was engaged in COVID-19 information seeking behaviour on a daily basis or even more frequently than that. Their primary sources were news sites, social networking sites, and television broadcasts. Traditional media, such as printed newspapers and radio broadcasts, were scarcely utilized. We speculate that one reason is that the latter do not provide information with the immediacy that the digital media allow.

Both Need for Cognition and Need for Cognitive Closure are associated with increased knowledge of COVID-19 and the ability to reject conspiracy theories about COVID-19. Thus, the extent to which our respondents acquired knowledge about COVID-19 is related to the extent to which they enjoy being engaged in their own thought processes and to the extent to which they seek a coherent interpretation of the information they have gathered. These two variables had an additive effect on levels of COVID-19 knowledge. While descriptive analyses suggest these relations can predominantly be explained by differences in confidence levels, future research should focus on an appropriate separation of the constructs of judgement accuracy and judgement confidence. Even though this study is framed within the context of the COVID-19 pandemic, our findings can be extended beyond this specific context. We expect cognitive motivations to be useful in distinguishing how people derive and elaborate on information from similar media environments as the ones we investigated in the current study.

Data availability

The datasets generated during and/or analysed during the current study are available in the Open Science Framework repository, https://osf.io/38b65/.

CHAPTER 5



“What are those stripes in the sky?” An experimental study on exposing web users to a conspiracy theory

Boot, A.B., Dijkstra, K., & Zwaan, R.A. (submitted). What are those stripes in the sky?”
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Abstract

The conditions that engender conspiratorial beliefs should be better understood, as these misbeliefs can have harmful consequences (e.g., denial of legitimate election results or ignoring health guidelines against viral contagion). We investigated the susceptibility of high-educated Web users to adopt a novel conspiracy belief from a website. As an exemplar of a conspiracy theory, this ostensibly real website presented the "chemtrails" conspiracy (i.e., toxic sprays from airplanes) and a digital petition against its operation. After exposure to the website, participants were asked whether they believe in the existence of chemtrails, i.e., a measure of *explicit belief*. Signing the petition was considered as an opaque behavioral measurement of *implicit belief* in these chemtrails. Contradicting our hypothesis, participants were more likely to report explicit belief in the existence of chemtrails than they were to sign the petition. Remarkably, approximately half of the participants to whom the conspiracy claim was novel reported to believe in the existence of chemtrails after reading the website. Exploratory findings further suggest that this credulousness is associated with a more positive sentiment towards the website and more daily mobile social media usage.

Keywords

conspiracy beliefs, misinformation, chemtrails, truth bias, conspiracy website, belief measurement

New media on the internet such as social networking sites, microblogs, and social news-aggregation sites have become important gateways to the most topical news. These online platforms can be a double-edged sword, allowing for more freedom of expression and opinion while also exposing users to controversial misinformation. For example, media users have been exposed to unfounded conspiracy narratives about the coronavirus pandemic, such as the notion that it was a hoax or that the virus was human-made. Consequently, coronavirus conspiracy believers have reported to be less compliant with governmental health policies aimed at reducing the widespread infection (Imhoff & Lamberty, 2020). Another consequence of unfounded conspiracy narratives on new media was the U.S. Capitol riot on Jan. 6, 2021. This was an attempt to overturn the outcome of the presidential election and was provoked by unfounded conspiracy beliefs about election-fraud on social media (Calvillo et al., 2021). The current experimental study aimed to examine the susceptibility of media users to adopt a novel conspiracy belief from a website.

Contrary to what is commonly assumed, conspiracy beliefs are not unique to the current digital age (van Prooijen & Douglas, 2017). In fact, the Adaptive Conspiracism Hypothesis proposes that early hunter-gatherers developed a conspiracy detection trait in times of intergroup conflict (van Prooijen & van Vugt, 2018). While a tendency to detect conspiracies possibly provided a reproductive advantage in early human history, it also means people can be genetically predisposed to “detect” conspiracies that are not real (i.e., false positives). For example, conspiracies can be misperceived by attributing agency or intentionality to negative events where it does not exist (Douglas et al., 2016). If conspiracy accusations are unfounded, such that the espoused claims are demonstrably false or unjustified, then belief in such conspiracy claims is problematic because they can invoke actions that have drastic negative consequences (e.g., ignoring Covid-19 health policies, partaking in riots against legitimate election results). In line with this view, previous research has indicated that conspiracy beliefs can be detrimental to health, interpersonal relationships, and safety (van Prooijen & Douglas, 2018). In such cases, conspiracy beliefs can be regarded as harmful misperceptions (Flynn et al., 2017). Considering the ubiquity of conspiratorial misinformation on the Web and the potential consequences of belief in such claims, it is important to gain insights into the conditions under which Web users develop these misperceptions. Specifically, these insights can contribute to interventions that can safeguard media users against false conspiracy claims and other types of misinformation on the Web.

Misconceptions are rooted in the way people search, process, and interpret information. For instance, people are inclined to search for information that reinforces prior beliefs (i.e., confirmation bias), and tend to counterargue ideas that contradict prior beliefs (i.e., disconfirmation bias). Misconceptions, then, can arise from the motivation to reach a preferred conclusion (Kunda, 1990; Taber & Lodge, 2006). More fundamentally, however, misconceptions are caused by a tendency to believe rather than to doubt, to be credulous rather than skeptical towards new information. Gilbert and colleagues (1993) refer to this phenomenon as the Spinozan account of belief. They proposed that "belief is first, easy, and inexorable", whereas "doubt is retroactive, difficult, and only occasionally successful". Accordingly, belief may be an inevitable initial stage of comprehension, whereas doubt or rejection may be an active operation that can undo the initial belief.

Multiple studies on information processing provide evidence that the initial stage of comprehension is belief rather than disbelief (i.e., truth bias). In situations when people are exposed to false information while being distracted (i.e., high cognitive load), they are more likely to believe false information than when they are not distracted (i.e., low cognitive load; Gilbert et al., 1993). Moreover, a recent study by Pantazi and colleagues (2018) suggests that a truth bias might persist regardless of cognitive load. Specifically, the authors found that false statements were more often misremembered as true and would influence participants' judgments, a finding that was independent from a distraction task. Another example is the Truth-Default Theory (TDT), which proposes that people have the default presumption that others tell the truth (Levine, 2014). Thus, a wide array of evidence indicates a general inclination towards credulousness rather than skepticism; people are biased to accept new information as veracious. This implies that media users are prone to believe new information they encounter on the Web as well.

Truth bias can be explained by automatic cognitive processes. Dual-processing theories on reasoning generally refer to this as a type 1 (or system 1) process, which is characterized as automatic, superficial, intuitive, and implicit; type 2 can be described as analytical, reflective, retrospective, and explicit (Evans, 1984; Kahneman, 2003; Petty & Cacioppo, 1986; Strack & Deutsch, 2004; Wason & Evans, 1974). Type 1 reasoning is a cognitive mechanism that helps to explain misperceptions because it is intuitive rather than rational; it is inherently more error-prone than type 2 reasoning. Importantly, previous findings suggest that conspiracy beliefs are also derived from intuitive processes (i.e., type 1) rather than analytical cognitive processes (Swami et al., 2014; van Prooijen & Douglas, 2018). Situations where people tend to passively consume information are more likely to induce these intuitive processes. Not surprisingly, then, misperceptions (including false conspiracy beliefs) can be situational. Moreover, misperceptions can be rooted in false inferences or misinterpretations. For example, attribution studies have shown that people initially infer dispositional explanations from observed behaviors instead of situational explanations (i.e., correspondence bias or attribution bias; (Gilbert & Malone, 1995). Notably, these dispositional explanations are reminiscent of the finding that conspiracy believers tend to ascribe intentionality where it does not exist (Douglas et al., 2016). For instance, government guidelines against the spread of a virus (i.e., situational explanation) might be interpreted as a malicious intent to exert control over the public (i.e., dispositional explanation).

If truth bias, type 1 reasoning, and attribution errors can explain general misperceptions, this implies people can be prone to believe in false conspiracy narratives as well. More specifically, if Web users passively consume misinformation about a supposed conspiracy, enabling intuitive type 1 reasoning, how susceptible are they to accept and adopt this conspiracy claim?

There is an important caveat in the comparison of false conspiracy beliefs with general misperceptions: conspiracy beliefs can be more profound and consequential than other types of misperceptions. Compare the notion that ‘the coronavirus pandemic was a hoax’ with the notion ‘bacteria are bad’. The former misperception has much greater societal and interpersonal implications relative to the latter. Sunstein and Vermeule (2009) have described a conspiracy theory as:” An effort to explain some event or practice by reference to the machinations of powerful people, who attempt to conceal their role”. This means conspiracy narratives can offer readily available explanations for uncertainties or complex problems pertaining a certain state of affairs, such as a worldwide pandemic. Therefore, conspiracy beliefs have been associated with an intolerance for uncertainty, or a need for cognitive closure (Marchlewska et al., 2018b; Webster & Kruglanski, 1994b). This is supported by the observation that historic periods with increased uncertainty, such as societal crises, instigate conspiracy beliefs (van Prooijen & Douglas, 2017). Thus, in the comparison with general misperceptions, conspiracy views distinctively arise from feelings of uncertainty.

The need to solve uncertainty (i.e., the need for cognitive closure) fosters a “connecting-the-dots” type of reasoning, a desire to find meaningful relationships. For example, conspiracy believers tend to perceive patterns in random stimuli (van der Wal et al., 2018; van Prooijen et al., 2018). This tendency to misperceive patterns or relationships is dispositional, but we expect it can be situational as well. Consider a situation in which a conspiracy theory is introduced within the context of - and as a solution to - an alleged uncertainty. For instance, a website can introduce a conspiracy theory to a reader by presenting a line of reasoning that includes both arguments about suspicious observations (engendering feelings of uncertainty) and a supposed explanatory conspiracy. Such an elaborate introduction is perhaps likely to convince the reader to adopt this conspiracy belief, even if the reader is not predisposed to engage in conspiracy thinking. To examine this, we built a website that would elaborately introduce a conspiracy theory to the reader in an online experiment.

As an exemplar of a conspiracy theory, we chose the “chemtrails” conspiracy theory. This conspiracy theory entails the misperception that the white stripes from airplanes (i.e., condensation trails) are toxic chemicals that are sprayed for malevolent purposes by a secret organization. A study by Xiao and colleagues (2021) shows that the internet plays an important role in the instigation and proliferation of this conspiracy belief, which was revealed through in-depth interviews with chemtrail believers and former chemtrail believers.

We aimed to simulate a situation in which a Web user *passively* encounters the chemtrails conspiracy claim. We considered this approach as more ecologically valid than conventional truth discernment tasks. Particularly, if a participant is explicitly instructed to evaluate the veracity of a set of statements or the credibility of a specific source of information, then there is prior knowledge (or at least a suspicion) that some of the statements are true and some are false. It is likely that people become more skeptical when they are explicitly instructed to discern facts from falsehoods. In support of this notion, a recent study indicated that interventions designed to improve discrimination between true and false news induce a bias towards "false" responses (Modirrousta-Galian & Higham, 2022). Presumably, people are more credulous when they encounter novel information in an every-day situation, when they tend to passively consume information, use intuitive type 1 reasoning, and are unwary of any truth discernment necessities. If people are explicitly asked for their belief, this question could potentially induce more reflective cognition (i.e., type 2 processing), and perhaps, would result in skepticism towards new information. Therefore, we aimed to distinguish an implicit measure and an explicit measure of belief in chemtrails in our experiment.

The experiment

Participants (i.e., psychology undergraduates) were instructed to browse the website under the impression that they would subsequently receive questions about it. The seemingly real website resembled a science-oriented social networking platform and introduced the conspiracy theory about chemtrails (see Figure 5.1). Participants did *not* receive any instructions about the credibility or the veracity of the website and were *not* informed about the conspiratorial content beforehand. Thus, they were unaware of any truth discernment necessities and were anticipated to rely on their default online behavior and "natural" online information processing. We measured the participants' browsing behavior to assess *implicit belief*. Specifically, we implemented an option to either sign or pass a digital petition that supported the conspiracy view (see Figure 5.2). This petition entailed a cause against the operation of chemtrails. In a subsequent survey, we assessed *explicit belief* using the question "Do you believe chemtrails exist?" ("Yes"/ "No"). With this experiment, we could compare the two dichotomous measures of belief (i.e., implicit vs. explicit) regarding a conspiracy theory and their probability distributions in a within-subjects design.

Figure 5.1. Experimental stimulus: Ostensibly Real Science-oriented Blog Website Introducing the Chemtrail Conspiracy. A custom website, with the visual appearance and functionalities of a social networking and blogging platform, introduced a conspiracy theory about chemtrails to the participant.

Figure 5.2. Experimental Measure of Implicit Belief in the Chemtrail Conspiracy. The website recorded the participant's choice to sign or pass a petition against the operation of chemtrails (i.e., a measure of implicit belief in the chemtrail conspiracy theory).

We hypothesized that belief in a conspiracy theory would be more likely when the reader is not externally prompted to think about its veracity (i.e., implicit belief), whereas belief in a conspiracy theory would become less likely if the reader is explicitly asked to report their belief (i.e., explicit belief). Thus, we expected that the probability of signing the anti-chemtrail petition without reporting to believe in the existence of chemtrails would be higher than the probability of reporting explicit belief without signing the petition. As seen in (1), the probability of implicit belief (IB) and not explicit belief (EB') was expectedly higher than the probability of not implicit belief (IB') and explicit belief (EB).

$$P(IB \cap EB') > P\left(IB' \cap EB\right) \qquad (1)$$

Exploratory questions

In addition to our confirmatory analysis, exploratory analyses were performed to gain more insight into the persuasiveness of the website. First, we considered that the persuasiveness of the website would be more accurately measured among readers to whom the conspiracy theory was novel because this group would not have a predetermined stance on the conspiracy claim's veracity. Therefore, we asked what the probability was that participants (i.e., psychology undergraduates) *without* preconceptions about chemtrails would endorse the chemtrail conspiracy claim (RQ1a), and we explored this endorsement within the group *with* preconceptions about chemtrails (RQ1b). We also examined the persuasiveness of specific misinformation statements, which were false premises underlying the supposed conspiracy conclusion (e.g., "Normal airplane trails dissolve within a few seconds."). Specifically, we asked what the probabilities were that participants endorsed these misinformation statements from the website (RQ2).

Additional exploratory analyses were performed to establish the readers' motivations and predispositions to believe or disbelieve the website. We explored whether explicit belief in chemtrails was associated with more positive opinions about the website in terms of the perceived value, the shareability, and the credibility (RQ3). Moreover, we aimed to explore how a predisposition of personal media usage (e.g., daily time spent on computers, phone, the internet, social media platforms) was related to explicit belief in chemtrails. Presumably, participants' prior exposure to conspiracy views is inherently related to the type of media sources they use, and/or personal media usage might be associated with a specific type of information processing behavior. Therefore, we asked whether there were differences in personal media usage between the participants that explicitly believe chemtrails are real and participants who do not believe in the existence of chemtrails (RQ4).

Method

Preregistration

The preregistration of this study can be found under https://osf.io/dzq4p. Notably, the preregistration includes a secondary hypothesis (i.e., H2) which was not tested in the current experiment.

Participants

This study was approved by the Ethics Review Committee DPECS Erasmus University Rotterdam (application reference 21-033). In total, 207 Dutch psychology students participated in this online experiment. Twenty-one participants (10%) were excluded: seventeen participants were excluded for missing entries, and four participants were excluded for disingenuous responses (i.e., reporting to disbelieve in the existence of chemtrails while also reporting to believe with high confidence that the government hides important information about chemtrails). The final sample size was 186 (147 females, $Mean_{age}$ = 20.85, SD = 2.68).

Design and materials

The online experiment was based on a custom website, which was built using CSS and JavaScript combined with Qualtrics’ survey tool software. The experimental task and the Qualtrics questionnaire can be viewed on OSF (https://osf.io/py8k9). The initial task page seemingly redirected to an external webpage using an embedded secondary task screen and a fake loading animation. This means participants were likely to be unaware the “external” webpage was part of the survey website and that their click responses were being measured. Moreover, participants were not notified beforehand about the conspiracy story on the website, nor were they prompted with other descriptive information. They were only instructed to read an article on an external webpage. The apparent demarcation between the task instruction page and the “external” webpage, as well as the unspecific task instruction (i.e., “read the article”) were implemented to increase the ecological validity of the experiment. Specifically, the aim was to engender more “natural” internet browsing behavior, to reduce socially desirable responses, and/or to minimize second-guessing of the research goals.

The external website was called “*Ongekende Feiten*” (translation: “Unknown Facts”) and had the appearance of a social networking and blogging platform (see Figure 5.1). The webpage showed a user interface reminiscent of a social networking site (e.g., a navigation menu, a search option, profile registration, and user reactions). The main content shown was an article posted fourteen days earlier by a supposed online user (without any credentials) with the username “peter_vandoorn” (a common Dutch first name followed by a common Dutch last name). This apparent online author made a case for the existence of chemtrails. The first paragraph was intended to be thought-provoking by relating to the reader’s personal experience without being too controversial. Specifically, it described the relatable observation of (airplane) stripes in the sky and showed a recognizable visual example in a complementary picture. This first premise, the observation of white stripes in the sky, was undisputable.

The second premise was that normal airplane exhaust fumes dissipate within seconds. This second premise is false because the trails can persist for hours under the right conditions (Office of Air and Radiation (OAR), 2000). Given these premises, the author concluded that most airplane trails in the sky are not normal airplane exhaust fumes as many believe. Subsequently, the author continued to misinform the reader by entertaining the notion that these mysterious trails are actually chemtrails, and that the government plays a nefarious role in hiding important information about them. The website article ended with a reference to a citizen initiative against the operation of chemtrails and provided a signable digital petition for the reader to support that cause.

Procedure

Participants received a link to an introductory webpage with information about the task's duration and a general description. They were asked to perform the task in a quiet room and to prevent and minimize any potential interruptions. The overall task was described as consisting of three components: a reading task, a dexterity game, and a brief questionnaire. After providing consent, participants were informed about an upcoming reading task on an external website. First, participants performed a browser game (i.e., dexterity game) to focus their attention on the screen, which also made the transition from the task screen to the supposed external chemtrail article more opaque. After the browser game, a loading animation implied that the external website was being loaded and the participant was being "redirected" to the external website. On this website, a small window overlayed the left side of the screen. This window showed task information and indicated an external connection with the preceding task website (see Figure 5.1).

After reading through the article about chemtrails, participants were presented with an option to sign (or to skip) an anti-chemtrail petition. They could use a CAPTCHA code to go back to the task screen. This prevented participants from going back without seeing the petition. After this, participants received a questionnaire starting with the question *"Do you believe chemtrails exist?"*. Subsequently, participants could fill in response matrices regarding their views on the value of the article (i.e., *attitude*), the *shareability*, the *credibility*, (dis)agreement with specific false statements from the article, personal media use, and demographic information. After the questionnaire, participants were debriefed about the misinformation on the website and were provided with a factual and scientific explanation of airplane trails including relevant sources. They were informed that the goal of the website was to examine how the reader would respond to the conspiracy theory. Finally, participants were instructed not to disclose their personal experience of the task with other students and were thanked for their participation.

Measures

Two dichotomous measures were used to assess *implicit belief* and *explicit belief* in chemtrails: Participants either *signed* or did *not sign* the anti-chemtrail petition (i.e., implicit belief) and answered either *yes* or *no* to the question “*Do you believe chemtrails exist?”* (i.e., explicit belief). Participants were also asked: *“Have you heard or read about chemtrails before reading the website?”*. The response options were: “*Yes*”, “*No*”, and “*I don’t know*”. Belief in specific statements from the website was measured with two separate questions: “*Is this true?”* (“*Yes” / ”No”)* and “*How confident are you?”* (five-point scale). Furthermore, three different scales with three items on a five-point scale were used to assess personal opinions about the website: *Attitude* (i.e., the personal interest, the perceived informativeness, and the perceived educational value of the website), *Shareability* (i.e., the willingness to share or recommend the website), and *Credibility* (i.e., the perceived accuracy, the perceived authenticity, and the believability of the website). *Personal media usage* was based on self-reports of the daily time spent on different media devices and media platforms.

Analyses

To test our hypothesis as seen in (1), we compared implicit and explicit dichotomous measures of belief in a 2 x 2 contingency table and performed a McNemar’s test for paired nominal data (McNemar, 1947). To answer exploratory research questions RQ1a and RQ1b (i.e., what the probabilities were that the groups with and without preconceptions about chemtrails would endorse the chemtrail conspiracy claim), we examined the percentage of endorsement within each group. Exploratory research question RQ2 (i.e., whether readers endorsed misinformation) was answered by examining the proportions of endorsement (and median ratings of reported confidence) across different misinformation statements from the website. The remaining two exploratory research questions, RQ3 and RQ4 (i.e., whether belief in chemtrails was associated with more positive opinions towards the website and/or distinct patterns of personal media usage), were answered by comparing 95% confidence intervals (CI) across groups.

Results

Confirmatory analysis

A McNemar’s test revealed a significant difference in the proportion of implicit belief versus explicit belief in the chemtrail conspiracy theory; 10.2% of participants signed the anti-chemtrail petition whereas 52.7% of participants reported that they believe chemtrails exist, $p < .001$. However, our directional hypothesis as seen in (1) was not supported. Instead, Table 5.1 shows the difference in the probabilities is evidently in the opposite direction. That is, the probability of signing the anti-chemtrail petition without reporting explicit belief is lower than the probability of not signing the anti-chemtrail petition while reporting explicit belief.

Table 5.1 Contingency Table of Belief Measures

Implicit belief measure: Anti-chemtrail petition	**Explicit belief measure: “Do you believe chemtrails exist?”**		
	Yes	**No**	*Total*
Signed	16 (8.6%)	3 (1.6%)	*19 (10.2%)*
Not signed	82 (44.1%)	85 (45.7%)	*167 (89.8%)*
Total	*98 (52.7%)*	*88 (47.3%)*	*186 (100%)*

Exploratory analysis

First, we explored what the probability was that participants (i.e., psychology undergraduates) *without* preconceptions about chemtrails would endorse the chemtrail conspiracy claim (RQ1a). There were 131 participants (70.4%) who reported to have never heard or read about chemtrails before reading the website (i.e., without preconceptions). Within this group, 69 participants (52.7% of the group) reported to believe in the existence of chemtrails. Thus, a substantial proportion of participants who were unfamiliar with the notion of chemtrails still reported to believe chemtrails exist. This outcome suggests more than half of the participants who were newly introduced to the notion of chemtrails by the website appeared to have adopted a belief in its existence. Furthermore, we explored the endorsement of the conspiracy claim among the group *with* preconceptions about chemtrails (RQ1b), which comprised 49 participants (26.3%[1]), of whom 28 participants (57.1% of the group) reported to believe in the existence of chemtrails. These results show that more than half of the participants were convinced by the website that chemtrails exist, irrespective of whether the notion of chemtrails was novel or not.

We also examined the probabilities that participants endorsed specific false claims from the website (RQ2), as seen in Table 5.2. Notably, two false statements were endorsed by a majority. The final statement in Table 5.2, “*The government hides important information about chemtrails.*”, directly refers to a conspiracy and was endorsed by fewer participants. Still, .25 can be regarded as a remarkable proportion for a claim that entails the accusation that the government plays a nefarious role. Also remarkable is the .67 endorsement probability for the claim that normal airplane trails dissolve within few seconds, as this contradicts visual experience. This suggest that these participants consider long lasting stripes they observe to be “abnormal” airplane trails.

1 The remaining 3.3% of the total sample were six participants who answered: “*I don’t know*” to the question: “*Have you heard or read about chemtrails before reading the website?*”.

Table 5.2 Truth Discernment Responses for Misinformation Statements from the Website

Statement	Endorsement probability	Confidence * (median rating)
“Normal airplane trails dissolve within a few seconds.”	.67	Highly confident (4)
“Chemtrails are easily recognized as they linger much longer in the air than condensation trails.”	.60	Considerably confident (3)
“On spray days there are multiple airplanes that leave an array of chemtrails in the sky.”	.45	Considerably confident (3)
“The government hides important information about chemtrails.”	.25	Considerably confident (3)

Note. Participants evaluated the statements based on the preceding question “Is this true?” and could respond with either “Yes” or “No”. Then, participants could indicate the confidence they had in their previous answer on a five-point scale (1 not confident at all – 5 extremely confident). * The median confidence rating is derived from the group that endorsed the statement.

We additionally explored how explicit belief in the existence of chemtrails was related to opinions about the website (RQ3), as seen in Figure 5.3. Participants who reported to believe in the existence of chemtrails were relatively more positive about the website on three different aspects: (1) They considered the website’s content to be more valuable, (2) they reported a relatively higher willingness to share the website with others, and (3) they rated the website as relatively more credible.

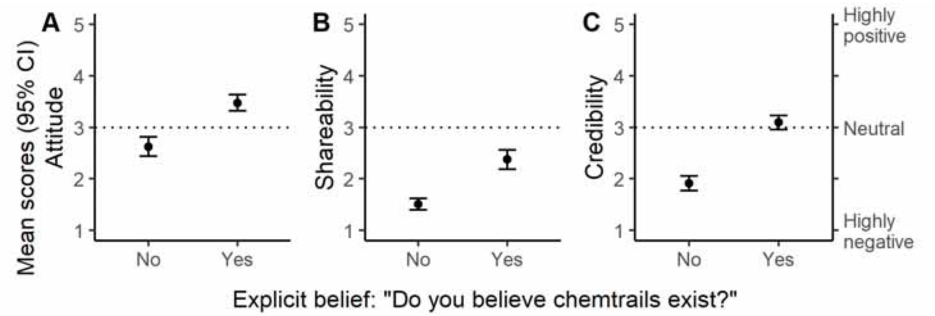


Figure 5.3. Opinions About the Website Grouped by Explicit Belief in the Existence of Chemtrails. The y-axes represent the outcome variables Attitude, Shareability, and Credibility, which were each measured with three items; Cronbach’s alphas are .78, .85, and .89, respectively. The group sizes were 88 (“No”, 47%) and 98 (“Yes”, 53%). Spearman’s ranked correlation coefficients are .46 (A), .48 (B), and .67 (C).

Finally, we explored how media use was related to belief in the existence of chemtrails (RQ4). Figure 4 shows that the group that showed explicit belief in the existence of chemtrails also reported to spend more daily time on their phone (Δt = 1h:5m), WhatsApp (Δt = 47m), and social media (Δt = 48m). However, there were no significant differences between the groups in their reported times spent on computer use, watching videos on YouTube, or other websites or blogs.

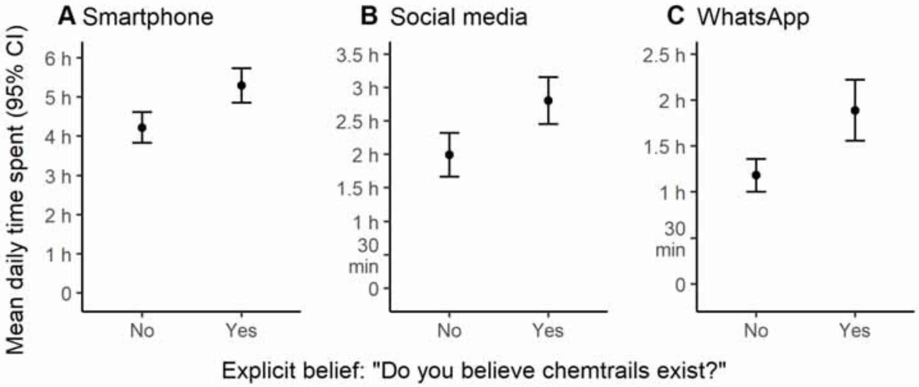


Figure 5.4. Reported Media Use Grouped by Explicit Belief in the Existence of Chemtrails. Participants were asked "How much time do you spend on a free day on ___?". The category social media was further specified with the parenthesized text "(Instagram, TikTok, Facebook)'". Spearman's ranked correlation coefficients are .23 (A), .25 (B), and .26 (C).

Discussion

The aim of our experiment was to examine susceptibility among internet users to adopt a novel and erroneous conspiracy theory. The conspiracy theory was introduced on an ostensibly popular scientific blog website and entailed the notion that the long-lasting trails left by airplanes are "chemtrails". We measured belief in this conspiracy theory in two different manners: through an implicit measure of belief based on an option to sign an anti-chemtrail petition, and through an explicit measure by asking the participant for their belief in the existence of chemtrails. We expected that participants would be more likely to sign the petition than they would report to believe in the existence of chemtrails. The results of our confirmatory analysis showed the reverse effect. Unexpectedly, the website had convinced many participants to believe in the existence of chemtrails, but it was unlikely to invoke the action of signing the anti-chemtrail petition.

A potential explanation is that signing a petition appears as more consequential than merely answering a question; active participation in the petition implies not only agreement with the espoused conspiracy claims but also a willingness to support a cause against the continuation of the alleged conspiracy activities. Therefore, the decision to sign the petition might require a belief system with a higher degree of certitude (Usó-Doménech & Nescolarde-Selva, 2016). Remarkably, half of the participants appeared convinced by the blogpost as they answered "yes" to the question "Do you believe chemtrails exist?" This suggests that an introduction to this conspiracy theory was sufficient to engender a novel point of conjecture among many participants. Still, a belief system with a high degree of certitude, which would be more likely to invoke the action of signing the petition, would likely require more time, (motivated) reasoning, and experience to form. Therefore, the specific stage of belief formation might have been an important factor with respect to how their belief informed the participants’ decisions.

The stages of belief formation have been referred to as “seizing” and “freezing” phenomena by Kruglanski and Webster (1996). As such, their theory describes a crucial demarcation: the initial inception of a belief system and its crystallization. The former stage implies a state of heightened need for cognitive closure (NCC), in which people have a need for answers or explanations, and therefore, are relatively susceptible to persuasion attempts. The latter manifests as a reluctance to continue information processing, to be “closed-minded”, and to maintain a belief despite counter evidence. The seizing stage might be inherently related to truth bias; in turn, the freezing stage can be associated with directionally motivated reasoning. Perhaps, a belief system that has been “frozen” has a sufficient certitude to invoke actions, such as signing a petition. On the other hand, a belief that is still in the freezing process would possibly be less likely to invoke such actions.

In the current study, all participants were debriefed immediately after the experiment. They were informed about the misinformation on the website and were provided with a factual explanation of airplane trails. As such, we can only speculate about the consequences of leaving participants misinformed at the end of the task. Possibly, some participants would encounter contradicting information sometime after the experiment, while still being in the seizing process. Therefore, they would correct their initial position and accept that they were previously misinformed. Other participants would perhaps be more inclined to jump to conclusions, to “freeze” their initial belief (i.e., higher need for cognitive closure), and would preemptively inoculate themselves against any counterevidence. The current experiment was comparatively limited by only indicating how participants were influenced by the chemtrail website directly after reading it. Nevertheless, our exploratory research findings indicate many participants were credulous towards the chemtrail notion, at least during the task.

The first exploratory research question was focused on the participants’ credulousness towards the chemtrail website if the notion of chemtrails was novel or not (RQ1a and RQ1b). Remarkably, more than half of the participants in both groups reported to believe in the existence of chemtrails. We found that participants were credulous towards specific false claims as well (RQ2). For example, 67% of the participants endorsed the false premise “Normal airplane trails dissolve within a few seconds.” from the website. The statement “The government hides important information about chemtrails.” yielded a relatively lower endorsement rating with 25%. Still, one in four participants reported to believe that the government plays a nefarious role in concealing supposed chemtrail operations. These exploratory findings indicate a selective credulousness: While only a minority would accept the veracity of a supposed conspiracy, a majority would still accept false premises that are foundational to the conspiracy theory.

The implication of this selective credulousness is that, even if readers initially reject the notion of a conspiracy, they can still be misinformed and deceived by a conspiracy website. At first glance, a conspiracy accusation might appear as irrational. However, conspiracy theory advocates have the freedom to elaborately express their views on the Web, using arguments about abnormal observations and false premises to infer the operation of conspiratorial activities. Such an argument might appear as coherent and well-contemplated to the reader. If readers begin to acknowledge the misinformation underlying the conspiracy theory, this might provoke feelings of suspicion in favor of the conspiracy narrative. Over time, this conjecture could perhaps lead to more radical conspiracy beliefs.

The third exploratory research question was aimed at comparing belief groups on their overall opinion towards the website (RQ3). Results show that participants who reported to believe in the existence of chemtrails had a relatively more positive sentiment towards the website than participants who reported to disbelieve: Chemtrail believers found the content more valuable, showed higher willingness to share the website, and perceived the website as more credible than non-believers. Not surprisingly, more positive opinions about the website are associated with a higher chance to believe the website's chemtrail conspiracy claim. Importantly, however, this shows that multiple measures corroborate the influence that the website had on the readers.

The final exploratory research question was about the relationship between explicit belief in chemtrails and personal media usage (RQ4). We found that chemtrail believers spend more daily time on their phone and on social media (e.g., Instagram, TikTok, Facebook) than non-believers (RQ4). However, computer and internet use were not different between these groups. Previous studies have indicated a relationship between social media use and conspiracy beliefs as well (Jamieson & Albarracín, 2020; Stempel et al., 2007). This relationship has been found to be moderated by conspiracy thinking, the tendency to interpret salient events as the result of conspiracies (Enders et al., 2021). In the current study, social media were not likely to causally promote the belief in the chemtrail conspiracy theory because most participants were unfamiliar with the chemtrail conspiracy theory before they read the website.

There might be an alternative explanation for the relationship between belief in the existence of chemtrails and self-reported social media and phone use: People who spend more time browsing their mobile social media apps tend to passively consume more information (e.g., reading stories, news, comments, status updates from followees[2]/followers), and therefore, they might be more credulous towards

2 A followee is a social media user who has their posts monitored by other users.

novel information. A previous study on the behavioral analysis of credulous Twitter users (i.e., users who follow many bots[3]) showed that they produce more original content and interact more often with content originated by bots (Balestrucci et al., 2021). An important consideration, however, is that user data accessed through the API are limited to features that reflect active engagement (e.g., number of original posts, shared posts, replies); passive engagement such as the time spent browsing or the number of read posts is more obscure. Expectedly, social media users who have longer and/or more frequent mobile browsing sessions consume information more passively (i.e., type 1 processing), and therefore, are perhaps more credulous towards novel information. This speculation remains to be tested in a confirmatory analysis.

An important consideration is that the current study's sample comprised first- and second-year psychology students. Importantly, this sample is not representative of the entire internet user population. Presumably, academic students are relatively more likely to employ scientific skepticism than non-university educated people; they would presumably prefer empirical evidence over anecdotal evidence before they accept novel claims. Nevertheless, we found a 52.7 percent likelihood that participants would believe in the existence of chemtrails after reading the pseudo-scientific blog article. Previous research has indicated a negative relationship between education level and conspiracy beliefs (van Prooijen, 2017). Therefore, non-university educated people would possibly be even more inclined to become convinced of a novel conspiracy theory. Future experimental research on credulousness towards misinformation and conspiracy claims on the web could compare readers of different education levels.

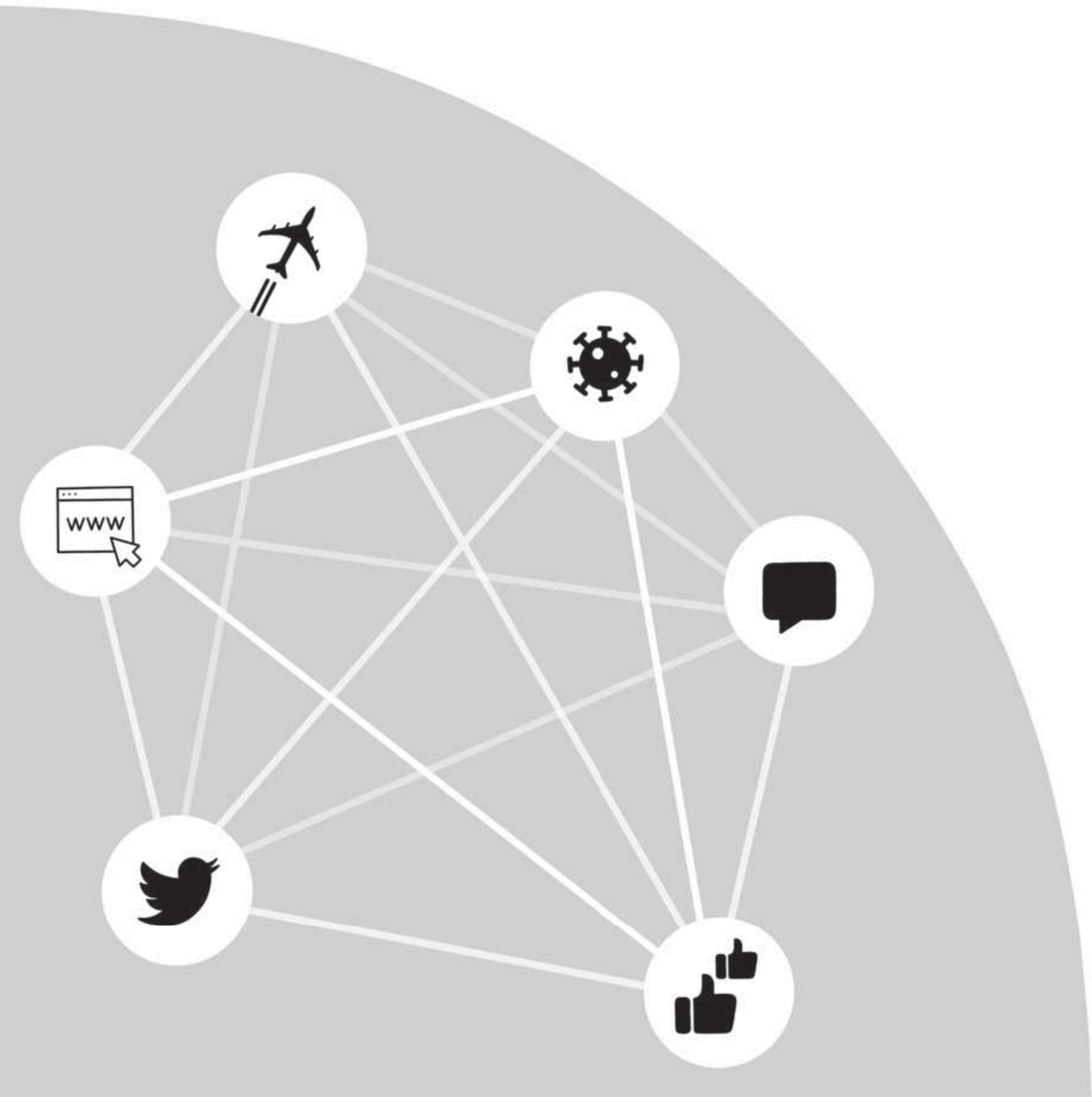
The current experiment showed that even high-educated Web users are vulnerable to form false beliefs or false conjectures based on a misinformative conspiratorial website about chemtrails. This credulousness was evident among half of the participants, under ecologically valid conditions: Participants were not prompted with truth discernment instructions, and the website was ostensibly real and external from the task screen. Against our hypothesis, many participants reported their explicit belief in the existence of chemtrails after reading the website, while they had insufficient certitude to sign an anti-chemtrail petition as well. Exploratory findings suggest that explicit belief in the existence of chemtrails is associated with higher perceived value, shareability, and credibility of the website. Additionally, self-reports of media use suggest a relationship between credulousness and mobile social media usage. Future research should focus on dispositional and situational factors of the susceptibility to conceive false conspiracy beliefs. For instance, the concurrent availability of contradicting information could perhaps lower the credibility of a supposed conspiracy.

3 Bots are automated accounts, which are more likely to generate spam content and disinformation compared to genuine human-operated accounts.

Conclusion

New media allow for unconstrained expression of personal views, including false conspiracy beliefs and other misinformation. As stated before, it is important to understand the susceptibility of Web users to adopt false conspiracy beliefs, especially since these beliefs can have drastic social and societal consequences. Our research indicates people are susceptible to accept and endorse conspiratorial misinformation from websites. Web users should be cautious and attempt to scrutinize online information, even if an argument appears coherent and satisfactory. Our findings contribute to a broader research domain of online mis- and disinformation and show an urgence to establish methods that prevent Web users from adopting false beliefs.

CHAPTER 6



General discussion

This PhD thesis is focused on the dynamic interplay between cognitive and linguistic processes in the realm of digital media. As digital media have proliferated and become integral facets of daily life, their pervasive influence extends to how individuals consume information, communicate, and shape the social dynamics of modern society. Therefore, it is paramount to understand how individuals think, process information, and communicate in the digital age. We employed diverse research methodologies to explore this topic comprehensively, encompassing experimental and observational studies conducted within specific digital media contexts. We derived four pivotal sub-questions: (1) 'In what ways do restrictions on message length in social media platforms influence users' writing style and language choices?' (2) 'How do peer-generated comments and ‘Likes’ influence the processing and evaluation of online news content?' (3) 'What role does cognitive motivation play in shaping the information-seeking, processing, and interpretation of Covid-19-related facts and falsehoods?' (4) 'To what extent are internet users susceptible to adopting false conspiracy narratives from a website?' These questions have been explored in the previous four chapters of this thesis. The following section of this discussion outlines the principal findings of each study and elucidates their contributions to the primary research topic of this thesis.

In Chapter 2 we investigated how the language usage in tweets was affected by an increase in the maximal message length. After the character-limit change on Twitter, people used more article words, conjunction words, and preposition words. This suggests texts contain more peripheral information. The observed increase in these parts-of-speech suggests a shift towards more elaborate language structures to accommodate the expanded message length. Additionally, character-conserving writing styles were not needed as much as before the character-limit change, which resulted in less frequent usage of informal types of textese. The decreased frequency of informal textese usage reflects changes in linguistic norms within the social media context, highlighting the dynamic nature of language adaptation in digital environments.

In Chapter 3 we examined the cognitive effects of peer-user comments and Likes on a news website, which provided insight into how social interactions on digital platforms influence individuals' perceptions and attitudes. The findings revealed that negative peer-user comments exert a significant impact on readers, leading to negative attitudes, decreased intent to share, reduced agreement with conveyed ideas, and diminished perceptions of public opinion and article credibility. This highlights the cognitive processing of social feedback and its influence on individuals' evaluations of digital content. Moreover, Likes did not affect readers' opinions as much as comments, which underscores the nuanced nature of cognitive responses to different forms of social interaction on social media platforms. Overall, this research contributes valuable insights into the cognitive mechanisms underlying social media engagement and its implications for information processing and decision-making in digital environments.

In Chapter 4, we examined how individuals gather and interpret information about Covid-19 and how this relates to specific predispositions of cognitive motivation. The findings revealed that approximately three-quarters of participants searched for information about Covid-19, and most of them searched for information on a daily basis. This frequency of information-seeking behavior about Covid-19 was not directly linked to individual differences in Need for Cognition (NC) or Need for Cognitive Closure (NCC). However, these cognitive motivations did positively correlate with knowledge about Covid-19 and the rejection of conspiracy statements. This suggests that cognitive motivation plays a role in shaping individuals' responses to information about the pandemic and their susceptibility to misinformation. Furthermore, the observation that higher levels of Covid-19 knowledge are associated with increased compliance with government measures underscores the practical implications of cognitive factors in shaping behavioral responses to digital media information. These results provide insights into the cognitive dimensions of information processing and decision-making in the context of digital media use during a global health crisis.

Building on these insights, Chapter 5 shifts the focus to belief formation and decision-making in response to information from unverified sources on the internet. The internet provides a publicly accessible platform where individuals can freely publish information on websites without the need for scientific vetting or scrutiny. Therefore, understanding the cognitive processes that underpin belief formation and decision-making in response to information from unknown sources on websites is of paramount importance. In Chapter 5, we investigated the susceptibility of psychology undergraduates to adopt a novel conspiracy belief from a website. We made an ostensibly real social platform on which an unknown author posted a supposed conspiracy story. To examine the effect of this narrative on the readers we performed an *implicit* measure of belief, specifically an option to sign a petition against the operation of this conspiracy. We compared this implicit measure with an *explicit* measure: the question 'Do you believe chemtrails exist?". We expected that the implicit measure would be more likely to engender automatic type I reasoning, and therefore, would harbor truth bias and increase credulousness towards the conspiracy narrative. The explicit measure, on the other hand, was expected to be more likely to induce feelings of doubt or more analytical type II reasoning, and therefore, would expectedly increase skepticism towards the conspiracy narrative. The aim of this comparison between implicit and explicit measures of belief in the conspiracy narrative was to provide a nuanced and ecologically valid understanding of cognitive reasoning mechanisms in response to digital media content, as opposed to "artificial" survey behaviors.

Contrary to expectations, the results in Chapter 5 revealed a different pattern: the explicit measure was expected to evoke more skepticism than the implicit measure, but participants were more likely to report their belief in the conspiracy narrative (explicit measure) than they would sign the petition (implicit measure). This suggests complex cognitive dynamics at play, wherein individuals may express differing levels of belief depending on the context and measurement method. Surprisingly, roughly half of the participants who never heard about the conspiracy before reading the website reported to believe in the existence of chemtrails. Thus, if the line of reasoning is comprehensive and ostensibly coherent, then the narrative becomes compelling. This stresses the importance of educating young individuals to improve their media literacy and critical thinking skills. Moreover, the exploratory findings uncovered associations between belief in the conspiracy narrative, opinions about the website, and mobile social media usage, highlighting the interconnected nature of cognitive processing and digital media engagement.

Overall, the research presented in this thesis underscores several key aspects of how digital media influence their users. From shaping language production to influencing information processing and belief formation, digital media platforms play a pivotal role in shaping cognitive and linguistic processes. By elucidating these dynamics, this thesis contributes valuable insights into the multifaceted effects of digital media on language, cognition, and information processing. In the next section we discuss further implications, and we highlight the similarities and discrepancies between the current studies.

Implications and comparisons between the current studies

Our first study shows that message length limits can affect language usage. A broad implication of this finding is that language production within social media environments is partially dependent on the communicative features of the platforms. These features can provide alternative ways for users to express themselves (e.g., paralinguistic digital affordances, emojis, pictures, videos), but they can also constrain the users' ability to convey their original messages. Nonetheless, linguistic constraints can promote users to find creative solutions to convey their thoughts in alternative ways. X (formerly known as Twitter) was designed for users to share single thoughts rather than elaborate multifarious texts. By imposing a character limit, users are forced to be more concise, encouraging them to use character space more efficiently and parsimoniously. This brevity is a defining feature of the platform, and possibly even an indispensable feature that ensures a user-friendly experience. The platform allows many "voices to be heard", but users have limited cognitive resources to process all these "voiced" ideas and opinions. Therefore, the brevity of the platform's messages allows users to comprehend the information while they browse through a manifold of ideas, opinions, and topics from various sources and users.

The relaxation of Twitter's character-limit from 140 to 280 characters increased the relative frequencies of preposition-, conjunction-, and article words, whereas the relative frequencies of character-conserving textese decreased. These findings imply that people can be creative with their language production and can adapt their messages to conform to the imposed brevity of the platform. This defining feature of X (formerly Twitter) messages remains well-appraised and was inherited from the character limit previously imposed by the short message service (SMS). Interestingly, former restrictions in communication technology, such as the available bandwidth to send and receive texts, remain to influence online language usage up to the present day (e.g., the use of textese on X).

Other restrictions of digital media communication have also influenced online language usage. For example, early computer-mediated communication lacked the non-verbal information conveyed during face-to-face discourse. Examples of these non-verbal cues are facial expressions, gestures, body language, paralinguistics (e.g., intonation, volume of speech). Thus, in addition to the character-conserving writing style of textese, digital media required additional linguistic solutions to compensate the lack of these non-verbal cues. This resulted in the advent of paralinguistic digital affordances (e.g., Likes) and emojis (Hayes et al., 2016; Kaye et al., 2017; Walther & D'Addario, 2001). This shows that people find alternative methods to express themselves whenever they experience restrictions in their capacity to communicate. Interestingly, the character-conserving writing style explored in Chapter 2, as well as the paralinguistic digital affordances examined in Chapter 3, both stem from the inherent limitations of early digital communication.

Our second study, reported in Chapter 3, has shown that comment sections can negatively impact how readers evaluate editorial content. This finding has major implications for digital journalism. A potential consequence of adding a comment section is that readers tend to utilize peer-users' opinions to form their own opinions about editorial content. Importantly, our research indicates that readers are more influenced by negative opinions than positive opinions, which can reduce the perceived credibility and shareability of the editorial content. This bias suggests that the mere presence or visibility of a comment section is likely to be more detrimental than beneficial to the reader's evaluation and interpretation of the content, which potentially diminishes the reader's trust in the publisher. These implications of our findings can be taken into consideration when online publishers design and develop a platform to distribute editorial content. A caveat, however, is that comment sections do provide user feedback and interaction, which improves overall user engagement, and therefore, the publisher's ad revenue. Thus, completely removing comment sections might be a suboptimal decision, depending on the revenue model of the platform. Alternatively, then, it is preferable to hide comment sections by default. This allows readers to create comments if they choose to do so, and at the same time, does not influence readers who are not intrinsically motivated to use the comment section.

Both Chapter 3 and Chapter 5 demonstrate the significant impact of others' beliefs and perspectives shared on social media platforms on shaping the views and beliefs of readers. In Chapter 3, we investigated how Likes and peer-user comments influence the processing of online news content. Notably, the comments that were used in the experiment were highly subjective, and participants were not explicitly directed to engage with them or informed about their existence beforehand. This suggests that the inclusion of subjective negative opinions alongside news content has the potential to influence how readers interpret the information presented. Clearly, individuals are susceptible to adopting and incorporating the views and ideas of others into their own perspectives, particularly when those views include negative criticisms.

Similar to the findings reported in Chapter 3, Chapter 5 also indicates people can be influenced by the beliefs and views of others, such as conspiracy narratives they encounter on the Internet. We found that participants were likely to believe conspiratorial misinformation posted on a blog website. Half of the participants who never heard about the conspiracy notion of chemtrails before the experiment reported to believe in the existence of chemtrails after reading the website. Notably, this credulousness occurred among a sample of high-educated participants (i.e., psychology students), who would expectedly be more likely to employ scientific skepticism than low-educated people. Our findings in Chapter 3 and Chapter 5 imply that the Internet and social media can influence how users perceive events and affairs. That is, Internet- and social media users' views can be influenced both by misinformation as well as the subjective opinions of peer users.

Our findings reveal a striking vulnerability among social media and web users: they are prone to believe misinformation that they encounter. Remarkably, despite using a sample of highly educated internet users who presumably have a high level of media literacy, we found a significant number of subjects to believe in false claims from a website. Ideally, social media developers take the responsibility to protect their users and proactively prevent them from becoming exposed to misinformation. For example, fact-checking can be implemented to identify false or altered content. In turn, this content can be addressed by reducing the distribution in users' feeds or informing users by flagging content or the corresponding user accounts. Flagging misinformation has been shown to reduce misperceptions and to diminish its distribution and exposure among users (Amazeen et al., 2016; Bode & Vraga, 2015; Liang et al., 2022).

Chapter 4 and Chapter 5 both involve research on belief in conspiracy narratives, but there is an important distinction between the research designs. This distinction might explain a discrepancy in the prevalence of reported conspiracy belief between these studies. In Chapter 4 we performed a survey in which we examined the level of belief in Covid-19-related conspiracy statements (e.g., "The coronavirus was released by the Chinese government to prevent overpopulation."). We found that the reported endorsement of these conspiracy statements was very low (i.e., close to 0%). In contrast, in Chapter 5 we exposed participants to a chemtrail-conspiracy-promoting website and found that half of the participants reported a belief in the existence of chemtrails and a quarter of participants endorsed the notion that "the government hides important information about chemtrails". The designs of these studies and their respective results indicate a crucial distinction between 'current belief in false conspiracy narratives' and 'the potential to adopt a novel conspiracy belief'. This means that, even if a person has no currently evident conspiracy views, they can potentially be prone to adopt a novel conspiracy view.

Social media platforms provide the ability to spread fringe beliefs to a wide audience, and therefore, they should have the responsibility to protect their users from these views. For example, conspiratorial misinformation can be posted by an individual without meaningful credentials nor any other authority on the topic. Regardless, other users can be susceptible to perceiving this misinformation as veracious, as indicated by our experiment in Chapter 5. Consequently, users who have no prior personal conspiracy views nor the incentive to search for conspiracy ideas can still adopt false conspiracy beliefs. Perhaps, this might even result in pro-active search behavior, where users start to engage in online communities that tend to echo the conspiracy narrative. Therefore, it is important that social media platforms moderate their content as swiftly as possible and minimize users' exposure to these types of misinformation. This can prevent users from conjecturing and forming false beliefs, and it prevents the potential consequences of such beliefs as well.

Strengths and limitations

An important feature and strength of the studies reported in Chapter 3 and Chapter 5 is the ecological validity of the experimental designs and stimuli. In Chapter 3, we built a news website showing news articles with comment sections. In Chapter 5, we built a blog website presenting a conspiracy narrative. An important aim for the online experiments of these studies was to ensure that participants would behave naturally. If the stimuli appeared to be artificially devised for the purpose of the experiment, this would likely impact participant behavior to the point that it is different from everyday behavior. Moreover, we ensured that our research objectives were opaque to the participants during the experiments. For example, in the instructions for the participants in Chapter 3, the Likes and peer-user comments were not mentioned because we did not want to influence how the participants would utilize these social cues. Similarly, the instructions for the experiment in Chapter 5 did not mention the presence of a conspiracy narrative. Thus, our experimental designs and participant instructions ensured a high ecological validity.

An unexpected challenge within the current PhD research trajectory was the occurrence of the Covid-19 pandemic. Social isolation measures against the spread of the coronavirus made it difficult to conduct research that involved interpersonal contact and impeded our ability to recruit participants other than undergraduates from our university. Nonetheless, the social disruptions caused by the pandemic created a valuable opportunity to investigate its cognitive effects on information processing by using an online survey study (Chapter 4).

In Chapter 2, we investigated the effects of a change in the maximal message length on the language usage on Twitter. The character-limit change on Twitter provided an opportunity to investigate linguistic effects of message length constraints. However, this means that we only analyzed the linguistic effects of a message length limit on Twitter (currently X), a distinct platform with unique lexical features and its own online discourse style. Ideally, the effect of a message length limit (or relaxation) would be examined across different online platforms to isolate linguistic effects of length constraints from platform-specific confounds. This would enhance the generalizability of the results. Alternatively, the effects of length constraints could be investigated using an experimental design. For instance, participants can be presented with a news story and can then be instructed to write a message that conveys an opinion about that story. The experimental manipulation could be the character limit of the text entry field. This design would isolate the linguistic effects of a character limit from extraneous factors such as topicality or platform-specific discourse styles.

The Twitter API in combination with the Netherlands eScience Center tweet repository (which is no longer publicly available) allowed for the collection of a large corpus of Twitter messages, which comprised approximately two million Dutch tweets created over a period of four weeks. The ability to analyze such a large-scale dataset makes obsolete the conventional approach to hypothesize about the effects at the population level. Particularly, the size of the corpus we collected *is* effectively the size of the entire population of Dutch Twitter messages (within a limited timeframe of four weeks). The benefit of this large-scale approach is that we found population effects of the CLC. This means we found true effects rather than be forced to extrapolate effects based on a relatively limited sample size, which is inherently prone to sampling bias. An important side note is that examining a population sized corpus renders p-values meaningless. That is, the meaning of the p-value, the probability of rejecting the null hypothesis when it is in fact true (i.e., a type I error), becomes irrelevant when the sample effect *is* the true effect.

Paradoxically, the large scale of our corpus might be considered a limitation regarding the linguistic effects of the CLC. That is, while we found evidence that overall language usage was affected by the CLC, a criticism might be raised on how relevant and practically meaningful these effects are on the individual Twitter user's level. In other words, can a character limit manipulation predict how one person would formulate their message? Of course, this type of critique applies to many conclusions in the social sciences, which often derive from arbitrarily chosen cut-off points between statistical significance and non-significance. However, the notion that found effects are practically trivial can be easily refuted in case of linguistic inquiry. That is, language is a phenomenon that exceeds individual behavior, as it is inherently a collective behavior. This justifies examining linguistic effects at the population level.

Another limitation across the studies reported in Chapters 3-5 is the representativeness of our samples. We invited psychology undergraduate students to participate in two experimental studies, and we used the Prolific platform to recruit participants for our online survey study. It should be noted that these samples are drawn from societies that are Western, Educated, Industrialized, Rich and Democratic (WEIRD; see Henrich et al., 2010). These types of societies have been shown to be among the least representative populations for generalizing about humans. Therefore, our findings can only be justifiably generalized to WEIRD populations, while social media and the Internet are used globally among a variety of populations. Moreover, our sample in Chapter 4 showed low conspiracy endorsement, which might have limited the generalizability of our results. Specifically, an accurate representation of the relationship between cognitive motivation and conspiracy beliefs would require a balanced sample that includes both low *and* high conspiracy beliefs among the participants, especially if the relationship is non-linear.

In Chapter 4, we hypothesized that higher NCC would predict higher confidence during the Covid-19 truth discernment task (H2). Specifically, an avoidance of ambiguity, a need for predictability, and a tendency to be closed-minded (i.e., sub-scales of NCC) would expectedly be associated with more confident answers on the Covid-19 Knowledge Test. The descriptive results appeared to support this hypothesis: participants high in NCC responded relatively more frequently with "I am sure" than "I think" and "I don't know". However, the construct validity of the outcome variable Covid-19 Knowledge, which we used in the inferential statistical analysis to test our second hypothesis, was suboptimal. Specifically, the outcome variable in the Covid-19 truth discernment task reflected a combination of two conceptually independent constructs: the accuracy of the judgments (i.e., correct or incorrect) and the level of confidence in personal knowledge (i.e., "I am sure", "I think", "I don't know"). Since we used a single five-point ordinal scale, these constructs were not independent (i.e., 1 = "I am sure this is not true", 2 = " I think this is not true", 3 = "I don't know", 4 = "I think this is true", 5 = " I am sure this is true"). Moreover, high NCC was expectedly associated with more confident correct answers as well as more confident false answers. This potentially rendered the item-scores of high vs. low NCC participants to be more extreme (i.e., 1 or 5 rather than 2-3), and would also imply a non-linear relationship between NCC and Covid-19 Knowledge.

We expected that people low in NC but high in NCC would be more likely to endorse conspiracy statements about Covid-19. More specifically, this combination of cognitive motivations would, on the one hand, make a person less likely to acquire factual knowledge about the pandemic while, on the other hand, make a person more likely to make injudicious decisions and hasty conclusions. As discussed, the low endorsement of conspiracy statements among our Prolific sample in Chapter 4 might have limited our ability to test this hypothesized interaction effect between NC and NCC on conspiracy beliefs. However, the suboptimal construct validity of our Covid-19 conspiracy belief measure, which conflates both accuracy and confidence constructs, might have also undermined our ability to find the interaction effect. That is, high NCC participants would be more likely to answer with high confidence; if a high NCC person rejects a conspiracy statement with high confidence (i.e., “I am sure this is not true.)”, this would yield a maximum item-score of five points, which compensates other highly confident endorsements of conspiracy statements with a minimum item-score of one point. Again, a low construct validity and/or non-linearity in the relationship between cognitive motivation and the outcome variables might have limited our ability to test our hypothesis.

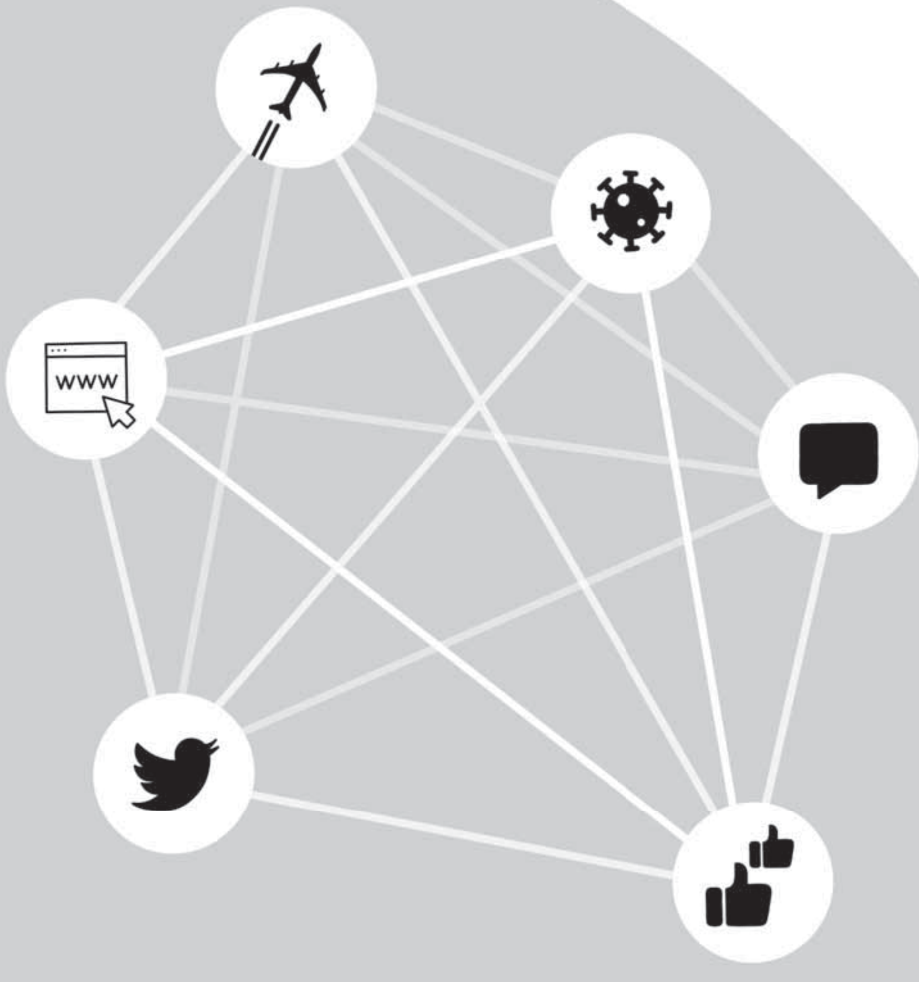
In the study reported in Chapter 5, we measured belief in statements from a conspiracy website using two separate questions: “Is this true?” (Yes/No) and “How confident are you?” (Five-point scale: 1 Not confident i.e. ‘I guessed the answer’ - 5 Extremely confident i.e. ‘I cannot be wrong’). These measurements would separate truth discernment accuracy from confidence, and therefore, had a higher construct validity compared to the conspiracy belief measure as well as Covid-19 Knowledge measure in Chapter 4. However, in the study reported in Chapter 5, we did not include the NC and NCC scales. This means we did not test how cognitive motivation was associated with conspiracy beliefs, since this was not the research objective of this study. Future research on the relationship between NC, NCC, and conspiracy beliefs might benefit from using separate measurements for truth discernment accuracy and confidence.

Concluding remarks

We examined cognitive and linguistic aspects of digital media usage. We found that message length constraints in social media communication can affect online language production, promoting linguistic solutions that conserve character space. Moreover, we found that the opinionated environments of social media can influence how people interpret and evaluate editorial content. Particularly, news website readers are influenced by the negative and subjective opinions of peer users. We also found that, during the Covid-19 pandemic, digital media were important affordances in peoples' need to acquire information and affairs related to the coronavirus. In the evaluation of claims about the pandemic, truth discernment behaviors are shown to be associated with certain cognitive motivations. Specifically, the Need for Cognition and the Need for Cognitive Closure predicted factual knowledge about the coronavirus and the capacity to reject false conspiracy narratives about the pandemic. Finally, we established a vulnerability among internet users to interpret false claims they encounter on the Web as truths, such that even highly educated internet users can accept conspiratorial misinformation as veracious. Together, these findings highlight the effects of message constraints, online environments, cognitive motivations, and susceptibility to misinformation in the digital age.

The results of this research contribute to a deeper understanding of both the cognitive and linguistic effects of digital communication. On the one hand, the dynamic and fast-paced environment of social media platforms has given rise to novel linguistic conventions, showing the evolving nature of language itself. On the other hand, digital media provide a ceaseless opportunity to learn more about the world, while also providing the affordance to "interact with the world". This latter feature harbors opinionated environments, subjective perspectives, and false claims. Our research indicates that digital media users can be influenced by these social features, as they utilize others' perspectives and narratives to form personal beliefs and opinions about the world. As we move forward in the digital age, it is essential to recognize the significance of adapting our understanding of language and cognition to accommodate the shifting paradigms of online communication. This thesis underscores the importance of continued research in this domain, as the landscape of digital media is ever evolving, and our understanding must evolve in tandem.

CHAPTER 7



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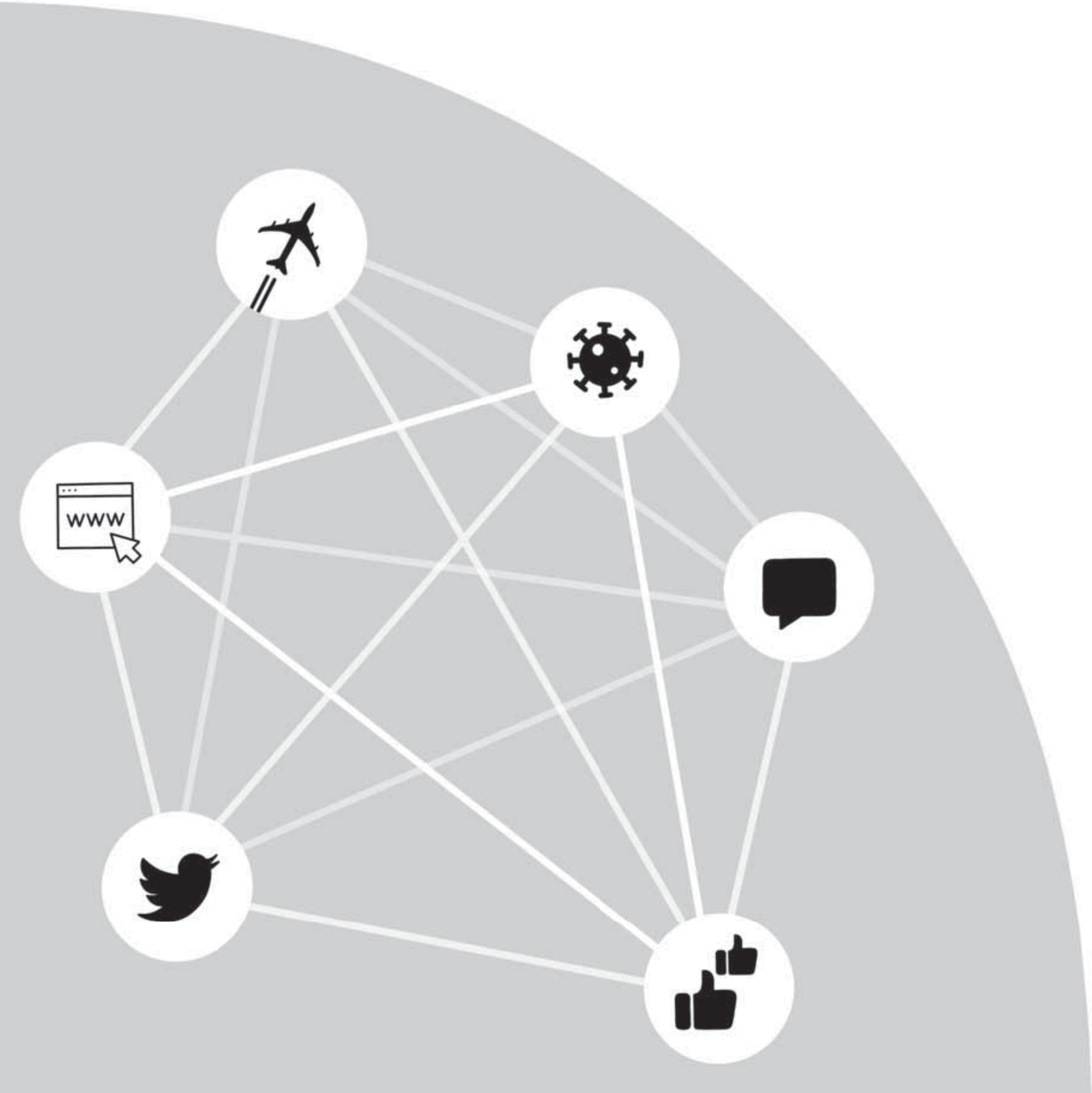
CHAPTER 8



Appendices

Appendix A - Supplementary Tables

Table S3.1 Participant Demograpics: Nationality (Chapter 3)

Country	n	%
The Netherlands	284	68.9
Germany	24	5.8
Turkey	9	2.2
Netherlands	6	1.5
Viet Nam	6	1.5
Poland	5	1.2
Bulgaria	4	1.0
France	4	1.0
Romania	4	1.0
Finland	3	0.7
Greece	3	0.7
India	3	0.7
Italy	3	0.7
Slovakia	3	0.7
Ukraine	3	0.7
UK	3	0.7
No entry	2	0.5
Australia	2	0.5
Brazil	2	0.5
Georgia	2	0.5
Ireland	2	0.5
Japan	2	0.5
Luxembourg	2	0.5
New Zealand	2	0.5
Russia	2	0.5
Spain	2	0.5
Syria	2	0.5
USA	2	0.5

Note. Individual participants reported other nationalities: Azerbaijan, Ecuador, Indonesia, Jordan, Kazakhstan, Kenya, Lebanon, Lithuania, Mexico, Morocco, Nigeria, Norway, Pakistan, Peru, Rwanda, Singapore, South Korea, Macedonia, Trinidad and Tobago, Tunisia, and Venezuela.

Tables S4.1-S4.5: Demographic Details of Prolific Research Participants (Wave 1, N = 501)

Table S4.1 Participant Demographics: Career Field (Chapter 4)

Category	n	%
Student	100	20.0
Information Technology	64	12.8
Unemployed	56	11.2
Health Science and Health Care	46	9.2
Marketing, Sales, and Service	51	10.2
Education and Training	34	6.8
Science, Technology, Engineering, and Mathematics	47	9.4
Arts, Audio/Video Technology, and Communications	29	5.8
Business Management and Administration	22	4.4
Finance	16	3.2
Transportation, Distribution, and Logistics	14	2.8
Manufacturing	12	2.4
Law, Public Safety, Corrections, and Security	12	2.4
Government and Public Administration	12	2.4
Hospitality and Tourism	10	2.0
Human Services	9	1.8
Agriculture, Food and Natural Resources	7	1.4
Other: Retired	6	1.2
Other: Self-employed	3	0.6
Architecture and Construction	4	0.8
Other: Military	2	0.4
Other*	15	3.0

Note. * Other career fields reported by individual participants: associate, aviation, blogger, building management, clergy, educational publishing, freelancer, insurance, internet analyst, risk analyst, sex worker, sports, telecoms, and writing.

Table S4.2 Participant Demographics: Education

Highest educational achievement	n	%
Bachelor's degree in college (4-year)	155	30.9
High school graduate	119	23.8
Some college but no degree	88	17.6
Master's degree	85	17.0
Associate degree in college (2-year)	27	5.4
Professional degree (JD, MD)	12	2.4
Less than high school degree	9	1.8
Doctoral degree	6	1.2

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Table S4.3 Participant Demographics: Nationality

Nationality	n	%
United Kingdom	165	32.9
United States of America	101	20.2
Poland	63	12.6
Portugal	57	11.4
Greece	17	3.4
Canada	13	2.6
Italy	10	2.0
Spain	10	2.0
Hungary	7	1.4
Germany	6	1.2
Netherlands	6	1.2
Estonia	5	1.0
France	4	0.8
India	4	0.8
Australia	3	0.6
South Africa	3	0.6
Austria	2	0.4
Brazil	2	0.4
Israel	2	0.4
Other*	21	4.2

Note. * Other countries reported by individual participants: Armenia, Belgium, Chile, Colombia, Czech Republic, Denmark, Finland, Iceland, Indonesia, Ireland, Latvia, Lithuania, Mexico, New Zealand, Nigeria, Romania, Singapore, Slovenia, Switzerland, Venezuela, and Viet Nam.

Table S4.4 Participant Demographics: Native Language

Native language	n	%
English	283	56.5
Polish	64	12.8
Portuguese	57	11.4
Greek	16	3.2
Spanish	13	2.6
German	9	1.8
Italian	9	1.8
Dutch	7	1.4
Hungarian	7	1.4
Estonian	5	1.0
French	5	1.0
Hebrew	2	0.4
Other*	24	4.8

Note. * Other native languages reported by individual participants: Afrikaans, Arabic, Armenian, Bengali, Catalan, Czech, Danish, Finnish, Hindi, Icelandic, Indonesian, Kiswahili, Korean, Latvian, Lithuanian, Malayalam, Romanian, Russian, Scottish, Slovenian, Tamil, Ukrainian, Urdu, and Vietnamese.

Table S4.5 Participant Demographics: Gender Identity

Gender	n	%
Male	257	51.3
Female	238	47.5
Prefer not to say	2	0.4
Transgender	1	0.2
Other: not specified	1	0.2
Other: genderqueer	1	0.2
Other: nonbinary	1	0.2

Tables S4.6-S4.11: Cognitive Motivation and the COVID-19 Knowledge Test (Wave 1); Comparing Four Types of NC and NCC Groups

Table S4.6 Descriptive Statistics of Need for Cognition Score and Need for Cognitive Closure Score (N=501)

Scale	Mean	SD	Median	Min	Max	95% CI
Need for Cognition	61.96	10.77	62	23	88	[61.01, 62.90]
Need for Cognitive Closure	164.15	20.08	163	107	239	[162.40, 165.91]
Order	43.19	7.6	43	17	60	[42.52, 43.85]
Predictability	33.03	6.86	33	13	48	[32.43, 33.63]
Decisiveness	25.62	6.59	25	7	42	[25.04, 26.20]
Ambiguity	38.75	5.96	39	22	54	[38.23, 39.27]
Closed Mindedness	23.56	5.08	24	8	42	[23.12, 24.01]

Table S4.7 Need for Cognition and Need for Cognitive Closure Scores Found in the Current Study and Previous Research

	M (SD)	N
Need for Cognition		
Current study	61.96 (10.77)	501
(Furlong, 1993)	61.50 (11.40)	61
(Kernis et al., 1992)	62.66 (9.17)	116
(Miller et al., 1991)	62.34 (9.62)	98
(Peltier & Schibrowsky, 1994)	66.70 (9.37)	130
Need for Cognitive Closure		
Current study	3.91 (.48)	501
(Djikic et al., 2013)		87
Group 1	3.97 (.44)	
Group 2	3.79 (.37)	
(Roets & Van Hiel, 2011) *	3.77 (.74)	1584

* In this study the 41-item revision of the Need for Cognitive Closure Scale was used (Roets & Van Hiel, 2007).

Table S4.8 COVID-19 Knowledge Test True Statements Responses; Grouped on High and Low NC and NCC

Item veracity	Knowledge Test answers	NC	NCC	Mean %	95% CI	
True statements (12 items)	*"I am sure is true"*	High	High	63.5	[58.6,	68.5]
		High	Low	53.8	[48.7,	59.0]
		Low	High	64.2	[59.9,	68.5]
		Low	Low	47.8	[40.5,	55.0]
	"I think this is true"	High	High	25.0	[20.7,	29.3]
		High	Low	32.3	[27.4,	37.1]
		Low	High	23.2	[19.0,	27.4]
		Low	Low	32.5	[26.7,	38.3]
	"I don't know"	High	High	6.0	[4.3,	7.8]
		High	Low	7.8	[6.0,	9.6]
		Low	High	4.6	[3.2,	6.1]
		Low	Low	12.5	[8.5,	16.5]
	*"I think this is **not** true"*	High	High	3.0	[1.7,	4.3]
		High	Low	4.6	[3.1,	6.0]
		Low	High	5.3	[3.8,	6.8]
		Low	Low	5.8	[3.9,	7.6]
	*"I am sure this is **not** true"*	High	High	2.5	[1.1,	3.8]
		High	Low	1.5	[0.8,	2.2]
		Low	High	2.6	[1.5,	3.7]
		Low	Low	1.4	[0.5,	2.4]

Note. High and Low NC were determined by a median split of the scores. High and Low NCC based on the lower and upper quantiles of scores. Importantly, the interquartile range of NCC scores were excluded. Thus, the values in this table represent 50% of the original sample. Group sizes are 61 (Hi-NC, Hi-NCC), 78 (Hi-NC,Lo-NCC), 61 (Lo-NC, Hi-NCC), and 52 (Lo-NC, Lo-NCC).

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Table S4.9 COVID-19 Knowledge Test False Statements Responses; Grouped on High and Low NC and NCC

Item veracity	Knowledge Test answers	NC	NCC	Mean %	95% CI	
False statements (12 items)	*"I am sure is true"*	High	High	5.3	[3.4,	7.3]
		High	Low	3.8	[2.3,	5.4]
		Low	High	5.2	[3.3,	7.1]
		Low	Low	3.4	[1.3,	5.4]
	"I think this is true"	High	High	10.5	[8.2,	12.8]
		High	Low	11.6	[9.9,	13.4]
		Low	High	13.1	[10.6,	15.6]
		Low	Low	17.0	[13.6,	20.4]
	"I don't know"	High	High	11.6	[8.9,	14.3]
		High	Low	13.9	[11.3,	16.5]
		Low	High	10.8	[8.0,	13.6]
		Low	Low	20.5	[16.2,	24.8]
	*"I think this is **not** true"*	High	High	21.6	[18.1,	25.1]
		High	Low	27.5	[23.1,	31.8]
		Low	High	23.1	[19.2,	27.0]
		Low	Low	25.0	[20.6,	29.4]
	*"I am sure this is **not** true"*	High	High	51.0	[46.2,	55.7]
		High	Low	43.2	[38.8,	47.5]
		Low	High	47.8	[42.8,	52.8]
		Low	Low	34.1	[28.1,	40.2]

Note. High and Low NC were determined by a median split of the scores. High and Low NCC based on the lower and upper quantiles of scores. Importantly, the interquartile range of NCC scores were excluded. Thus, the values in this table represent 50% of the original sample. Group sizes are 61 (Hi-NC, Hi-NCC), 78 (Hi-NC,Lo-NCC), 61 (Lo-NC, Hi-NCC), and 52 (Lo-NC, Lo-NCC).

Table S4.10 COVID-19 Conspiracy Statements Responses; Grouped on High and Low NC and NCC

Item veracity	Knowledge Test answers	NC	NCC	Mean %	95% CI	
Conspiracy statements (7 items)	*"I am sure is true"*	High	High	0.7	[-0.3,	1.7]
		High	Low	0.0	[0.0,	0.0]
		Low	High	0.0	[0.0,	0.0]
		Low	Low	0.3	[-0.3,	0.8]
	"I think this is true"	High	High	1.4	[0.0,	2.8]
		High	Low	1.3	[-0.1,	2.7]
		Low	High	3.3	[0.5,	6.0]
		Low	Low	2.7	[0.7,	4.8]
	"I don't know"	High	High	4.4	[-0.2,	9.1]
		High	Low	13.6	[7.7,	19.4]
		Low	High	10.8	[5.3,	16.2]
		Low	Low	17.9	[10.1,	25.6]
	*"I think this is **not** true"*	High	High	12.9	[6.5,	19.3]
		High	Low	20.1	[13.6,	26.7]
		Low	High	17.6	[11.2,	23.9]
		Low	Low	28.3	[20.0,	36.6]
	*"I am sure this is **not** true"*	High	High	80.6	[72.7,	88.5]
		High	Low	65.0	[56.7,	73.4]
		Low	High	68.4	[59.5,	77.3]
		Low	Low	50.8	[40.2,	61.5]

Note. High and Low NC were determined by a median split of the scores. High and Low NCC based on the lower and upper quantiles of scores. Importantly, the interquartile range of NCC scores were excluded. Thus, the values in this table represent 50% of the original sample. Group sizes are 61 (Hi-NC, Hi-NCC), 78 (Hi-NC,Lo-NCC), 61 (Lo-NC, Hi-NCC), and 52 (Lo-NC, Lo-NCC).

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Table S4.11 COVID-19 Negated Conspiracy Statement Responses; Grouped on High and Low NC and NCC

Item veracity	Knowledge Test answers	NC	NCC	Mean %	95% CI	
Negated conspiracy statement (1 item)	*"I am sure is true"*	High	High	49.2	[36.5,	61.8]
		High	Low	33.3	[22.8,	43.9]
		Low	High	31.1	[19.4,	42.9]
		Low	Low	17.3	[6.9,	27.7]
	"I think this is true"	High	High	27.9	[16.5,	39.2]
		High	Low	34.6	[24.0,	45.2]
		Low	High	24.6	[13.7,	35.5]
		Low	Low	30.8	[18.1,	43.4]
	"I don't know"	High	High	11.5	[3.4,	19.5]
		High	Low	12.8	[5.4,	20.3]
		Low	High	24.6	[13.7,	35.5]
		Low	Low	32.7	[19.8,	45.6]
	*"I think this is **not** true"*	High	High	3.3	[-1.2,	7.8]
		High	Low	11.5	[4.4,	18.7]
		Low	High	11.5	[3.4,	19.5]
		Low	Low	11.5	[2.8,	20.3]
	*"I am sure this is **not** true"*	High	High	8.2	[1.3,	15.1]
		High	Low	7.7	[1.7,	13.6]
		Low	High	8.2	[1.3,	15.1]
		Low	Low	7.7	[0.4,	15.0]

Note. High and Low NC were determined by a median split of the scores. High and Low NCC are based on the lower and upper quantiles of scores. Importantly, the interquartile range of NCC scores were excluded. Thus, the values in this table represent 50% of the original sample. Group sizes are 61 (Hi-NC, Hi-NCC), 78 (Hi-NC,Lo-NCC), 61 (Lo-NC, Hi-NCC), and 52 (Lo-NC, Lo-NCC).

Tables S4.12-S4.16: Demographic Details of Prolific Research Participants (Wave 2)

Table S4.12 Participant Demographics: Career Field (N = 326)

Category	n	%
Student	59	18.1
Information Technology	47	14.4
Unemployed	35	10.7
Marketing, Sales, and Service	27	8.3
Health Science and Health Care	24	7.4
Science, Technology, Engineering, and Mathematics	24	7.4
Education and Training	19	5.8
Arts, Audio/Video Technology, and Communications	17	5.2
Business Management and Administration	17	5.2
Finance	13	4.0
Government and Public Administration	9	2.8
Manufacturing	9	2.8
Human Services	7	2.1
Transportation, Distribution, and Logistics	7	2.1
Hospitality and Tourism	6	1.8
Law, Public Safety, Corrections, and Security	6	1.8
Agriculture, Food and Natural Resources	2	0.6
Architecture and Construction	2	0.6
Other: Retired	6	1.8
Other (please specify)	3	0.9

Note. * Other career fields reported by individual participants were blogger, educational publishing, freelancer, internet analyst, risk analyst, sex worker, sports, telecoms, and writing. Participants could choose multiple career field topics, therefore n total is larger than the sample size.

Table S4.13 Participant Demographics: Education

Highest educational achievement	n	%
Bachelor's degree in college (4-year)	90	27.6
High school graduate	85	26.1
Master’s degree	66	20.3
Some college but no degree	56	17.2
Associate degree in college (2-year)	17	5.2
Professional degree (JD, MD)	7	2.2
Less than high school degree	4	1.2
Doctoral degree	1	0.3

Table S4.14 Participant Demographics: Nationality

Nationality	n	%
United Kingdom	108	33.1
United States of America	53	16.3
Poland	46	14.1
Portugal	39	12.0
Greece	12	3.7
Italy	8	2.5
Canada	7	2.2
Hungary	7	2.2
Spain	7	2.2
Estonia	4	1.2
Australia	3	0.9
France	3	0.9
India	3	0.9
Netherlands	3	0.9
Brazil	2	0.6
Israel	2	0.6
South Africa	2	0.6
Other*	17	5.2

Note. * Other countries reported by individual participants: Armenia, Austria, Belgium, Chile, Czech Republic, Finland, Germany, Indonesia, Ireland, Latvia, Lithuania, Mexico, New Zealand, Nigeria, Romania, Slovenia, and Switzerland.

Table S4.15 Participant Demographics: Native Language

Native language	n	%
English	173	53.1
Polish	46	14.1
Portuguese	39	12.0
Greek	11	3.4
Spanish	9	2.8
Hungarian	7	2.2
Italian	7	2.2
Dutch	4	1.2
Estonian	4	1.2
French	3	0.9
German	3	0.9
Hebrew	2	0.6
Other*	18	5.5

Note. * Other native languages reported by individual participants: Arabic, Armenian, Bengali, Czech, Danish, Finnish, Hindi, Indonesian, Kiswahili, Korean, Latvian, Lithuanian, Malayalam, Romanian, Russian, Scottish, Slovenian, Ukrainian, and Urdu.

Table S4.16 Participant Demographics: Gender Identity

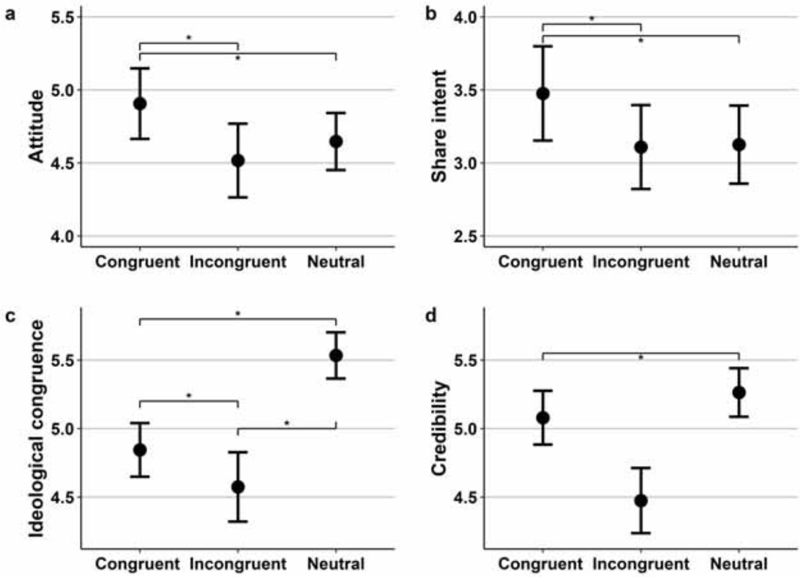
Gender	n	%
Male	167	51.2
Female	154	47.2
Prefer not to say	2	0.6
Transgender	1	0.3
Other: not specified	1	0.3
Other: genderqueer	1	0.3
Other: nonbinary	167	51.2

Table S4.17 Wave 2: Descriptive Statistics COVID-19 Knowledge Test (N = 326)

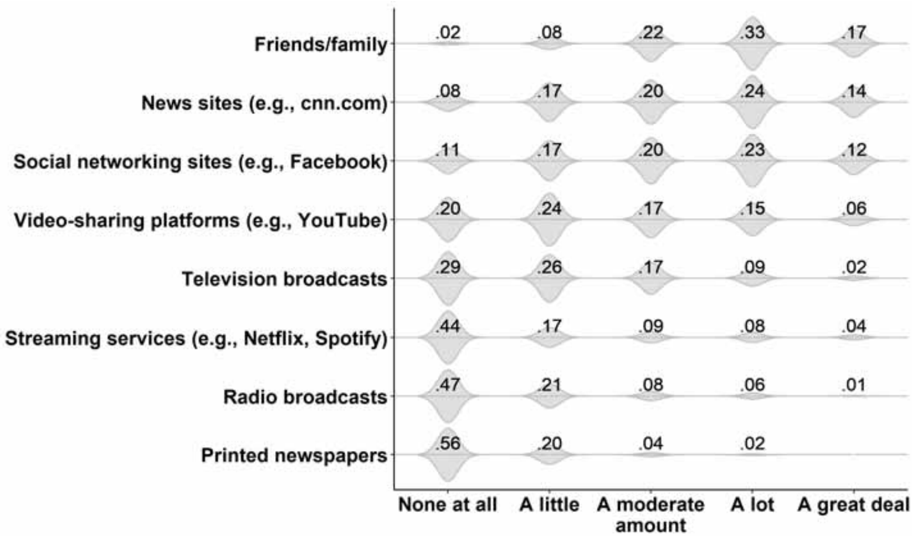
Item veracity	Knowledge Test answers	Mean percentage	SD	95% CI		Min	Max
True statements (16 items)	*"I am sure this is true"*	43.5	20.9	[41.3,	45.8]	0	16/16
	"I think this is true"	29.8	17.3	[28.0	31.7]	0	14/16
	"I don't know"	14.4	10.5	[13.3,	15.5]	0	9/16
	*"I think this is **not** true"*	8.0	8.1	[7.1,	8.9]	0	10/16
	*"I am sure this is **not** true"*	4.2	8.7	[3.3,	5.2]	0	16/16
False statements (16 items)	*"I am sure this is true"*	5.1	6.4	4.4	5.8]	0	6/16
	"I think this is true"	12.5	9.4	[11.5,	13.6]	0	9/16
	"I don't know"	14.5	12.8	[13.1,	15.9]	0	10/16
	*"I think this is **not** true"*	22.4	15.7	[20.7,	24.1]	0	13/16
	*"I am sure this is **not** true"*	45.5	21.5	[43.2,	47.8]	0	16/16
Conspiracy statements (7 items)	*"I am sure this is true"*	0.9	4.7	[0.4,	1.4]	0	3/7
	"I think this is true"	3.2	10.5	[2.1,	4.4]	0	5/7
	"I don't know"	11.3	22.3	[8.8,	13.7]	0	7/7
	*"I think this is **not** true"*	19.4	26.9	[16.5,	22.3]	0	7/7
	*"I am sure this is **not** true"*	65.2	37.1	[61.1	69.2]	0	7/7
Negated conspiracy statement (1 item)	*"I am sure this is true"*	26.7	44.3	[21.9,	31.5]	Not applicable for a single item	
	"I think this is true"	26.7	44.3	[21.9,	31.5]		
	"I don't know"	22.7	42.0	[18.1,	27.3]		
	*"I think this is **not** true"*	12.9	33.6	[9.2,	16.5]		
	*"I am sure this is **not** true"*	11.0	31.4	[7.6,	14.5]		

A

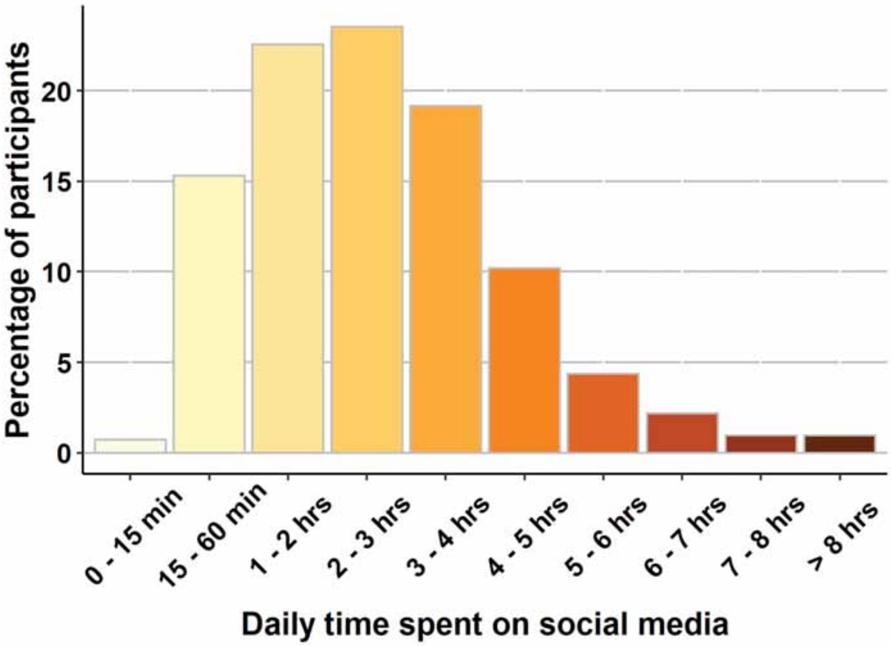
Appendix B - Supplementary Figures



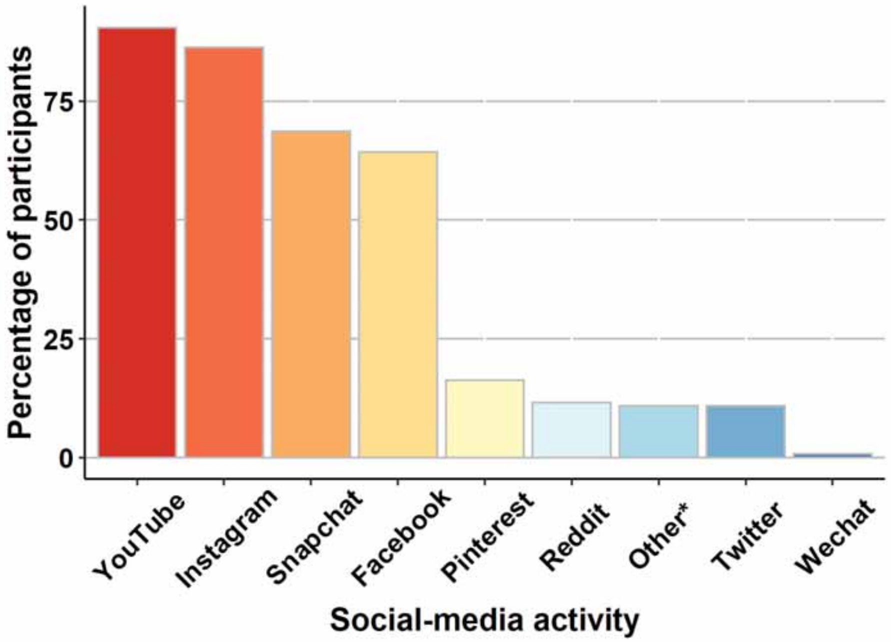
Supplementary Figure S3.1. Main effects of article-content type. Participants viewed three news articles on a manipulated but ostensibly real social networking site. The error bars represent 95% CIs, significant differences ($p < .011$) are indicated with asterisks. The outcome variables were attitude (a), share intent (b), ideological congruence (c), credibility (d), and perceived public attitude (presented in Figure 3c in the main text).



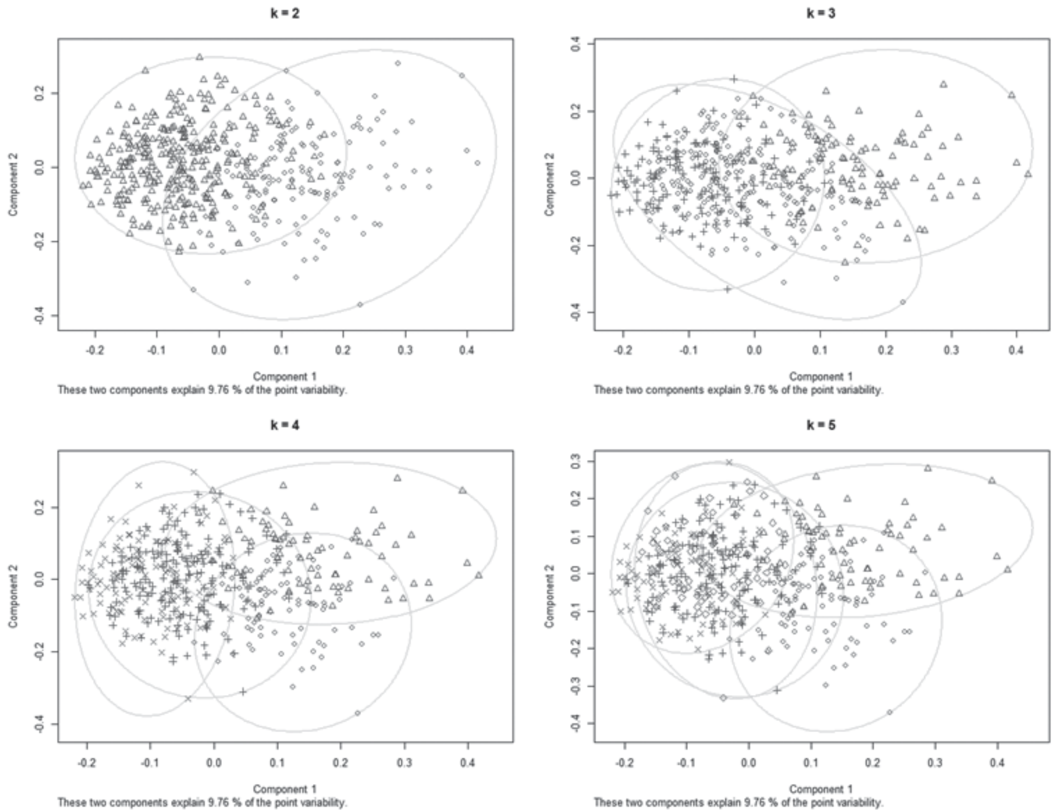
Supplementary Figure S3.2. Media use. Proportions of participants per response option.



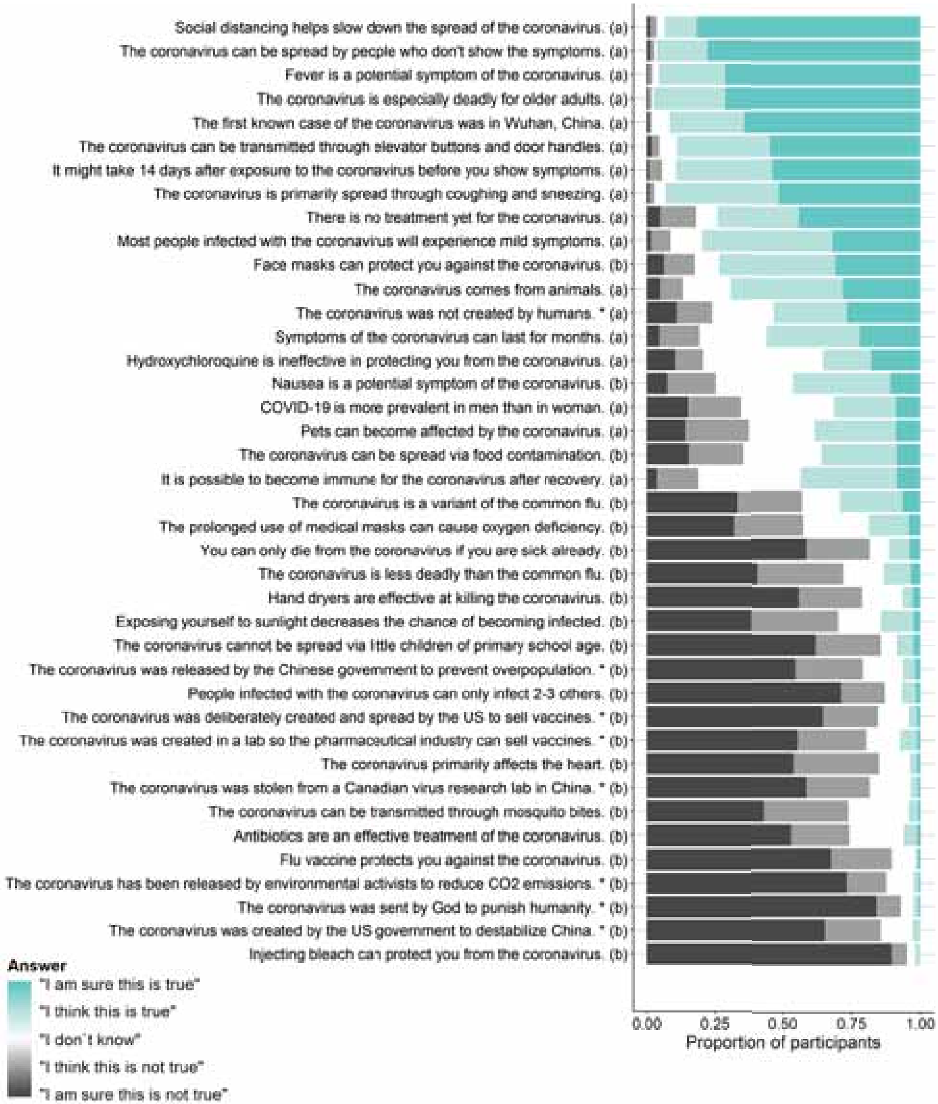
Supplementary Figure S3.3. Daily time spent on social media.



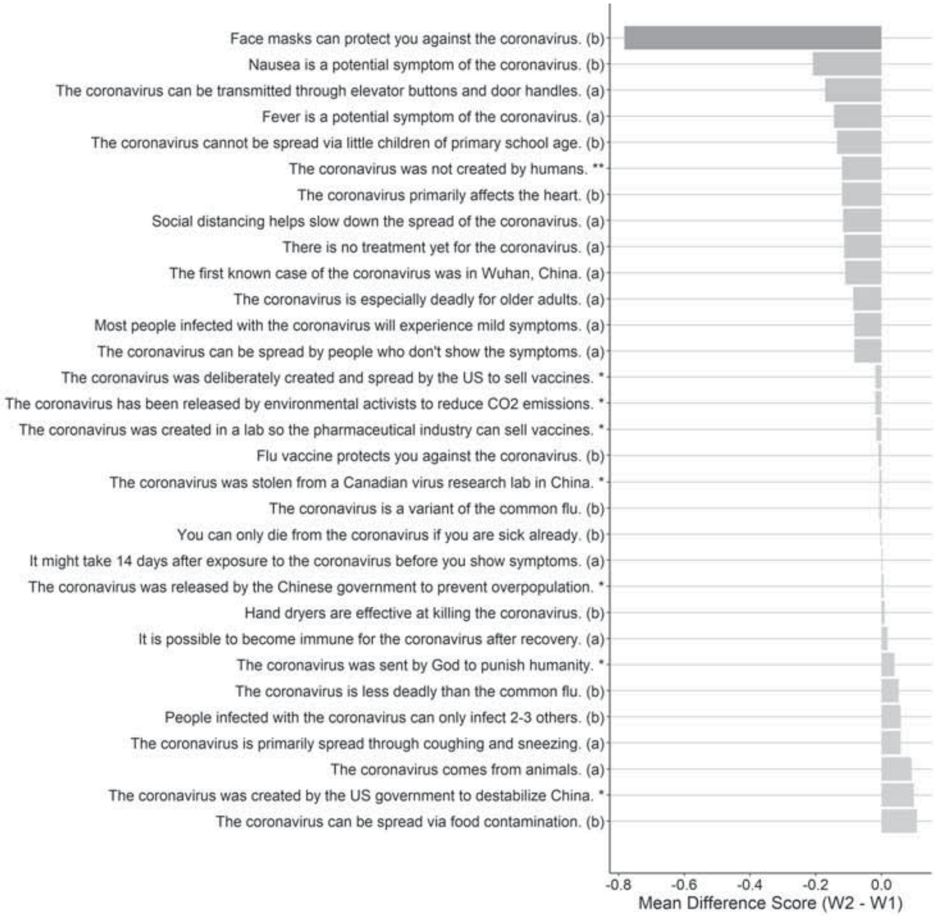
Supplementary Figure S3.4. Frequently used platforms.



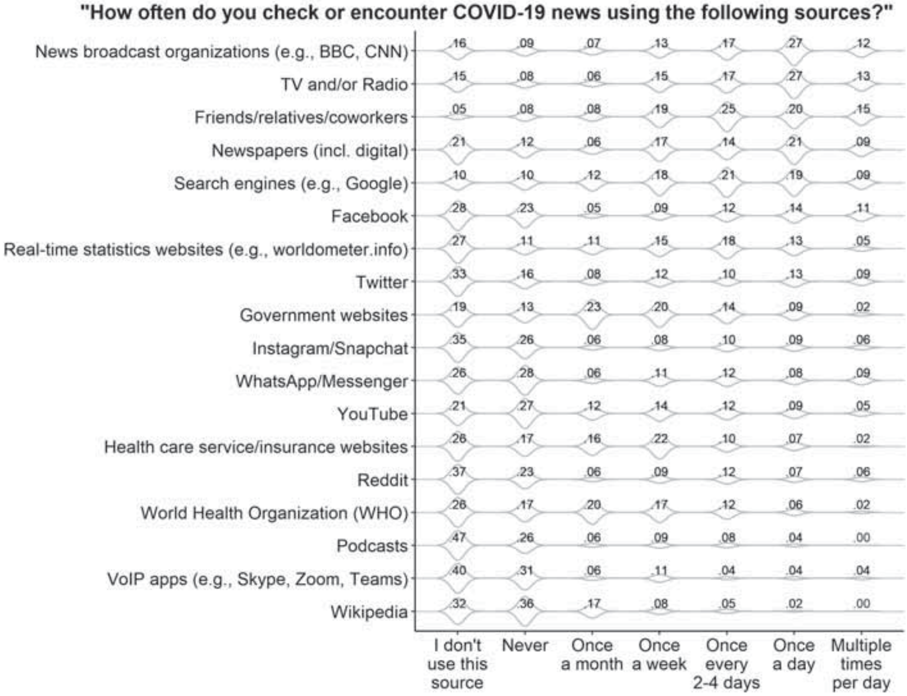
Supplementary Figure S4.1. Cluster Analysis. Cluster plots for 2, 3, 4, and 5 clusters. The 32 items of the COVID-19 Knowledge test (24 items), Conspiracy Rejection (8 items), NCC scores, NC scores, time spent on social media, frequency of checking COVID-19 updates, deaths per million in a respondent's country (on March 27th), measuring the use of sources consulted for information on COVID-19 (14 items), and reasons for consulting news sources (5 items). Given that many of these variables have an ordinal measurement level, the cluster analysis was based on the general dissimilarity coefficient of Gower (1971), calculated using the *daisy* function from the *cluster* R-package (Maechler et al., 2019). The resulting dissimilarity matrix was subsequently used as input for analyses in which the data was partitioned into k (k = 1, 2, 3, 4, and 5) clusters "around medoids", a more robust version of k-means clustering. All analyses used the *pam* function from the *cluster* package (Maechler et al., 2019).



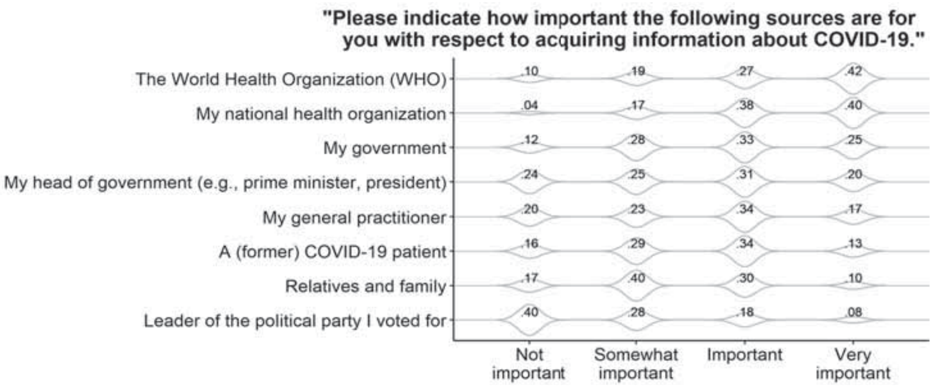
Supplementary Figure S4.2. COVID-19 Knowledge Test Wave 2 (N = 326). True (a), false (b) and conspiracy (*) statements.



Supplementary Figure S4.3. Difference Scores COVID-19 Knowledge Test. Mean difference scores between Wave 1 and Wave 2 for true (a), false (b) and conspiracy (*) statements in the COVID 19 Knowledge Test. Negative values indicate lowered accuracy.

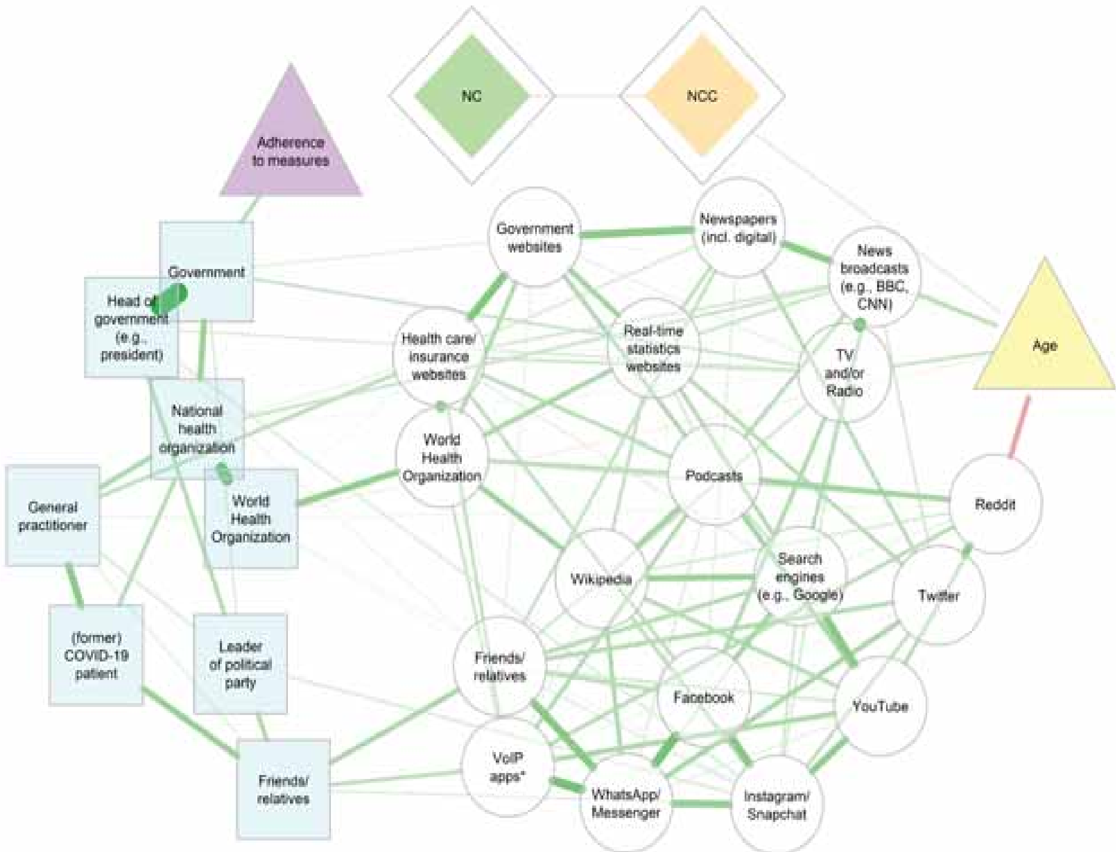


Supplementary Figure S4.4. Media Use Wave 2. Frequency by which different sources are consulted for COVID-19 information.



Supplementary Figure S4.5. Respected Sources Wave 2. The perceived importance of different sources for COVID-19 information.

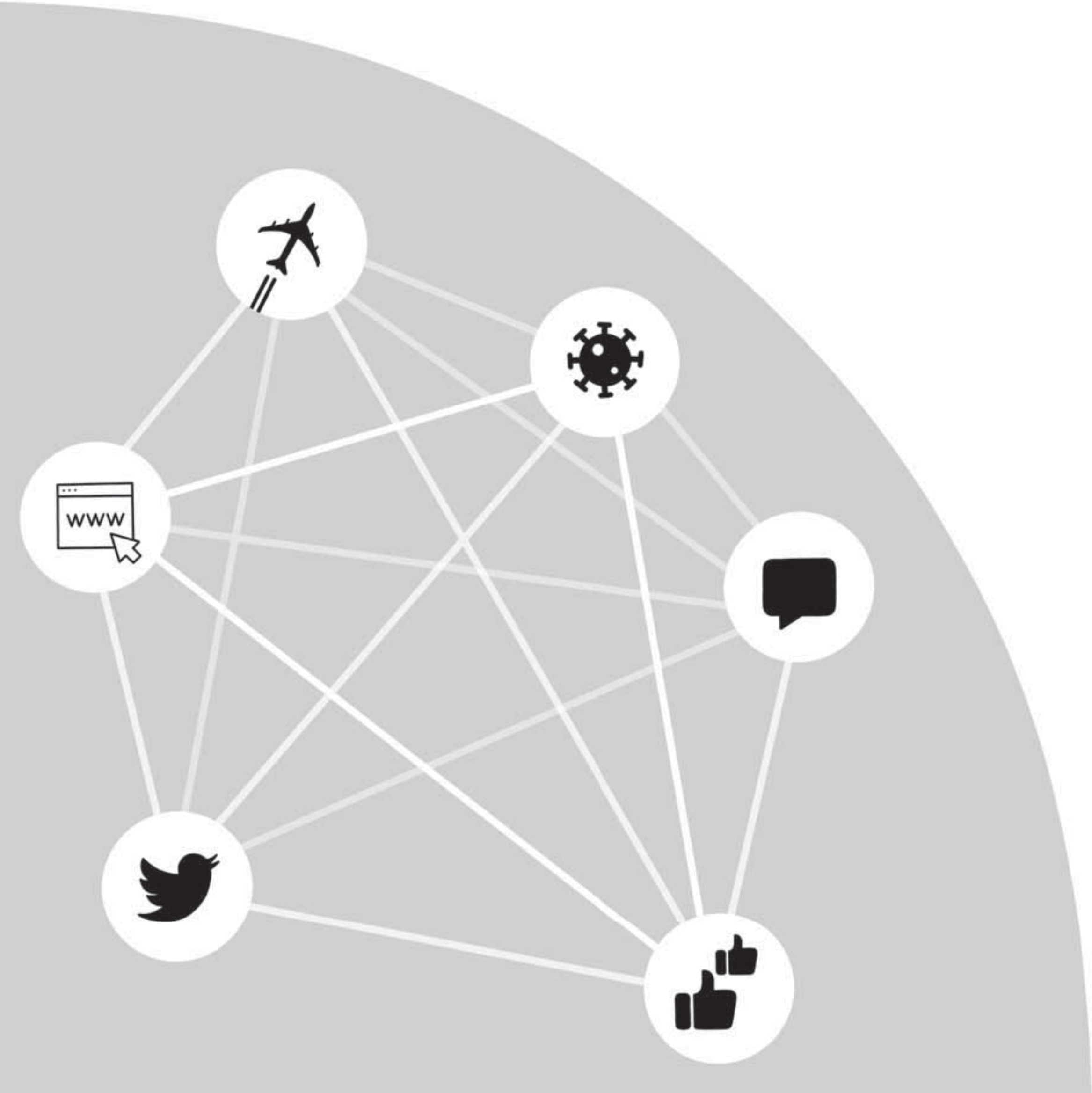
A



Supplementary Figure S4.6. Network Analysis Wave 2. Network analysis displaying the relations between NC, NCC, the perceived importance of different sources (blue squares), sources that are used to acquire information about COVID-19 (white circles), adherence to (government-imposed) measures, and age.

A

CHAPTER 9



Summary

Nederlandse samenvatting

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Publications

Acknowledgements

Summary

As digital media have proliferated, their influence on how individuals consume information, communicate, and shape social dynamics has become profound. Understanding how individuals think, process information, and communicate in the digital age is essential. Therefore, this PhD thesis explores the cognitive and linguistic aspects of digital media usage.

Chapter 2 investigated how restrictions on message length in social media platforms influence users' writing style and language choices. Particularly, we examined the impact of Twitter's character-limit increase from 140 to 280 characters on language usage in tweets. The findings indicated that with the expanded message length, users employed more article, conjunction, and preposition words, suggesting more elaborate language structures. This shift reflects changes in linguistic norms within the social media context, emphasizing the dynamic nature of language adaptation in digital environments.

Chapter 3 explored how peer-generated comments and 'Likes' influence the processing and evaluation of online news content. We found that negative peer-user comments significantly impact readers, leading to negative attitudes, decreased intent to share, reduced agreement with conveyed ideas, and diminished perceptions of public opinion and article credibility. In contrast, 'Likes' did not significantly affect readers' opinions, highlighting the nuanced nature of cognitive responses to different forms of social interaction on social media platforms. These insights contribute to understanding the impact of social media engagement on information processing and decision-making.

Chapter 4 examined the role of cognitive motivation in information-seeking, processing, and interpretation of Covid-19-related facts and falsehoods. We found that while the frequency of Covid-19 information-seeking behavior was not directly linked to individual differences in Need for Cognition (NC) or Need for Cognitive Closure (NCC), these cognitive motivations positively correlated with knowledge about Covid-19 and the rejection of conspiracy statements. Higher levels of Covid-19 knowledge were also associated with increased compliance with government measures, underscoring the practical implications of cognitive factors in shaping behavioral responses to digital media information during a global health crisis.

Chapter 5 explored the susceptibility of internet users to adopting false conspiracy narratives from a website. Using an online experiment, we exposed psychology undergraduates to a – to them novel - conspiracy belief on a fake, but ostensibly legitimate, social news-aggregation platform. The study compared implicit and explicit measures of belief in a conspiracy narrative. Contrary to expectations, participants reported higher belief in the conspiracy narrative on the explicit measure

than they did on the implicit measure. This suggests complex cognitive dynamics where individuals may express differing levels of belief depending on the context and measurement method. Surprisingly, half of the participants who had never heard about the conspiracy before reported believing in its existence, highlighting the importance of media literacy and critical thinking skills.

The research presented in this thesis underscores several key aspects of how digital media influence their users. From shaping language production to influencing information processing and belief formation, digital media platforms play a pivotal role in shaping cognitive and linguistic processes. The relaxation of Twitter's character limit led to increased usage of preposition, conjunction, and article words while decreasing the use of informal textese, reflecting adaptability in language production. This linguistic adaptability is a response to the inherent limitations of early digital communication, such as the lack of non-verbal cues, which prompted the use of paralinguistic digital affordances and emojis.

Comment sections on news websites can negatively impact how readers evaluate editorial content, with negative opinions exerting a more significant influence than positive ones. This has major implications for digital journalism, suggesting that the mere presence or visibility of a comment section may be more detrimental than beneficial to readers' evaluation and interpretation of content. While user feedback and interaction improve overall engagement and ad revenue for publishers, hiding comment sections by default might strike a balance between user engagement and content credibility.

The research also revealed a striking vulnerability among social media and web users to believe misinformation. Even academically educated individuals, such as psychology students, can accept conspiratorial misinformation as true. This highlights the responsibility of social media platforms to protect their users by implementing measures such as fact-checking and content moderation to minimize exposure to misinformation. The studies in Chapters 3 and 5 demonstrate the significant impact of others' beliefs and perspectives shared on social media platforms on shaping the views and beliefs of readers. This susceptibility extends to adopting false conspiracy beliefs, indicating that social media and the internet can influence users' perceptions of events and affairs. The findings emphasize the importance of educating young individuals to improve their media literacy and critical thinking skills.

In conclusion, this thesis examined cognitive and linguistic aspects of digital media usage, highlighting the effects of message constraints, online environments, cognitive motivations, and susceptibility to misinformation.

Nederlandse Samenvatting

In het huidige digitale tijdperk worden het internet en sociale media steeds belangrijkere middelen om informatie te verkrijgen, te communiceren en sociaal verbonden te zijn. Het is daarom essentieel om te begrijpen hoe deze toenemende afhankelijkheid van digitale media mensen kan beïnvloeden. Hoe gaan digitale-mediagebruikers om met informatie op het internet? Hoe communiceren mensen via digitale kanalen en wat voor invloed heeft dit op het taalgebruik? Deze cognitieve en taalkundige aspecten van het gebruik van digitale media zijn onderzocht in dit promotieonderzoek.

In hoofdstuk 2 hebben we onderzocht hoe restricties op de lengte van berichten op sociale media de schrijfstijl en taalkeuzes van sociale-mediagebruikers beïnvloeden. We hebben onderzocht wat de invloed was van de verhoging van Twitter's karakterlimiet van 140 naar 280 karakters op het taalgebruik in tweets. De resultaten tonen dat de uitbreiding van de berichtlengte ertoe heeft geleid dat gebruikers meer lidwoorden, voegwoorden en voorzetsels gebruiken, wat wijst op meer uitgebreide zinsstructuren. Bovendien werden er relatief minder vormen van 'textese' toegepast, dat zijn informele schrijfstijlen om karakterruimte te besparen. Deze verschuiving weerspiegelt veranderingen in taalkundige normen binnen sociale media en toont de dynamische aard van taalgebruik in sociale media.

Hoofdstuk 3 is gericht op de impact van reacties en 'likes' op de verwerking van online nieuws. Uit de resultaten bleek dat negatieve reacties van gebruikers een aanzienlijke invloed hebben op lezers. Negatieve reacties leiden namelijk tot negatieve houdingen, een verminderde bereidheid om het nieuws te delen, minder overeenstemming met de inhoud, een verlaagd beeld van de publieke opinie en verminderde geloofwaardigheid van het artikel. Daarentegen hebben 'likes' geen significante invloed op de meningen van lezers. De bevindingen tonen de impact van sociale media-interactie op informatieverwerking en besluitvorming, voornamelijk dat informatie negatiever geïnterpreteerd en verwerkt kan worden door de meningen van andere gebruikers op sociale media.

In hoofdstuk 4 hebben we de rol van cognitieve motivatie onderzocht in het zoekgedrag naar informatie en het verwerken en interpreteren van feiten en onjuistheden met betrekking tot Covid-19. Onze bevindingen waren dat hoewel de frequentie van Covid-19-informatiezoekgedrag niet direct gekoppeld was aan individuele verschillen in *Need for Cognition* (NC) of *Need for Cognitive Closure* (NCC), deze cognitieve motivaties positief gecorreleerd waren met kennis over Covid-19 en de verwerping van complotstellingen. Een hogere mate van Covid-19-kennis was ook geassocieerd met een betere naleving van overheidsmaatregelen. Dit toont aan dat cognitieve factoren een belangrijke rol spelen bij het gebruik en de verwerking van informatie via digitale media.

Hoofdstuk 5 is gericht op de vatbaarheid van internetgebruikers om onjuiste complotverhalen van een website als waarheid aan te nemen. Door middel van een online experiment hebben we psychologiestudenten blootgesteld aan een complotgeloof op een nep, maar ogenschijnlijk echt-bestaand sociale mediaplatform. We vergeleken in dit experiment een impliciete en expliciete meting van geloof in het complotverhaal. Tegen onze verwachtingen in, rapporteerden participanten vaker expliciet dat ze geloofden in het complotverhaal vergeleken met de impliciete meting. Dit toont aan dat er complexe cognitieve factoren zijn waarbij individuen verschillende niveaus van geloof kunnen uiten, afhankelijk van de context en de meetmethode. Verrassend genoeg rapporteerde de helft van de deelnemers die nog nooit van het complot hadden gehoord, te geloven in het bestaan ervan, wat het belang van mediawijsheid en kritisch denkvermogen benadrukt.

Het onderzoek gepresenteerd in dit proefschrift toont verschillende belangrijke aspecten van hoe digitale media de gebruikers kunnen beïnvloeden. Van het beïnvloeden van taalgebruik tot het beïnvloeden van informatieverwerking en het vormen van meningen, spelen digitale mediaplatforms een cruciale rol in de cognitieve en taalkundige processen. De uitbreiding van Twitter's karakterlimiet leidde tot een toename in het gebruik van voorzetsels, voegwoorden en lidwoorden, terwijl het gebruik van informele taal afnam. Dit toont aan dat het taalgebruik kan veranderen door beperkingen in het vermogen om te kunnen communiceren. De veranderingen in het taalgebruik en de uitvinding van nieuwe ‘parataalkundige’ manieren (likes, emojis, enz.) om te kunnen communiceren zijn een reactie op de inherente beperkingen van digitale communicatie, zoals karakterlimieten en het ontbreken van non-verbale signalen in de communicatie.

Reactiesecties op nieuwssites kunnen een negatieve impact hebben op hoe lezers nieuws evalueren, waarbij negatieve meningen een grotere invloed uitoefenen dan positieve. Deze bevindingen hebben belangrijke implicaties voor digitale journalistiek en suggereren dat de loutere aanwezigheid of zichtbaarheid van een reactiesectie mogelijk al een negatief effect kan hebben op de interpretatie van het nieuws. Gebruikersfeedback en interacties zijn echter wel van belang voor de advertentie-inkomsten van digitale nieuwsplatforms. Het is mogelijk verstandig om reactiesecties standaard te verbergen. In dat geval kunnen gebruikers namelijk reageren als zij dat graag willen doen, tegelijkertijd wordt de interpretatie van het nieuws minder beïnvloedt door negatieve reacties wanneer deze standaard verborgen zijn.

Dit onderzoek toont ook een opvallende kwetsbaarheid van digitale-mediagebruikers om misinformatie als waarheid aan te nemen. Zelfs academisch opgeleide individuen, zoals psychologiestudenten, kunnen misinformatie over een denkbeeldig complot als waarheid gaan zien. Dit benadrukt de verantwoordelijkheid van sociale mediaplatforms om hun gebruikers te beschermen door maatregelen zoals *fact-checking* en contentmoderatie te implementeren. Hiermee kan blootstelling aan misinformatie mogelijk beperkt worden. Ons onderzoek wijst op de impact van de overtuigingen en meningen van anderen op lezers. Deze vatbaarheid voor misinformatie reikt zelfs tot het aannemen van valse complotverhalen. Sociale media en het internet kunnen overtuigingen en ideologieën van gebruikers beïnvloeden. Onze bevindingen benadrukken het belang van het onderwijzen van jonge digitale mediagebruikers om hun mediawijsheid en kritisch denkvermogen te verbeteren.

Kortom, dit proefschrift onderzoekt de cognitieve en taalkundige aspecten van het gebruik van digitale media, waarbij de effecten van communicatieve beperkingen, online omgevingen, cognitieve motivaties en vatbaarheid voor misinformatie worden belicht.

Portfolio

Curriculum Vitae

Arnout Boot was born in Capelle aan den IJssel, in the Netherlands on August 21 in 1992. From 2012 to 2016. He obtained a bachelor degree in Psychology and a master's degree after following the Master program 'Brain and Cognition' at Erasmus University Rotterdam, The Netherlands. In November 2017, he started his PhD research at the department of Psychology, Education, and Child Studies at Erasmus University Rotterdam. His PhD research is presented in this thesis.

Publications

Boot, A. B., Dijkstra, K., & Zwaan, R. A. (2021). The processing and evaluation of news content on social media is influenced by peer-user commentary. Humanities and Social Sciences Communications 2021 8:1, 8(1), 1–11. https://doi.org/10.1057/s41599-021-00889-5

Boot, A. B., Eerland, A., Jongerling, J., Verkoeijen, P. P. J. L., & Zwaan, R. A. (2021). Gathering, processing, and interpreting information about COVID-19. Scientific Reports 2021 11:1, 11(1), 1–17. https://doi.org/10.1038/s41598-021-86088-3

Boot, A. B., Tjong Kim Sang, E., Dijkstra, K., & Zwaan, R. A. (2019). How character limit affects language usage in tweets. Palgrave Communications 2019 5:1, 5(1), 1–13. https://doi.org/10.1057/s41599-019-0280-3

Submitted manuscripts

Boot, A.B., Dijkstra, K., & Zwaan, R.A. "What are those stripes in the sky?" An experimental study on exposing web users to a conspiracy theory.

Conference presentations and workshops

2019. Speaker. How Character Limit Affects Language Use in Tweets. DPECS Graduate Research Day 2019.

2019. Speaker. Twitter content analysis in R, Society for the Improvement of Psychological Science (SIPS) 2019 Meeting.

2020. Speaker. Experimental Research in Progress; Beliefs in Conspiracy Theories on the Web. MISDOOM Symposium 2020. https://2020.misdoom.org/accepted-papers/

2021. Speaker. Gathering, Processing, and Interpreting Information About Covid-19. ESSB COVID Conference, Rotterdam.

2021. Speaker. Cognitive and Linguistic Aspects of Social Media Use. Belgian Association of Psychological Science (BAPS) Junior Board Webinar.

Guest lectures

2018. Speaker. Social Media, Digital Media & Memory. Psychology bachelor course 2.1 Memory.
2019. Speaker. Social Media, Digital Media & Memory. Psychology bachelor course 2.1 Memory.
2020. Speaker. Text Mining. Psychology bachelor B&C course 3.4.
2020. Speaker. Neuroimaging. Psychology bachelor B&C course 3.4.

Courses

2018. English Academic Writing for PhD Candidates (2 EC).
2018. Data Visualisation, Web scraping, and Text Analysis in R (2.5 EC).
2018. Digital Research Methods for Textual Data (2.5 EC).
2018. Professionalism and integrity in research (1.5 EC).

Teaching activities

2018. Supervision bachelor thesis. Twitter Content Analysis.
2018. Tutor. Psychology B&C 4.2C Language and Brain.
2019. Tutor. Psychology B&C 3.4C - Foundations of Cognitive Brain Research.
2019. Supervision bachelor thesis. Twitter Content Analysis.
2020. Tutor. Psychology B&C 3.4C - Foundations of Cognitive Brain Research.
2020. Supervision bachelor thesis. Twitter Content Analysis.
2020. Coordinator. Practicum PDM 4.2P Text Mining and Data Visualization with R.
2021. Coordinator. Practicum PDM 4.2P Text Mining and Data Visualization with R.
2022. Coordinator. Psychology 1.4C The Human Body.
2022. Coordinator. Psychology 1.4P Practicum Neuropsychological Diagnostics.
2022. Coordinator. Psychology B&C 3.6C The Brain
2022. Coordinator. Psychology B&C 3.6P Practicum Brain Anatomy
2022. Supervision bachelor thesis. Twitter Content Analysis.
2022. Supervision bachelor thesis. The Role of Neuromodulatory Systems in Alzheimer's Disease.
2022. Coordinator. Practicum PDM 4.2P Text Mining and Data Visualization with R.

Organization symposia

2020. DPECS Graduate Research Day 2020
2021. DPECS Graduate Research Day 2021

Acknowledgments

Completing this thesis has been a challenging journey, one that extended beyond the typical duration due to my commitments in teaching activities as well as my new job as a researcher outside academia. Balancing my new role while finishing my thesis was a significant struggle, especially after my PhD candidate contract ended. The Covid-19 pandemic also threw a spanner in the works. I remember March of 2020 as a surreal period, when the pandemic started. The last physical meeting of our department was the Graduate Research Day at Podium aan de Maas in Rotterdam. The next day the Dutch government imposed stay-at-home measures against the spread of the coronavirus. Working from home was nice and easy for me, perhaps a bit too easy. I believe the pandemic and the work-from-home situation instigated the hermit in me. Looking back, I realize I became somewhat isolated from my department and colleagues, perhaps more than I should have. Nonetheless, I am deeply grateful for the support and encouragement I received along my PhD journey.

I also realize that I have accidentally written the acknowledgements in English, despite many of the recipients of my acknowledgements being Dutch. But at this point I will just continue to do so, as I prefer the cadence and - to me - more poetic nature of the English language.

First and foremost, I would like to express my profound gratitude to my promotors, Rolf and Katinka, for their guidance, expertise, and support throughout this process. Your insights and encouragement were invaluable. Rolf, our meetings about my research were always a highlight, often turning into brainstorming sessions that felt more like idea-bearing adventures. I believe I experienced academia's high in those moments, the academic counterpart to runner's high. I also enjoyed the moments when we digressed and talked about music or other things. Katinka, thank you for reaching out to me during my radio silence when I was 'buried' in my other job. I appreciate your kindness, guidance and your highly constructive feedback on my work. Thank you both for your understanding and appreciation of my independent work style, and for reeling me back in after becoming somewhat detached from my original PhD trajectory.

I am thankful to my former PhD colleagues from the Brain and Cognition section of our department: Yiyun, Jianan, and Lara. Thank you for being great sparring partners to talk about my research. Your camaraderie and support were essential during the early stages of this journey. Additionally, I extend my gratitude to other friends and former colleagues: Miranda, Roger, Wei, Hannah, Yuri, Ildeniz, Marcello, Brechtje, Rob, Loïs, Tessa, and Sander. I appreciate our conversations during lunch times and talking about our shared experiences.

Special thanks go to Donna, Milou, Anniek, and Tom for the enriching experience of organizing the Graduate Research Day symposia together. It was a pleasure working with you all and contributing to the PhD community of DPECS. Those planning meetings were a blend of chaos and creativity, with just enough caffeine to keep us going.

I would also like to express my gratitude to those who contributed to my research. I am deeply thankful to Erik for inviting me to the eScience Center in Amsterdam and providing me with research tools that were indispensable in gathering and analyzing our extensive corpus of Dutch Tweets. Special thanks to Joran for his significant contribution to the data analysis in Chapter 4. I am also very grateful to Anita and Peter for their invaluable collaboration as co-authors on Chapter 4. Their expertise and support have greatly enriched this work.

I wish to thank the members of our Language Comprehension meetings. A big thank you to Oliver, Steven, Jasmijn, Brechtje, Huib, Bjorn, and Lesya for their contributions to these meetings and our wonderful discussions.

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I'd also love to give special thanks to my close family members: Larissa, Jauco, Thijs, Elize, Celine, Matt, Max, and Emma. I'm proud to be your brother and uncle. And to my in-laws, Opa Nol, Oma Ans, Linda en Ron, thank you for all the Sunday mornings with coffee and kaiserschmarrn.

To my loving parents, who have supported me unconditionally, your belief in me has been the foundation of my perseverance. Thank you for always being there for me, even when my explanations of my research made your eyes glaze over. Your love and support have been my anchor.

To Polly, our beloved dog, thank you for your comforting presence, silly leg stretches, and expressionless beady-eyed gazes. Your journey from the streets of Romania to our home is a testament to resilience and love, and I am grateful for every moment with you.

My deepest thanks go to Jacky. Your constant support and understanding through my struggles have been my greatest strength. Without you, this journey would have been impossible. Your patience, encouragement, and love have been my steadfast support. Thank you for standing by me, for believing in me, and for being my partner in all things.