What drives unverified information sharing and cyberchondria during the COVID-19 pandemic?

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What Drives Unverified Information Sharing and Cyberchondria during the COVID-19 Pandemic?

Abstract: The World Health Organization has emphasised that misinformation – spreading rapidly through social media – poses a serious threat to the COVID-19 response. Drawing from theories of health perception and cognitive load, we develop and test a research model hypothesising why people share unverified COVID-19 information through social media. Our findings suggest a person's trust in online information and perceived information overload are strong predictors of unverified information sharing. Furthermore, these factors, along with a person's perceived COVID-19 severity and vulnerability influence cyberchondria. Females were significantly more likely to suffer from cyberchondria, with males were more likely to share news without fact checking their source. Our findings suggest that to mitigate the spread of COVID-19 misinformation and cyberchondria, measures should be taken to enhance a healthy scepticism of health news while simultaneously guarding against information overload.

Keywords: COVID-19, Pandemic, Fake News, Cyberchondria, Misinformation, Information Overload

1. Introduction

"We're not just fighting an epidemic; we're fighting an infodemic" - WHO Director-General Tedros Adhanom Ghebreyesus[1].

Defined as *"False or inaccurate information, especially that which is deliberately intended to deceive"* (Lazer et al. 2018), misinformation poses a serious threat to public health during pandemics such as the COVID-19 (Zarocostas, 2020). The rapid spreading of such misinformation is amplified by social media and could result in the lack of adherence to recommended public health measures, or engagement in non-recommended behaviours. One clear example of disseminated misinformation during the COVID-19 pandemic suggested 5G cellular network towers contribute to the spread of the virus, reportedly causing people to attack network towers[2]. Such is the magnitude of misinformation circulating through social media, that the World Health Organization (WHO) Response Strategy specifically identifies tackling the COVID-19 'infodemic' as a research priority[3].

Misinformation is not a new problem. Since the beginning of this century, the quantity and dissemination of misinformation have grown exponentially (Kim and Dennis, 2019), ultimately leading the World Economic Forum to list online misinformation as one of the top 10 global threats to humanity in 2018. Prior research suggests that misinformation can fuel health anxiety (Lewis, 2006), poor health related decisions (Allcott and Gentzkow, 2017) and impair individuals' and health officials' ability to accurately evaluate the severity of on-going situations and take necessary actions (Kata, 2010; Sommerlad, 2020). The motivation for the present study stems from the unique global disrupting event that is the COVID-19 pandemic, in which the above scenarios are likely to be heightened or experienced in a new way. The pandemic emerged in late 2019 in Wuhan, China, and quickly spread globally (Chinazzi, et al., 2020) with the WHO declaring COVID-19 a global pandemic on March 11th, 2020. Amid the COVID-19 lockdown and social distancing rules, many have turned to social media websites and apps to pass time, engage with friends, and to keep themselves informed. While the ability to communicate and share information with others can have positive impacts on well-being during disrupting times, studies show that misinformation about COVID-19 flourished through social media in spring 2020 (Cinelli et al., 2020; Rovetta and Bhagavathula, 2020).

Numerous agencies, including the WHO, have made calls to develop interventions reducing the spread of COVID-19 misinformation. The first step to developing such interventions is to understand why people share unverified COVID-19 related information through social media. An interesting possible consequence of social media use during COVID-19 which may be connected to the spread of misinformation is cyberchondria. Therefore, from a health perception and information load perspective, the aim of this study is to empirically determine the specific individual drivers of COVID-19 social media misinformation sharing and cyberchondria. Previous studies on why people share fake news or misinformation on social

[1] WHO Director-General Tedros Adhanom Ghebreyesus at the Munich Security Conference on Feb 15.
[2] For more information on COVID-19 fake news, see World Health Organization Busting COVID-19 myths at: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public/myth-busters
[3] WHO response strategy: http://origin.who.int/blueprint/priority-diseases/key-action/Coronavirus_Roadmap_V9.pdf

media have found several explanators, of which high trust in online sources is pertinent (Talwar et al., 2019; Khan and Idris, 2019). However, studies focusing on human factors in misinformation sharing during a major health-crisis such as COVID-19 are missing. It is important to examine misinformation behaviours in such contexts as people make different decisions about information when driven by fear and anxiety (Allen et al. 2014). As an example, there is evidence that information-seeking during pandemics is more common in those experiencing worry or fear (Lin et al. 2014). Similarly, previous research suggests that when in a state of fear or distress, peoples' usage patterns and perceptions of social media alters significantly to the extent they can become overloaded and fatigued (Maier et al., 2014; Whelan et al., 2020b). Building on this existing work, we investigate the drivers of COVID-19 specific misinformation and cyberchondria.

To achieve our research objectives, we draw from theories of health perception (i.e. perceived susceptibility and perceived severity) and information load (i.e. information trust and information overload) to develop and test a research model hypothesising the drivers of COVID-19 misinformation and cyberchondria. We test the model with survey data from 294 Facebook users from Bangladesh using the PLS-SEM analysis technique. The results revealed both information factors are associated with increased cyberchondria and sharing unverified information. The health factors had no impact on sharing unverified information, but did predict increased cyberchondria. Finally, we found no direct relationship between suffering from cyberchondria and sharing unverified information. In terms of contribution to COVID-19 and future global crises, these findings can be used to design evidence-based interventions to curb the acceptance and spreading of misinformation. Extending the existing literature, our study confirms cognitive load to be a central factor triggering the sharing of unverified COVID-19 information on social media. Individual users, Government agencies, and social media providers can leverage these insights to implement targeted measures mitigating the spread of unverified COVID-19 information.

2. Background

2.1 Social Media and Misinformation Sharing

To assess the existing literature pertaining to misinformation and social media, we conducted a network visualisation of the relevant papers available through the Scopus database over the past 10 years. The resulting visualisation (see Figure 1) shows the literature on misinformation and social media to be grouped into three broad themes. One stream (top left) broadly focuses on applying computer science approaches to detect and prevent the spread of misinformation. A second stream (bottom left) considers the impact of social media misinformation on politics, science, and society in general. The third stream (right) focuses on the relationship between misinformation and population health. It is largely the latter stream from which this study draws from and contributes to. Exemplar misinformation studies are also provided in Table 1.

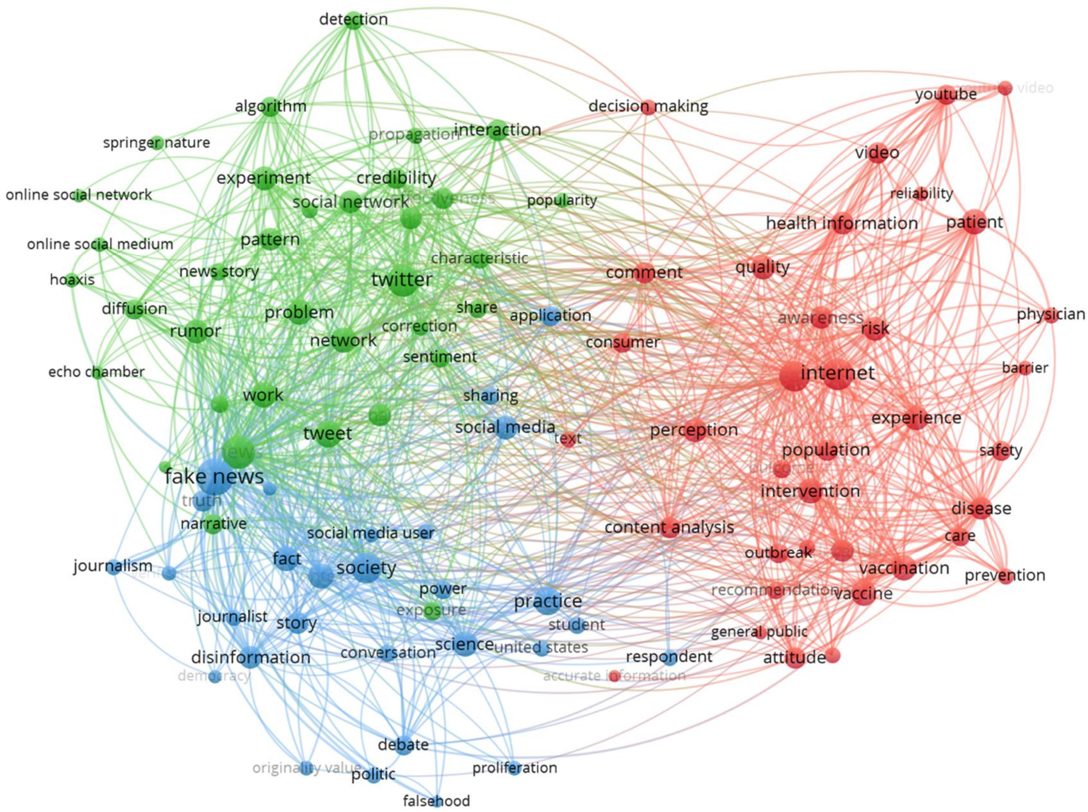

Figure 1. Visualizing the Social Media and Misinformation Literature

Table 1. Summary of the extant empirical studies on fake news and misinformation.

Author(s)	Sample	Context	Theory	Findings
Chadwick and Vaccari, 2019	2,005 survey responses	A representative sample of UK citizens	Online civic culture	Almost half of people who share news (42,8%) admitted to have shared misinformation. Roughly a quarter of the people sharing misinformation are never corrected. Sharing unverified information is mostly motivated by social reasons, to inform others and to self-express. 18,7% of people who share information are motivated by upsetting others.
Chen et al., 2015	171 survey responses	Students in two public universities in Singapore	Uses and gratifications approach	Sharing misinformation is driven by the information's content itself as well as the social media users' social impulses. Women are more likely to share misinformation compared to their male counterparts.
Del Vicario et	67 public pages (32	Social media and	Data-driven study	It is difficult for humans as well as for algorithms to distinguish

al., 2016	conspiracy, 35 science news)	web pages		misinformation from science. Source verification and critical thought is needed. Misinformation births mistrust, paranoia and rumours, and its spread is accelerated by confirmation bias.
Howard et al., 2017	138,686 tweets on Twitter	Michigan - based voters during the 2016 US election	Data-driven study; Grounded theory approach.	Fake news and misinformation were shared more often than professionally researched news in the observed dataset. Misinformation is packaged not only in the news format, but also into humour, opinions and other formats.
Huang et al., 2015	11 interviews	Social media users during the Boston Marathon Bombings in 2013	Grounded theory approach	Physical and emotional proximity during crises increase information sharing. Information overload as well as a rapid speed of new information contribute to increased probability of the emergence and propagation of fake news.
Khan and Idris, 2019	396 survey responses	Cross-sectional survey on internet source verification	Theory of reasoned action; Theory of planned behaviour	Unverified information sharing is increased by the following four factors (1) Lack of experience of online environments; (2) Lack of Information seeking and verification skills; (3) A lazy attitude towards verifying information; and (4) High trust of online information.
Kim and Dennis, 2019	445 experiment participants	Two experiment s on the impact of presentatio n of articles on source critique	Nudge theory	Directing readers to look at the source of the article makes them pay more attention to the credibility and reliability of the information. Confirmation bias has a major effect: users are significantly likelier to believe and share articles aligning with their existing beliefs.
Talwar et al., 2019	1022 survey responses	WhatsApp users	Social comparison theory; rational choice theory; self-determinati on theory	Sharing fake news was predicted by online trust, self-disclosure, fear of missing out and being tired. Social comparison, self-disclosure and social media fatigue negatively impact fake news sharing.

Previous studies have found several mechanisms that affect the spread of misinformation on social media, one of which is the use of bot armies to manipulate the platform algorithms to boost the visibility of 'fake news' articles (Lazer et al., 2018; Weedon et al., 2017). Another mechanism relates to people themselves, who can be driven by wishes to either inform or hurt others (Chadwick and Vaccari, 2019). Interestingly, medical professionals themselves were more likely to spread dread rumours than wish ones (Chua and Banerjee 2018). Reports also suggest that some groups of people believe and spread false news due to ideological reasons (Wolfe, 2002). Indeed, prior work postulates confirmation bias as one of the primary causes why people share misinformation (Kim and Dennis, 2019). Studies have argued that the polarising impact of social media contributes to the spread of fake news by reinforcing the confirmation bias and creating and maintaining social echo-chambers where certain information rarely gets challenged (Spohr, 2017).

With regards to the number of people circulating fake news articles, almost half of those sharing news articles report to have at some point shared misinformation (Chadwick and Vaccari, 2019). Whether people share the misinformation onwards in social media is influenced by the relevance, shock value, and believability of the content rather than its source (Chadwick and Vaccari, 2019; Chen et al., 2015; Huang et al., 2015). A lack of experience in online environments and a resulting trust in online information, as well as laziness in verifying the information source and lack of critical thinking skills, are also reasons contributing to people sharing misinformation (Khan and Idris, 2019; Talwar et al., 2019). It is almost impossible to accurately determine whether a piece of news is reliable simply based on the news article itself (Del Vicario et al., 2016), and therefore, additional sources for verifying the information are needed. A recent study has demonstrated that nudging readers to pay attention to the news source lowers the sharing of misinformation (Kim and Dennis, 2019).

As the COVID-19 virus developed into a global pandemic, media of all kinds were filled with reports and speculation related to the causes and consequences of the disease. Google search trends displayed sharp increases in searches of COVID-19 spiking in February 2020 (Husnayain et al., 2020). The rapid dissemination of information and speculation also brought an abundance of COVID-19 related misinformation, forcing the WHO to create a news tracker to dismiss persistently shared fake news (World Health Organization, 2020). Contrasting the COVID-19 infodemic to prior misinformation literature (Table 1), there are two major novel factors at play: (1) the looming threat of the pandemic disease; and (2) an increased number of unclear, ill-structured and non-focused, yet highly important, information regarding the disease and response. Consequently, understanding these factors and their effects on misinformation sharing on social media is important.

While quite an amount of empirical investigations have been conducted into the spread of misinformation through social media, there is a dearth of studies which specifically consider the phenomenon whilst people are in the midst of a pandemic. As previously noted, peoples' decision-making processes are significantly altered when driven by fear and anxiety (Allen et al. 2014). Thus, our study will address this gap in our knowledge by specifically focusing on the misinformation drivers within the COVID-19 context.

2.2 Cyberchondria

The term cyberchondria is derived from the term, hypochondriasis, which is a condition about excessively and chronically worrying about being seriously ill (Starcevic and Berle, 2015). Hypochondriasis was mixed together with cyber to reflect the cause of this mental state emanating from the cyberworld, more specifically the internet (Starcevic and Berle, 2013). Thus, cyberchondria is defined as online health searches with a worsening of anxiety or distress (Starcevic and Berle, 2013). Increased time spent searching online for symptoms has been associated with functional impairment and increased anxiety (Doherty-Torstrick et al., 2016; Mathes et al., 2018), as well as problematic internet use (Vismara et al., 2020). Thus, it is clear cyberchondria can be impairing and harmful for individuals (Mathes et al., 2018).

Literature on what causes cyberchondria (summarised in Table 2) shows that it is strongly correlated with anxiety. For example, researchers reported that anxiety sensitivity increases cyberchondria (Doherty-Torstrick et al., 2016; Norr et al., 2015; Vismara et al., 2020). Information overload has been found to be linked to cyberchondria (White and Horvitz, 2009) through the continued seeking of reinforcing information (Norr et al., 2015). Cyberchondria has not been found to be connected to age, gender or even the actual medical status (Fergus and Spada, 2017). However, metacognitive beliefs (Fergus and Spada, 2017) as well as factors such as distaste for ambiguity (McMullan et al., 2019), and intolerance of uncertainty (Norr et al., 2015), play roles in developing cyberchondria.

Table 2. Summary of literature on the causes of cyberchondria

Author(s)	**Sample**	**Findings**
Doherty-Torstrick et al., 2016	731 survey participants. (cross-sectional)	Anxiety regarding an illness and its severity is the strongest predictor of online symptom searching. Increased time searching symptoms online leads to increased anxiety and functional impairment.
Fergus and Spada, 2017	Two cross-sectional studies: N= 337 and N = 260	Cyberchondria is not predicted by age, gender or even current medical status. Metacognitive beliefs have a moderate-strong influence on cyberchondria.
Mathes et al., 2018	462 survey participants (cross-sectional)	Cyberchondria is related to, but distinct from health anxiety. Cyberchondria was uniquely found to lead to functional impairment and use of health services.
Norr et al., 2015	526 survey participants. (cross-sectional)	Cyberchondria is fuelled by anxiety sensitivity and intolerance of uncertainty. It may also be caused by a mistrust towards health professionals.
Vismara et al., 2020	61 research articles. (systematic literature review)	Cyberchondria is connected to low self-esteem, anxiety and anxiety sensitivity, a distaste for ambiguity, a certain set of meta-cognitive beliefs, over-focus on pain, hypochondriasis, obsessive compulsive disorder and generally problematic internet use.
White and Horvitz, 2009	515 people who had done an online search related to health	Cyberchondria is caused by information overload and can have prolonged negative interruptive effects. To combat cyberchondria search engine architects have the responsibility to promote websites where accurate

	symptoms. (longitudinal)	and reliable health information is available.

Previous studies have not considered the relationships between sharing unverified information and cyberchondria. The context of COVID-19 offered us an opportunity for investigating both of these together, as the pandemic escalated into a global health crisis with situation reports, personal stories and updates spreading rapidly through social media. Indeed, the lock-down enacted in many countries forcing workplaces and social activities to close, may have the unintended consequence of escalating issues related to social media consumption, as people have more time at their disposal to overload on social media content.

2.3 Theoretical Foundation

Understanding cyberchondria and misinformation sharing needs to take into account both health risk and technological factors. Accordingly, we adopt three relevant theories, two which incorporate the health behaviour aspect: (1) health belief model (HBM); and (2) protection-motivation theory (PMT); and a third which encompasses the impact of technology: (3) cognitive load theory (CLT).

HBM emerged in the 1950s from research aiming to understand the effectiveness of health education programmes (Sheeran and Abraham, 1996). The model links demographic variables and psychological characteristics to affective and cognitive states such as perceived susceptibility, perceived severity, health motivation, and perceived benefits. These are then connected to the behavioural responses (Sheeran and Abraham, 1996). In addition, the model includes a construct about external impulses for action often labelled “cues to action”, which also have an impact on the behavioural response (Sheeran and Abraham, 1996).

HBM has been widely used in studies about designing and investigating health behaviour change interventions (Eldredge et al., 2016; Orji et al., 2012), but also in other fields such as cybersecurity (Ng et al., 2009). Another theory, which is often used in a similar way as HBM to understand health behaviour, is PMT (Prentice-Dunn and Rogers, 1986). PMT considers the reasons why humans adapt protective health measures, which in the case of the COVID-19 pandemic are, for example, washing hands and self-isolation. A review study on PMT identified perceived threat to be the main driver behind protection motivation (Bish and Michie, 2010). For the current study, we employ the concepts of perceived susceptibility and perceived severity to conceptualise perceived threats (i.e. health beliefs) in our research model. The reasoning is that the two are featured in both HBM and PMT, and previous studies have found these constructs to be the significant predictors for health motivation during pandemic situations (Bish and Michie, 2010; Farooq et al., 2020). Perceived severity is defined as the individual’s appraisal of the severity of the situation with regards to health consequences (Ling et al., 2019) whereas perceived susceptibility is an appraisal of the probability of being vulnerable in the given situation (Ling et al., 2019).

In addition to the theories explaining health behaviours, a theoretical viewpoint accounting for the impact of technology is also necessary. As our aim is to investigate social media use and information sharing, a theory of particular relevance is CLT. The theory is built on the biological basis that the human memory is divided into short term and long term memory, and that the human brain has limited processing capability which may get overloaded (Sweller, 2011). Only small amounts of new information can be processed at a time, with findings suggesting that unclearly structured or large packets of information make learning and acquiring the knowledge difficult for humans (Sweller, 2011; Paas et al., 2003). While CLT was originally used primarily as a theory in instructional science and learning (Chandler and Sweller, 1991), it has since been applied to understand human ability to acquire knowledge in any situation. One particular application is online environments such as social media, where an abundance of information can be too much for the human cognitive circuit to process causing cognitive overload (Chang and Ley, 2006; Zeng et al., 2010).

Cognitive overload has been shown to decrease social trust between people (Samson and Kostyszyn, 2015), and towards AI systems (Zhou et al., 2017). Humans overloaded by information are likely to make careless decisions as they are unable to process surrounding information and experience less self-control (Samson and Kostyszyn, 2015). Stemming from our review of the CLT literature, the constructs of information trust (Talwar et al., 2019) and information overload (Whelan et al., 2020a) are likely to be salient in explaining misinformation decisions. Hence, these two constructs were brought in as components of our research model.

3. Research Model and Hypotheses

3.1 Effects of Online Information

The human trust in journalistic content has declined during the past few decades (Lewandowsky et al., 2017). Among theorised causes for this are the internet and social media, which allow people a more direct access to information than what was previously possible (Lewandowsky et al., 2017; Settle, 2018). Through social media, individuals have the potential to detect biases in traditional news reporting but at the same time, are exposed to non-rigorous journalism. Furthermore, it has been documented that algorithms can filter only preferred news to individuals, which reinforces existing biases they may have (Bakshy et al., 2015; Spohr, 2017). While this can increase harmony within social sub-groups, it simultaneously serves to increase inter-group conflict and makes people less prepared to hear opposing views (Settle, 2018).

In recent years, a significantly large quantity of fake news and misinformation have been shared on social media (Chadwick and Vaccari, 2019), at times even more frequently than news backed up with journalistic ethics and rigor (Howard et al., 2017). Fake news articles that manage to spread far typically resemble real news to such an extent that it is difficult for both humans and algorithms to distinguish the two from each other (Del Vicario et al., 2016). People who have high trust on online information are increasingly likely to share reliable news onward, but also fake news reports and misinformation (Khan and Idris, 2019, Talwar et al., 2019). Accordingly, we hypothesise the following.

H1: Online information trust increases the sharing of unverified COVID-19 information.

Huang et al. (2015) interviewed social media users in the aftermath the Boston Marathon Bombings and found that the abundance of information and speed of newly occurring events reduced people’s ability to verify the information they heard and read. This contributed to an increased spread of misinformation. The finding can be understood through the lens of CLT, which postulates that humans have limited working memory. In novel situations where new information is being presented at high volumes, the human cognitive capacity gets overloaded, which may lead to social media fatigue (Maier et al., 2014; Whelan et al. 2020b) and trigger the evolutionary instinct to retreat away from the difficult-to-conceptualise information (Sweller, 2011). Once humans are fatigued, it reduces their ability to make sense of the situation they are in, and hinders their judgement and decision making, for example, with regards to what news is backed up by journalistic rigour and what is not. Applying such scenarios to the COVID-19 pandemic suggests when humans are overloaded with information, they are less likely to go through the extra trouble of verifying information sources (Whelan et al., 2020b). Thus, we hypothesise the following.

H2: Information overload increases the sharing of unverified COVID-19 information.

In today’s world, one should clearly not trust all information they are exposed to on social media. When online information is not critically assessed, cognitive dissonances, cognitive overload, and anxiety emerge (Khan and Idris, 2019; Metzger and Flanagin, 2013; Samson and Kostyszyn, 2015). Despite these apparent negative attributes attached to the trustworthiness of online information, our society is dependent upon online information (Metzger and Flanagin, 2013). Simply distrusting all online information is not an option. Cognitive skills on evaluating information sources are needed (Auberry, 2018; Chadwick and Vaccari, 2019). Based on these findings, it follows that without the habit or ability to evaluate the reliability of online news and information, combined with the prevalence of online misinformation, trusting online information sources can give birth to unfounded worries about personal health, specifically during the COVID-19 pandemic. Thus, we propose the following.

H3: Online information trust increases COVID-19 related cyberchondria.

In the case of COVID-19, several factors could contribute to increased cognitive load. First, the situation was new, which forced people to acquire new knowledge. Second, the situation developed fast and posed a looming health risk, forcing humans to adapt to the new knowledge quickly. Third, through social media, individuals across the globe shared their experiences, with lots of news appearing all the time, some real, some fake. The quantity of information further made it difficult to understand the actual state of the situation. Fourth, as the knowledge was being generated and shared rapidly, not all of it could be clearly structured and presented in an optimal and understandable way. The resulting lack of clarity further contributed to increased cognitive overload of online news readers and social media users. Previous studies of cyberchondria suggest it is associated with information overload (White and Horvitz, 2009) and uncertainty (Norr et al., 2015). Likewise, anxiety about health positively correlates with the amount of information sought online, ultimately influencing health related decisions (Eastin and Gunisler, 2006). Applying these insights to the COVID-19 pandemic, we hypothesise the following.

H4: Information overload increases COVID-19 related cyberchondria.

3.2 Effects of Health Beliefs

HBM postulates that both perceived susceptibility and severity are major drivers of human behaviour in the face of health risks (Sheeran and Abraham, 1996). For example, a recent study showed perceived severity of the COVID-19 pandemic to be a significant predictor for self-isolation intention (Farooq et al., 2020). When investigating social media use after the Boston Marathon Bombings, Huang et al., (2015) found emotional and physical proximity to increase the likelihood of sharing unverified information. The mechanism leading to this observation may be linked to the perceived relevance of the situation, as, for example, medical professionals are more likely to spread rumours online when the rumour is relevant to them (Chua and Banerjee 2018). Consequently, when people are physically and emotionally closer to danger, they feel a higher level of severity and susceptibility, which in turn translates into behavioural action.

During the COVID-19 pandemic, as people were advised to self-isolate and to work from home remotely, they also had more time to be online. This reportedly increased social media use and could be seen in search engine trends (Husnayain et al., 2020; Rovetta and Bhagavathula, 2020). An analysis of the microblogging site Weibo users during COVID-19 revealed that the pandemic situation increased anxiety and reduced life-satisfaction (Li et al., 2020). Furthermore, social media use in particular during COVID-19 was linked to mental health problems (Gao et al., 2020). Taken together, the reported health anxiety and mental health issues cause additional strain on social media users. This hinders their ability to go through the extra trouble of verifying news sources and checking the authenticity of COVID-19 information they encounter. Thus, we propose the two following hypotheses.

H5: Perceived severity increases unverified COVID-19 information sharing.

H6: Perceived susceptibility increases unverified COVID-19 information sharing.

Cyberchondria is inextricably linked to health anxiety (Starcevic and Berle, 2013; White and Horvitz, 2009). Since COVID-19 was declared a global pandemic, most news feeds globally were consumed with information about it. The swarm of information released about COVID-19 communicated the severity of the situation, with individuals appraising this information by evaluating the personal threat as well as their ability to cope with it (Rogers and Prentice-Dunn, 1997). Published work on the COVID-19 pandemic demonstrates it to have increased health anxiety in people (Gao et al., 2020; Li et al., 2020). As postulated by PMT, a natural consequence of a severe threat appraisal is to search for more information on the topic in order to cope with the situation. In practice, this means going online to search for more information on COVID-19, and the more severe the threat appraisal, the stronger the conviction to search for information (Farooq et al., 2020). Husnayain et al., (2020) showed COVID-19 related searches to have skyrocketed as the pandemic was developing, which suggests that perceived severity and susceptibility of the situation may increase cyberchondria. Thus, we propose two hypotheses.

H7: Perceived severity increases COVID-19 related cyberchondria.

H8: Perceived susceptibility increases COVID-19 related cyberchondria.

Finally, we focus on the relationship between COVID-19 related cyberchondria and sharing unverified COVID-19 information. From previous studies we know that cyberchondria is a health anxiety issue characterised by repeated and excessive online searches for health information (Vismara et al., 2020; White and Horvitz, 2009). This exposes social media users to a multitude of information sources, increasing the likelihood of also encountering fake news and misinformation. Due to the difficulty of distinguishing fake news from real information (Del Vicario et al., 2016), being exposed to misinformation can lead to developing false health conceptions. As cyberchondria is typically driven by the need to find reassurance for (subjective) health beliefs (Vismara et al., 2020), developing false conceptions regarding health combined with cyberchondria can lead to the reading and sharing of misinformation. We argue that in the COVID-19 pandemic context, the rapid development of the situation and the enormous quantity of unclearly structured information, some of which is was misinformation, may have fuelled the process of developing false health conceptions. Thus, it is reasonable to hypothesise that cyberchondria increased sharing of unverified information.

Another support for our hypothesis stems from the notion of cyberchondria being related to addictions and compulsive behaviour (Ivanova, 2013; Vismara et al., 2020). In a state of obsession and addiction, rational behaviour may be more difficult to uphold. Furthermore, addiction may lead to having less mental resources to fact check and verify news that are encountered. Bringing these two connections together into the context of the COVID-19 pandemic, we propose that cyberchondria positively influences sharing unverified information. Thus, we propose our final hypothesis.

H9: COVID-19 related cyberchondria increases the sharing of unverified COVID-19 information.

Our final research model connecting the proposed hypotheses is shown in Figure 2.

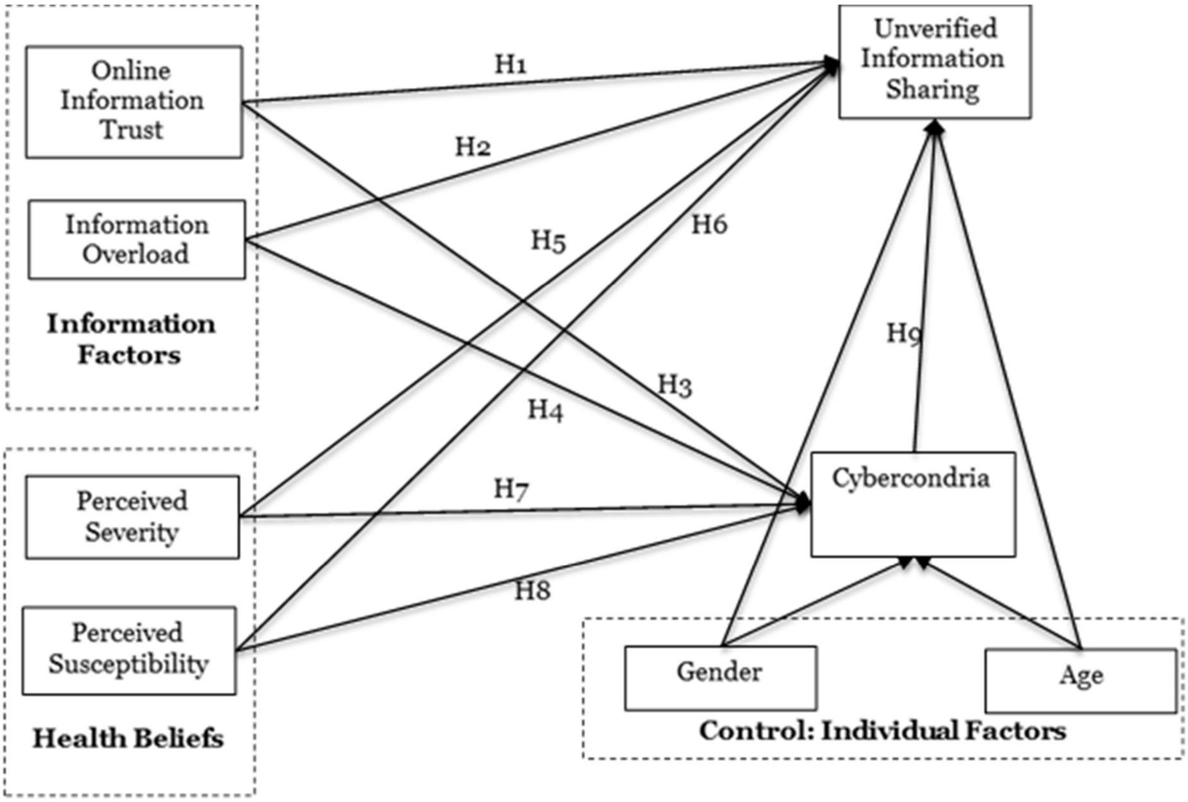

Figure 2. The Research Model

4. Methodology

4.1 Study context

This study was conducted in Bangladesh in March 2020 when the COVID-19 pandemic had been declared a global pandemic by the WHO. To better understand the context, we briefly describe the situation in Bangladesh and the social media use in the country during the data collection period. According to recent statistics by the Internet World Stats, approximately 100 million people in Bangladesh have access to the Internet and around 34 million people use social media[4]. Among the social media users, around 93.28% people use Facebook, 3.31% use YouTube and the remaining people social media platforms are, for example, Twitter, Instagram, Linkedin and Pinterest[5].

The first three cases of COVID-19 in Bangladesh were officially reported on 8th March 2020[6]. Two months later on 12th May 2020, a total of 15,619 people were reported to have been infected, 239 were reported to have died from COVID-19 and 2,902 had recovered. In addition,

[4] Internet World Stats usage and population statistics, https://www.internetworldstats.com/stats3.htm#asia, (accessed on 8th April, 2020).
[5] Social media stats Bangladesh, https://gs.statcounter.com/social-media-stats/all/bangladesh, (accessed on 8th April, 2020).
[6] Bangladesh confirms its first three cases of coronavirus, Reuters.https://www.reuters.com/article/us-health-coronavirus-bangladesh-idUSKBN20V0FS, (accessed on 8th April, 2020).

68,324 people were placed in home-quarantine and 473 people in compulsory isolation[7]. As a response to the COVID-19 pandemic, the government closed all educational institutes on between 18th of March and 31st March, which was later extended to last at least until 16th May. On the 26th of March, the Bangladeshi Government deployed the military for a 10-day period to supervise and review the treatment of COVID-19 patients, enforce the quarantine and ensure people kept social distance to others as ordered. From the same day, all public and private offices and markets were shut down. Citizens were advised to stay home unless forced by emergencies and follow the preventive measures suggested by health officials.

4.2 Data collection

Data was collected from Bangladeshi social media users via an online survey in March 2020. Most constructs and corresponding survey items were taken from validated scales adapted from prior literature with minor changes to fit with the study context. The only exception was unverified COVID-19 information sharing, which was developed for this study. In doing this, we followed the construct development procedure outlined by Moore and Benbasat (1991) as follows.

First, we interviewed five active Facebook users who had shared COVID-19 related information. The users were identified among the Facebook friends (3 males, 2 females) of one of the authors. When choosing the users for the scale development process we ensured that the sample was heterogeneous and had a diverse socioeconomic background. We asked the five participants to describe what they do once they encounter a new piece of information before sharing it on social media. Only one respondent mentioned that if the information source is unknown to them, they quickly try to verify the information by searching on Google for confirmation. If they find similar information from other trusted sources, they shares the news onward. Other four respondents mentioned that they do not usually verify information, but still share it to raise awareness among their friends. They stated that even if the information may be partially true, they preferred to share, and thought everyone can make up their own mind regarding that piece of information. Furthermore, they did not see any possible harm in doing this.

Based on the above interviews, as well as a recent study on fake news by Talwar et al. (2019), we generated five initial items for measuring the sharing of unverified information. We then asked six more Facebook users, among them one senior researcher who uses Facebook, to review the items. At this stage, one of the items was removed based on an estimation that it would not correlate with the other items and in fact measured a slightly different construct. Once we had four accepted items, still following the guidelines by Moore and Benbasat (1991), we conducted a card-sorting exercise with four Facebook users. The participants were asked to group the items and provide a definition of the group. At this stage, all items were sorted into a single group by the participants. Therefore, these four items were deemed suitable for measuring the construct of unverified information sharing and were included in the survey.

After drafting the online survey, we asked 15 respondents from Bangladesh to provide feedback on the questionnaire. A few minor edits were made based on the received feedback.

[7] Corona Info BD, IEDCR. https://corona.gov.bd/, (accessed on 8th April, 2020).

The final questionnaire with all constructs, related survey items and their sources is presented in Appendix 1.

The survey was distributed to 1000 randomly selected students, faculty and alumni of two universities in Bangladesh via email, and was available online from March 20th until March 31st 2020. We received 299 completed responses, of which 294 were acceptable. The demographic information of the respondents is presented in Table 3. Approximately 60% of our respondents were male. All our respondents had accounts in one or more social media platforms. 92% of respondents reported that they use Facebook as one of the main sources to know more about COVID-19, which aligned with the Internet World Stats report about social media use in Bangladesh.

Table 3. Demographic information of survey respondents.

	Distribution (%)
Gender	
Female	40
Male	60
Age	
Less than 25	50
26-34	24
35-44	23
45 and above	3
Living Situation	
Living Alone	7
Living in shared apartment	7
Living with family/children	86

4.3 Data analysis and results

We tested the reliability and validity of our data before testing the structural model. For this, we used the PLS-SEM based approach using the tool, SmartPLS. For testing the reliability and validity, we used the thresholds set by Fornell and Larcker (1981). We ensured that each item loading was above 0.7, construct's composite reliability (CR) was above 0.8, and average variance extracted (AVE) was above 0.5. As shown in Table 4 all items had loadings greater than 0.7, CRs above 0.8 and AVEs above 0.5. This was the case for the scale adopted from previous literature as well as for the scale measuring unverified information sharing which was developed for this particular study. Thus, we confirmed that our data have sufficient levels of convergent validity.

Table 4: Item loadings, means, standard deviations, CRs and AVEs of constructs

Construct	CR	AVE	Item	Mean	std.	Loading
Information Overload	0.83	0.61	IO1	3.58	1.00	0.80
			IO2	3.57	0.96	0.79
			IO3	3.76	0.93	0.75
Perceived susceptibility	0.83	0.70	PSUS1	3.62	1.03	0.80
			PSUS2	3.6	0.91	removed
			PSUS3	2.5	1.05	0.88
Cyberchondria	0.80	0.57	CYBER1	3.26	1.07	removed
			CYBER2	3.65	1.02	0.81
			CYBER3	3.56	1.03	0.74
			CYBER4	3.57	0.98	0.71
Perceived Severity	0.83	0.71	PSEV1	4.39	0.92	0.76
			PSEV2	4.46	0.90	0.92
			PSEV3	3.63	1.03	removed
Online Information Trust	0.95	0.91	OT1	3.02	0.99	0.96
			OT2	3.10	0.98	0.95
Unverified information sharing	0.91	0.84	MISS1	3.12	1.05	0.91
			MISS2	3.21	1.10	0.92
			MISS3	3.15	0.99	0.92
			MISS4	3.01	0.89	0.91

In order to test for the discriminant validity, we investigated the inter-constructs correlations and the square roots of the AVE values (see Table 5). We observe that the inter-constructs correlations were much lower than the square roots of AVEs. We also investigated the loadings and cross-loadings (see Appendix 2) to make sure that the loadings are higher than the cross-loadings. This analysis confirmed that the employed constructs in our research model discriminate against each other.

Table 5. The inter-construct correlations and square roots of the AVE values.

	Age	CyberChondria	Gender	Information Overload	Unverified information sharing	Online Information Trust	Perceived Susceptibility	Perceived severity
Age	1.00							
CyberChondria	-0.04	0.75						
Gender	-0.19	0.21	1.00					
Information Overload	-0.02	0.35	0.11	0.78				
Unverified information sharing	0.03	0.08	-0.12	0.15	0.92			
Online Information Trust	0.03	0.11	-0.05	-0.05	0.29	0.95		
Perceived Susceptibility	0.12	0.33	0.08	0.22	-0.036	-0.05	0.84	
Perceived severity	-0.02	0.28	0.09	0.04	0.033	0.024	0.28	0.84

In addition to the discriminant and convergent reliability, we checked for potential threats of common method bias. In SPSS, we first conducted Harman's single factor test using principal component analysis technique. This test showed no single factor explained the majority of the variance in our data. We also conducted the common method factor test (Liang et al., 2007). In SmartPLS, we re-used all the items to make a common method factor. Then we calculated each items' variances explained by the method factor and by the actual assigned factors in the PLS model. Next, we calculated the age variances explained by the method factor (average: 0.01) and the assigned factors (average: 0.57). As the method variance was small, we concluded that the common method bias is not an issue for our model.

Finally, we conducted the structural model test. The results are displayed in Figure 3. Six out of the nine hypothesised relationships were supported by our data. Furthermore, we observed that our control variable gender (1=male, 2=female) had a negative effect on unverified information sharing and a positive effect on cyberchondria. We observed no effect of age on either of our dependent variables.

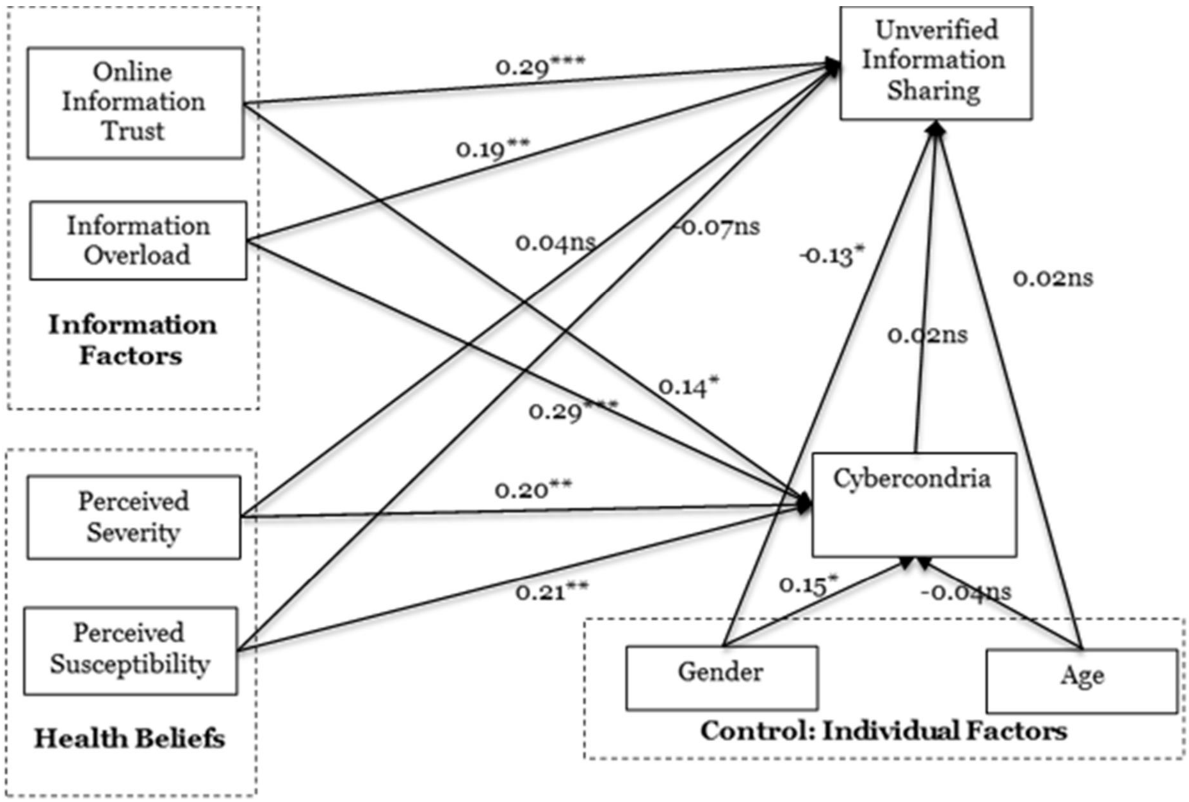

Figure 3. PLS analysis results (***p<0.001; **p<0.01; *p<0.05)

4.3 Post hoc analysis

Following the structural model results, we conducted two post hoc analyses to probe whether gender or age moderates any of our hypothesised relationships. To this end, we allowed both age and gender to interact with all the predictors of cyberchondria and unverified information sharing. The results are shown in Appendix 3.1 and 3.2. We observed that all interaction terms predicting cyberchondria and unverified information sharing were non-significant except two. The interaction term of information overload and age ($p<0.05$) as well as the interaction term of perceived severity and age ($p<0.05$) had significant negative effects on both cyberchondria and unverified information sharing. The result that age moderates the relationship between information overload and unverified information sharing, such that the effect of information overload decreases for older people, indicates that younger people are more susceptible to reacting to information overload by sharing COVID-19 misinformation. Furthermore, young people experiencing information overload were also at an increased risk of suffering from cyberchondria. These findings may be explained by the fact that older people may have better self-regulation capabilities (see Gwyther and Holland, 2012), and are thus, not heavily impacted by information overload. This may also explain as to why younger people were more likely to share COVID-19 misinformation and develop cyberchondria when their perceived severity of the situation was high, as well as the finding that age had a moderating effect on perceived severity and misinformation sharing and perceived severity and cyberchondria.

Contrary to our hypotheses, health belief factors and cyberchondria had no significant influence on unverified news sharing. Thus, we decided to probe this finding further. We conducted another post hoc analysis investigating the moderating effects of information overload and online trust on these relationships. The results are shown in Appendix 3.3. We observe that information overload actually reinforces the influence of cyberchondria on unverified information sharing ($p<0.05$). Thus, while the hypothesised relationships were not supported, there may be a link between cyberchondria and sharing unverified information after all, specifically via the interaction with information overload. As a health anxiety issue, cyberchondria is characterised by obsessive online searching for information. A situation such as COVID-19 can make this situation worse as the novelty and unpredictability gives rise to an abundance of ill-structured and sometimes conflicting online information, all of which can be impossible to make sense of. Our findings suggest that in such situations people suffering from cyberchondria may look for confirmation to their opinions by sharing information through social media.

5. Discussion

5.1 Key Findings

We summarise our key findings as follows.

First, sharing unverified information on COVID-19 was predicted by trust in social media news and social media overload, but not by the measured health threats: perceived severity of COVID-19 and perceived susceptibility to contracting the disease. The fact that the health beliefs showed no influence on sharing unverified information sharing suggests that while COVID-19 misinformation might increase worry about personal health, the worry for personal health does not lead to propagating that news further. However, even though people's experience of COVID-19 related cyberchondria did not influence the sharing of unverified information on social media, information overload was found to reinforce the effect of cyberchondria on unverified information sharing.

Second, we observe that both measured information factors (online information trust and information overload) increased the sharing of unverified COVID-19 information as well as COVID-19 related cyberchondria. Information overload had the stronger influence on cyberchondria, but information trust had the stronger influence on misinformation. Also, both measured health belief factors (perceived severity and perceived susceptibility) increased cyberchondria. Thus, all hypotheses predicting cyberchondria were confirmed.

Third, we observed that gender had significant effects on both cyberchondria and unverified COVID-19 information sharing. Females experienced higher levels of cyberchondria than males. This finding contrasts a recent study that found gender has no effect on cyberchondria (Fergus and Spada, 2017). The data also suggests that females had a lower tendency to share unverified information on social media compared to their male counterparts. This also contrasts with previous research, which has observed females to be more likely to share misinformation (Chen et al., 2015). The effect of age was measured but it had no significant direct effect on any of the constructs. However, our post hoc analyses showed that age attenuates the effects of information overload and perceived severity on both cyberchondria and unverified information sharing. This suggests that older people experience less cyberchondria and share less unverified information due to information overload and perceived severity compared to younger people.

5.2 Theoretical implications

Based on our findings we propose three theoretical implications. It is important to acknowledge that our study focused specifically on the COVID-19 pandemic, which is an extremely unique global disrupting event. Thus, the contributions may be limited to the COVID-19 pandemic. Further research is needed to determine if the theoretical contributions we propose extend to general misinformation scenarios beyond COVID-19.

First, our work is to the best of our knowledge the first to unite misinformation sharing and cyberchondria together via observing factors impacting both. In addition, we observed these factors during the COVID-19 global pandemic, which offered a novel research context for making contributions (see Corley and Gioia, 2011; Hambrick, 2007). Accordingly, this work opens up a new unexplored research area and combines theories from both health behaviour literature and IS to understand the studied relationships. Our study offers perspectives into how information overload during novel and unprecedented situations might accelerate the propagation of misinformation due to the human factor. Our paper initiates new discussions on identifying, but also controlling the underlying factors that contribute to the spread of fake news during global crises such as the COVID-19 pandemic. Moreover, our study confirms cyberchondria to be a side-effect of the COVID-19 pandemic.

Second, developing a new construct is viewed as a major contribution in IS research (see Whetten, 1989; Mäntymäki et al., 2020). In this paper, we developed a new construct, namely unverified information sharing, applied to COVID-19, to capture how social media users may propagate fake news or misinformation without authenticating the information. Therefore, we contribute to the literature on fake news (e.g. Del Vicario et al., 2016; Howard et al., 2017) by providing a validated scale. This construct can prove valuable to researchers wishing to extend our work on COVID-19, and it can also be amended to explore unverified information sharing in other contents, such as politics and science.

Third, we identified several novel associations in our study. We found that online information trust and information overload are the two main antecedents of sharing unverified information on social media. Talwar et al. (2019) found online trust as the most important antecedent of fake news sharing. Khan and Idris (2019) also reported possible association between higher levels of trust and unverified information sharing. We confirm the findings of these prior studies in the context of the COVID-19 pandemic. At the same time, we extend the prior literature (Talwar et al., 2019; Khan and Idris, 2019) by showing information overload as another main antecedent of sharing unverified information on social media, however this finding may be tied to the context of COVID-19. Huang et al. (2015) in their interview-based research concluded that information overload was related to fake news sharing during Boston bombings. Our study verifies this finding using a quantitative approach in the context of COVID-19. We also identified four factors, namely online information trust, information overload, perceived severity and perceived susceptibility that had positive influences on cyberchondria. Our contributions are summarised in Table 6.

Table 6. Summary of the main theoretical contributions of the current study.

Contribution type	**Description**	**Area of contribution**
Underexplored research area	Research on understanding factors that affect fake news sharing and cyberchondria has been limited. Lack of research in the context of a global pandemic such as COVID-19. Limited understanding on what factors influence cyberchondria, especially during pandemics such as COVID-19.	Literature on fake news (e.g. Khan and Idris, 2019; Chen et al., 2015; Talwar et al., 2019), cyberchondria (Vismara et al., 2020; White and Horvitz, 2009; Mathes et al., 2018; Starcevic and Berle, 2013), and behaviour during pandemics (Farooq et al., 2020; Van et al., 2010).
New construct development	We developed a new construct, namely unverified information sharing, and used it to the context of COVID-19.	Fake news and misinformation sharing on social media (e.g. Khan and Idris, 2019; Chen et al., 2015; Talwar et al., 2019)
Novel association among constructs	We tested the associations between the newly developed construct and other constructs in the model, especially cyberchondria.	Literature on information overload (e.g., Whelan et al., 2020a), fake news (e.g. Khan and Idris, 2019; Chen et al., 2015; Talwar et al., 2019), and cyberchondria (Starcevic and Berle, 2013; Vismara et al., 2020).

5.3 Practical implications

Based on our findings, we suggest intervention strategies which nudge people to consume manageable amounts of COVID-19 content through social media, could be effective in reducing the spread of misinformation and cyberchondria in this crisis situation. While nudging interventions have been found to be effective when dealing with artificially created and benign misinformation (e.g. celebrity gossip), their efficacy when applied to real and personally involved crises have yet to be empirically tested (Kim and Dennis, 2019). Additionally, due to COVID-19, many people are out of work or unable to partake in social activities, and thus have more time to consume social media content. Information overload may well be an unintended consequence of the COVID-19 crisis which exacerbates the problems of misinformation and cyberchondria. Health organisations can use our findings to educate social media users to consume content in a sustainable manner and thus avoid these problems. Likewise, social media companies have a significant role to play in curbing COVID-19 misinformation. WhatsApp has already introduced restrictions on the forwarding of messages containing

COVID-19 related information, while Google directs people searching for COVID-19 related information to trusted websites. Our findings suggest that if social media companies restrict the amount of COVID-19 specific information people are exposed to, this would be effective in curbing the misinformation and cyberchondria problems.

5.4 Limitations and Future Research

As a cross-sectional survey, our results did not account for any change that might have occurred in the observed behaviour during the COVID-19 pandemic. Answers to the survey were collected from university educated people in Bangladesh who were using social media. As such, the results might not be representative of the entirety of the Bangladeshi or world population. Indeed, advanced education has been proposed as an important factor in reducing the sharing of unverified information (Auberry, 2018; Chadwick and Vaccari, 2019; Ireland, 2018). Otherwise, based on age and gender distribution in our sample, we consider our participants to constitute a diverse and reliable sample.

Lewandowsky et al., (2017) argue that research, investigating misinformation should be situated within a wide context, taking into account technological, political and societal factors. Looking at our study from this perspective, we theorised two sets of independent variables (information and health factors) specifically relevant during COVID-19 and looked at how they influence misinformation sharing and cyberchondria. Future research could expand on the current study by taking into account other dimensions in this complex topic, such as those of the political and societal nature. In practice, this could mean further investigations into the role, responsibility and ability of governments and platform developers to direct social media users towards trustworthy and clear information, warding against information overload and consequently cyberchondria, as well as impulses to read and share fake news. On a societal level, we encourage future research to look at the impact of cyberchondria on psychological well-being during global pandemics such as the COVID-19, and designing measures for mitigating the negative impacts.

Samson and Kostyszyn (2015) proposed that cognitive overload is one of the causes for the observed increase in mistrust, and that trust can be increased by reducing cognitive load. Cognitive load has also obvious effects on perceptions on information, including health information, and information overload (Sweller, 2011). In the current work we did not measure the respondent’s cognitive load during COVID-19 and reading online information, but future work could expand on the model by taking into account the impact of cognitive load on both the health and information factors. As information overload was connected to both misinformation sharing and cyberchondria, we find CLT promising in explaining misinformation sharing and cyberchondria during COVID-19, and invite practitioners as well as scholars to empirically investigate whether efforts to reduce cognitive load experienced by individuals during pandemics can alleviate the sharing of misinformation and experiencing of cyberchondria.

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Appendix 1: Survey items and their sources

Construct and Source	Item
Information Overload (Whelan et al., 2020a)	IO1: I am often distracted by the excessive amount of information on social medial about Coronavirus (COVID-19)
	IO2: I find that I am overwhelmed by the amount of information that I process on a daily basis from social media about Coronavirus (COVID-19)
	IO3: I receive too much information regarding the Coronavirus (COVID-19) pandemic to form a coherent picture of what's happening
Perceived susceptibility (Ling et al., 2019; Farooq et al., 2020)	PSUS1: I am vulnerable to contracting Coronavirus (COVID-19) in given circumstances
	PSUS2: I don't think I am likely to get the Coronavirus (COVID-19)
	PSUS3: I am at risk of catching the Coronavirus (COVID-19)
Cyberchondria (Jokić-Begić et al., 2019)	CYBER1: After reading information about Coronavirus (COVID-19) online, I feel confused.
	CYBER2: I feel frightened after reading information about Coronavirus (COVID-19) online.
	CYBER3: I feel frustrated after reading information about Coronavirus (COVID-19) online.
	CYBER4: Once I start reading information about Coronavirus (COVID-19) online, it is hard for me to stop.
Perceived Severity (Farooq et al., 2020; Ling et al., 2019)	PSEV1: The negative impact of Coronavirus (COVID-19) is very high
	PSEV2: Coronavirus (COVID-19) can be life-threatening
	PSEV3: The Coronavirus (COVID-19) is a serious threat for someone like me
Online Information Trust (Talwar et al., 2019)	OT1: I trust the information that is shared on social media
	OT2: I trust the news that is shared on social media
Unverified information sharing Self-developed	MISS1: I often share information or news on COVID-19 without checking its authenticity.
	MISS2: I share information or news on COVID-19 without checking facts through trusted sources.
	MISS3: I share information or news on COVID-19 without verifying it.

	MISS4: I share information or news on COVID-19 even if sometimes I feel the information may not be correct.

Appendix 2: Loadings and cross-loadings

	CyberChondria	Information Overload	Unverified Information Sharing	Perceived Severity	Perceived Susceptibility	Online Trust
CYBER1	**0.81**	0.20	0.01	0.28	0.30	0.11
CYBER3	**0.74**	0.32	0.09	0.17	0.21	0.02
CYBER4	**0.71**	0.28	0.07	0.20	0.25	0.12
IO1	0.29	**0.80**	0.14	0.04	0.13	-0.05
IO2	0.30	**0.79**	0.07	0.01	0.19	-0.05
IO3	0.22	**0.75**	0.15	0.05	0.24	-0.00
MISS1	0.05	0.14	**0.91**	-0.03	-0.00	0.29
MISS2	0.10	0.13	**0.92**	0.05	-0.01	0.24
MISS3	0.15	0.10	**0.92**	0.06	0.05	0.20
MISS4	0.09	0.05	**0.91**	0.09	0.01	0.19
PSEV1	0.24	0.06	-0.05	**0.76**	0.25	0.02
PSEV2	0.24	0.02	0.07	**0.92**	0.24	0.01
PSUS1	0.32	0.24	0.05	0.28	**0.80**	-0.03
PSUS3	0.24	0.15	-0.09	0.20	**0.88**	-0.05
OT1	0.10	-0.02	0.31	0.00	-0.04	**0.96**
OT2	0.11	-0.07	0.23	0.04	-0.05	**0.95**

Appendix 3.1: Interaction effects of Age and Gender on Cyberchondria

Predictors	**Predicting Cyberchondria**
Online trust	0.14*
Information overload	0.30***
Perceived severity	0.19**
Perceived susceptibility	0.22**
Gender	0.11*
Age	-0.09ns
Online trust*Gender	-0.06ns
Information overload*Gender	-0.02ns
Perceived severity*Gender	-0.04ns
Perceived susceptibility*Gender	0.06ns
Online trust*Age	0.06ns
Information overload*Age	-0.17*
Perceived severity*Age	-0.10*
Perceived susceptibility *Age	0.07ns
R^2	33%

Appendix 3.2: Interaction effects of Age and Gender on unverified information sharing

Predictors	**Predicting unverified information sharing**
Online trust	0.29***
Information overload	0.21**
Perceived severity	0.07ns
Perceived susceptibility	-0.04ns
Gender	-0.13*
Age	-0.04ns
Online trust*Gender	-0.07ns
Information overload*Gender	-0.08ns

Perceived severity*Gender	-0.05ns
Perceived susceptibility *Gender	0.09ns
Cyberchondria*Gender	-0.07ns
Online trust*Age	-0.06ns
Information overload*Age	-0.12*
Perceived severity*Age	-0.10*
Perceived susceptibility *Age	0.00ns
Cyberchondria*Age	0.09
R^2	20%

Appendix 3.3: Interaction effects of information overload and online information trust on unverified information sharing

Predictors	**Predicting unverified information sharing**
Online trust	0.27***
Information overload	0.13*
Perceived severity	0.06ns
Perceived susceptibility	-0.06ns
Gender	-0.12*
Age	-0.00ns
Cyberchondria*Information overload	0.13*
Perceived susceptibility*Information overload	0.05ns
Perceived severity*Information overload	0.06ns
Cyberchondria*Online trust	0.07ns
Perceived susceptibility*Online trust	-0.04ns
Perceived severity*Online trust	0.03ns
R^2	17%