EXAMINING FACTORS AFFECTING SHARING OF ONLINE INFORMATION ABOUT COVID-19: AN INTERGRATED MODEL

A thesis submitted in partial fulfilment of the requirements for the Degree of Master of Commerce in Information Systems

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Abstract

The plethora of unverified Covid-19 information circulating on the internet has catalysed into unwarranted health misinformation, disinformation, and rumours. Prior research has indicated that the spread of unverified information leads to misinformation (Huang et al., 2022). Health misinformation circulating online, particularly in a pandemic, develops into an infodemic and negatively affects individuals in countless ways (Tran et al., 2022). As prior research has recommended, the key to curbing the spread of health misinformation is to focus on individual information sharing drivers and to address those factors accordingly (Huang et al., 2022). The understanding of information sharing is currently fragmented, with research on information sharing emerging from different disciplines and theories. This research incorporates factors from different theories and collectively examines them in the context of unverified Covid-19 information sharing online.

Drawing on the Elaboration Likelihood Model (ELM), this study develops a theoretical model aimed at explaining unverified Covid-19 information sharing. Factors are carefully selected from existing literature, to provide a comprehensive model of unverified information sharing. These factors include information credibility, argument quality, information quality, source credibility, status seeking gratification, altruism, e-health literacy, information overload, and health beliefs (perceived susceptibility and perceived severity).

An online survey was conducted with 235 participants and data analysis was performed using SPSS software. Results revealed that status seeking gratification and information overload influenced unverified Covid-19 information sharing on online platforms. These findings indicate that the peripheral route (which requires less cognitive effort to comprehend information) has a stronger effect on predicating individual online information sharing behaviours than the central route (which requires more cognitive effort to comprehend information), suggesting that people are less likely to evaluate the information they find online, whether or not it is of good quality, before they share it. These results can inform policy makers in directing their efforts to develop and refine interventions that combat unverified information sharing.

Keywords: *Unverified information sharing, Covid-19, online platforms, health misinformation, Elaboration Likelihood Model.*

Chapter 1: Introduction

1.1 Introduction to the topic

The pervasiveness of internet technologies and online platforms that support individuals' sharing of user generated content (UCG) has led to an increase in the sharing and consumption of online information. A crisis such as the Covid-19 pandemic amplifies the situation as it has promoted the sharing of any information including unverified information about the novel virus. Prior research has indicated that the escalation in online information sharing has been fuelled by social media platforms, which have afforded their users great convenience of sharing information without careful examination and enquiry of the information content (Apuke and Omar, 2021a). Thus, making a prior media consumer to become the new media distributor (Shu et al., 2017).

In addition, online information can be easily altered anonymously, plagiarised, misinterpreted and target-distributed to vulnerable audiences (Johnson and Kaye 2010), and with a visible lack of information gatekeepers to monitor online information spreading (Smith and Seitz, 2019; Steffens et al., 2019), this has resulted in extensive amounts of misinformation circulating online. The consequence of all this, is large volumes of unverified health information coming into circulation.

Prior research has identified unverified information sharing as a major cause of the prevalence of health misinformation during the Covid-19 pandemic (Huang et al., 2022). The fundamental impact of this rapid spread of health misinformation especially during a pandemic is that it generates and escalates fear, anxiety, and general misconceptions of the novel infectious disease (Sallam et al., 2020). The resulting effect is poor decision-making practises such as the consumption of poisonous substances like bleach or fish tank cleaners in an attempt to cure COVID-19 infection, in turn leading to deaths or severe health consequences (Tran, Valecha and Rao, 2022). Health misinformation has also been linked to an increase in the spread of the virus as individuals would not adhere to instructions provided to minimise the spread of the virus and to keep themselves safe (Roozenbeek et al., 2021). As a result, the impacts of health misinformation have become more severe and irreversible, such as death or lifelong after-effects of the disease (Tasnim, Hossain and Mazumder, 2020).

More recently health misinformation has been linked to vaccine hesitancy (Garett and Young, 2021), making the World Health Organisation (WHO) regard health misinformation as one of the top ten global threats to public health in 2019 (WHO, 2019). Understanding why people share unverified information online is important as unverified Covid-19 information circulating online promotes the spread of health misinformation, which in turn has been found to lead to various types of harm, such as life harm, injury harm, financial harm, emotional harm, confusion harm, and trust harm (Tran et al., 2020). So, since the spread of health misinformation presents a major public health challenge for the health systems of many nations (Tasnim, Hossain and Mazumder, 2020), pinpointing the determining factors of unverified information sharing online particularly during pandemic times is essential to control its spread and in turn ensuring that the above-mentioned scenarios are eradicated.

This vast spread of unverified information shared on online platforms coupled with a heavy reliance of the internet, has brought into question the veracity and credibility of online information (Metzger, 2007), and the resulting negative real-world implications prompts this study to examine individual sharing behaviours of Covid-19 information online. By including items that evaluate the quality of the information and the credibility of the source, as well as individual motivations and competencies, we can analyse different factors in order to better recognize the determining factors of unverified Covid-19 information shared online and seek to discover if and why people share Covid-19 information online without first verifying it.
In short, this study aims to examine the factors that influence unverified Covid-19 information sharing online.

While the spread of unverified information sharing on online is not a new phenomenon, the resulting impacts are extensive, particularly during the Covid-19 pandemic. The World Health Organisation dubbed the phenomenon an “infodemic” (Tentolouris et al. 2021, p. 1). This term is broadly defined as, “excessive information which includes false and misleading information, circulating during a disease outbreak, resulting in public confusion, risk-taking behaviours, and a mistrust in health authorities.” (Bradd, 2020).

1.2 Motivation of the Study

It comes as no surprise that research into eradicating the spread of unverified information sharing behaviour has intensified recently, emerging from different disciplines such as Information Systems (IS), Communication, Psychology, Healthcare, and Library Studies. The investigation of this topic has increased substantially between 2020 and 2021 (Li et al., 2022). This is primarily due to the rapid increase in circulation of unverified information. Various studies have found that it is becoming a common occurrence for people to share unverified information (Laato et al., 2020), as a result, making it difficult for ordinary people to differentiate between accurate and inaccurate information (Whelan et al., 2020).

As such, certain steps have been taken to combat the spread of unverified information, such as government intervention (Funke and Flamini, 2018); introducing corrective measures by offering E-health literacy support (Ahmed et al., 2020; Pulido et al., 2020a), and utilising science and technology to expose misinformation (De Beer and Matthee, 2020). Below we discuss these interventions in detail.

1.2.1 Interventions to combat the spread of unverified information sharing

To try and combat the sharing of harmful health misinformation, several interventions have been implemented, but they have not been completely successful. For example, governments from countries such as India, Brazil, China, and Indonesia have introduced strict laws to prosecute and punish misinformation creators and spreaders (Funke and Flamini, 2018). Additionally, policy makers have also run campaigns to raise community awareness on health misinformation issues. These approaches have so far been unsuccessful, in part due to existing low trust in governments, distrust in science and a distrust in health officials’ (Roozenbeek et al., 2021).

Other strategies to deter the spread of health misinformation such as introducing corrective measures as well as offering E-health literacy support (Sullivan, 2019; Pulido et al., 2020a) have been implemented. Approaches such as banning suspected misinformation spreaders (Mourad et al., 2020); introducing social correction which involves the role of peers and influencers in correcting health misinformation (Bode and Vraga, 2018), as well as increasing the presence of health experts and organisations to educate and empower (Ahmed et al., 2020; Pulido et al., 2020b) have been implemented. These measures have similarly been unsuccessful, with reports of health misinformation being linked to social media influencers and celebrities, nicknamed “the disinformation dozen” (Reneau, 2021). Twelve people were liable for 73 per cent of anti-vaccination posts on Facebook in 2021 (Reneau, 2021). Likewise, reports of celebrities, such as, Nicki Minaj sending out unverified information on Twitter about the Covid-19 vaccine causing impotency, promoted vaccine hesitancy (Murphy, 2021). Additionally, Kepes (2021) pointed out that addressing low levels of science literacy on online platforms can be a challenge, stating that people in several countries do not have access to basic introductory science education, making it difficult for many to distinguish between correct and incorrect health information online.

Finally, online misinformation detection and interventions methods have also been sought. Researchers like, Conroy et al. (2016) and Beer and Matthee (2020) have presented methods that detect fake news through models that analyse text or check facts through different machine learning techniques. Some social networks such as Facebook, Twitter, Reddit, and Instagram employed misinformation detection models on their sites, which alert users of possible misinformation (Marr.

2020). While these linguistic, machine learning and detection approaches have been successful at detecting information shared on general social platforms, health misinformation that is spread through direct messaging, in personal correspondences and in small groups (the echo chamber effect), continues to escalate the problem (Wang and Song, 2020).
Furthermore, Vosoughi et al. 2018 argued that people were spreading misinformation faster and more extensively. In fact, the spread and distribution of misinformation made a much greater impact in social media echo chambers – having a greater reach and impact. The unavailability of technology-based filters capable of controlling what is being shared in small social groups made the spread more rapid and escalated the problem further.

Considering these failed attempts, it has become apparent that understanding why people share health misinformation is a fundamental step to combating the spread of health misinformation. More specifically, understanding the role of individuals in the spread of unverified information (Huang et al., 2022). Khan and Idris (2019) also revealed that individuals can play a major role in controlling the spread of misinformation.

As such, there has been an influx of research from different disciplines in this topic focussing on the factors that motivate individuals to share unverified information online. Thompson et al, 2019 examined the determinants of news sharing behaviours on social media and found that, information sharing and status seeking gratification had a strong effect on news sharing. This study utilised the Uses and Gratification theory to examine individual motives for sharing news on Facebook.

Khan and Idris (2019) focused on the individual factors that influence the spread of misinformation on social media and determined that sharing of information on social media without verification is predicted by Internet experience, Internet skills of information seeking, sharing and verification attitude, and belief in the reliability of information. This study focused on individual aspects such as level of education, income and skills as well as individual beliefs.

Laato et al (2020) investigated unverified information sharing on social media and found individual trust in online information and perceived information overload being strong predictors of unverified information sharing. Apuke and Omar (2021b) examined factors that predict the sharing behaviour of fake news on Covid-19 among social media users and found that altruism, information sharing, socialisation, information seeking, and pass time predicted the sharing of false information about COVID-19.

Shah and Wei (2022) examined whether and how source credibility and information quality affected online engagement during the COVID-19 pandemic. Their investigation revealed that source credibility and information quality have a significantly positive relationship with perceived benefit, and perceived benefit is a strong predictor of online public engagement.

As the research in unverified information sharing is in its infancy, and despite the efforts of the current research, gaps occur as the available research focuses on single factors such as, individual motivations (Thompson et al., 2019; Apuke and Omar, 2021b; Talwar et al., 2019) on their own. Other researchers have focused on individual competences (Khan and Idris, 2019; Laato et al, 2020) and information factors, such as the source of the information, the argument, and the information quality (Shah and Wei, 2022) but none have incorporated all these factors in one model. Research that concentrates on individual factors such as motivations, competencies and beliefs, as well as message attributes, such as source credibility, argument quality and information quality to predict information sharing in the context of Covid-19 unverified information sharing online remains scant. Combining all these factors in one model gives a more comprehensive outlook on information sharing and helps identify the most significant factors that predict online information sharing. To the best of our knowledge, we are not aware of a study that examines all these individual factors and message attributes together, in the context of unverified Covid-19 information sharing on online platforms.

1.3 Objective of this study

To address this gap, the aim of this research is twofold. First, the study intends to address the gap in the current literature on understanding the specific underlying factors that promote sharing of unverified Covid-19 information on online platforms. By including information factors (argument quality, information quality, source credibility); motivation factors (status seeking, gratification and altruism), health beliefs (susceptibility and severity) and competencies (e-health literacy and information overload) in the one comprehensive model, we propose a new model inspired by reputable existing literature from different disciplines to help inform existing understanding of Covid-19 unverified information sharing on online platforms.

This study employs the Elaboration Likelihood Model (ELM) as a theoretical framework to explore factors that influence the spread of unverified Covid-19 information online. The ELM was selected as it allows for different constructs to be included within its initial elements (Petty and Cacioppo, 1984b). As such, the integrated model introduced in this study utilises the central route of the ELM to examine information constructs such as argument quality, information quality, and information credibility when sharing unverified Covid-19 information online. This is mainly because when individuals use this route, elaboration is high, and individuals examine the information in a persuasive message carefully with sound reasoning to reach a conclusion.

In accordance with the ELM, the peripheral route, is utilised by individuals when elaboration is low, and individuals are not inclined to process the information carefully (Petty and Cacioppo, 1984b). Instead, other heuristic cues are employed which message receivers use as decision principles, as they require little information processing (Petty and Cacioppo, 1984b; O'Keefe, 2013). So, within the peripheral route, source credibility, status seeking gratification, altruism, e-health literacy, information overload, perceived severity, and perceived susceptibility were included in the integrated model to examine if these cues could prompt or guide an individual in evaluating unverified information online about Covid-19 prior to sharing it.
Taken together, this leads to the following research question:

1.4 What are the factors affecting the sharing of unverified online information on Covid-19?

Understanding the underlying factors that influence an individual to evaluate information prior to sharing unverified Covid-19 information online is important for both theoretical and practical reasons. Theoretically, such research will enrich the online information sharing literature, focusing on previously unexplored constructs, and extending it to measure factors such as motivations, competencies, and beliefs as well as factors such as source credibility, argument quality and information quality within the ELM framework.

Using the central route of the ELM, we explore factors such as argument quality, information quality and information credibility and examine their role in unverified Covid-19 information sharing on online platforms. Within the peripheral route we include heuristic cues that individuals can use to evaluate information prior to sharing unverified information online. These heuristics cues include source credibility and motivations such as status seeking gratification and altruism, competences such as e-health literacy and information overload, as well as health beliefs such as perceived severity and susceptibility.

From a practical point of view, this study can help pinpoint factors that influence individuals to evaluate unverified information prior to sharing such information, particularly in a crisis such as the Covid-19 pandemic. These factors can help inform policy makers to form unique strategies that will combat misinformation spread during future global pandemics and avoid another infodemic.

1.5 Thesis Structure

Chapter 1: Introduction

This first chapter introduces the study and gives a summarised background to the topic of unverified information sharing. It illuminates the importance and relevance of the research topic and presents the gap in the literature which the study aims to fill, as well as introducing the research question and outlining the expected contributions.

Chapter 2: Literature Review

In the second chapter, prior literature and theories on online unverified information sharing are reviewed. This chapter consists of three sections. The first section gives a detailed introduction to the topic of unverified information sharing, introduces the definitions and different contexts in which the topic was presented in the literature, as well as its impacts.

The second section discusses the theoretical frameworks that have been utilised in the literature on this topic, and it introduces the ELM Model, the theory behind this research and discusses the reasons for utilising this model and theory.

The final section arranges the proposed factors inside the ELM, within the two influence mechanisms and discusses these factors individually.

Chapter 3: Hypothesis Development

Drawing on existing theories and existing literature, a new conceptual model is proposed that illustrates the key factors that predicts the sharing of unverified information online and theorised associations between them.

The factors associated with sharing unverified Covid-19 information are discussed in detail and hypotheses are developed.

Chapter 4: Methodology

This chapter outlines the research approach and strategies utilised in this project together with development of the research instrument. The data collection methods and data analysis methods are also discussed and explained.

Chapter 5: Findings and Data Analysis

In this chapter the results of the investigation are reported and presented. Initially, the sample is described, and following that, the results of the analysis are presented.

Chapter 6: Discussion

Chapter 6 discusses the investigation results from the data analysis as well as assessing the impacts of each concept, and the implications of the associations and hypotheses formed in Chapter 3.

Chapter 7: Conclusion

This chapter discusses the theoretical and practical implications of the findings from the study, illustrates the research limitations and gives suggestions for future research.

Chapter 2: Literature Review

This chapter discusses and reviews the current literature on the topic of online information sharing. We discuss the key theories, themes and concepts in this topic. This chapter is divided into three parts, the first section gives a detailed background to the topic of online information sharing, introducing the definitions and different contexts the topic was presented in within the literature, as well as its impacts. The second section discusses the theoretical frameworks that have been utilised in the literature on this topic, and introducing the ELM Model, the theory behind this research. The final section arranges the proposed factors within the ELM and within the two influence mechanisms, discussing each factor individually.

2.1 Sharing of unverified information

Li et al. (2017) described the internet as being an open-cyber space where anyone with computer skills can upload self-created content to the web without accreditation by experts or authoritative agencies. As such, it is often characterised by information that is unverified and of questionable quality. The spread of new information before it is validated becomes an issue particularly when this new information is found to be inaccurate. The sharing of information online presents a challenge as there cannot be enough gatekeepers to monitor the content for its authenticity and accuracy (Smith and Seitz, 2019). There is simply no possibility of having all news articles, personal blogs and personal correspondence that go through different echo chambers checked for their authenticity prior to being shared and spread online, considering the enormity of the internet and the number of daily users. With this comes the issue of people encountering unverified, inaccurate information. Previous research has shown that inaccurate information rapidly becomes prevalent in large groups influencing people to act in unfavourable ways, and so negatively impacting on individuals' livelihoods and overall wellbeing when this information is utilised in important decision making (Li et al. 2017).

It is especially interesting with the Covid-19 Pandemic how the internet and social media have become the main source of general information and current affairs for many people. Additionally, in periods such as the Covid-19 pandemic, the need for information, coupled with the frequent use of the internet and social media platforms, has made it a perfect breeding ground of new information topics relating to the Covid-19 virus (Bhagat and Kim, 2022). Evaluating the credibility of the new information and authenticating it before sharing becomes especially important to support good decision making and to avoid the impacts of misinformation spread. However, previous researchers, like Laato et al. (2020) suggested that individuals still share information without determining its authenticity or credibility.

2.1.1 Background to online information sharing

The online environment has become a platform to get real time updates, gather data or material for general information seeking, health information seeking, and overall decision making. Online platforms such as social media are increasingly becoming primary news sources and prevalent information sharing platforms. Furthermore, the role of the internet and social media keeps evolving and a becoming medium that provides everyday health information to otherwise inexperienced persons. Furthermore, due to their wide availability and ease of use, online platforms have become tools that many use to gather health information to help potentially in their decision-making processes (Wong and Cheung, 2019). As such, this, coupled with the rapid technological advancements, has fuelled information exchange and, as Khan and Idris (2019) discovered, encouraged unverified information sharing as well.

The increase in demand for health information, has in turn brought a surge of online information available for people to take in (Mun et al., 2013). According to Abbey Lunney, director at The Harris Poll, a survey in the United States that tracks public opinion, motivations, and social sentiment; many consumers are finding their healthcare experience ‘taxing and burdensome’. Consumers are wanting healthcare to mimic the e-commerce world, where their healthcare shopping can be simple and streamlined. But as previous researchers like Mun et al. (2013) found, while the availability of health information online can be regarded to be beneficial to individuals and society, not all information is correct and credible. The internet and social media platforms have become swamped with misinformation, fake news, disinformation, and rumours (Lewandowsky et al., 2017) As such, the vastness of online health information (Chu et al., 2017), its uncertain origins, as well as its questionable veracity, has resulted in an escalation of unverified health information circulating online which when found to be inaccurate becomes health misinformation.

Discerning what is correct and useful when sifting through health information can also sometimes be a challenge (Chu et al., 2017). Additionally, a lack of e-health literacy skills that many internet users suffer (Kepes, 2021), has resulted in information seeking and sharing being an uncertain and precarious pursuit (Chu et al., 2017), that often results in unfavourable effects. Appropriately, this has triggered a widespread research of unverified information sharing (Islam et al., 2020).

General health information seeking, and sharing is relevant and can be a positive thing as it supports better decision making, introduces individuals to new possibilities, and brings people peace of mind

(Wathen and Burkell, 2002). Analysis of information and sharing it, especially during a pandemic can give people confidence in their decision making (Wathen and Burkell, 2002). In fact, health misinformation spread online is not a new phenomenon, it has existed for a long time (Dentith, 2018; Anderson, 2018; Lazer et al., 2018 and Brennen, 2017). The spread of unverified information online prompted a new field of study called Infodemiology, which, according to Eysenbach (2009), is “the science of distribution and determinants of information in an electronic medium, specifically the Internet, or in a population, with the ultimate aim to inform public health and public policy” (p. 1).

Each time there is a new virus or pandemic that people are not familiar with, there is an increase in conspiracy theories, rumours and dissatisfaction circulating on social media to fill the information void (Purnat et al., 2021; Dramé, 2020), and offer solutions, simple remedies, and instant responses. For example, when the Zika virus, the Polio, the HIV- AIDS and Ebola viruses came about, misinformation about these pandemics emerged, to answer questions that people had and to feed their curiosity (Wang et al, 2019).

The Covid-19 pandemic has not been an exception: according to *Newshub*, (2021, Nov 11), health misinformation spread during the Covid-19 pandemic has increased substantially, fuelling protests, vaccine resistance and relationship breakdowns. In fact, due to the rapid spread of misinformation, Dr. Adhanom Ghebreyesus, the Director General of the World Health Organisation, remarked in a speech that, “the recent pandemic was not only an epidemic but also an infodemic, as the misinformation about the virus was spreading faster and more easily than the virus itself, and so was just as dangerous” (Tentolouris et al. 2021, np.).

2.1.2 Terminology

Sharing of unverified information has been described differently in existing literature. Laato et al., (2020) define it as individual’s sharing of information without first authenticating it. The unverified information shared may be either true or untrue, but the sender of the information would not have taken the time to verify it before they decided to share it. When found to be inaccurate or untrue, it becomes misinformation (Wu et al., 2019). Sharing of unverified information online has become a topic that has gained traction due to the rapid increase of misinformation, disinformation, rumours, and fake news on different online platforms. This rapid increase of unverified information sharing has quickly become an issue of contention and a headache for governments, health policy makers, authorities, scientists, and society (Lazer, 2018; Merchant and Asch, 2018). Several scholars have come up with different descriptions of the resulting effects misinformation, fake news and rumours.

Suarez-Lledo and Alvarez-Galvez (2021) described health misinformation as “a health-related claim that is based on anecdotal evidence, false, or misleading owing to the lack of existing scientific knowledge” (p. 2). Anderson (2018) defines fake news as, “information that is largely inaccurate, misleading, unsubstantiated, manipulated or completely fabricated that is being passed off as truthful, authoritative and accurate” (p. 2). Myer et al. (2017) labelled rumours as “unconfirmed bits of information” (p. 764) and disinformation refers to false or misleading information that one spreads deliberately to deceive (Wardle and Derakhshan, 2018). According to Li et al. (2022), these terms are distinguished with consideration of the deliberate intention to harm. In the case of fake news and disinformation, the incorrect information will have been created and spread with the intention to deceive (Wardle and Derakhshan, 2017; Zannettou et al., 2019; Lazer et al., 2018). The terms ‘misinformation’ and ‘rumours’ are used to describe distorted information with no deliberate intention to deceive or harm (Li et al., 2022; Zannettou et al., 2019).

The labels, ‘fake news’ and ‘misinformation’ have become prevalent during what is referred to as the post truth era, a period defined by Lewandowsky et al. (2017) and other researchers, including Lazer et al. (2018) as a time when claims led to eroded trust in scientific facts and reality, so much so that facts are no longer acknowledged and scientific evidence does not matter anymore. Rochlin (2017) argues that fake news in the post-truth era replaces facts with emotions, and therefore, the post-truth era framework is an “emotion-based market” (p. 6). In other words, fake news in this post truth era is in a way manipulating individual mental preparedness. This post-truth era empowers people to choose their own reality, where everything is subjective, and any evidence is overshadowed by beliefs. In short, the post-truth era tolerates and accepts lies, and rewards dubious behaviour. Misinformation and fake news are not just meant to misinform but to deceive and manipulate the overall intellectual well-being of society (Lewandowsky et al., 2017).

2.1.3 The prevalence of unverified information sharing and misinformation

Sharing of unverified information online has become a prevalent research topic due to recent technological advancements supporting online interaction, such as Web 2.0. This website design supports user interactions including higher levels of information sharing and interconnectedness among internet users. In the view of Khan and Idris (2019), this “new reality” provides individuals with the same power to produce and distribute information online as large media producers. Unlike 20 years ago, when media distribution was linked to traditional sources and main news channels, who were guided by a code of ethics when releasing any publication, and had a reputation to uphold and regulations to follow (Lazer, 2018; Merchant and Asch, 2018, Williamson, 2016), today’s information is spread and distributed in the form of blogs, tweets or social media profiles and comments, making the former media consumer, the new media distributor (Johnson and Kaye 2010).

In addition to the increase in reliance on the internet for information, Karnowski et al. (2018) highlighted that online information sharing between individuals has escalated at unprecedented scales. With Ciampaglia et al. (2015) describing the internet as a tool that transports lies at incredible speeds such that truth cannot keep up and Metzger (2007) reiterating that, such availability of ready to share information online, together with heavy reliance on the Internet, brings to question the credibility of information, as such, the need to verify information found online has become apparent. This is especially important for individuals seeking information online to make critical life decisions, as health misinformation, particularly during a pandemic, is prevalent and has devastating impacts.

2.1.4 The impacts of online health misinformation

According to Caceres et al. (2022), Covid-19 online misinformation has played a role in worsening the pandemic. Health misinformation has negative impacts on individuals and society level alike. Misinformation concerning the incidence, prevalence, and spread of the virus has contributed significantly to the complacent attitude of individuals towards this crisis. Below we discuss the impacts related to health misinformation during the Covid-19 Pandemic and other pandemics as well.

Figueira and Oliveira (2017) pointed out some of the observed negative impacts of the circulation of Covid-19 misinformation on individuals, including high anxiety and high stress levels. Leibovitz et al. (2021) examined the mental health consequences of conspiracy theories during the Covid Pandemic and found that there was an association between conspiracy theories and high anxiety levels. Likewise, a study carried out in Iraqi Kurdistan (Ahmad and Murad, 2020) revealed that due to misinformation shared on social media about the severity of the disease, panic erupted among a majority of young adults, resulting in psychological anxiety.

Furthermore, Goyal et al (2020) reported of a 50-year-old father of three from India who committed suicide upon learning that he had been diagnosed with COVID-19. This occurred after he had viewed various alarming videos of the Covid-19 viruism where Chinese victims were collapsing and dying in the streets after contracting the disease. Essentially, misinformation on the novel virus intensified the fear and resulted in psychological distress and poor decision making.

According to Lewandowsky et al. (2017), misinformation has also increased the growing distrust in the natural sciences that both individuals and society share, resulting in more people questioning experts' recommendations. Bin Naeem and Kamel Boulos (2021) in their overview discovered that the Covid-19 vaccines has been questioned by many due to misinformation circulating online, prompting people to boycott the urgent calls by officials to get vaccinated. Reports claimed that the development of the vaccine was hurried and so it could not be safe; they claimed that the Covid-19 vaccine alters the genetic makeup of an individual, and that it negatively affects fertility; they also claimed that the vaccine will implant a microchip in the body when administered, prompting protests and vaccine hesitancy (Gunther, 2022). Additionally, Busari and Adebayo (2020) reported that in Nigeria, health officials encountered several cases of overdose of chloroquine (a drug used to treat malaria) following news on the claimed effectiveness of the drug for treating COVID-19. As such, the growing distrust in health officials and science is increasing and threatening lives.

This distrust in health experts and health professionals is not unique to the Covid-19 pandemic. According to Fung et al. (2016), during the 2014 Ebola pandemic, misinformation fuelled hostility towards health care professionals and aid workers, prompting them to fear for their lives. Disinformation and misinformation pertaining to the Ebola virus, also escalated the spread and caused more deaths as individuals stayed at home and did not seek help from professionals, regardless of being unwell (Fung et al., 2016).

Osborne (2020) stated that, misinformation fueled anti-lockdown protests, people defied the rules of staying apart, due to misinformation circulating online stating that the virus did not exist. With Jose and Duran (2021) reporting of anti-lockdown protests taking place in the United States and spreading to Australia, Williams (2021) reported of the same protests occurring in New Zealand, this massive spread of Covid-19 misinformation and the protests birthed new and more powerful strains of the virus (Geddes, 2021).

Misinformation prompted people to lose trust in experts in favour of peers (Lewandowsky et al., 2017). As such, misinformation did not just create confusion in the form of anti-lockdown protests, but it also escalated the virus with the birthing of new variants. Further, rumours and misinformation that the disease could not have been caused by a virus, but by the then new 5G technology, circulated on social media, fuelling the already out of hand infodemic (Bruns, Harrington and Hurcombe, 2020). These rumours prompted believers of this misinformation in the Netherlands, the United States of America (USA) and the United Kingdom to burn down and destroy millions of dollars' worth of infrastructure that supported the new 5G network (Osborne, 2020; Bruns, Harrington and Hurcombe, 2020). These negative impacts cost the respective governments millions of dollars to replace and repair the infrastructure and pushed the technological advancements back.

Furthermore, misinformation pertaining to the pandemic encouraged panic buying and stockpiling, thus creating food insecurity at local levels (Liu and Huang, 2020). In countries like India and the USA, fear of national lockdowns provoked by misinformation prompted people to panic buying of grocery items such as toilet paper, thus disturbing the supply chain that could not cope with the rapid escalation of demand. In the USA, food insecurities among lower socioeconomic groups and other vulnerable populations intensified (Sukhwani et al., 2020; Huang et al., 2021).

2.1.5 Why people share information online

As the impact of information sharing escalates, researchers have embarked on a quest to figure out why people share information online. Pennycook et al. (2021) established that the drastic escalation in sharing of information online is the main reason why fake news spreads. With Chadwick and Vaccari (2019) reporting that about half of the people who share information online acknowledged that they had shared misinformation, examining the determinants of information sharing could help to dissipate the spread of misinformation. Different researchers from different disciplines, utilising different theories, have set out to examine the reasons why people share. In this section we discuss the existing literature in this topic and identify some of the key factors that predict online information spread.

Khan and Idris (2019), while examining the factors that predict unverified information sharing on social media, found that people share when they lack the ability to verify the information, as well to access the knowledge to seek for information. Additionally, their findings revealed that people share unverified information because they are not interested in verifying the information. These findings align with Crook et al. (2016), who found that individuals with higher e-health literacy skills shared information less than those with lower health literacy. Huang et al. (2015) revealed that emotional proximities also affect individual competencies, such as information overload. Researchers such as Laato et al. (2020), in their study examining the determinants of unverified information sharing, found that information overload was a predictor of unverified information sharing. Huang et al. (2022) likewise found that information overload correlated positively with unverified information sharing on WeChat. As such, individual competencies [or lack of], such as e-health literacy and information overload [defined as a state of feeling overwhelmed due to exposure to an excessive amount of complex, ambiguous, and uncertain COVID-19 information from online platforms and a limited capacity to process this information (Huang et al., 2022)], encourage online information sharing.

Individual motivations similarly affect online information sharing. For example, Thompson et al. (2019) investigated status seeking gratification, information sharing, socialising, entertainment and pass time to determine which of these factors influenced news sharing behaviour on social media. They found that motivations such as status seeking gratification and information sharing predicted news sharing behaviour. Apuke and Omar (2021) examined factors that predicted fake news sharing on Covid-19 among social media users and found that altruism was the most significant factor that predicted fake news sharing on Covid-19. Additionally, Lee and Ma (2012) in their study found that individuals who were highly motivated to seek status, to socialise and to seek information shared more on social media. As such, motivations play a role in the sharing of information online.

Attitudes and beliefs also affect information sharing. Individuals share based on their own beliefs and opinions (Wang et al., 2019) and, if there is a lack of information or information that is challenging people's beliefs (Lewandowsky et al., 2017), individuals are more likely to seek information from like-minded people who share their same beliefs and opinions (Jang et al., 2019). As such, the existence of the echo chamber effect is reinforced, confirmation biases are strengthened, and beliefs are formed or established. Beliefs shape individual thinking and behaviour. Studies have examined the role of beliefs in online information sharing, with researchers acknowledging that future research should focus on this area, examining the role that beliefs play in sharing. One such study is Shang et al. (2020), who investigated the factors that influence older adults sharing health information, found that perceived susceptibility was positively associated with health information sharing intention.

Finally, research also revealed that several other factors affect the sharing of information online. These include information content (Chen et al. (2015), and online trust (Talwar et al. (2019). Chen et al. (2015) investigated the reasons why students share information and found that, among other things, they were driven by information content. Additionally, Talwar et al. (2019) found that fake news sharing is predicted by online trust.

2.1.6 Research aims

The understanding of information sharing is currently fragmented, with information sharing research emerging from different disciplines and theories. To address this problem, this study attempts to bring together, from various studies, key factors such as individual competencies [e-health literacy and information overload], individual motivations [status seeking gratification and altruism], health beliefs [perceived severity and perceived susceptibility] into one model, and to identify the strong predictors of the sharing of unverified Covid-19 information on online platforms. Petty and Cacioppo (1984b) revealed that people process information through different processing routes. As this investigation aims to examine key factors that have been observed by prior literature to predict online information sharing, we utilise the ELM model as our fundamental theory. This model is preferred as it allows for other factors from other theories to be incorporated in it. Additionally, the ELM groups constructs depending on the level of elaboration and motivation an individual possesses to process the persuasive message.

Although prior research identifies various factors, for example, information that is spread online is comparable to a persuasive message, information characteristics such as the quality of the information and the strength of the argument within the message can lead people to accept the message and find it credible or trustworthy. As such, we examine the impact of informational factors [argument quality and information quality] in the central route, as well as source credibility, to evaluate which of these factors predict information credibility and, in turn, we assess if information credibility impacts on the sharing of unverified Covid-19 information online.

It is therefore expected that information credibility would mediate the impact of the informational factors and source credibility on unverified information sharing. All other constructs are expected to have a direct impact on information sharing. The study will therefore examine the relationship between individual competencies [e-health literacy and information overload], individual motivations [status seeking gratification and altruism], health beliefs [perceived severity and perceived susceptibility] and the dependent variable, unverified information sharing.

In the next section, we discuss the core theories that underlie the research model, as well as the other theories from which the key factors originate.

2.2 Theoretical framework

In this section we examine the Elaboration Likelihood Model (ELM) of Petty and Cacioppo (1984), which is the fundamental theory of this study, and we outline how these different factors are incorporated within the ELM to comprehensively examine the key factors that influence the sharing of unverified information on Covid-19 on different online platforms. Next, we discuss the theories that underlie the factors that are expected to influence information sharing. These are the Uses and Gratification Theory of Katz (1974), which incorporates factors such as altruism and status seeking gratification. Then we examine the Health Belief Model of Hochbaum (1958), which mainly reviews behavioural change and incorporates factors such as perceived susceptibility and perceived severity. Finally, we review the Cognitive Load Theory of Sweller (1988), to understand better the influence of information overload on information sharing.

2.2.1 The Elaboration Likelihood Model (ELM)

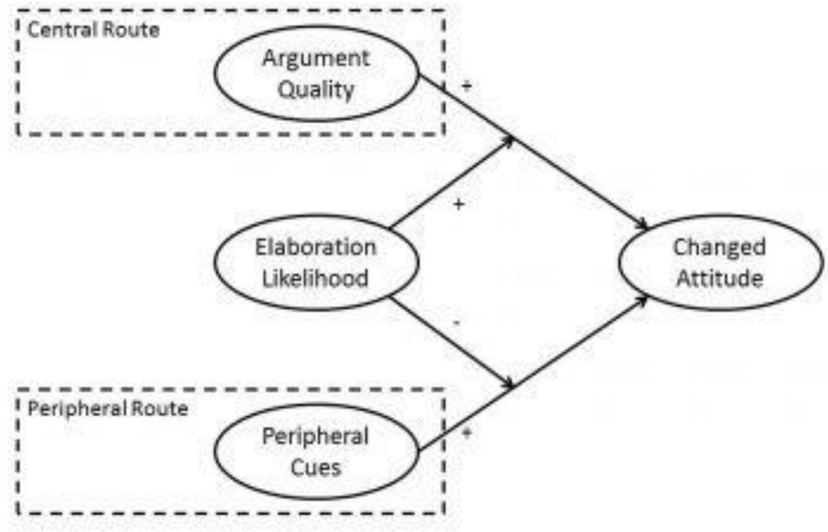


Figure 2.1: The Elaboration Likelihood Model

Adopted image from Geddes (2018, np.).

The ELM is a dual process theory that describes change of attitude or behaviour through persuasion. According to Petty and Cacioppo (1980), in this framework, recipients are viewed as being either constantly reasoning and carefully meditating on the given persuasive messages or always unconcerned about the persuasive message presented to them. Petty and Cacioppo (1980) point out that different factors or a combination of factors affect individual need and ability to intricately consider the facts in the argument. As such, individuals process information through either the central route (when issue relevant thinking is high, and elaboration is high) or the peripheral route (when elaboration is low and heuristic cues are used to reach a conclusion based on superficial analyses).

2.2.2 The Central route of the ELM

The central route represents the persuasion process where the motivation and the ability to process is high, i.e., high elaboration (Petty and Cacioppo, 1980). Petty and Cacioppo (1984b) further reiterates that when engaging the central route, the individual is likely to scrutinize and evaluate the true merits of the persuasive message presented. According to the ELM, when the central route is engaged, the individual carefully examines the given information in the persuasive message and the message context i.e., the facts. Additionally, according to Petty and Cacioppo (1984b), to evaluate information, individuals utilising the central route can compare the information in the persuasive message with information previously known on the subject. As such, the strength of the argument and the quality of the information is analysed to evaluate and critically judge the information and therefore determine the success or failure of the persuasive message.

Krosnick and Petty (1995) found that decisions made using the central processing route effectively form strong attitudes that resist change, persist overtime and motivate and direct behaviour. For this reason, in accordance with Krosnick and Petty (1995) findings, according to Geddes (2018), the e-commerce market and the electronic Word of Mouth (eWOM) research is heavily reliant on the Elaboration Likelihood Model. This is in anticipation that the presented persuasive message will be processed using the central route with the intention that the individual will return to repurchase the same product or service, ignoring other brands.

As such, the central route of the ELM is characterised by careful elaboration and evaluation of information. Decision making and behavioural change occurs after careful consideration. Factors that are included in the central route include but are not limited to, argument quality, information quality and information credibility.

2.2.3 The Peripheral Route of the ELM

When the peripheral route is engaged, the individual or the audience are not motivated to examine the message carefully, and so they utilise a lower level of elaboration to process the persuasive message (Petty and Cacioppo, 1984a). This persuasion route is activated when an individual or target audience do not particularly care about the argument, or information imbedded in the persuasive message. Rather, the audience are more influenced by other factors to determine the credibility of the message (Petty and Cacioppo, 1984; O’Keefe, 2013).

Petty and Cacioppo (1984b) highlighted that when the peripheral route is engaged, other heuristic cues such as source credibility, reputation and attractiveness guide the individual’s existing beliefs. Therefore, an individual relies on other attention-grabbing stimuli, rather than extensive processing of the information presented. These cues therefore influence their behaviour change or formation (Bhattacherjee and Sanford, 2006). Petty and Cacioppo (1984a) further determined that when peripheral processing is engaged, elaboration can be influenced by different factors stemming from their motivations and their competencies to influence an individual’s final decision-making process.

Goh and Chi (2017) established that existing beliefs, time availability, complexity of the message, level of education, and the number of times the message has been presented to an individual especially in online platforms, influence elaboration and the route of persuasion. Further, involvement with media content, the individual's need for recognition and the inability for an individual to engage in the topic at hand enables the peripheral persuasion process to also be activated (O'Keefe, 2013). In information sharing research, motivations such as status seeking gratification, entertainment gratification, pass time gratification, socializing, information sharing (Thompson et al, 2019) and altruism (Apuke and Omar 2021) suggest that the peripheral process rather than the central processing is engaged during decision making.

2.2.4 The ELM in previous research

The ELM is a dual process theory of persuasion that analyses and poses to identify the recipient susceptibility to the persuasive message presented and to determine if there is a change in behaviour or attitude (Petty and Cacioppo, 1984b). This model of persuasion has been utilised in different disciplines exploring how people process persuasive messages differently and how the outcome of the process affects attitude.

Studies in Acceptance Research have used the ELM as a referent theory to theorize information technology acceptance. Bhattacherjee and Sanford (2006) examined impacts of argument quality and source credibility constructs on perceived usefulness and attitude in Information Technology acceptance. Similarly, Li (2013) employed the ELM as their significant theory for information systems acceptance, exploring the influence of persuasive messages (source credibility and argument quality) on factors such as social influence and an individual's intellectual and emotional responses on behaviour intention.

The ELM has also been used widely in eWOM communications studies to examine the effectiveness of persuasive eWOM messages (Ismagilova et al., 2021; Leong et al., 2019; Mishra and Satish, 2016; Park, 2008; Reyes-Menendez et al., 2019; Shankar et al., 2020; Wu, 2017). The whole e-commerce market is heavily dependent on successfully engaging an audience and using persuasive messaging to motivate them into changing their attitudes – moving from 'I need' to 'this lifestyle is for me' (Geddes, 2018, np.).

More recently, the ELM has been utilised to investigate the attitudes, influences, and behaviour changes in online information sharing, particularly in a crisis or pandemic such as the recent Covid-19 virus (Ali et al., 2022; Bhagat and Kim, 2022; Chen et al., 2021, Chen, Xiao and Mao, 2021; Huang et al., 2022; Wang et al., 2022). Huang et al., 2022 examined how information processing through the dual route influenced individual perceptions of online engagement during the pandemic. Chen et al., 2021 examined the influence of central and peripheral cues on an individual's belief in or identification of false news and further investigated the direct and moderating effects of information literacy.

Chen, Xiao and Mao (2021) utilised the ELM to characterise the usage of persuasion strategies and its influence on the propagation of misinformation-containing posts in the social media platform, Sina Weibo, to better understand the sociological and psychological mechanism behind the presentation and diffusion of online misinformation. Bhagat and Kim (2022) explored individuals' news-sharing behaviour and found that that online news quality, news source credibility, perception of online civic engagement, perceived influence on others, and social influence had a significantly positive association with news-sharing behaviours.

Next, we examine supporting theories with an aim to identify other key factors influencing information sharing.

2.2.5 The Uses and Gratification Theory

From a psychology perspective, researchers such as Thompson et al. (2019), Ma et al., 2011 and Apuke and Omar (2021) adopted theories such as the Uses and Gratification theory (U&G), examining sharing behaviours on different social media platforms and investigating the motives and determinants behind them. Studies focused on media usage motivations such as altruism, status seeking, socialization, information sharing, pass time, self-promotion, and entertainment to investigate if these individual needs fuelled sharing of unverified information online.

The factors we found to be more prominent within this theory are status seeking gratification (Thompson et al., 2019; Ma et al., 2011) and altruism (Apuke and Omar, 2021). As such, we adapt and incorporate these factors in our study.

2.2.6 The Health Belief Model (HBM)

The Health Belief Model (HBM) was initially developed by social psychologists Rosenstock, Hochbaum, Kegeles, and Leventhal in the 1950s to explain the increasing failure of people in the USA to participate in programs that prevent and detect disease (Hochbaum, 1958). With time the model was further developed by Kirscht to study people's responses to symptoms and behaviours regarding illness and disease, focusing on how they follow medical instructions and advice (Becker et al., 1977).

According to Champion and Skinner (2008), the HBM asserts that, for change of behaviour to happen, individuals should believe that the chances of experiencing a disease, or a risk of disease is high and believe that the condition is serious [perceived susceptibility and perceived severity]. As such, there is a belief in the efficacy of the advised change to reduce the impact or risk [perceived benefit]. Finally, the individual possesses a belief and is confident of the tangible benefits and costs of the recommended precautions [perceived barriers], and acts in a certain way [cues to action] or is confident in their ability to take action [self-efficacy].

From this theory we incorporate perceived susceptibility and perceived severity to our study to assess whether these factors that have been found to trigger behavioural health responses (Laato et al., 2020) could also affect individual information sharing behaviours, particularly during the Covid-19 pandemic.

2.2.7 The Cognitive Load Theory

According to Paas et al. (2003), the Cognitive Load Theory (CLT) began as an instructional theory based on assumptions regarding the characteristics of the human cognitive design. It was used to generate a series of cognitive load effects in different experiments. The theory states that the human brain is built on human memory storing information utilising short term memory till it is processed and then stored into the long-term memory. Sweller (2011) stipulates that the human brain has potentially limited processing capabilities, which can get overloaded. They go on to explain that excess information provided at the same time could lead to storing the information in their short-term memory and to failing to process this information in their long-term memory due to its volume and the time needed to process it. This would result in an individual being overloaded by information.

Drawing on CLT, researchers such as Laato et al. (2020) and Huang et al. (2022) found a link between information overload and unverified information sharing. This study therefore includes this factor into an integrated model of unverified information sharing.

2.3 Integrated model of unverified information sharing

Information sharing is a diverse topic, and the factors that influence information sharing are derived from different theories. Additionally, since prior research has indicated that a mixed theory method or the inter-disciplinary approach results in higher accountability of the estimated model (Khosrowjerdi, 2016), different researchers have integrated different theories into their research to better understand information sharing. Hur et al. (2017) integrated the ELM with the uses and gratifications theory; Bhagat and Kim (2022) integrated the ELM model with the Social Influence Theory (SIT); and both Laato et al. (2020) and Apuke and Omar (2021a) drew on the Affordance Theory together with the Cognitive Load Theory (CLT).

Due to this inter-disciplinary nature of unverified information sharing, additional factors have been proposed that expand the focus to include the *user's motivations, competencies, the source,* and the *information* in the message. As such, this study utilised the ELM as the core framework, integrating it with the CLT, HBM, and the U&G theory in order to identify key factors that influence information sharing. As such, in addition to examining the individual perceptions of the information in the message and the source of the message, utilising the original ELM framework, this study also includes constructs from the uses and gratifications theory. Emulating from Petty and Cacioppo (1984), who while discussing the multiple roles of persuasion within the ELM, revealed that, when the degree of elaboration is low, motivations may act as cues that gratify the users in one way or another, such that the need to elaborate the information provided for its accuracy would be overshadowed by the desire to feel superior or respected (Thompson et al., 2019), or by a need for recognition (O'Keefe, 2013). As such, within the peripheral route of the integrated model of unverified information sharing, we include motivations such as status seeking gratification and altruism.

Low elaboration results in individuals focusing or depending on other peripheral cues when faced with persuasive messages. As individual beliefs can be connected to behavioural responses (Sheeran and Abraham, 1996), beliefs regarding the perceived susceptibility and the perceived severity of a disease can serve as heuristic cues, particularly in a pandemic situation, which enable people to focus on information that aligns with their existing beliefs without having to evaluate the information prior to sharing it. As such, this study incorporates constructs from the HBM within the peripheral route.

Finally, according to O'Keefe (2013), competencies play an important role when individuals evaluate information. Petty and Cacioppo (1984b) highlighted that information processing can be affected by individual competencies, e.g., the ability to sufficiently grasp the information at hand. Competencies such as individual eHealth literacy and information overload can affect information processing, and so, impact on information sharing behaviour.

In summary, within the integrated model of unverified information, the central route includes argument quality, information quality and information credibility. Within the peripheral route, the constructs that were included are source credibility, motivations (altruism, status seeking gratification), competencies (e-health literacy, information overload) and health beliefs (perceived susceptibility and perceived severity), in order to better understand the determinants of unverified information sharing behaviour.

These are discussed below.

2.4 Central Processing Route

2.4.1 Argument quality

Lin et al., 2017 describe argument quality as the comprehensiveness of the information being shared or reviewed, describing how accurate, current and how relevant the message is and ultimately how convincing and persuasive the message is. Argument quality is the bedrock of the central processing in the ELM, determining informational influence under conditions of high elaboration (Sussman and Siegal, 2003).

Petty and Cacioppo (1984) found that, argument quality can also be determined by how relevant the message is to an individual and how convincing and persuasive the message is. Areni and Lutz (1988) reiterated that, argument quality can be viewed in two ways: a strong argument is anything in a persuasive message that elicits a positive response, and a weak argument is anything in a persuasive message that elicits a negative response. The strength of an argument will affect the user’s ability to believe the information (McKnight and Kacmar, 2007) when they evaluate it for further use.

Lim and Kim (2012) investigated the relationships between trust, information quality and intention, together with various trust levels in influencing behaviour intention to use health infomediaries. They utilised a survey instrument with 274 participants who were students at a university and found that information features such as relevance, reliability, and adequacy, influence trust in health infomediaries. In other words, all the determinants of argument quality help to contribute to the credibility of a message.

In another study carried out by Mun et al. (2013), where they surveyed 300 participants who had experience in the search of health information online, the researchers found that argument quality was a significant determinant of perceived information quality, which in turn influenced trust on the website and information. A study carried out by Teng et al. (2014) also corroborated previous research finding that argument quality was the most relevant of all antecedents and the most influential determinant of online reviews of persuasive eWOM messages in a social media context.

2.4.2. Information quality

Wang and Strong (1996) define information quality as the robustness of the information characteristics for the information user. Studies have regarded information quality as a multi-dimensional variable, Jin et al. (2009) in their online adoption model identified timeliness, correctness, and comprehensiveness as measures of information quality. Sha and Wei (2022) used currency, accuracy, and completeness as measures for individual perceptions of information quality on social networking sites.

Sussman and Siegel (2003) described information accuracy as the correctness of the output information while comprehensiveness is the completeness of the output information content. These information quality characteristics are essential to address challenges instigated by a pandemic, such as an infodemic. During a pandemic, the quality of the information spread online can help to avoid public health harm offline (Purnat et al., 2021). With the Covid-19 pandemic, research found that people used their time during isolation utilising online platforms, such that social networking sites (SNS) saw a rise of 61% in individual use (Nabity-Grover et al., 2020). People were sharing and seeking information together with engaging with family. With the spread of information on the rise, the quality of the information circulating is important, as according to Shim and Jo (2020) during a crisis, people are more inclined to receive and accept unverified information that presents negative implications.

As good quality information also entails timeliness, which is the availability of the output information at a time suitable for its use (Sussman and Siegel, 2003). During the pandemic, digital communication and social networking supported the escalation of real time information sharing (Purnat et al., 2021). The timing of information release determines its 'currency' and up-to-dateness. What is often observed during pandemics is the demand for accurate, clear, and credible information is not met by the supply, creating an 'information void' (Naudé and Vinuesa, 2021; Purnat et al., 2021; Shane and Noel, 2020; Zarocostas, 2020). When demand for certain information outstrips supply, that creates perverse incentives for the fabricating of data (Naudé and Vinuesa, 2021). This fabricated data can be linked to the vast quantities of misinformation and disinformation circulating online.

2.4.3 Information credibility

The plethora of unverified information sources, as well as the rise in the sharing of unverified information, raises concern toward the credibility of online information (Mackay and Lowrey, 2011). Appelman and Sundar (2016) define credibility as an individual's judgment of the veracity of the content of communication. Traditional means of information distribution minimised uncertainty about the credibility of the information as the sources of information would have been organisation-oriented, as from reputable newspapers, independent, as in individuals considered experts in their fields and interpersonal, based on direct relationships and communication (Viviani and Pasi, 2017). Fact checking this information would be relatively easy as the writers or reporters of this information were mostly professionals in their fields and had a reputation to maintain, so would fact check their own information prior to releasing the news (Lucassen and Schraagen, 2011).

Earlier research identified credibility as having two dimensions, trustworthiness and expertness (Hovland et al., 1953). Later research then included other dimensions depending on the context. The credibility of the information matters whether the information originates from an online blog (Yin et al., 2018), or from an official health information site (Chang et al., 2021), or a social networking site (Li and Suh, 2015). Evaluating the information for its credibility is even more important now with the rapid spread of unverified information (Li and Suh, 2015).

According to Petty and Cacioppo (1984), individuals evaluate the credibility of information in two ways. Either they focus on the facts in the information and assess the strength in the argument or they use cues that guide their evaluation and reach a conclusion. With the existence of the infodemic, assessing the information for its credibility [however one does it] prior to utilising the information is important.

2.5 Peripheral Route

2.5.1 Source credibility

With the online environment the way it is established, where there are no face-to-face interactions, nor are there any prior relationships between the information receiver and the information provider, people can freely express their opinions on just about anything and stay anonymous at the same time (Shamhuyenhanzwa et al., 2016). The information receiver is tasked with analysing the information given to determine the information credibility prior to using this information

Li and Zhan (2011) define source credibility as “the perceived ability and motivation of the message source to produce accurate and truthful information” (p. 2) Existing research aligns with these definitions, concluding that source credibility consists of expertness, trustworthiness, and source experience (Wu and Wang, 2011; Li and Zhan, 2011; Martin and Lueg, 2013; and Wei and Wu, 2013). Additionally, a source can also be perceived by how the information or website is presented i.e., the source style (Teng et al., 2014). All these attributes can serve as cues for individuals to determine information as credible. Previous research, e.g., Shah and Wei (2022), has found that source credibility has a positive effect on individuals’ perceived benefits. Further, source expertness and trustworthiness can be used as a basis to measure the credibility of the information to make an informed final decision (Hussain et al., 2017).

Source credibility has been determined as an important attribute in different studies. For example, Kelton et al. (2008) in their framework for trust in information determined that trustworthiness encompasses attributes such as competence, positive intentions, ethics and predictability. Ultimately the information provided by the trustor to the trustee in the instance will be accurate, current, comprehensive, believable, objective, valid and stable. In other words, the source of the information determines the accuracy and correctness of the information

A study carried out by Zhao et al. (2015) found that source trustworthiness has a positive correlation with perceived information usefulness in the context of online hotel reviews. In their study, Zhao et al. (2015) collected data from business travellers in Mainland China, where they surveyed and collected data from 269 respondents. They found that when the information seeker finds the source trustworthy, they are inclined to assume that the information is credible. Therefore, they would be less sceptical of the information and would use it in future decision making.

Shamhuyenhanzwa et al., 2016 conducted a study in an eWOM context, in a cross-sectional study in South Africa, with data collected from 362 respondents, and they found that source trustworthiness has a direct positive impact on eWOM credibility. On a similar subject matter, Teng et al. (2014) concluded that source credibility was an influential factor of eWOM messages in persuasive communication in the context of social media.

2.5.2 Altruism

According to Apuke and Omar (2021b), an altruistic behaviour is illustrated by individuals who share or give without expecting something in return or without hoping for a reward (Apuke and Omar, 2021b). When an individual acts in this manner, their motivation to help others stems from the need to promote the welfare of others without a conscious regard for personal interest (Hoffman, 1979). According to Plume and Slade (2018) altruism describes an individual's desire to help others and, in many studies, falls under the Uses and Gratifications Theory. The Uses and Gratifications Theory focuses on the needs, motives, and gratifications of media users (Bloomer and Katz, 1974) and satisfaction comes out of performance of the action.

Altruism has been investigated in different studies such as Knowledge Management (Wasko and Faraj, 2005; Hung et al., 2011; Fang and Chiu, 2010) revealing that it is positively associated with intentional knowledge gathering and sharing with no expected payment. Additionally, altruism was found to escalate the number of ideas generated and overall meeting satisfaction (Hung et al., 2011). Similarly, in business behaviour, particularly with respect to social brands (Shiau and Chau, 2015; Alcañiz et al., 2010), research found that altruism also had positive effects: increasing trust in the brand and overall satisfaction of the groups buying online (Shiau and Chau, 2015).

Further, in blogging, where studies explored the factors that influenced micro bloggers' intention to use the platform, it was revealed that altruism encouraged continual usage intention (Zhao and Cao, 2012). Finally, altruism has recently been investigated as a determining factor in online information sharing in different contexts such as fake news sharing (Apuke and Omar, 2021b), online sponsored advertisement sharing (Plume and Slade, 2018), general information sharing on social media (Ma and Chan, 2014) and verified information sharing on Covid-19 (Xia et al., 2021).

2.5.3 Status seeking gratification

Lee and Ma (2012) present status seeking in their study as sharing of information on social platforms that helps one to attain status among peers. Prior research has indicated that using social platforms provides that need to feel superior or respected, and therefore, rising in status (Thompson et al., 2019). Accordingly, this construct has been utilised repeatedly in information seeking and information sharing research to predict dependent variables such as intention to use (Lee et al., 2010), unverified information sharing on social media (Islam et al., 2020), intention to share news on social media (Thompson et al., 2019), and sharing of fake news (Apuke and Omar, 2020a).

Status seeking gratification in some studies falls under the Uses and Gratification theory (Thompson et al., 2019; Lee and Ma, 2012; Lee et al., 2010) as it emphasises the individual's choice of media and how this gratifies them. The Uses and Gratification theory was initially developed to examine how and why people use and adopt certain media (Katz and Blumler, 1974). The scope of research under this theory has expanded to include new technologies, video games and online platforms (Lee et al, 2010).

As prior research has demonstrated that people share knowledge to obtain peer recognition (Lee and Ma, 2012), Thompson et al, 2019 claimed that social media may satisfy the desire to feel superior and respected, and Islam et al. (2020) reiterating that people utilise this platform to interact as well as to share content, trying to present [themselves] as highly knowledgeable and skilled compared to other people, thus promoting their status.

2.5.4 Perceived susceptibility and perceived severity

Perceived susceptibility and perceived severity attempt to demonstrate in situations such as a widespread pandemic how individuals regard themselves as vulnerable to a certain virus or disease. Additionally, if an individual believes that the virus is dangerous and could harm them, they will take steps to protect themselves and their resulting behaviour will reduce the impact of contracting the virus or disease.

Consequently, if an individual believes that the existing virus could possibly have serious effects, their behaviour and actions will be positive and will act in a way that will protect themselves to avoid getting very sick or worse dying. In other words, if a person believes that the potential course of an action is beneficial to reduce the severity or the susceptibility of the disease, and they believe that the benefits of taking the action outweigh the perceived barriers to action, the individual will likely take the action that reduces the risk (Champion and Skinner, 2008).

Perceived severity and perceived susceptibility have been investigated previously in health and social behaviour, and in psychology, as well as medical care disciplines. More recently due to the pandemic, researchers hypothesised that there was a link between health beliefs and the spread of misinformation about the virus and the spread of the virus (Laato et al., 2020; Mai et al., 2021). Additionally, determining that people's responses, e.g., taking protective measures such as social distancing and wearing face coverings, was a result of their response to the given threat.

Laato et al., 2020 employed the HBM in their study, to examine health beliefs. They examined if perceived susceptibility and perceived severity predicted their dependant variable unverified information sharing during the Covid-19 pandemic. Mai et al. (2021), in their study investigated if health beliefs predicted attitudes towards social distancing.

2.5.5 E-health literacy

With the abundance of health resources online, these resources can only be helpful if individuals are able to utilise online platforms and search for the information they require, sifting through multitudes of additional information that might not be relevant to them. Norman and Skinner (2006) revealed that, making informed decisions on health and health information seeking requires people to know how to access, understand, and process the health information that meets their needs. The internet is a cheap and easy way to access health information, but the ability to know and understand the online environment is not only necessary, but essential (Bundorf et al., 2006). As such, online health information seeking needs individuals to have technical expertise and the know how to consider the accuracy of the information to ensure sound decision making.

This is especially critical now with the rise of health information online and the recent Covid -19 pandemic that triggered people to seek for and share health information more than ever before (Zarocostas, 2020; Yang et al., 2022). Of late, just knowing about the available resources online, and the websites where those resources can be found, is inadequate. The expertise to decipher from unverified information, and determine from it, what could be true and what could be misinformation is vital, so that the final decisions made using the information are helpful and not harmful.

Prior research has hypothesised that e-health literacy is associated with online information sharing (Zhang et al., 2018; Zhao et al., 2020; Briones, 2015; Lu and Zhang, 2021), determining that there is a positive association and that individuals with high eHealth literacy are willing to share health articles on social media.

2.5.6 Information Overload

Jacoby et al. (1974) describe information overload as a condition that occurs when the quantity of information supplied to process exceeds the limited human information processing capacity, once the processing capacity is surpassed, overload occurs. When too much information is received, such that there is a risk of real or perceived information overload, regardless of how useful or valuable the information is to the user, information overload tends to occur; and judgement on how to utilise the information is skewed (Crook et al., 2015).

Additionally, Chewning and Harrell (1990) found that performance (which is the quality of decisions made) correlated positively with the amount of information the individual receives, up to a certain point, but once that point is passed and further information is provided, performance will rapidly decline. O'Reilly, (1980) stipulates that the information provided beyond that point impacts negatively on decision making and results in information overload. Research in information overload has been previously carried out in the fields of accounting (Schick et al., 1990), management (Galbraith, 1974), marketing (Jacoby, 1984), and information systems (Ackoff, 1967), with the main focus of the studies being on performance and decision making prior to individuals being exposed to large amounts of information.

More recently, information overload has been explored as a factor in the rapid spread of misinformation on online platforms (Talwar et al., 2019; Laato et al., 2020). Furthermore, information overload has also been examined in health information sharing online. Studies revealed that when overloaded individuals fail to realise the importance and relevance of the health information, this same overload condition can affect information sharing (Crook et al., 2015; Eppler and Mengis, 2004), and in turn it fuels unverified information sharing (Laato et al., 2020).

Additionally, Huang et at. (2015) in their investigation after the Boston Marathon bombings, found that excess amounts of new information, incited by the novel situation, together with individuals' limited ability to make sense of the situation, increased the spread of misinformation and in turn exacerbated information overload. Similarly, during the Covid-19 pandemic, due to the abundant information circulating online about the novel virus (Huang et al., 2022; Laato et al., 2020; Talwar et al., 2019), research linked the spread of misinformation and fake news on social media to information overload.

2.6 Literature Gaps

Online information sharing is proving to be an important topic of discussion, particularly if the shared information happens to be unverified and/or inaccurate. Studies such as Fung et al. (2016), Figueira and Oliveira (2017), Bruns et al. (2020) and Leibovitz et al. (2021) have revealed the impacts of misinformation. As such, studies have emerged from different disciplines, attempting to pinpoint the factors that affect the sharing of unverified information online. Several studies have used the ELM to examine information sharing: Hur et al. (2017) amalgamated the ELM with the uses and gratifications theory, and Bhagat and Kim (2022) amalgamated the ELM model with the Social Influence theory. However, despite recognising the need for a mixed theory approach to examine information sharing factors, they do not incorporate the key suggested factors that existing literature points to, which can enhance our understanding of this topic.

As such, this study attempts to bridge this gap and add to the knowledge by examining the key factors affecting the sharing of information in the context of unverified Covid-19 information circulating online. We include factors that have not been included in one model before, incorporating it in an integrated model that includes factors from other theories, such as the Uses and Gratifications theory [status seeking gratification and altruism], the Cognitive Load Theory [information overload], and the Health Belief Model [perceived severity and perceived susceptibility]. Within the ELM, our referent theory, we include the original constructs from the ELM's central and peripheral routes, as well as additional factors from other disciplines, helping to give a more conclusive understanding of the factors that predict the sharing of unverified Covid-19 information online. Additionally, this provides a clearer view of the level of elaboration involved when one is presented with a persuasive message on Covid-19 and is inclined to sharing it.

This study adds to information sharing research by introducing this new and more comprehensive model for future studies to refer to.

Chapter 3: Research Model and Hypothesis Development

Drawing on existing theories and existing literature, this chapter introduces the proposed conceptual model, which illustrates the key factors that determine the sharing of unverified information online and the theorised associations between them. The factors are discussed in detail and hypotheses are developed and a summary of the hypotheses is presented in Table 3.1.

3.1 Research Model Formation

The literature studied revealed the theories and significant concepts in information sharing. While all theories discussed are established and well developed for different contexts of online information sharing, there were limitations with modelling unverified information sharing behaviours with either one of these theories individually.

Drawing on the Elaboration Likelihood Model (ELM), we developed a theoretical model that predicts sharing of unverified Covid-19 information on online platforms. This theoretical perspective was preferred as it helped the study to assess the underlying individual information sharing factors. Utilising the ELM, this study aims to reveal whether individual abilities and motivations when elaborating persuasive messages impact information sharing alongside. The ELM was especially selected as it is concerned with the influence processes and the impacts they have on human perception, attitudes, and behaviour, particularly in this study, where unverified information online can be viewed as a persuasive message that one can be manipulated to share. We aspire to identify the factors that influence this information sharing process by evaluating different factors from prior literature on the same topic.

Additionally, the ELM highlights the two routes of influence, and the effects of each route, i.e., whether an individual focuses on the message content (central route) or evaluates simple cues (peripheral route) to evaluate information prior to sharing it online, This clarifies the conditions a user may be influenced by (Petty and Cacioppo, 1986; Bhattacherjee and Sanford, 2006) and the attitude or behaviour they will adopt, whether they decide to share the unverified information or not.

To help develop this new model, we reviewed literature on the topic from different disciplines, and stemming from different theories. We then identified factors that have been observed to escalate the spread of unverified information sharing in different contexts, such as fake news, misinformation, rumours and disinformation on various social media platforms such as Facebook, or Weibo and We Chat. Next, we developed a new theoretical model that is inspired by existing literature and derived by the Elaboration Likelihood Model. We segmented the factors, placing the constructs that demand high elaboration such as argument quality, information quality and source credibility within the central route. Motivational factors (altruism and status seeking), health beliefs (perceived susceptibility and perceived severity), and competencies (e-health literacy and information overload) that could deter individuals to focus on other marginal cues and entail low elaboration were placed in the peripheral route. As informational constructs (argument quality and information quality) as well as source credibility assessed how individuals evaluated the information for its credibility prior to sharing it, information credibility was utilised as a mediating variable. These are summarised in Fig. 3.1.

As existing literature in this research topic is fragmented, this study integrated factors from different disciplines, incorporating them into one model as (independent variables) to determine individuals' level of elaboration prior to sharing information and applying it to the context of unverified Covid-19 information sharing online (the dependent variable).

We contribute to the literature on this topic by introducing new constructs in the core and the peripheral routes to examine and better understand the level of elaboration involved when one is presented with persuasive information online and is inclined to share it. Level of elaboration is important as it may help us to identify important aspects to form on, in this case, the peripheral route.

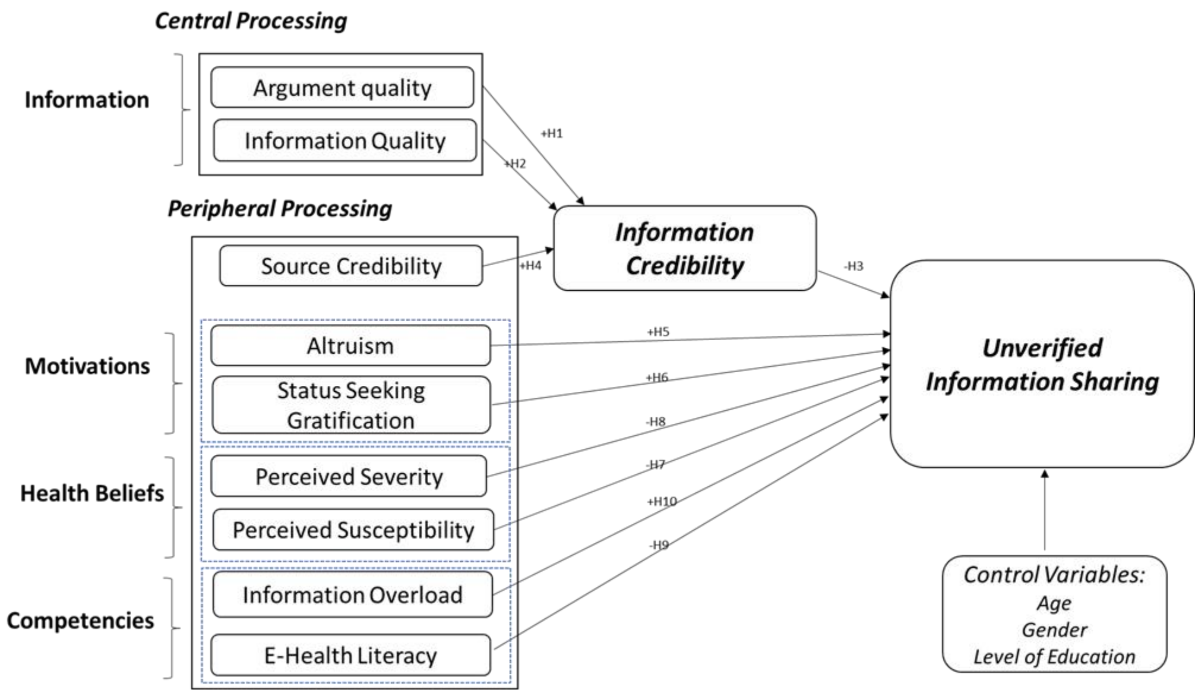


Figure 3.1: Integrated model of Unverified Information Sharing

3.2 Hypothesis Development

3.2.1 Argument quality

Argument quality refers to the persuasive strength of arguments embedded in an information message (Sussman and Siegel, 2003). Argument quality describes the substantial strength embedded in a persuasive message (Hussain et al., 2017). In accordance with the ELM, argument quality and source credibility help highlight the changes in individual attitudes and behaviour (Bhattacherjee and Sanford, 2006), as well, Petty and Cacioppo (1986) revealed that argument quality is a vital factor in informational influence. Since, the persuasive strength in the argument can make an individual accept or deny a message and as well, alter existing attitude, this study attempts to examine the role the quality of the argument has in the sharing of information.

Studies have revealed that perceived usefulness (Ha and Ahn, 2011), information credibility (Keshavarz, 2014), and information adoption (Sussman and Siegel, 2003) lead to information sharing. Once individuals perceive information as credible or useful, and adopt the information, they are likely to share it with others. Several studies have found that argument quality significantly impacts on perceived usefulness, information credibility, and information adoption. A study by Xu and Yao (2015) examined the effect of argument quality on the adoption of online reviews, and they found that argument quality has a positive impact on perceived value, further influencing the adoption of online reviews.

Li and Suh (2015) examined the factors that affect individual perception of information credibility on social media platforms. They found argument quality from the message credibility dimension as being the main determinant of information credibility. Luo et al. (2014) also found that argument quality positively affects information credibility. As it is likely that, once individuals find information credible, the likelihood increases of their sharing it with others. In the current study, we examine the association between argument quality and information credibility.

We argue that when individuals utilise their central route to process information in a persuasive message, the actual information rooted in the message will have been elaborated. As such, this careful elaboration and evaluation of the information will help determine information credibility.

As such we hypothesise that,

H1: Argument quality positively influences Information Credibility.

3.2.2 Information Quality

Information quality describes the consumers' perception of the information, based on a collection of decision criteria that cover accuracy, validity, usefulness, up-to-datedness, and impartiality (Sha and Wei, 2022). Information can be assessed as to how accurate, how comprehensive, and how up to date it is. The increase in internet usage, together with consumer sharing of opinions and reviews on products and services, affects the quality of the information online (Sardar et al., 2021). Given that presentation of information influences choice processes (Ball-Rokeach, 1998), including information sharing.

Information quality has been associated with information credibility (Luo et al., 2014; Sui and Zhang, 2021), user satisfaction, information adoption (Cheung and Thadani, 2012), perceived benefits (Sha and Wei, 2022), and when online users found information online satisfactory or credible, they are likely to share it with others, as such, these factors can positively affect online information sharing (Metzger, 2007). Additionally, Sha and Wei (2022) found information quality significant affecting perceived benefits of online engagement, highlighting that people are likely to reuse information they come across, through sharing it with others.

Luo et al. (2014) associated information quality with information credibility, highlighting that eWOM participants are likely to share information that they found credible. Sui and Zhang (2021) found information quality positively influenced perceived credibility of rebuttals concerning health misinformation. Studies done by Shim and Jo (2020) found an association between information quality and perceived benefits and findings by Cheung and Thadani (2012) associated information quality with information adoption. As previous studies support that information quality as well reduces the risk of uncertainty (Mun et al., 2013). This study investigates the effect information quality has on information credibility.

As Information quality falls within the central route, where elaboration is high, individuals are likely to analyse the information in the given message extensively examine it using the facts and details to determine credibility. Additionally, as previous studies have observed that the information in a message in part forms a reliable message (Wathen and Burkell, 2002), this study hypothesizes that:

H2: Information quality positively influences Information Credibility.

3.2.3 Information Credibility

Information Credibility is perceived differently by different individuals. With regard to information sharing, credibility is a challenge given the nature of the online environment, where information circulating online is not often fact checked or verified (Shu et al., 2017; Metzger, 2007). This study defines information credibility as the extent to which one perceives information to be believable (Li and Suh (2015). Prior research has found that people evaluate information credibility differently for the purpose of making credibility judgements (Petty and Cacioppo, 1984a; O'Keefe, 2013). Some individuals critically analyse the information provided [argument strength, information quality] and base it on prior knowledge (Petty and Ca, 1984), while others assess credibility by relying on heuristic cues [source of the message] to make easy and prompt judgments on information credibility (Petty and Cacioppo, 1984a; O'Keefe, 2013; Osatuyi, 2013).

Prior research has found that information credibility affects information adoption: for example, Jiang et al. (2021) examined how quality of the information affected individual information adoption on e-commerce platforms, and they found that information credibility affects individual intention to adopt information. The credibility of information has also been found to impact perceived usefulness. Erkan and Evans (2016) explored key factors of eWOM conversations on purchase intention, and their results revealed that eWOM credibility had a positive effect on information usefulness and, in turn, on purchase intentions. Additionally, Hajli (2018) found that information credibility was a significant factor on the development of online marketing, revealing that credibility supports both information usefulness and eWOM adoption.

With McKnight and Kacmar (2007) claiming that information credibility considerably impacts on an individual's will to do something, together with Smith and Vogt (1995) associating information credibility with behaviour change, and Sussman and Siegel (2003) associating information adoption with online information sharing, the current study investigates the role that information credibility plays in sharing of unverified Covid-19 information online. We argue that behaviour change, or manipulation of an individual, can impact on individual sharing behaviour. We hypothesise that the careful assessment and evaluation that occurs when one is making a credibility judgement will aid in the reduction of the sharing of unverified information online. We hypothesise as follows:

H3: Information credibility negatively influences unverified Covid-19 information sharing online.

3.2.4 Source Credibility

Source credibility refers to the recipient's perceptions of the trustworthiness and expertise of the information provider (Sussman and Siegel, 2003). It describes the trust the information receiver has in the source of the information (Ohanian, 1990). Individual in this case will be more inclined to scrutinize the source of the information as a way of evaluating it. The focus will be on the expertise and the trustworthiness of the source rather than the information content itself, i.e., information facts (Cheung et al., 2012), to determine the degree of influence. Prior literature identifies trustworthiness and expertise as the fundamental dimensions that measure source credibility (Luo et al., 2013).

Sui and Zhang (2021) examined the credibility-oriented determinants of health misinformation rebuttals and found that perceived source credibility had a positive relationship with perceived credibility. In addition, Li and Suh (2015) examined the factors that influence information credibility on social media platforms and they found that a significant relationship existed between source credibility dimensions, interactivity and transparency, and information credibility. Additionally, Luo et al. (2013) assessed the factors that affect credibility perceptions and they found that source credibility positively affects eWOM readers' perceptions of information credibility. Other researchers found that source credibility also has a positively effect on perceived online civil engagement (Bhagat and Kim (2022) and on information adoption (Hussain et al., 2017).

This study examines the influence of source credibility on information credibility. Together with the evidence from the literature, we contend that, in times of crisis or pandemics, often people will panic, and they will employ the peripheral route when evaluating information. As such, individual focus will be on heuristic cues, such as reviewing the trustworthiness or likeability of the source of the message, as opposed to checking the facts within the message. So, instead of assessing the information in the message for its accuracy and authenticity, low elaboration will prompt individuals to assess its source to form perceptions of information credibility. As such, if the information comes from what individuals deem to be a reputable source, they will view the message as being highly credible, therefore, we hypothesise as follows:

H4: Source credibility positively influences information credibility.

3.2.5 Altruism

Altruism describes an individual characteristic which entails doing something for others, without expecting anything in return (Apuke and Omar 2021). In relation to information sharing, this behaviour has been found to encourage the spread of information online as the altruistic person eagerly shares knowledge and news articles (Plume and Slade, 2018; Ma and Chan, 2014). Additionally, altruism was found to have a significant positive relationship with the spread of online advertisements on social media (Plume and Slade, 2018) and the spread of fake news online (Apuke and Omar, 2020).

In their study, Plume and Slade (2018) examined salient motivations to share sponsored advertisements in the context of tourism, and they found altruism to be a significant positive driver of intention to share sponsored tourism-related advertisements on Facebook. Shiau and Chau (2015) explored whether altruistic motivation is a significant factor in online group buying and they found that it is relevant to online group buying, highlighting that altruism among other factors was a significant positive predictor of trust and satisfaction.

Additionally, Apuke and Omar (2020) investigated the effects of fake news spreading in Nigeria and they found that people were motivated to share news mainly because of their civic obligation to inform others and provide advice or warning. This motivation to share led to the rapid increase of fake news. Further, Apuke and Omar (2021a) replicated those same results, finding altruism to be the most significant factor that predicted fake news sharing, while investigating altruism motivation in the context of sharing fake news about Covid-19.

As previous research supports the notion that people exercise altruism and share without verifying or considering the accuracy of the information (Apuke and Omar, 2020), the current study seeks to investigate the part altruism plays in exacerbating the spread of unverified information on Covid-19. We explore if an altruistic person would be more motivated to help others, such that the motivation to help would carry more weight and overshadow assessing the information for its credibility prior to sharing. We contend that those with greater altruistic behaviour would likely share unverified Covid-19 information online and so we hypothesise as follows:

H5: Altruism positively influences unverified Covid-19 information sharing online.

3.2.6 Status seeking gratification

Status seeking illustrates the individual desire to feel superior and respected by sharing information on social platforms to attain status among peers (Thompson et al., (2019). Prior research examining status seeking such as Apuke and Omar (2021a) and Islam et al. (2020) found that that users are provided with a platform on social media to explore content as well as share news and information, thus giving them an opportunity to promote themselves and their ideologies (Islam et al., 2020). Additionally, Norman (1988) asserted that affordances could be tied to an individual's values, aims, thoughts and capabilities, which provides them with a sense of self-importance and self-status (Ma et al., 2014).

Thompson et al. (2019) in their study investigating the determinants of news sharing on Facebook found that status seeking gratification has a strong effect on news sharing. Islam et al. (2020) investigated how motivational factors and personal attributes influence social media fatigue as well as the sharing of unverified information during the COVID-19 pandemic, and they found that motivational factors, which are closely linked to status seeking, encouraged the spread of unverified information sharing on social media.

As previous research has suggested, people have a fundamental need to belong, and with that comes the need to seek approval and recognition from others (Zhou, 2011). Additionally, studies have found that people tend to come up with different ways to enhance their image on social media (Islam et al., 2019) and maintain status, some even to the extent of sharing personal information in a bid to seek approval and relatedness from others (Nesi and Prinstein, 2015). We suggest that this need to belong, could also push people to share information that is unverified, in a bid to be the first to share, and receive some recognition from it.

As such, this study investigates the association between status seeking gratification and the spread of unverified information sharing on online platforms, hypothesising as follows,

H6: Status seeking gratification positively influences unverified Covid-19 information sharing online.

3.2.7 Health Beliefs

Perceived susceptibility describes an individual's belief about one's risk of experiencing a given threat, and perceived severity describes an individual's beliefs about the extent or magnitude of the threat to their life (Witte et al., 1996). Prior research found that the perceived severity of the Covid-19 pandemic is a significant predictor for self-isolation (Farooq et al., 2020). This shows that when people are faced with an unknown and dangerous situation, they perceive a greater level of susceptibility to the severity of the threat, and this in turn translates into behavioural action (Laato et al., 2020).

Such actions can be translated into information sharing online. For example, Shang et al. (2020), while examining factors that contribute to the likelihood of older adults sharing health information, found that perceived susceptibility is positively associated with the intention of sharing health information. We postulate from the findings of Farooq et al. (2020) and Mai et al. (2021) that when individuals feel they are at risk, they take precautions and make more calculated moves, taking extra steps such as verifying the information they find online prior to sharing, it in order to ensure that the existing threat can be swiftly dispelled. During the Covid-19 pandemic, if an individual exercised preventative measures such as mask wearing and self-isolation because they felt susceptible to the virus and if they believed the virus was severe, we argue that this behaviour would also reflect in their information sharing online.

Additionally, Simmelink et al. (2013) in a study exploring East African refugees, found that health beliefs shaped health behaviour and influenced interaction: as such, we postulate that if individual beliefs can affect behaviour and interaction, they can also affect individual sharing behaviours, such that stronger perceptions of susceptibility and severity would lead a person to check the information they receive before sharing it, so there would be less unverified information sharing.

In light of this, we hypothesise that:

H7: **Perceived susceptibility negatively influences unverified Covid-19 information sharing online.**

H8: Perceived severity negatively influences unverified Covid-19 information sharing online.

3.2.8 E-Health Literacy

E-Health literacy involves the individual capability to seek, understand, evaluate, and use online health information needed for health decision-making (Norman and Skinner (2006). This construct was adapted from health and online information literacy (Van der Vaart et al., 2011). As online platforms are increasingly becoming places where individuals search for health information (Van der Vaart et al., 2011), knowing where to find helpful health information and having the ability to differentiate between useful and unhelpful information is essential. Such knowledge helps people make informed decisions on healthcare and disease prevention (Czaja et al., 2013). Additionally, previous research has linked internet users with a higher health literacy, being inclined to engage more in online information practices with others i.e., seek and share information online (Chang et al., 2015, Wong and Cheung, 2019).

More recently, e-health literacy and information sharing has been further explored and the findings reveal that people with higher e-health literacy are more willing to share health articles on social media (Zhao et al., 2020). This may be due to their individual prior knowledge on the subject such that they share in order to instigate dialogue and further clarification (Chi et al., 2018). Additionally, Zhao et al. (2020) in their study investigating conditions under which eHealth literacy and content valence help to increase users' intentions to share, found that users with a high level of eHealth literacy were more likely to share health articles.

Consequently, due to the prior knowledge an individual has on the health subject and their skills in finding valuable health information online, we contend that a higher e-health literacy discourages the spread of unverified information, as users share information that they have prior knowledge on and possess information verification abilities. Furthermore, users would have more skills to find valuable information online prior to sharing it, so we hypothesise that,

H9: E-Health Literacy negatively influences unverified Covid-19 information sharing online.

3.2.9 Information Overload

Perceived information overload is described as a state of feeling overwhelmed due to exposure to an excessive amount of complex, ambiguous, and uncertain COVID-19 information from online platforms and a limited capacity to process this information (Huang et al., 2022). Researchers have characterized information overload based on the quantity and quality of information received at a given time in relation to the individual cognitive responses to the information (Eppler and Mengis, 2008). Prior research performed by Huang et al. (2015) supported the notion that emotional proximities during crises contributed to a rapid spread of misinformation. And so, studies have investigated the connection between information overload and misinformation sharing on social media and other online platforms particularly during the pandemic.

Laato et al., 2020 while investigating why people share unverified COVID-19 information through social media, found that perceived information overload was a strong predictor of unverified information sharing on social media. Bermes (2021) explored the relationship between information overload and fake news sharing on social media and found that information overload leads to an increased likelihood of fake news sharing by increasing consumers' psychological strain. Huang et al. (2022) in a bid to determine the spread of unverified information sharing, explored the association of information overload and unverified information sharing and found that perceived information overload was positively associated with unverified information sharing on We Chat.

Given this existing evidence, this study investigates the influence information overload has on unverified Covid-19 information sharing on online platforms. We argue that when one is overloaded with information, they will possess low elaboration and motivation to process the information contents prior to sharing it, as such, we hypothesise that:

H10: Information Overload positively influences unverified Covid-19 information sharing online.

Taken altogether, Table 3.1 shows a summary of the main hypotheses developed in this chapter.

Table 3.1: Research Hypotheses

H1	Argument quality positively influences Information Credibility.
H2	Information quality positively influences Information Credibility.
H3	Information credibility negatively influences unverified Covid-19 information sharing online
H4	Source credibility positively influences Information Credibility.
H5	Altruism positively influences the spread of unverified information online
H6	Status seeking gratification positively influences the spread of unverified information online
H7	Perceived susceptibility negatively influences unverified Covid-19 information sharing online
H8	Perceived severity negatively influences unverified Covid-19 information sharing online
H9	E-Health Literacy negatively influences the spread of unverified information online
H10	Information Overload positively influences the spread of unverified information online

Chapter 4: Methodology

This chapter outlines the research methodology utilised in this study. We discuss the research paradigm, which outlines the research approach and strategies utilised in the study as well as in the development of the research instrument. We then discuss the data collection methods and data analysis methods.

4.1 Research Paradigm

A research paradigm guides scientific enquiries by offering different assumptions and principles (Park et al., 2020). Research paradigms are viewpoints of knowledge (Varpio and MacLeod, 2020), that guide the way science is conducted, modelling the core elements, ontology, epistemology, axiology, methodology and the rigour (Bunniss and Kelly, 2010; Kneebone, 2002). There are different research paradigms: in this study we utilise the paradigm of positivism, so we focus on this research paradigm. In a positivist study, knowledge is derived from gathering facts so enquiry should be conducted in a way that is objective (Guba and Lincoln, 1994). To explain and predict a phenomenon, a theory is used to generate hypotheses that can then be tested and allow the principle of deductivism (asserting the validity of a conclusion) (Guba and Lincoln, 1994). Positivism relies on the hypothetico-deductive method to confirm the hypotheses and deduce where functional relationships lie between the variables – determining the explanatory factors, the independent variables, the dependent variables and the outcomes (Ponterotto, 2005).

In this research, we employ the Elaboration Likelihood Model (ELM) as our theoretical framework and adopts a positivist theory of knowledge. We adapt the ELM model into an integrated model of unverified information sharing. This model was compiled using different variables from different disciplines in the topic of online information sharing. These variables were chosen from reputable literature and incorporated in the one model. We built testable hypotheses and designed a questionnaire to establish the factors that influence ‘Unverified Information Sharing”.

As a positivist study often calls for an absence of bias due to researcher influences (Park et al., 2020), this study collected data using an online survey, with the help of a data collection agency. The researcher could not influence the participants in any way. There was total separation between the researcher and the participants.

As the positivist methodology additionally highlights the need in research for variables to be controlled and manipulated (Shadish, 2002), this study employs a quantitative research method. Empirical data is analysed to examine relationships between variables (Park et al., 2020) with the help of the Statistical Package for the Social Sciences (Version 28) as a data analysis tool. Details on the reasoning behind choosing SPSS will be discussed in section 4.2.3. The findings are expected to inform the theory and contribute to the literature.

4.2 Research Design

4.2.1 Data collection

The survey was created in Qualtrics, and Mechanical Turk (Mturk) was used to recruit participants for this survey. Mturk is an online portal operated by Amazon and is widely used by academics and businesses to collect questionnaire data. This study used Mturk as it was within the budget of the research and the data collection was relatively quick. As Mturk is largely American platform, most of the respondents of the survey were based in the USA.

The online portal supports anonymity; as the researchers only have access to the respondents' worker ID numbers, anonymity is guaranteed for the participants. This survey targeted audiences aged 18 years and older, who had encountered Covid-19 information online and chosen to share it with others. All screening questions were set such that the respondents were required to answer them before proceeding. Any participant who answered 'no' to the screening questions was not permitted to take part in the survey and would be redirected to the last survey completion message. Additionally, if a participant did not consent to participate in the survey, they would likewise be redirected to the last page of the survey.

The first page contained the information page, detailing the number of questions in the survey and the approximate duration to complete the survey. This page explained to the respondents that this was an anonymous survey, and that they were free to withdraw from taking part in the survey at any time. Additionally, the respondents were notified that the results of the study would be published in a master's thesis and that this thesis will be available to the public through the UC library. Results could also be published in peer-reviewed academic journals and be presented during conferences or seminars and through other publications to wider professional and academic communities.

4.2.2 Instrument development and design

The survey was divided into three parts. Part A included the survey introduction which briefly restates the number of questions in the survey and the survey duration, and provides the survey instructions, and the screening questions. Parts B and C contained the main questions in the survey, and part D included the demographic questions, as well as an open question that allowed the participants to offer any comments on sharing of unverified health-related information they had found online on COVID-19.

4.2.3 Instrument Design

In this study, the eleven constructs of interest were argument quality, information quality, source credibility, altruism, status seeking gratification, e-health literacy, information overload, health beliefs (susceptibility and severity), information credibility and sharing of unverified information All constructs were adapted from prior research and adapted to relate to the context of Covid-19 unverified information sharing online.

Most constructs, (i.e., Argument quality, Information quality, Information credibility, Source credibility, Status seeking gratification, Altruism, E-health literacy, Health beliefs and Information overload) were assessed using a seven-point Likert scale from 'Strongly Disagree' to 'Strongly Agree.' Unverified information sharing was rated on a seven-point scale from 'Never' to 'Always.'

A detailed list of the constructs, their sources, and the adapted questions are presented in Table 4.1.

Survey Instrument is attached in Appendix B.

4.2.4 Scale Development

Table 4.1: Constructs and Items

Constructs and Source	Items
Argument Quality (AQ) Adapted from Bhattacherjee and Sanford (2006)	The online information about Covid-19 that I shared was: AQ1: Informative AQ2: Helpful AQ3: Valuable AQ4: Persuasive
Information Quality (IQ) Adapted from Zha et al. (2018)	The online information about Covid-19 that I shared was: IQ1: Up to date IQ2: Accurate IQ3: Comprehensive
Information Credibility (IC) Adapted from Li and Suh (2015)	This online information about COVID-19 is: IC1: Believable IC2: Factual IC3: Credible IC4: Trustworthy
Source Credibility (SCR) Adapted from Bhattacherjee and Sanford (2006)	The person providing the COVID-19 information: SCR1: Was knowledgeable on this topic SCR2: Was trustworthy

	SCR3: Was credible SCR4: Appeared to be an expert on this topic
Status Seeking Gratification (SSG) Adapted from Thompson et al. (2019)	I share online COVID-19 information because: SSG1: It helps me feel important SSG2: It helps me to gain status SSG3: It helps me to look good SSG4: I feel peer pressure to share SSG5: It helps me gain respect
Altruism (ALT) Adapted from Apuke and Omar (2021)	I share online COVID-19 information because: ALT1: I like assisting others ALT2: It feels good to assist others to resolve their issues ALT3: I want to inspire others ALT4: I want to offer information to others ALT5: I want to advise others
E-Health Literacy (HLIT) Adapted from Norman and Skinner (2006)	HLIT1: I know what health resources are available online HLIT2: I know where to find helpful online health resources HLIT3: I know how to find helpful online health resources HLIT4: I know how to use the internet to answer my health questions HLIT5: I know how to use the health information I find online to help me HLIT6: I have the skills to evaluate the health information I find online HLIT7: I can tell high-quality from low-quality online health information HLIT8: I feel confident in using online information to make health decisions
Information Overload (IO) Adapted from Laato et al. (2020)	IO1: I am often distracted by the excessive amount of online information about COVID-19 IO2: I find that I am overwhelmed by the amount of online information about COVID-19 that I process on a daily basis IO3: I receive too much information regarding COVID-19 to form a coherent picture of what's happening
Health Beliefs: Susceptibility (SUSC) Adapted from Laato et al. (2020)	SUSC1: I am vulnerable to contracting COVID-19 in given circumstances SUSC2: I think it is likely that I will contract COVID-19 SUSC3: I am at risk of catching COVID-19
Health Beliefs: Severity (SEV) Adapted from Laato et al. (2020)	SEV1: The negative impact of COVID-19 is very high SEV2: COVID-19 can be life-threatening SEV3: COVID-19 is a serious threat for someone like me
Unverified Information sharing Adapted from Laato et al. (2020)	UIS1: I often share online information about COVID-19 without checking its authenticity UIS2: I share online information about COVID-19 without checking facts through trusted sources UIS3: I share online information about COVID-19 without verifying it UIS4: I share online information about COVID-19 even if sometimes I feel the information may not be correct

4.2.5 Ethical Considerations

The survey for this study was reviewed and approved by the University of Canterbury Human Ethics Committee. In line with the guidelines of the Human Research Ethics Committee (HREC), this research was considered low risk, as it did not cause any known harm, did not invade privacy, and did not gather personal or sensitive information about or from individuals or collect information without consent.

The participants were provided with information at the start of the survey, notifying them that their participation in the study was entirely voluntary, that they were free to withdraw at any time, and that any information they had entered up to that point would be deleted from the data set. As this was an anonymous survey it was not possible to withdraw their information after they had completed the survey.

The approval letter from the HREC for this study is attached in Appendix A.

4.3 Data Analysis Approach

This study utilises SPSS - Version 28 as the statistical analysis tool to evaluate the data from the survey. This analysis tool was chosen due to its popularity within academic circles and it being a widely used and widely available data analysis package (Arkkelin, 2014). SPSS allows multiple different types of data analysis, transformations, and outputs. This study employed the Qualtrics online application to create and run the survey: SPSS supports the analysis and data modification of the structured data from Qualtrics. Data can be downloaded as an SPSS data file with raw data, all its variables and the value labels.

Also, SPSS supports descriptive and bivariate statistics, which allowed this study to perform reliability and validity assessments of the measuring instrument, as these are the two main criteria by which an instrument is assessed (Blunch, 2012). Validity measures confirm that the instrument has measured what it was supposed to. “Construct validity is the extent to which a set of measured items reflect the theoretical latent items they are designed to measure, as such, it [construct validity] deals with the accuracy of measurement” (Hair 2009, p. 675). To assess validity, Confirmatory Factor Analysis (CFA) is used, and the rule of thumb suggests loadings should ideally be 0.7 or higher (Hair, 2009).

Additionally, this study employs the Fornell-Larcker criterion, suggested by Fornell and Larcker (1981) to check the discriminant validity of measurements models. According to this technique, the square root of the average variance extracted must be greater than the correlation with the other constructs under study (Fornell and Larcker 1981; Ab Hamid et al., 2017).

Further, reliability evaluates an instrument's consistency, i.e., the instrument should give close to identical results if the measurements are repeated under the same conditions (Blunch, 2012). Reliability of quantitative data is achieved by analysing the variation and covariation of the elements. This study uses Cronbach's alpha (Hair et al., 2010), composite reliability (Bagozzi and Yi, 1988) and Average Variance Extracted (AVE) (Fornell and Larcker, 1981) to evaluate the reliability of the constructs. Additionally, the item loadings were assessed from results obtained by carrying out a confirmatory factor analysis within SPSS.

Furthermore, this study took steps to ensure that common method bias would not impact on the study. "Common method bias entails the variance attributable to the method of measurement rather than the constructs the measures represent" (Podsakoff et al., 2003, p. 1). Harman's single factor test was carried out in SPSS by examining the exploratory factor analysis results and confirming that the first extracted factor does not explain more than fifty percent of the variance (Harman, 1976).

Finally, SPSS was used in this study because it allows many different types of data analysis, transformations, and outputs, and it is a data analysis package that is constantly being reviewed, updated, and revised, to ensure that it is up to date with the latest trends in statistical data.

Chapter 5: Findings and Data Analysis

In this chapter, the findings of the research are presented. Initially, the sample is described; following that, the data analysis stages were discussed and, finally, the results of the tests are presented.

5.1 Sample Characteristics

There was a total of 283 survey respondents and, of those, only 235 were usable. 39 were discarded because the respondents answered ‘no’ to some of the filter questions and could not complete the survey. A further 9 responses were discarded due to respondents completing the survey too fast (speedsters), or they answered every question with the same rating, contradicting themselves in some cases (straight liners). The survey had a usable completion rate of 83%.

The demographic questions captured the gender, the age, and the level of education of the participants. Table 3 below provides more detail of the sample’s demographic descriptive statistics. The survey was aimed at persons who had viewed and shared Covid-19 information with others and who were 18 years and above. The demographics distribution consisted of 120 (51.1%) females and 112 (47.7%) male participants. Most of the participants had a bachelor’s degree (53.6%) and were between 26-34 years (30.6%).

Table 5.1: Sample Demographics

Category	Number	Percentage
Gender		
Female	120	51.1%
Male	112	47.7%
Other	3	1.3%
Age		
18-25 years	13	5.5%
26-34 years	72	30.6%
35-44 years	57	24.3%
45-54 years	45	19.1%
55-64 years	35	14.9%
65 years and over	12	5.1%
Not specified	1	0.4%
Level of Education		
Less than high school diploma	4	1.7%
High school diploma or equivalent	21	8.9%
Some college but no degree	27	11.5%
Associate degree	20	8.5%
Bachelor’s degree	126	53.6%
Postgraduate degree, e.g., Master’s or Doctoral degree	37	15.7%

5.2 Research Findings

This section presents the findings of the data analysis of the data collected from the measurement instrument utilising Statistical Package for the Social Sciences (SPSS). The data analysis phase was carried out in two stages, as suggested by Gerbing and Anderson (1988). In stage 1; we set out to ensure the measures in our instrument were valid and reliable. In stage 2; we assessed the several hypothesized relationships of the research model.

5.2.1 Measurement Model

The research model consisted of 11 constructs, with 10 independent variables and one dependent variable (Unverified Information Sharing). Table 5.2. reports the descriptive statistics.

Additionally, all reliability and validity tests were conducted in SPSS.

Table 5.2: Descriptive Statistics for the Constructs

Construct	No. of items	Means	SD
Argument Quality	4	5.87	0.80
Information Quality	3	5.84	0.91
Information Credibility	4	6.02	0.92
Source Credibility	4	5.99	0.88
Status Seeking	5	3.43	1.93
Altruism	5	5.54	0.93
E-health Literacy	8	5.88	0.71
Information overload	3	3.41	1.81
Health Beliefs - Susceptibility	3	4.54	1.64
Health Beliefs - Severity	3	4.95	1.53
Unverified Info Sharing	4	2.78	1.82

Evaluation of the measurement model elicited from reliability tests. Reliability was assessed by analysing the variation and covariation of the elements (Internal consistency). Internal consistency was evaluated by assessing Cronbach's alpha and the composite reliability (CR). Values for the CR and the Cronbach's alpha of the elements should exceed the threshold of 0.7 to indicate reliability (Hair et al., 2010; Bagozzi and Yi, 1988). For these tests, Confirmatory Factor Analysis (CFA) was conducted in SPSS, the results showed that all CR and Cronbach's alpha values for all constructs exceeded the thresholds, indicating that internal consistency for all constructs was acceptable. See Table 5.3

Table 5.3 Construct reliability, CA, AVE values and Item loadings

Constructs	Items	Item Loadings	Cronbach's Alpha	CR	AVE
Argument Quality (AQ)	AQ_1	0.84	0.81	0.89	0.66
	AQ_2	0.87			
	AQ_3	0.88			
	AQ_4	0.65			
Information Quality (IQ)	IQ_1	0.83	0.79	0.88	0.71
	IQ_2	0.89			
	IQ_3	0.81			
Information Credibility (IC)	IC_1	0.84	0.91	0.94	0.79
	IC_2	0.90			
	IC_3	0.91			
	IC_4	0.89			
Source Credibility (SC)	SCR_1	0.87	0.90	0.93	0.76
	SCR_2	0.88			
	SCR_3	0.88			
	SCR_4	0.87			
Status Seeking Gratification (SSG)	SSG_1	0.94	0.96	0.97	0.86
	SSG_2	0.95			
	SSG_3	0.95			
	SSG_4	0.86			
	SSG_5	0.94			
Altruism (ALT)	ALT_1	0.88	0.81	0.88	0.59
	ALT_2	0.85			
	ALT_3	0.69			
	ALT_4	0.67			
	ALT_5	0.73			
E-Health Literacy (HLIT	HLIT_1	0.79	0.90	0.99	0.61
	HLIT_2	0.82			
	HLIT_3	0.84			
	HLIT_4	0.75			
	HLIT_5	0.77			
	HLIT_6	0.77			
	HLIT_7	0.69			
	HLIT_8	0.79			
Information Overload (IO)	IO_1	0.95	0.95	0.97	0.90
	IO_2	0.96			
	IO_3	0.94			
Health Beliefs: Susceptibility (SUSC)	SUSC_1	0.91	0.91	0.94	0.85
	SUSC_2	0.92			
	SUSC_3	0.93			
Health Beliefs: Severity (SEV)	SEV_1	0.92	0.85	0.91	0.78
	SEV_2	0.86			
	SEV_3	0.87			
Unverified Information Sharing (UIS)	UIS_1	0.96	0.95	0.97	0.87
	UIS_2	0.93			
	UIS_3	0.95			
	UIS_4	0.89			

Validity assessment was conducted with construct validity and convergent validity being examined to avoid any multicollinearity issues. To achieve this, Average Variance Extracted (AVE) and item loadings were examined. Fornell and Larcker (1981) suggest that the AVE for each construct must be at least 0.5, indicating that the construct accounts for more than half of its indicators. Additionally, each item loading was examined to ensure that every item surpassed the threshold of 0.7. Table 5.3 shows item factor loadings are 0.7 or above. These results confirm high convergent data validity. CFA was conducted to obtain the AVE and CFA was conducted to obtain the item loadings. See Table 5.3

Additionally, utilising the Fornell-Larcker criterion, we assessed for discriminant validity in the model. This method compares the square root of the construct AVE and then compares it to the correlations of the other factors. SPSS was used to calculate the cross correlations and Microsoft Excel was used to calculate the square roots of AVE. The square roots are all larger than the cross correlations, which verified the sufficient discriminant validity of the constructs in the instrument. See Table 5.4 below.

Table 5.4: Square Root of AVE and Cross Correlations

	AQ	IQ	IC	SCR	SSG	ALT	HLIT	IO	SUSC	SEV	UIS
AQ	**0.81**										
IQ	0.70	**0.84**									
IC	0.73	0.80	**0.89**								
SCR	0.72	0.66	0.78	**0.87**							
SSG	-0.01	-0.11	-0.19	-0.15	**0.93**						
ALT	0.49	0.43	0.41	0.49	0.21	**0.77**					
HLIT	0.50	0.50	0.47	0.57	-0.06	0.43	**0.78**				
IO	-0.07	-0.16	-0.24	-0.17	0.63	0.11	-0.14	**0.95**			
SUSC	0.20	0.10	0.07	0.15	0.26	0.24	0.09	0.44	**0.92**		
SEV	0.30	0.29	0.30	0.31	0.07	0.31	0.26	0.24	0.65	**0.88**	
UIS	-0.04	-0.16	-0.23	-0.18	0.68	0.13	-0.13	0.64	0.32	0.13	**0.93**

Key: AQ = Argument Quality; IQ = Information Quality; IC = Information Credibility; SCR = Source Credibility; SSG = Status Seeking Gratification; ALT = Altruism; HLIT = Health Literacy; IO = Information Overload; SUSC = Susceptibility; SEV = Severity, UIS = Unverified Information Sharing.

5.2.2 Common Method Bias

To address Common Method Bias (CBM), we conducted an EFA, with principal components and the results revealed that the first factor accounts for 38.33% (which is less than the cut-off value of 50%) so does not account for the majority of the variance observed, therefore it passes the Harmans Test (Harman, 1976).

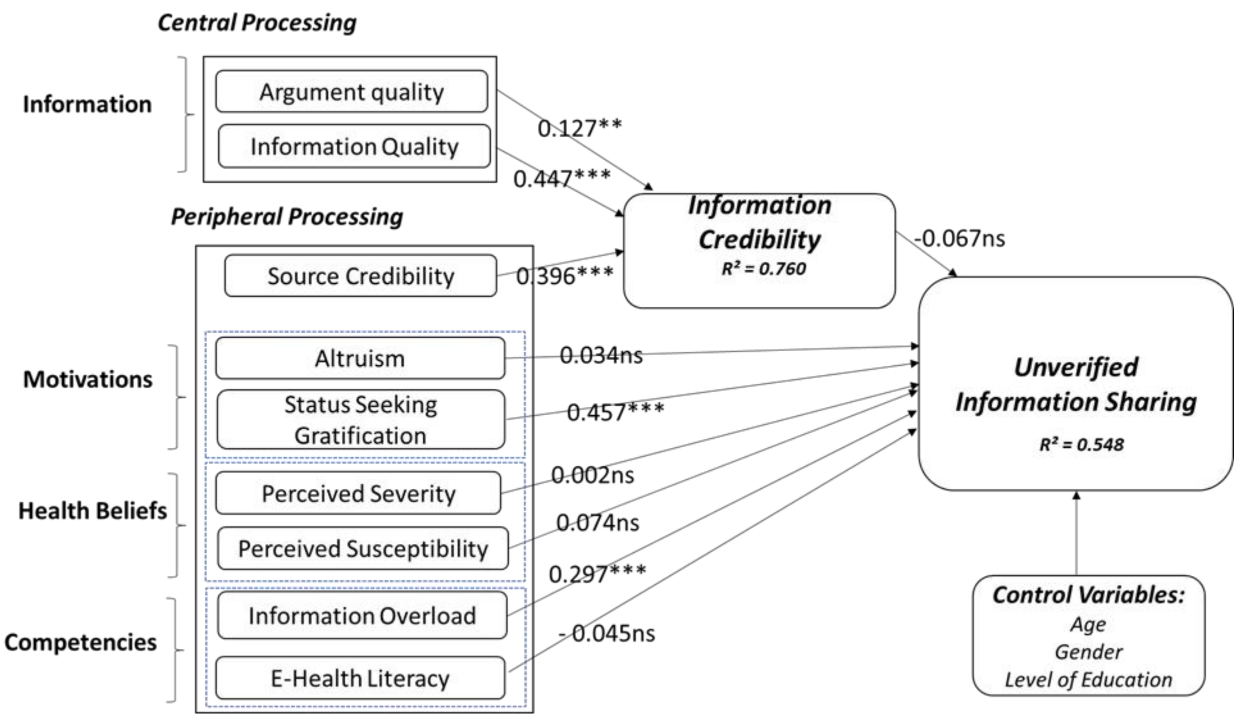
5.2.3 Structural Model

The structural model analysis results are shown in Fig.5.1.

Table 5.5: Main effects test

Model	Standardized Coefficients Beta	Sig.	Results
1	0.064	1.000	
Argument Quality	0.127	0.015	Supported
Information Quality	0.447	<0.001	Supported
Source Credibility	0.396	<0.001	Supported
2			
Status Seeking Gratification	0.457	<0.001	Supported
Altruism	0.034	0.543	Not Supported
E-Health Literacy	-0.045	0.433	Not Supported
Health Beliefs - Susceptibility	0.074	0.245	Not Supported
Health Beliefs - Severity	0.002	0.974	Not Supported
Information Overload	0.297	<0.001	Supported
Information Credibility	-0.067	0.282	Not Supported
Dependent Variable: Unverified Information Sharing (R Square = 0.548)			
Information Credibility (R Square = 0.760)			

*Significance level: * p < 0.10; ** p < 0.05; *** p < 0.001*



*Significance Level: * p < 0.10; ** p < 0.05; *** p < 0.001*

Fig.5.1: Research model results

5.3. Results from the Structural Model

We performed a linear regression to test the effects of the independent variables on the mediating variable, Information Credibility, and on the dependent variable, Unverified Information sharing. Table 5.5 shows that Model 1 is significant: Information Credibility R square = 76%, with F = 5.251 and $P \leq 0.001$; and Model 2 is also significant, Unverified Information sharing R square = 54.8%, with F = 30.334 and $P \leq 0.001$

Fig 5.1 reveals the results of the data analysis. The study examined factors that predict the sharing of unverified Covid-19 information on online platforms. In the first model with information credibility as the dependent variable, and with argument quality, information quality and source credibility as independent variables, the findings show Argument Quality ($\beta = 0.127$; $p \leq 0.05$), Information Quality ($\beta = 0.447$; $p \leq 0.001$) and Source Credibility ($\beta = 0.396$; $p \leq 0.001$).

When the online survey was conducted to collect data, respondents were asked to leave additional comments at the end of the survey (if they wished to) with regard to Covid-19 unverified information sharing. The finding that source credibility is an important factor influencing information credibility together with informational factors (information quality and argument quality) aligns with the majority of comments submitted by respondents as well as previous literature by Shamhuyenhanzwa et al. (2016) and Shah and Wei (2022). All correlations were significant in Model 1, with Information

Quality having a greater influence on information credibility than argument quality and source credibility. Hypotheses H1, H2 and H4 were supported.

In Model 2 with Unverified Information Sharing as the dependent model, only two components in the peripheral processing influenced Unverified Information Sharing significantly. The two constructs were Status Seeking Gratification and Information Overload. Status Seeking Gratification was significant ($\beta = 0.457$; $p \leq 0.001$): hence hypothesis H6 was supported. Information Overload was also significant ($\beta = 0.297$; $p \leq 0.001$), and so Hypothesis H10 was also supported.

All other constructs in the peripheral processing had no significant effects: Altruism ($\beta = 0.034$), E-health literacy ($\beta = -0.045$), Susceptibility ($\beta = 0.074$) and Severity ($\beta = 0.002$). Hence, hypotheses H5, H7, H8 and H9 were not supported.

Additionally, Information Credibility ($\beta = -0.067$) had no significant effect on unverified information sharing. Hence hypothesis H3 was not supported.

5.4 Summary

In this chapter, the findings of the data analysis and the assessment of the structural model are presented. We initially described the sample demographics, reviewing the participants' gender, age groups, and level of education. A large proportion of participants were young adults, with ages ranging from 26 to 44 years. 163 of the 235 participants had a bachelors' degree or better. The demographic report is followed by the construct analysis, with descriptive statistics for the constructs presented. The analysis of the measurement instrument was then conducted, and evaluation criteria were employed to examine the validity and reliability of the items in their respective factors. The results showed that the measurements met the expected thresholds for reliability and validity. The structural model was then analysed, and the results reported. The results showed that the factors accounted for 52% for Information Credibility and all three antecedents, i.e., argument quality, information quality and source credibility, were significant. The model likewise accounted for 53% for unverified information sharing, and two variables were significant, namely., status seeking gratification and information overload. In the next chapter we discuss these findings and their implications for research as well as for practice.

Chapter 6: Discussion

Chapter 6 discusses the research findings from the data analysis. Initially a brief overview outlining the study objectives is presented, then the chapter assesses the findings presented in Chapter 5 for each factor and the implications of the associations and hypotheses formed in Chapter 3.

We review the significance of the factors in the central route, as well as the factors in the peripheral route, as revealed in the data analysis, and we discuss the implications of these results. The study examines different factors that predict the sharing of unverified information. Assessed in two stages, Model 1 includes the informational factors that have an indirect association with unverified information sharing, with information credibility as a dependant variable. Model 2 includes factors that have a direct association with unverified information sharing, including motivational factors (status seeking gratification and altruism), competency factors (information overload and e-health literacy), health beliefs (perceived susceptibility and perceived severity) and information credibility. As such, below, the results for Model 1 are discussed first, followed by Model 2.

6.1 Overview

In this study we define unverified information sharing as, "individual's sharing of information without first authenticating it" (Laato et al., 2020). During crisis situations such as the recent Covid-19 pandemic, individuals engage more actively in information sharing for two reasons: first, the physical and emotional instability that is caused by the crisis prompts people to seek and share information in order to get a general understanding of the phenomenon (Huang et al., 2015). Secondly, the need for information for instructional purposes and for decision making is also intensified (Khan and Idris, 2019; Wathen and Burkell, 2002). This results in a vast spread of information that may be unverified.

As sharing information that is unverified has been identified as a cause of misinformation (Huang et al., 2022), evaluating information for its credibility is expected to reduce the spread of unverified information. By evaluating information credibility, people verify its accuracy and origin prior to sharing, as such limiting the occurrence of misinformation. During the Covid-19 pandemic, the spread of misinformation was found to encourage poor decision making, escalate fear and cause anxiety over the Covid-19 virus (Tran et al., 2022). And since research has found that people still share information without determining its credibility (Laato et al.,2020), evaluating why people share information that is not credible, and understanding what influences individual credibility evaluation, could be the first step on the way to eradicating misinformation sharing online.

The aim of this study is to examine the factors that affected the sharing of unverified information online during the Covid-19 pandemic. Existing literature had discovered different factors that predict information sharing, from different disciplines, in different contexts, and utilising different theories. Research into information sharing that gives a broad overview of the key factors that predict information sharing has been scarce. Existing literature has mainly focused on, for instance, motivational factors that predict information sharing: for example, altruism and status seeking, or competencies, like information overload and e-health literacy, or informational factors like, information quality and source credibility. This study selected from across these categories some of the prominent factors identified by the existing literature that predict information sharing and, with the help of the integrated model for unverified information sharing, we set out to identify those factors that most predict the sharing of unverified Covid-19 information online. This was done to get a comprehensive outlook on unverified Covid-19 information sharing.

Particular interest was on the causal mechanisms through which people made information sharing decisions, and the ELM, with its distinct processing routes, illuminated these causal mechanisms, and helped identify the factors that influence the sharing of unverified Covid-19 information online. The information receiver is tasked with analysing the information given to ascertain the credibility of the information prior to using this information. Within the central route (where influence is achieved through the user's thoughtful examination), there was an assumption that individuals would examine the informational elements within a message and be influenced to accept the information after a thorough evaluation of its *quality* and *strength*, and altogether use this to determine the *credibility* of the information prior to sharing it. The factors within this persuasion setting are argument quality and information quality.

During the Covid-19 pandemic, the quality of the argument and information were important, as digital communication and social networking supported the escalation of real time information sharing (Purnat et al., 2021). The timing of information release determines its currency and up-to-dateness. What is often observed during pandemics is that the demand for accurate, clear, and credible information is not met by the supply, creating an 'information void' (Naudé and Vinuesa, 2021; Purnat et al., 2021; Shane and Noel, 2020; Zarocostas, 2020). When demand for certain information outstrips supply, that creates perverse incentives for the manufacturing of information (Naudé and Vinuesa, 2021) which amounts to misinformation.

Additionally, unofficial information was spread on social media sites and platforms, where more people accessed it, as opposed to official government information that was often available on government websites, where fewer people frequented (Lewandowsky et al., 2017). It became important for people to evaluate informational elements within Covid-19 messages circulating online for its credibility prior to sharing. As people have also been found to evaluate information for its credibility by utilising cues such as the source of the message (O'Keefe, 2013), this study examined the influence of informational factors (argument quality and information quality) as well as source credibility on information credibility. The results for these factors are presented and discussed below.

6.2. Results from Model One with Information Credibility as the Dependant Variable.

6.2.1 Argument Quality

We examined the influence that argument quality had on information credibility. The findings demonstrate a significant and positive effect for argument quality on information credibility ($\beta = 0.127$; $p \leq 0.05$), and therefore hypothesis H1 is supported. This result suggests that the quality of the argument in the information has an effect on whether the information is perceived as credible. When individuals encounter information online, particularly during a pandemic, evaluating it for its credibility is imperative prior to sharing it due to the very large amounts of misinformation circulating online.

This result aligns with Li and Suh (2015), who also found an association between argument quality and information credibility. This finding in the context of Covid -19 information suggests that when people find Covid-19 information online they perceive as helpful, valuable and informative, they are influenced to accept it as credible and adopt that information. Previous research found that argument quality is a vital factor in informational influence (Petty and Cacioppo, 1986), which leads to a participatory behaviour by the information receiver (Tyagi et al., 2022). In the context of Covid-19, informational influence can positively impact individual behaviours, prompting them to exercise preventative measures against the virus and importantly, will influence them to avoid sharing unverified information online, as such, eradicating misinformation.

6.2.2 Information Quality

Hypothesis H2 examined the effects of information quality on information credibility. The finding reveals that information quality had a significantly positive effect on information credibility ($\beta = 0.447$; $p \leq 0.001$). This result was expected, and it supported our hypothesis, which presumed that that information quality would positively influence information credibility. This finding also aligned with the findings of from Luo et al. (2014) and Sui and Zhang (2021), who also found that information quality was positively associated with information credibility.

These results indicate that, when people encounter Covid-19 information online, the quality elements of the information help them to evaluate the information in order to determine its credibility. Information credibility, particularly during a pandemic, is important because of the large quantities of misinformation circulating online. By assessing the information for its accuracy, comprehensiveness and up-to-datedness (currency), this will contribute to its credibility and people can have peace of mind in utilising that information, for example, sharing it with others.

This rigorous attempt at assessing the information quality, which in turn influences information credibility, would also help prevent Covid-19 misinformation circulating online. Misinformation has been linked to poor decision-making and deters people from following health instructions, such as mask wearing and social distancing (Roozenbeek et al., 2020).

6.2.3 Source Credibility

Hypothesis H4 investigates the effect of source credibility on information credibility. The results suggest that source credibility positively affects information credibility ($\beta = 0.396$; $p \leq 0.001$). This hypothesis was supported. This result was expected and aligns with existing literature, including Shamhuyenhanzwa et al. (2016), who found that source trustworthiness positively impacted eWOM credibility, together with Shah and Wei (2022), who found that source credibility had a positive effect on perceived benefits. Additionally, research also found that the source of the message also determines the acceptability and the reliability of the information (Tyagi et al., 2022).

Some comments from the online survey read:

"I would always verify information I find, coming from unknown sources and even known media sources. I only share information, without verifying authenticity, if it comes from a trusted, verified account, like Johns Hopkins or WHO".

"If I read an article that quotes something from the CDC, then I am inclined to believe the information".

"The ONLY type of Covid-19 information I have ever shared, without verifying, was from a known entity that could be trusted - such as the CDC or Dr. Anthony Fauci.....".

"I consider verification of health-related information provided by my government to be unnecessary".

"I think sharing this kind of information can be beneficial in certain circumstances. If one has knowledge of the source and it's general reputation for being trustworthy, then I don't think it is always necessary to verify the information. If the source doesn't seem legit, then I wouldn't share unverified health-related information.".

These comments reiterate that when people encounter a new and urgent situation, such as a pandemic, they tend to focus on heuristic cues to make credibility judgments: this includes reviewing the source of the message (O'Keefe, 2013), and individuals during the Covid-19 pandemic, when receiving information, they likewise use heuristic cues, such as reviewing the source to evaluate the credibility of the information. When they receive information from sources that they view as credible, they, also accepted the message as credible and would see no reason to take extra steps to verify such information prior to sharing it with their peers. Source credibility is therefore an important factor influencing information credibility.

6.2.4 Information Credibility

Contrary to expectations, the findings revealed that information credibility had no significant effect on unverified Covid-19 information sharing on online platforms. Hypothesis H3 investigated the impact of information credibility on the sharing of unverified information on Covid-19 on online platforms. The data analysis did not support this hypothesis ($\beta = -0.064$; $p \geq 0.05$), inferring that information credibility had no effect on the sharing of unverified information on Covid-19.

This result was both unexpected and interesting, as it reveals that the credibility of information is not a leading factor when people are sharing information online; instead, prior research has revealed that people share for different reasons (as discussed in Chapter 2), being driven by different motives, for example, status seeking and altruism (Thompson et al., 2019). Additionally, due to the voluntary nature involved in information sharing (Capella et al., 2015), people must have a desire to share, and deeming information as credible will not on its own lead one to share the information. Our results reveal that evaluating information for its credibility did not lead to information sharing. Information credibility not having a significant impact on information sharing, to some extent explains why there is unverified information circulating online.

6.3. Results from Model Two with Unverified Information Sharing as the Dependant Variable.

According to Petty and Cacioppo (1984a), the peripheral route involves less cognitive resources; and so, individuals draw inferences through heuristic cues. Individuals, particularly during a pandemic, implement different strategies or shortcuts to evaluate information credibility; these heuristic cues have been known to lead people to focus on some informational features and to ignore the rest, ending up in a biased and unfavourable state (O'Keefe, 2013). Hence, within the persuasion setting, this study examined motivational factors, such as altruism and status seeking gratification, health beliefs, such as perceived susceptibility and perceived severity, as well as competencies like information overload and e-health literacy. Depending on the individual, and their abilities and motivations, the effects of these factors on unverified information differ.

6.3.1 Altruism

Hypothesis H5 investigated the impact of altruism on the sharing of unverified information on Covid-19 on online platforms. The data analysis found that the impact of altruism ($\beta= 0.034$) was not significant. This was unexpected and did not support our hypothesis; on the contrary, existing literature in information sharing, such as Apuke and Omar (2021a), and Apuke and Omar (2020) found altruism to be the most significant factors that predict fake news sharing in Nigeria. Bakhtawar et al. (2022) who carried out a similar study to Apuke and Omar (2021a), but in Pakistan, reported a weak though positive impact for altruistic attitude.

As an altruistic behaviour is fuelled by the need to help others, in a crisis such as the pandemic, people often need information relatively quickly; as such we expected that the need for satisfaction in helping someone with information would outweigh information evaluation, particularly if person want to be the first to help. In the context of this study, with information that claims to help with Covid-19 symptoms overflowing online (Tran et al., 2022), we expected that altruism would have a positive effect on unverified information sharing.

A plausible reason for the insignificant finding is that people were more inspired to share by factors other than altruism. This could be due to the realisation and knowledge of the health misinformation circulating online on Covid-19. As such, individuals' desire to help does not motivate people to share unverified information, in case they share information that is incorrect and hurts others, rather than helping them. Nevertheless, future more in-depth research is required to assess this association.

6.3.2 Status seeking gratification

Hypothesis H6 investigates the effect of status seeking gratification on the sharing of unverified information. The findings suggest that status seeking gratification positively affects the sharing of unverified information on Covid-19 on online platforms ($\beta = 0.457$; $p \leq 0.001$). As such, Hypothesis H6 is supported. This finding is in line with existing literature by Apuke and Omar (2021a), Islam et al. (2020), and Thompson et al. (2019), which claim that status seeking impacts on sharing behaviours on social media such that people are more likely to share to maintain status and to seek approval.

According to Nabity-Grover et al. (2020), during the Covid-19 pandemic, people used their time during isolation utilising online platforms, such that social networking sites (SNS) saw a rise of 61% in individual use. This coupled with Thompson et al.'s (2019) claims that social media may satisfy the desire to feel superior and respected. As people purposefully try to present themselves as highly competent (Islam et al., 2020), this could have encouraged status seeking behaviour. As such, individual need for approval and recognition from others (Zhou, 2011), together with online image enhancement overrides the need to verify information prior to sharing. The result is a vast spread of unverified information circulating online.

6.3.3 Health Beliefs

Hypotheses H7 and H8 investigated the impact of health beliefs (perceived susceptibility and perceived severity) on the sharing of unverified information on Covid-19. The data analysis found the impacts of susceptibility ($\beta = 0.074$) and severity ($\beta = 0.002$) were not significant. We expected that individual beliefs would have a negative impact on the sharing of unverified information, with the reasoning that people would not recklessly share information that they had not evaluated first as this would worsen the situation. However, the results were not significant, suggesting that individual beliefs did not influence information sharing. These results are in line with Laato et al., (2020) who also found that perceived severity and perceived susceptibility had no significant influence on the spread of unverified information sharing but did not align with the findings from Shang et al. (2020), who found that perceived susceptibility was positively associated with health information sharing intention, but perceived severity had a significant negative influence on health information sharing intention.

Compared to Shang et al. (2020), we attribute the non-significant result to the differences in the age demographics. In this current study, 80% of the respondents were young adults [who grew up in a digital world], meaning that the sample consisted of only 20% of older people. During the Covid-19 pandemic, reports that the virus mainly affected older people and people with underlying conditions (Calderón-Larrañaga et al., 2020) inclined younger people and people with no existing health issues to assume they were immune to the virus. As such, they would not believe that they were susceptible to the virus, and that it could have a severe impact on them. So, rather than be guided by health beliefs when deciding to share health information, one possible reason for the non-significant finding is that the younger persons were motivated to share by other factors, such as those that provided them with favourable benefits, for example, status seeking gratification.

6.3.4 E-Health Literacy

In this study, Hypothesis H9 examines the effect of E-Health Literacy on the sharing of unverified information on Covid-19. The findings suggest that e-health literacy ($\beta = -0.045$) was not significant. Once again this was unexpected, as prior literature had supported claims of strong ties between e-health literacy and information sharing, suggesting that users with higher levels of e-health literacy were more likely to share verified information online (Zhao et al., 2020).

We expected that e-health literacy would negatively influence the sharing of unverified information. The existing knowledge that the individual would possess on the subject, as well as the skills to find valuable and useful information, meant that the information the individual would share, would more likely be verified and accurate. Additionally, the ability for an individual to detect the veracity of the information circulating online and distinguish between misinformation and genuine information stems from e-health literacy skills (Norman and Skinner, 2006). As such, we expected that e-health literacy would negatively impact on unverified information sharing. In particular during the Covid-19 pandemic, higher levels of e-health literacy could have helped people identify misinformation that claimed that the virus would be treated by chlorine or bleach (Tran et al., 2022), thus reducing the spread of harmful information. Regardless of the insignificant result, training programs that support e-health literacy should be implemented because people need to be educated on where to find accurate and useful information, and people need to be aware of what is false in order to encourage good decision making.

6.3.5 Information Overload

Hypothesis H10 examined the impact of information overload on the sharing of unverified information on Covid-19 online. The findings suggest that information overload positively affects the sharing of unverified information on Covid-19 online ($\beta = 0.297$; $p \leq 0.001$), implying that when individuals are overloaded with information, they find it difficult to evaluate it. Existing literature supports this finding, with Laato et al. (2020) and Bermes (2021) both finding strong links between information overload and unverified information sharing.

This finding was to be expected: with information overload impairing the processing capacity, the psychological strain would be expected to have an impact on their judgement on information sharing. During the Covid-19 pandemic, there was an increased quantity of information on the new phenomenon circulating online (Khan and Idris, 2019) and it is likely that people shared information without verifying it due to overload. As such, the failure to process the facts in the information that stems from the individual being overloaded with information fuelled unverified information sharing online. Information overload is common during crises, and research from Huang et al. (2015)

supported this, additionally indicating that when an individual suffers from information overload, and elaboration and motivation to assess the information for its accuracy are also low, they are more likely to share unverified information.

6.4 Summary

This chapter synthesized the proposed hypotheses in *Chapter 3: Research Model and Hypothesis Development* and the findings reported in *Chapter 5: Findings and Data Analysis* and discussed the significance of the results. The results of the data analysis revealed that people are more motivated to share unverified information to enhance their image and improve their social status (status seeking gratification). This indicates that the need to share unverified information was strongly influenced by the desire to be liked and to seek others' approval. The analysis also revealed that people shared unverified information because they were overloaded with information such that the vast amount of information received would be difficult to process before sharing, and so they would just share without verifying (information overload). The overabundance of information online particularly during the pandemic means that people were presented with excessive amounts of information on Covid-19 (Huang et al., 2015) and sifting through all this information to find helpful and correct information is a mammoth task, so people would rather just share the information without verifying it.

Results also revealed that, while people assessed and evaluated the elements of the information and the source of the message to make judgments about the credibility of the information, the credibility of the information did not influence them to share the information. Information credibility was not a motivator in information sharing. Also, altruism, health beliefs and e-health literacy did not significantly affect the sharing of unverified information.

In the next chapter we discuss the theoretical and practical implications of these findings.

Chapter 7: Conclusion

This chapter gives a brief overview of the objective of this study. Then it discusses the theoretical and practical implications of the findings of the current research, together with the research limitations, and it closes with suggestions for future research.

This study examined factors that influence the sharing of unverified Covid-19 information online. Understanding of information sharing is currently fragmented with information sharing research emerging from different disciplines and theories. To identify the strong predictors of the sharing of unverified Covid-19 information online, this study brought together key factors from various studies, such as informational factors [argument quality, information quality and source credibility], competencies [e-health literacy and information overload], motivational factors [status seeking gratification and altruism] and health beliefs [perceived severity and perceived susceptibility] into one single model. The integrated model was tested with data collected from an online survey, and the findings have extended our understanding of what influences individuals to share unverified information online.

Below, the theoretical and practical implications and the limitations of this study are discussed, and future research directions are suggested.

7.1 Theoretical Implications

This study contributes to existing knowledge in several ways. Its initial contribution was in developing and testing a model of unverified Covid-19 information sharing, which considered the concurrent effects of informational factors [argument quality, information quality and source credibility], competency factors [e-health literacy and information overload], motivational factors [status seeking gratification and altruism], as well as health beliefs [perceived severity and perceived susceptibility]. This investigation found that unverified information sharing during the Covid-19 pandemic was significantly affected by status seeking gratification and information overload.

Secondly, this study revealed the associations that influence people to make information sharing decisions. On a theoretical level, the study aimed to provide a detailed view of how motivational, beliefs, and competency heuristic cues interact to influence credibility perceptions, and how the mediating role of information credibility affected unverified information sharing. These findings would help reveal the process through which people evaluate information, form credibility judgements and, finally, decide on whether or not to share unverified information. The results are significant for, although Sussman and Siegal (2003) had suggested that information credibility could lead to information sharing, the results in this study did not support this claim. In the context of this study, information credibility did not influence individual sharing patterns: rather other stronger factors affected the sharing of unverified information on Covid-19. One of these factors is status seeking gratification, where individuals are willing and motivated to share unverified information to improve their status online, through greater acknowledgements, e.g., Facebook likes, more people reading the posts, and this ultimately helps the individual to feel important, and to gain respect and endorsement of status (Thompson et al., 2019). This finding is interesting because it highlights the effects of the transition that has occurred due to the pervasiveness of internet technologies and online platforms, where people treat information sharing as a strategy to uplift their status and to gain recognition. This challenges our current view from existing literature that individuals share information online in order to help others (Apuke and Omar, 2021a), or that they share information that is thought provoking, and significant, or where the argument within the information is compelling and persuasive (Sussman and Siegal, 2003; Bhattacherjee and Sanford, 2006).

Another one of these factors that was found to influence information sharing is information overload. This finding indicates that people share unverified information because they are encountering considerably more information on Covid-19 than they can handle; in essence, people’s failure to process information and assert what is credible prior to sharing has exacerbated unverified information sharing. This finding further highlights the effects of the extensive volumes of information circulating online. While computers and computer technologies can handle the extensive creation of new information and the vast spread of it (big data), human cognitive abilities can only process so much at any given time before they become overloaded (Sweller, 2011). In the end, people cannot differentiate between accurate and false information (Whelan et al., 2020), and so they will often share Covid-19 information that is harmful and escalates fear (Tran et al., 2020), resulting in an infodemic. These findings have convincingly challenged our current view and deepened our understanding of this topic.

7.2 Practical Implications

On a practical level, the results in the current study can help direct communities and the providers and designers of social media platforms alike to focus on particular interventions to combat the sharing of unverified Covid-19 information. This study explicitly shows that status seeking gratification and information overload significantly affect the sharing of unverified Covid-19 information. Specific to the results of the current study, the fundamental need to belong is a key push that is fuelling the infodemic (Nesi and Pristein, 2015). Since similar research has found that when individuals are found to have shared misinformation (Chadwick and Vaccari, 2019), this can affect their reputation within their circle of friends, so social media sites should continue to flag unverified information, as this could help limit the spread. It is hoped that individuals will be more aware of this possibility and think twice before sharing. Further, the providers and designers of social media platforms can offer options where only verified information is displayed or where information is limited based on the rating. Additionally, government and health organisations should disseminate credible information as soon as possible, to counteract misinformation on platforms that many people frequent: this way, if status seekers have a need to share, they can share accurate information. This fills the information void when people are looking for information to deal with a crisis and shows the need to fill the information void quickly.

Additionally, the results also revealed that this infodemic is also the result of an oversupply of information. For online users, this highlights the danger of an oversupply of information, particularly in physically and emotionally draining situations. Research has found that during a crisis, information sharing escalates and this rapid spread of information, in a short space of time, fuels information overload for many (Huang et al., 2015). To combat this, people should be more aware of where to find credible information. When people have credible information, it is hoped that they will not search continuously for additional information to the extent that they get overloaded. As such, e-health literacy skills will help with finding credible information and support individual ability to differentiate between credible information and misinformation. This will also help them to cope with what is presented, i.e., what to ignore so as to reduce overload.

The findings in this study showed that, in the context of sharing unverified COVID information, the peripheral route of the ELM had a greater impact on individual engagement behaviours than the central route. This illustrates that in crisis times, like during a pandemic, people rely more on heuristic cues and motivations to influence their sharing patterns. These findings highlight that, in a case of urgency, the lower cognitive effort required for the peripheral route can lead individuals to take shortcuts when making information sharing decisions and, as such, share unverified information. These results thus confirm and add to existing research that reviewed online engagement behaviours and found the peripheral route to show more dominance over the central route (Sha and Wei 2022). These results highlight the need for policy makers to focus and refine existing interventions to implement measures that require less cognitive elaboration, for instance, social influence. Both prior research and the findings of this current study have shown that the source of a message affects information credibility, and so impacts on decision making (Hussain et al., 2017). Government officials and policy makers should utilise social media influencers to share accurate information on Covid-19 and encourage desirable actions as opposed to undesirable actions, such as posting anti vaccination posts, and in turn reduce the spread of unverified Covid-19 information.

Ultimately, the need for good quality information released online cannot be overstated. Policy makers should continue to refine the current interventions and utilise social media influencers to distribute credible information. This is in the hope that the more there is accurate and credible information circulating online, the more chances there will be for individuals to encounter such information, and the more they will share the credible information rather than the misinformation.

7.3 Limitations and future research

This study has a few limitations. The initial limitation stems from the sample of respondents used. While Mturk is said to allow for a diverse demographic of respondents who participated in the survey, their sample characteristics do not fully align with the US population (Sheehan, 2018). For instance, about 90% of the sample in this current study had some college education or better. According to Duffin (2022) from *Statista.com*, in 2021, only 37.9% of Americans aged 25 years and over have some college education or better, so a greater representation of respondents across the levels of education was not captured in this survey. The implications of this are that information sharing patterns of more than half of the American population were not recorded or represented in this survey. Additionally, 80% of respondents were also between the ages of 26 - 54 years. This is the age group that is predominantly computer and online competent and the older generation, which according to Shang et al. (2020) have different sharing patterns, was not well represented. Future research should therefore aim to have a more representative sample, incorporating all ages and education levels in order to gain an in-depth picture of the sharing of unverified Covid-19 information.

Second, the results in this study revealed a number of unsupported hypotheses. These results did not support previous research (Apuke and Omar, 2021a; Shang et al., 2020; Zhao et al., 2020), and the reasons for the discrepancy are unclear; so, it is suggested that future research should examine these relationships further. This could be done by expanding the model, and by including variables such as intention to use, information adoption or attitude as mediating variables to the dependent variable, unverified information sharing, to get a broader view of the sharing of unverified information online.

Finally, this study conducted an online survey to collect data and, while respondents could voluntarily leave a comment at the end of the survey, more information is required to gain a better understand of the topic. To address this limitation, future research could conduct mixed mode surveys (Biemer and Lyberg, 2003), which incorporate more than one method of data collection in one study. Therefore, in addition to online surveys, future research could also conduct face to face structured interviews in order to collect more information and obtain a more in depth understanding of the respondents and better understand the findings.

7.4 Summary

The aim of this study was to examine the factors that motivate individuals to share unverified Covid-19 information online. Drawing on the ELM, we developed a theoretical model that aimed to identify key factors that influence the sharing of unverified Covid-19 information. Various factors were identified and selected from existing literature, such as argument quality, information quality, information credibility, source credibility, status seeking gratification, altruism, e-health literacy, information overload, and health beliefs. These constructs were incorporated into one model to create an integrated model of unverified information sharing, which gives a comprehensive view of the sharing of unverified Covid-19 information.

The findings of the online survey conducted with 235 respondents, mainly based in the United States of America, revealed that status seeking gratification and information overload influenced individual sharing of unverified Covid-19 information on online platforms. The less cognitive effort associated with peripheral route factors in this case, such as individual motivations (status seeking) and competences (information overload) respectively, likely influenced individuals to tap more into heuristic cues that led them to share unverified information online on Covid-19.

In summary, the results revealed that the peripheral route had a greater impact on individual perception and behaviours than the central route (which involves more cognitive effort). This is in line with the findings of Sha and Wei (2022), and Xu and Warkentin (2020). The probable rationale for this is the limited cognitive effort that is required when employing this route; as such, people are less likely to scrutinize information they find online to clarify whether it is of good quality before they share it. The implications for practice and research are discussed and recommendations provided for future research.

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Appendix A: Human Research Ethics Committee Approval Letter

UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

HUMAN RESEARCH ETHICS COMMITTEE

Secretary, Rebecca Robinson
Telephone: +64 03 369 4588, Extn 94588
Email: human-ethics@canterbury.ac.nz

Ref: HREC 2022/57/LR

22 August 2022

Yvonne C Gumbo
Accounting and Information Systems
UNIVERSITY OF CANTERBURY

Dear Yvonne

Thank you for submitting your low risk application to the Human Research Ethics Committee for the research proposal titled "Examining Factors Affecting Sharing of Online Information About Covid-19".

I am pleased to advise that this application has been reviewed and approved.

With best wishes for your project.

Yours sincerely

Dr Dean Sutherland
Chair, Human Research Ethics Committee

University of Canterbury Private Bag 4800, Christchurch 8140, New Zealand. www.canterbury.ac.nz

F E S

Appendix B: Survey Instrument

Survey Information

UC School of Business and Law – Department of Accounting and Information Systems
Phone: +64 3 369 3775
Email: yvonne.gumbo@pg.canterbury.ac.nz
September 9, 2022
HREC Ref: HREC 2022/57/LR

A STUDY EXAMINING FACTORS AFFECTING SHARING OF ONLINE INFORMATION ABOUT COVID-19.

Kia ora,

You are invited to participate in a research study examining **FACTORS AFFECTING SHARING OF ONLINE INFORMATION ABOUT COVID-19**. This study is being conducted by Yvonne Gumbo from the University of Canterbury ׀ Te Whare Wānanga o Waitaha. Other research team members include Nelly Todorova and Annette Mills. The study is being carried out as a requirement for a master's degree in Information Systems.

This research aims to examine factors that influence sharing of unverified online information about Covid-19.

You are invited to participate in this research because you have responded to a request for participants. Your participation is voluntary (your choice). If you decide not to participate, there are no consequences. Your decision will not affect your relationship with me, the University of Canterbury, or any member of the research team.

If you choose to take part in this research, please complete the online survey that follows this information page. The survey involves answering 16 questions about information sharing through different online channels. Completing the survey should take 10 minutes.

Are there any potential benefits from taking part in this research?
We do not expect any direct benefits to you personally from completing this survey. However, the information gathered will potentially benefit future research in the field of unverified information

sharing to try and curb the massive spread.

Are there any potential risks involved in this research?

We are not aware of any risks to participants in the research.

What if you change your mind during or after the study?

You are free to withdraw at any time. To do this, simply close your browser window or the application (App) the survey is presented on. Any information you have entered up to that point will be deleted from the data set. As this is an anonymous survey it will not be possible to withdraw your information after you have completed the survey.

What will happen to the information you provide?

All data will be anonymous. We will not be able to identify you or link your identity with any responses you provide. All data will be stored on the University of Canterbury's computer network in password-protected files. All data will be destroyed five years after completion of the study/publication of study findings. I, Yvonne Gumbo will be responsible for making sure that only members of the research team use your data for the purposes mentioned in this information sheet.

Will the results of the study be published?

The results of this research will be published in a master's thesis. This thesis will be available to the general public through the UC library. Results may be published in peer-reviewed, academic journals. Results will also be presented during conferences or seminars and through other publications to wider professional and academic communities. You will not be identifiable in any publication. I will send a summary of the research to you at the end of the study if you request this. If you provide an email address for this purpose, it will not be linked with your survey responses.

Who can I contact if I have any questions or concerns?

If you have any questions about the research, please contact Yvonne Gumbo: yvonne.gumbo@pg.canterbury.ac.nz. For any concerns, please contact Nelly Todorova: nelly.todorova@canterbury.ac.nz or Annette Mills: annette.mills@canterbury.ac.nz

This study has been reviewed and approved by the University of Canterbury Human Research Ethics Committee (HREC). If you have concerns or complaints about this research, please contact the Chair of the HREC at human-ethics@canterbury.ac.nz.

What happens next?

If you would like a PDF version of this information sheet, please email Yvonne Gumbo at: yvonne.gumbo@pg.canterbury.ac.nz. Please read the following statement of consent and start the survey below.

Statement of consent

I have read the study information and understand what is involved in participating. By completing the survey and submitting my responses, I consent to participate.

- ☐ Yes
- ☐ No

Part 1

Have you ever shared online information about Covid-19 with others?

- ☐ Yes
- ☐ No
- ☐ I don't remember
- ☐ I wish not to say

Scenario

Think about one situation when you have seen information online about COVID-19 and you have chosen to share it with others without verifying it. This information can be either from social media, an official government website, or any other website or online platform. Consider this scenario when answering the following questions.

Part 2

Thinking about the scenario you just recalled; select a source you saw the information from:

- ☐ Social Media platforms e.g., Facebook, Twitter
- ☐ Messaging service app e.g., WhatsApp
- ☐ Official Government websites
- ☐ Official Health Information sites
- ☐ Other (please specify) …………………………………………….

Consider the scenario above where you shared online information about COVID-19 without verifying it. Please indicate to what extent you agree or disagree with the following statements.

Q1. The online information about Covid-19 that I shared was:

- Informative
- Helpful
- Valuable
- Persuasive

Q2. The online information about Covid-19 that I shared was:

- Up to date.
- Accurate.
- Comprehensive.

Consider the scenario above where you shared online information about COVID-19 without verifying it. Please indicate to what extent you agree or disagree with the following statements.

Q3. The person providing the COVID-19 information:

- Was knowledgeable on this topic.
- Was trustworthy.
- Was credible.
- Appeared to be an expert on this topic.

Consider the scenario above where you shared online information about COVID-19 without verifying it. Please indicate to what extent you agree or disagree with the following statements.

Q4. I share online COVID-19 information because:

- It helps me feel important
- It helps me to gain status
- It helps me to look good
- I feel peer pressure to share
- It helps me gain respect

Q5. I share online COVID-19 information because:

- I like assisting others
- It feels good to assist others to resolve their issues
- I want to inspire others
- I want to offer information to others

- I want to advise others.

Q6. Please indicate to what extent you agree or disagree with the following statements:

- I know what health resources are available online
- I know where to find helpful online health resources
- I know how to find helpful online health resources
- I know how to use the internet to answer my health questions
- I know how to use the health information I find to help me
- I have the skills to evaluate the health information I find
- I can tell high-quality from low-quality online health information
- I feel confident in using online information to make health decisions

Q7. Please indicate to what extent you agree or disagree with the following statements on the volume of information you have come across online on Covid-19?

- I am often distracted by the excessive amount of online information about COVID-19
- I find that I am overwhelmed by the amount of online information about COVID-19 that I process on a daily basis.
- I receive too much information regarding COVID-19 to form a coherent picture of what's happening

Q8. Please indicate to what extent you agree or disagree with the following statements on the significance or magnitude of the Covid-19 virus?

- I am vulnerable to contracting COVID-19 in given circumstances
- I think it is likely that I will contract COVID-19
- I am at risk of catching COVID-19
- The negative impact of COVID-19 is very high
- COVID-19 can be life-threatening
- COVID-19 is a serious threat for someone like me

Q9. Consider the scenario above where you shared online information about COVID-19 without verifying it. Please indicate to what extent you agree or disagree with the following statements.

This online information about COVID-19 is:

- Believable.
- Factual.
- Credible.

- Trustworthy.

Q10. Please indicate to what extent you agree or disagree with the following statements:

- I often share online information about COVID-19 without checking its authenticity.
- I share online information about COVID-19 without checking facts through trusted sources.
- I share online information about COVID-19 without verifying it
- I share online information about COVID-19 even if sometimes I feel the information may not be correct

Demographics

Gender

☐ Male

☐ Female

Age

☐ 18-25 years old

☐ 26-34 years old

☐ 35-44 years old

☐ 45-54 years old

☐ 55-64 years old

☐ 65 years old and above

Education Level

☐ Less than high school diploma

☐ High school diploma or equivalent (e.g., GED)

☐ Some college but no degree

☐ Associate degree

☐ Bachelor’s degree

☐ Postgraduate degree e.g., Master's degree, Doctoral degree

☐ Prefer not to say

☐ Other ____

Comments

If you have any comments on people sharing of unverified health-related information they have found online (e.g., COVID-19 information), please provide them in the space below. Your comments will be greatly appreciated.