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From information seeking to information avoidance: Understanding the health information behavior during a global health crisis

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ABSTRACT

Individuals seek information for informed decision-making, and they consult a variety of information sources nowadays. However, studies show that information from multiple sources can lead to information overload, which then creates negative psychological and behavioral responses. Drawing on the Stimulus-Organism-Response (S-O-R) framework, we propose a model to understand the effect of information seeking, information sources, and information overload (Stimuli) on information anxiety (psychological organism), and consequent behavioral response, information avoidance during the global health crisis (COVID-19). The proposed model was tested using partial least square structural equation modeling (PLS-SEM) for which data were collected from 321 Finnish adults using an online survey. People found to seek information from traditional sources such as mass media, print media, and online sources such as official websites and websites of newspapers and forums. Social media and personal networks were not the preferred sources. On the other hand, among different information sources, social media exposure has a significant relationship with information overload as well as information anxiety. Besides, information overload also predicted information anxiety, which further resulted in information avoidance.

1. Introduction

The quick spread of the novel coronavirus disease (COVID-19) has disrupted life across the globe. It has brought a halt to worldwide trade, movement, and socialization in society. Soon after the World Health Organization (WHO) declared COVID-19 a global pandemic, the governments issued advisories to their people to restrict the spread of COVID-19. These advisories contained recommendations such as travel restrictions, closure of educational institutions, marketplaces, and public places, along with recommending social isolation to restrict the spread (Fang, Nie, & Penny, 2020; Wilder-Smith & Freedman, 2020). Governments used mass media, print media, and the internet to mobilize the community, convey precautionary measures to the people, and inform them about the supportive measures and channels. The people themselves resorted to different information sources, predominantly internet-based sources, to learn about the COVID-19. Being health conscious amid the emerging uncertainty, people immediately started

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searching for COVID-19 information, such as its symptoms and precautionary measures (Bento et al., 2020). According to Statista (2020), people used various sources to keep themselves informed about the COVID-19. Among these sources, mass media (TV and radio), print media (newspapers and magazines), social media (Facebook, Twitter, etc.), search engines such as Google, family, and friends, and scientific and official websites are prominent. The available statistics from Google trends also confirm that people worldwide were actively seeking COVID-19 related information online (Fig. 1).

In the event of a public health emergency like COVID-19, or a disaster, the information sources help people make sense of the situation, learn precautionary measures, and reduce anxiety caused by the uncertain situation during a disaster or disease outbreak (Chao, Xue, Liu, Yang, & Hall, 2020). While helpful, information sources, especially mass media, print media, and Internet-based sources, can create new problems. The content available from these sources may amplify the risk perceptions and fear, especially when individuals cannot discern between real and fake news, adversely affecting the mental health and well-being of the masses (Laato S., Islam A.N., Islam M.N. & Whelan E, 2020a; Kasperson et al., 1998). Another negative outcome of a multitude of information sources, in general, is information overload. This situation occurs when handling and processing a wealth of information from multiple information sources become cumbersome, leading to information overload (Beaudoin, 2008). This overload of information has been found to create stress, fatigue, exhaustion, and even discontinuation of the use of information sources in recent studies (Fu, Li, Liu, Pirkkalainen & Salo, 2020; Guo, Lu, Kuang & Wang, 2020 ; Matthews, Karsay, Schmuck & Stevic, 2020). Students found information overload as a cause of psychological stress (Eppler, 2015), negative emotions (Zhang, Ma, Zhang & Wang, 2020), negative effects, depressive symptoms, trait anxiety, and trait anger (Swar, Hameed & Reychav, 2017). Studies also show that information overload, in general, adversely affects human information processing capacity (Eppler & Mengis, 2004). It can even lead to discontinuation of information seeking (Swar et al., 2017), the use of information sources (Zhang et al., 2020), and, ultimately, information avoidance (Chae, 2016). High levels of uncertainty and newspaper stories about treatment create health information overload (Jensen et al., 2017).

In the context of COVID-19, if information sources become a source of mental ill-being or start creating information overload, the result could be detrimental to society’s collective measures against the COVID-19. For example, people will start avoiding information seeking and consulting different information sources. In this way, they will not be updated with the changing situation. To better understand the role of information sources, researchers have started looking into the role of different information sources towards psychological well-being and coping behavior during the COVID-19. A recent study on COVID-19 shows that social media is associated with adverse psychological outcomes, while no such relation was found with traditional media (mass and print media) (Chao etal., 2020). Another study shows that exposure to a variety of information sources results in information overload, which negatively affects coping measures related to COVID-19, as well as the intention to take coping behavior (Farooq, Laato, & Islam, 2020). The study above also shows that information overload was higher among the individuals who used social media as a source of information for COVID-19. Further, it has been found that information overload results in cyberchondria, an excessive and chronically worrying state of feeling ill (Laato, Islam, Farooq & Dhir, 2020b). An important area that still needs investigation is the impact of different information sources on information behavior during the COVID-19. In the context of COVID-19, it is important to find answers to questions such as, what information sources create information overload during COVID-19? And, how does information overload affect information behavior in the COVID-19 context? Further, it has been suggested to conduct context-specific inquiries (such as type of disease, setting, and user groups) to understand health-related information-seeking behavior (Pian, Song, & Zhang, 2020).

In line with Pian et al. (2020) suggestions and the questions raised above, this study aims to complement the existing research on information overload in general and COVID-19, in particular, by addressing two aspects. First, to investigate the effect of a variety of information sources on information overload. Second, to study the consequences of information load explicitly related to information behavior. In this regard, using the Stimulus-Organism-Response (S-O-R) framework, we proposed a model which was then tested with

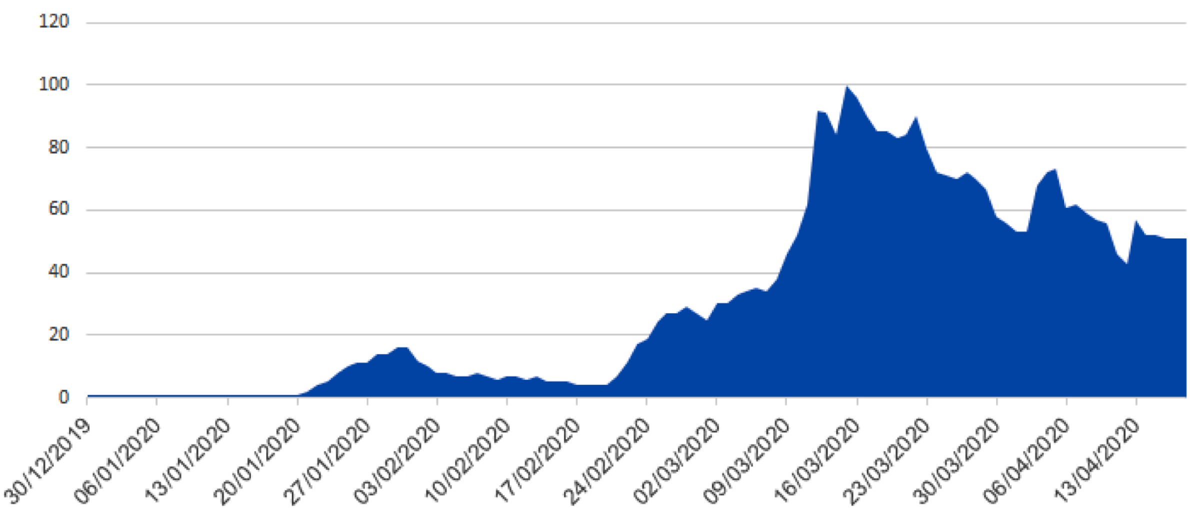

Fig. 1. Global search interest in Coronavirus adopted from Google (dated 18 April 2020).

the help of $N = 321$ responses collected during the peak time of the COVID-19 pandemic in Finland (March 2020). Structural equation modeling (SEM) in SmartPLS was used for testing the hypotheses.

2. Background

2.1. Information overload

Information overload is a state in which an individual cannot process incoming information and communication, making the information ineffective, and finally, towards the termination of information processing (Beaudoin, 2008). In general, "too much information at hand, exacerbated by the multiple formats and channels available for its communication" leads to information overload (Bawden & Robinson, 2009, p.3). The concept of information overload is not new. In 1970, Toffler defined information overload as "the excessive flows and amounts of data or information that can lead to detrimental computational, physical, psychological, and social effects" (1970, p.311–315). However, recently, it has received a lot of attention, especially in social media and virtual collaborations (Roetzel, 2019). During 2000–2018 thirty one empirical studies have been conducted in the area of health information overload (Khaleel et al., 2020).

Literature reports several negative consequences of information overload. Phillips-Wren and Adya (2020) identified information overload as one of the decision stressors. Information overload also found to have adverse implications for psychological well-being, such as stress, information anxiety, depressive symptoms, exhaustion, fatigue, and similar others (Bawden & Robinson, 2009; Fu et al., 2020; Guo et al., 2020; Matthews et al., 2020; Swar et al., 2017)), and adversely affect the well-being of the people (Matthews et al., 2020). Further, information overload has been found related to the discontinuation of social media networks (Fu et al., 2020) and information avoidance behavior (Guo et al., 2020). Information overload can also reduce decision quality, impacting information behavior (Speier, Valacich, & Vessey, 1999).

2.2. Information anxiety

Wurman (1989) originated the idea of information anxiety by defining it as "information anxiety is produced by the ever-widening gap between what we understand and what we think we should understand. It is the black hole between data and knowledge" (p.34). However, later in Wurman (2001) , Sheddroff added that "Information anxiety can have many forms, only the first of which is the frustration with the inability to keep up with the amount of data present in our life. What makes this worse is that the data is not just passive, but actively inserting itself into our environment, our attention" (p.16.).

Information anxiety is generally related to technological and library anxiety (Hartog, 2017). Technology and the library both are mediums to disseminate information. If people feel anxiety regarding these mediums, they may be reluctant to visit these channels and avoid active information seeking. Library anxiety is generally related to library settings, whereas information anxiety goes beyond the library space (Eklof, 2013). Information anxiety could be a result of many factors, such as low familiarity with the information channels, less technical knowledge and expertise, technostress (Ahmad & Amin, 2012), and, of course, information overload (Feng and Agosta, 2017; Lee, Son, & Kim, 2016a; Matthews et al., 2020 ; Swar et al., 2017). Information anxiety adversely affects decision-making processes and induces information avoidance (Bawden & Robinson, 2020; Golman, Hagmann, & Loewenstein, 2017 ; Swar et al., 2017).

2.3. Information avoidance

Information avoidance is ignoring relevant information and useful information sources because there is too much to deal with (Case, Andrews, Johnson, & Allard, 2005). While information avoidance minimizes the chances of interaction with unnecessary information, at the same time, it diminishes the chances to receive relevant information. From a cognitive viewpoint, individuals have limited capacity to process information, and if not adequately addressed, the outcome will be information overload (Sharit & Czaia, 2018). They avoid information acquiring and make decisions based on limited information (Dai, Ali, & Wang, 2020). As a result, the errors in the processing of information and messages they receive begin to increase. They overlook things, make mistakes, misunderstand messages, and so forth. Thus, people deliberately avoid information that threatens their happiness and well-being (Carnegie Mellon University, 2017; Golman et al., 2017).

Information avoidance can be of different types: inattention, physical avoidance, biased interpretation of information, and forgetting, for example (Dai et al., 2020 ; Golman et al., 2017). In health contexts, information avoidance can occur in several ways, for example, avoiding healthcare staff (Shepperd, Emanuel, Howell, & Logan, 2015), risk information (Deline & Kahlor, 2019), and even the prognosis (Derry, Epstein, Lichtenthal, & Prigerson, 2019). Health information avoidance behavior is affected by four types of factors, physiological, psychological, personal cognition, and external environmental (Chuang & Chiu, 2019). In the current situation, when the whole world is facing the COVID-19 pandemic, an excessive amount of information is available on different information sources/channels. The available information on COVID-19 while one end can be conflicting, on other, it can trigger stress and anxiety, adversely affecting psychological well-being (Bawden & Robinson, 2009; Swar et al., 2017). In this situation, people may start avoiding information on COVID-19.

3. Theoretical foundation

3.1. Theoretical framework

The current study investigates the individuals' health information behavior during COVID-19, underpinning the Stimulus-Organism-Response (S-O-R) framework, shown in Fig. 2 (Mehrabian & Russell, 1974). The S-O-R framework conceptualizes that environmental stimulus affects an individual's internal state called an organism, which leads to a behavioral response. Mehrabian and Russell (1974) further explained that our behaviors are the responses that are outcomes of the organism, a cognitive and affective process, whereas a stimulus triggers the organism. The conceptualization of the S-O-R framework allows us to understand the relationship of stimuli with the response, enabling the formulation of models containing affective and cognitive intermediary layers (Xu, Benbasat, & Cenfetelli, 2014).

The S-O-R framework has been largely applied to understand human behaviors, particularly for understanding consumers' behaviors (Chopdar & Balakrishnan, 2020; Gao & Bai, 2014; Xu et al., 2014). However, lately, this framework has been successfully applied to examine human behaviors during the COVID-19 pandemic (Laato et al., 2020a; Zheng et al., 2020). Concerning outbreaks/epidemics, it has been confirmed from the literature (based on S-O-R framework) that human behaviors change due to environmental factors, for example, consumer purchasing behaviors (Laato et al., 2020a), health management behavior (Farooq et al., 2020), social behavior and individual's psychological state (Zheng et al., 2020). Therefore, it is considered equally important to investigate the health information behavior during the COVID-19 pandemic from the lens of the S-O-R framework. Furthermore, the construct, that is, information overload, information anxiety, and information avoidance, has already been successfully examined by applying the S-O-R framework in the context of information behaviors on social media (Cao & Sun, 2018; Fu et al., 2020).

For the current study, it is hypothesized that both environmental stimulus and internal stimulus of an individual affect individual behaviors. Therefore, to investigate health information behavior, two types of stimuli were included in the study: environmental stimuli and internal stimulus. Environmental stimuli are imposed by the external environment and are somehow not in control of the person, whereas internal stimuli are related to an individual's own preference/interest and motivation. Since a wide range of information sources have been used during the COVID-19 pandemic, we focus particularly on the information sources exposure as an external stimulus, rather than the knowledge or awareness accumulated from the sources. In line with previous research (Cao & Sun, 2018; Fu et al., 2020) who studied the effect of information overload on the discontinuation of social media use, we used information overload as another external stimulus. The COVID-19 brought uncertainty at both individual and societal levels. People want to know about COVID-19 to minimize uncertainty. Therefore, we propose the information-seeking behavior as an internal stimulus in our study. As the organism is an individual's inner state of mind (cognitive and affective) therefore, we propose information anxiety (measuring psychological well-being) as an organism and information avoidance as a response.

3.2. Research hypotheses and model

3.2.1. Information seeking and information sources

Internet search data showed that people started actively searching about COVID-19 symptoms and hand sanitizers as their states announced the first COVID-19 case (Bento et al., 2020). Musarezaie, Samouei, Shahrzadi, and Ashrafi-Rizi (2019) argued that individuals' exposure to stress and concerns about their health status develop health information needs, and they search more frequently and from various information sources. It is already confirmed that active information seekers do not trust a single source (Huff et al., 2014; Statista, 2020) and tend to consult several information sources (Nelson, 2018). In the context of health information, the consumers use multiple information resources several times (Zhang, 2012) - perhaps due to their concern and sensitivity to the phenomena. Clarke et al. (2016) conducted a literature review and identified that health information seekers consult various information sources, including technology-based sources, print sources, and human sources such as close social ties and traditional mass media. In the context of COVID-19, people have been found to use different information sources such as the internet, traditional media, family members, as well as peers (Wang et al., 2020). Based on the above-mentioned evidence from the health information behavior literature, we propose the following hypotheses in the context of COVID-19:

H1a: Information seeking is positively related to the frequency of 'Personal Network' exposure
H1b: Information seeking is positively related to the frequency of 'Mass Media' exposure
H1c: Information seeking is positively related to the frequency of 'Print Media' exposure
H1d: Information seeking is positively related to the frequency of 'Social Media' exposure
H1e: Information seeking is positively related to the frequency of 'Other Internet Sources' exposure

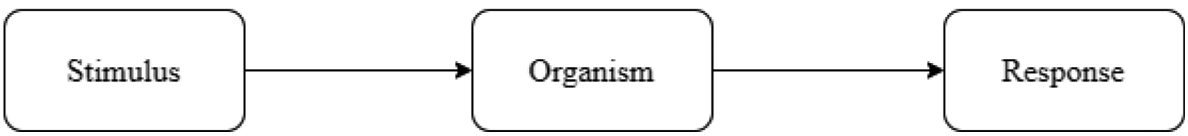

Fig. 2. S-O-R framework (Mehrabian & Russell, 1974).

3.2.2. Information sources exposure and its impact

Literature reports that exposure to different types of information sources positively correlates to the individual's sense of information overload and information anxiety.

Individuals consult a variety of information sources for seeking knowledge and advice in different contexts. (Clarke et al., 2016 ; Farooq et al., 2016; Ramsey, Corsini, Peters, & Eckert, 2017). Previous studies show a relationship between information source exposure and information overload. For example, Youtube exposure has been proved a significant predictor of perceived information overload, either it is used actively or passively (Cao & Sun, 2018; Matthews et al., 2020). Eppler and Mengis (2004) articulated information technology, including e-mails, the internet, and the Intranet (Bawden, 2001), rise in the number of television channels, and various distribution channels for the same content (Edmunds & Morris, 2000) as some of the causes of information overload. The individuals' who pay greater attention to news through social media, smartphones, and tablets significantly perceive more information overload (Lee, Kim & Koh, 2016b). Excessive health-related internet use significantly predicts a higher perceived health information overload (Jiang & Beaudoin, 2016).

Similarly, Serçekuş, Gencer, and Özkan (2020) reported that the frequency of information source exposure is positively correlated with cancer information overload. Farooq et al. (2020) further established a positive association between information overload and social media use in the COVID-19 context. Considering that different information sources have been found sources of information overload in a different context and that social media use is associated with information overload in the COVID-19 context, we propose the following hypotheses:

H2a: Individuals who report more frequent 'Personal Network' sources exposure will perceive a higher level of information overload.

H2b: Individuals who report more frequent 'Mass Media' sources exposure will perceive a higher level of information overload.

H2c: Individuals who report more frequent 'Print Media' information sources exposure will perceive a higher level of information overload.

H2d: Individuals who report more frequent 'Social Media' information sources exposure will perceive a higher level of information overload.

H2e: Individuals who report more frequent 'Other Internet Sources' exposure will perceive a higher level of information overload.

Information sources exposure/engagement has also been positively associated with the individual's state of information anxiety. This association has been proved in different contexts. For example, (Lee, Kim & Koh, 2016b) found that the level of attention to news through social media was significantly associated with the perceived news information overload which further was related to psychological stress and negative emotion (anxiety). In the context of health information, consumer's engagement with multiple information sources increases the likelihood of information overload and information anxiety (Bapat, Patel, & Sansgiry, 2017). Therefore, it is assumed that the frequency of different information sources exposure is a stimulus that directly affects the individual's state of information anxiety in the COVID-19 context as well, and the following possible relationships are proposed:

H3a: Individuals who report more frequent 'Personal Network' sources exposure will perceive a higher level of information anxiety
H3b: Individuals who report more frequent 'Mass Media' sources exposure will perceive a higher level of information anxiety
H3c: Individuals who report more frequent 'Print Media' sources exposure will perceive a higher level of information anxiety
H3d: Individuals who report more frequent 'Social Media' sources exposure will perceive a higher level of information anxiety
H3e: Individuals who report more frequent 'Other Internet Sources' exposure will perceive a higher level of information anxiety

3.2.3. Information overload and its impact

Swar et al. (2017) confirmed that perceived information overload has a significant positive relationship with psychological ill-being. The feelings of cognitive strain (Jones, 1997; Schick, Gorden, & Haka, 1990) , stress (Lee, Son & Kim, 2016a), confusion, depressive symptoms (Matthews et al., 2020), anxiety (Bawden & Robinson, 2009), and low motivation (Baldacchino, Armistead, & Parker, 2002) are the outcome of information overload. The following hypothesis is proposed to study the relationship between information overload and information anxiety:

H4: The greater feeling of information overload will result in greater information anxiety.

3.2.4. Information anxiety and information avoidance

Information anxiety, being a cluster of negative emotions, may result in information avoidance. Information avoidance is also known as non-seeking behavior. Over the last fifty years, information avoidance behavior has been primarily studied in the context of health information, as it tends to be conceptualized as a coping mechanism for dealing with potentially unwanted information (Manheim, 2014). It has already been proved that individuals ignore information and try to be selective in consulting information (Bawden, 2001; Sairanen & Savolainen, 2010). Golman et al., 2017) considered anxiety as one of the seven distinct psychological mechanisms that can produce information avoidance. Similarly, Swar et al. (2017) reported that psychological ill-being constructs (negative affect, depressive symptoms, and trait anger) created by online health-related information overload negatively impact individuals' online health information search behavior. Lately, Dai et al. (2020) reported that fatigue (tiredness, disappointment, loss of interest, or decreased need/ motivation) has a positive relationship with individuals' inactive social networking websites usage intention. Hence, literature provides evidence of an association between information anxiety and information avoidance behavior, and therefore, the following hypothesis is proposed in the context of COVID-19:

H5: Information anxiety is associated with an individual's state of information avoidance behavior.

Based on the above discussion, we propose the research model shown in Fig. 3.

4. Methodology

4.1. The context

Data for the study was collected from students, staff, and faculty members of three universities during April 2020 using a web-based questionnaire in Webropol, an online platform. Collecting data from both the aforementioned population allowed us to collect data from a diverse population, in terms of age, gender, and household. Moreover, reaching out to the general population for data collection would have been challenging, given the pandemic situation. Data was collected for about four weeks (from April 4th to April 29th). The first case in Finland was reported on January 29th' and the government imposed restrictions on March 16th by closing all educational institutions, public places, public gatherings, and similar others (Muhonen and Nalbantoglu, 2020). On the day we started data collection, 2261 confirmed cases were reported in Finland, and the numbers were rising, and by April 28th, there were 5056 confirmed cases Terveyden ja hyvinvoinnin laitos (2020). We stopped data collection as on April 29th Government decided to open the schools, giving the perception that the situation was under control.

4.2. Survey design and sample

As mentioned in the previous section, a web-based questionnaire was used to collect the data. The items for the questionnaire were mainly adapted from earlier literature, however, five items were included according to the contextual requirements. To ensure content validity, three subject experts (one from the field of information systems and two from the field of library and information science) examined the statements. They suggested minor changes to make the statements clearer. After that, the questionnaire was pilot tested using fifty responses (who were not part of the actual study) through a web-based questionnaire. The Cronbach's alpha value for all the constructs remained between 0.7–0.9, which was satisfactory and showed the reliability of the constructs used in the study. After that, a web-based questionnaire was prepared, and the link was shared among the potential respondents using e-mail lists, which include all the students, staff, and faculty members of the respective universities.

In the final questionnaire, after the introductory paragraph and informed consent, the participants were requested to respond to items measuring the constructs constituting the research model shown in Fig. 2. The demographic information was asked at the end. A nonprobability self-selecting sampling technique was used. A total of 321 responses were collected in four weeks. All the questions were mandatory, so missing data was not an issue. Furthermore, the examination of the dataset revealed no random responses. The demographic information of the study participants is shown in Table 1.

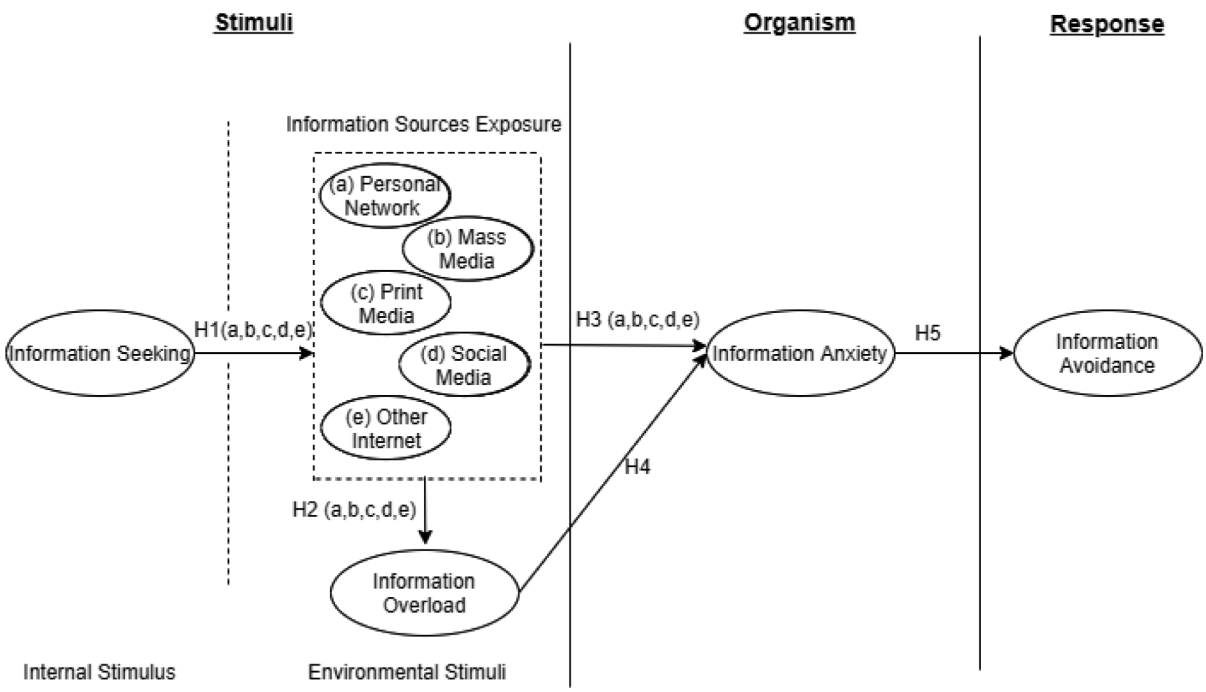

Fig. 3. Proposed Research Model based on the S-O-R Framework.

Table 1
Sample Characteristics.

Socio-demographic characteristics	% ($N = 321$)
Gender	
Male	41.4
Female	55.8
Prefer not to tell	3.7
Age	
Less than 20	9.0
21–25	41.4
26–34	21.2
35–44	13.4
45–54	9.0
55 and higher	5.9
Educational Level	
High School or Equivalent	26.8
Bachelor	37.1
Masters	19.6
Licentiate/PhD	16.5
Living Status	
Living alone	31.8
Living with Family	68.2

4.3. Measures

The survey questionnaire employed in this study included both single and multi-item constructs. The four primary constructs of the study, information seeking, information overload, information anxiety, and information avoidance, were measured using multiple items on a five-point Likert-type scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Information seeking was measured using four items, two were adapted from Yang and Kahlor (2013) , and the other two were self-developed. Information overloaded was measured using five items, three adapted from Williamson, Eaker, and Lounsbury (2012) , and two adopted from Farooq et al. (2020) . Information anxiety was measured using six items, out of which five were adapted from López-Bonilla & López-Bonilla (2011), and one was self-developed. Information avoidance was also measured using six items, out of which three were adapted from Guo et al. (2020) , one from Hmielowski, Donaway, and Wang (2019) , and one was self-developed. The frequency of use of twelve information sources was measured on a self-developed six-point continuous scale, that is, Never = 0 to More than 6 h = 5. Details of items and their sources are given in the Appendix. The questionnaire also included questions about gender, age, educational level, and living status.

4.4. Data analysis

The data was downloaded from the survey platforms in CSV files. An initial screening was conducted to remove any missing response and to check data normality. The frequency of information sources used was divided into five groups to measure 'exposure to information sources'. Exposure to the personal network, mass media, and print media was measured using single items, whereas exposure to social media and other internet sources was measured with the help of multiple items (detail in Table 5). Several items had skewness and kurtosis values higher than the threshold value (0.3) (Kline, 2005; Hair et al., 2014). We used partial least square structural equation modeling (PLS-SEM) in SmartPLS v3.2 to test our hypothesis. PLS-SEM, a multivariate technique, is particularly useful when data has normality issues, models with medium to high complexity, and hypotheses are exploratory (Hair, Hult, Ringle & Sarstedt, 2016).

PLS-SEM analysis takes place in two steps. In the first, the measurement model is tested to ensure the quality of constructs used in the model through reliability and validity testing (detail is given in Section 5.1. Measurement Model Testing). In the second step, structural model assessment is carried out to examine the relationship between the constructs using the path coefficient (β) and coefficient of determination (R^2). For significance testing, the complete bootstrapping procedure was run with 5000 samples, and no sign changes at a significance level of 0.05. We followed the guidelines by Hair et al. (2016) for evaluation and reporting results.

5. Results

5.1. Measurement model testing

5.1.1. Reflective constructs

The reliability of reflective measures was assessed through internal consistency, items reliability, convergent, and discriminant validity (validity). Cronbach's alpha (α) is used traditionally as a measure of internal consistency, composite reliability (CR) has been found as a better measure of internal consistency (Henseler, Ringle, & Sinkovics, 2009). Although we examined both α and CR, we are reporting only CR values in this paper. Item reliability was assessed with the help of item loadings. Average variance explained (AVE) was used to assess convergent validity, whereas the $HTMT_{0.85}$ ratio (Henseler, Ringle, & Sarstedt, 2015) was used for determining discriminant validity. The results of reflective measurement model testing are shown in Table 2.

The CR values for all the constructs were above the threshold of 0.70, and item loadings were above the recommended value of 0.70 (Hair et al., 2016). AVE of the reflective constructs was also higher than the threshold value (0.5) (Hair et al., 2016). Together, Tables 2 to 4 confirms the reliability and validity of the reflective constructs involved in the study. In the final model, Information seeking was measured with four items, information overload with five items, information anxiety, and information avoidance with six items each.

5.1.2. Formative constructs

Unlike reflective measures, the quality of formative constructs is assessed by examining collinearity, the significance of both outer weights, and item loadings on the given constructs (Hair et al., 2016). The variance inflation vector (VIF) should be between 0.2 and 5 (Hair et al., 2016). The significance of formative items was assessed by examining the significance (p-value) of outer weights first, then checking the item loadings, and lastly significance of item loadings, if required (Hair et al., 2016). If the outer weights are insignificant, then item loadings are examined. If items loadings are less than 0.5, then the significance (p-value) of the item loadings is checked. If the item loading is/are significant, the items are retained otherwise removed from further analysis. Table 5 shows the reliability and validity of formative variables.

As shown in Table 5, the VIF for all the formative items was between 1.223 and 2.156, showing no issue of collinearity. Out of nine formative items for information source exposure, only one item (OIS2) from other internet sources could not fulfill the quality criteria for formative constructs. Item loadings of OIS2 ($p = 0.52$) were insignificant. After the measurement model assessment, social media sources exposure was measured with five items, whereas other internet source exposures were measured with three items.

5.2. Structural model testing

As mentioned in the data analysis section, the structural model was tested by examining the path coefficients (β) and the coefficients of the determination (R^2). In this way, we examined the relationship of information seeking as an antecedent of information sources exposure and information load; the impact of information source exposure on information overload and information anxiety; the effect of information overload on information; and finally, the relationship between information anxiety and information avoidance. Fig. 4 shows the path coefficients (at $p < 0.05$) and coefficients of determination for Information overload, information anxiety, and information avoidance. For complete statistics, consult Table 5.

The results in Fig. 4 and Table 5 show that information seeking has a significant positive relationship with three out of five sources: Mass media exposure ($\beta = 0.18$, $p < 0.05$), print media ($\beta = 0.18$, $p < 0.05$), and other internet sources ($\beta = 0.33$, $p < 0.05$) substantiating hypotheses H_{1b}, H_{1c} and H_{1e}. Information seeking does not have a significant relationship with personal networks

Table 2
Measurement model for reflective measures.

Constructs	M	SD	Loadings	alpha	CR	AVE
Information Seeking	3.76	0.79				
IS1	3.75	1.01	0.77	0.80	0.87	0.63
IS2	3.85	0.97	0.77			
IS3	3.83	0.91	0.79			
IS4	3.60	1.09	0.84			
Information Overload	2.84	0.89				
OV1	2.90	1.19	0.79	0.85	0.89	0.62
OV2	2.87	1.15	0.80			
OV3	2.77	1.14	0.82			
OV4	3.07	1.09	0.74			
OV5	2.58	1.08	0.80			
Information Anxiety	2.46	0.90				
IA1	2.71	1.17	0.85	0.89	0.92	0.65
IA2	2.66	1.07	0.72			
IA3	2.42	1.11	0.87			
IA4	2.13	1.09	0.74			
IA5	2.38	1.14	0.85			
IA6	2.48	1.16	0.78			
Information Avoidance	2.31	0.84				
AV1	2.76	1.28	0.70	0.86	0.89	0.58
AV2	2.24	1.09	0.83			
AV3	2.31	1.04	0.78			
AV4	2.26	1.13	0.75			
AV5	2.22	1.11	0.77			
AV6	2.05	0.93	0.75			
Personal Network Exposure	2.37	1.05	1			
Mass Media Exposure	2.25	1.08	1			
Print Media Exposure	1.62	0.88	1			

The discriminant validity of the reflective constructs was assessed using the HTMT ratio, and results are shown in Table 3.

Table 3
Discriminant validity of the reflective constructs using $HTMT_{0.85}$ ratio.

Constructs	Information anxiety	Information avoidance	Information overload
Information Anxiety			
Information Avoidance	0.64		
Information Overload	0.84	0.59	
Information Seeking	0.19	0.43	0.13

Additionally, we also examined the Fornell-Larker criterion for discriminant validity. The square root of AVE of all four reflective constructs was found higher than its correlation with other constructs (Wong, 2013) (Table 4).

Table 4
Intercorrelations of the reflective constructs.

Constructs	Information anxiety	Information avoidance	Information overload	Information seeking
Information Anxiety	0.80			
Information Avoidance	0.57	0.76		
Information Overload	0.74	0.51	0.79	
Information Seeking	−0.17	−0.36	−0.10	0.79

Table 5
Measurement model statistics for formative constructs.

	VIF	Weights	*p*	Loadings	*p*
Social Media Sources Exposure					
SM1	1.344	0.25	0.19	0.61	0.00
SM2	2.156	0.47	0.02	0.87	0.00
SM3	1.263	0.27	0.12	0.62	0.00
SM4	1.873	0.42	0.03	0.81	0.00
SM5	1.553	−0.13	0.44	0.49	0.00
Other Internet Sources Exposure					
OIS1	1.223	−0.39	0.01	0.08	0.56
OIS2	1.463	−0.06	0.70	0.09	0.52
OIS3	1.253	0.71	0.00	0.81	0.00
OIS4	1.251	0.62	0.00	0.75	0.00

Note: Insignificant loadings are shown in italic.

Table 6
Structural model test results.

Hypotheses	Relationship	*B*	*t*	*P*	Results
H1a	IS–>PN	0.002	0.036	0.972	Not Supported
H1b	IS–>MM	0.177	3.542	0	Supported
H1c	IS–>PM	0.18	3.858	0	Supported
H1d	IS–>SM	−0.044	0.55	0.582	Not Supported
H1e	IS–>OIS	0.333	6.753	0	Supported
H2a	PN–>IO	0.091	1.495	0.136	Not Supported
H2b	MM–>IO	−0.048	0.837	0.403	Not Supported
H2c	PM–>IO	0.111	1.545	0.123	Not Supported
H2d	SM–>IO	0.273	4.572	0	Supported
H2e	OIS–>IO	0.013	0.21	0.833	Not Supported
H3a	PN–>AXE	0.062	1.487	0.138	Not Supported
H3b	MM–>AXE	−0.002	0.055	0.956	Not Supported
H3c	PM–>AXE	−0.014	0.386	0.7	Not Supported
H3d	SM–>AXE	0.114	2.133	0.033	Supported
H3e	OIS–>AXE	−0.024	0.583	0.56	Not Supported
H4	IO–>AXE	0.692	20.589	0	Supported
H5	AXE–>AV	0.564	13.828	0	Supported

Note: IS = Information Seeking, PN = Personal Network Exposure, MM = Mass Media Exposure, PM = Print Media Exposure, SM = Social Media Exposure, OIS = Other Internet Sources Exposure, IO = Information Overload, AXE = Information Anxiety, AV = Information Avoidance.

($\beta = 0.002$, $p = 0.97$) and social media ($\beta = -0.04$, $p = 0.58$). Thus, hypotheses H_{1a} and H_{1d} could not be supported.

Further, while examining the relationship between information sources exposure and information overload, only social media exposure had a significant relationship with information overload ($\beta = 0.27$, $p < 0.05$). All other information sources had an

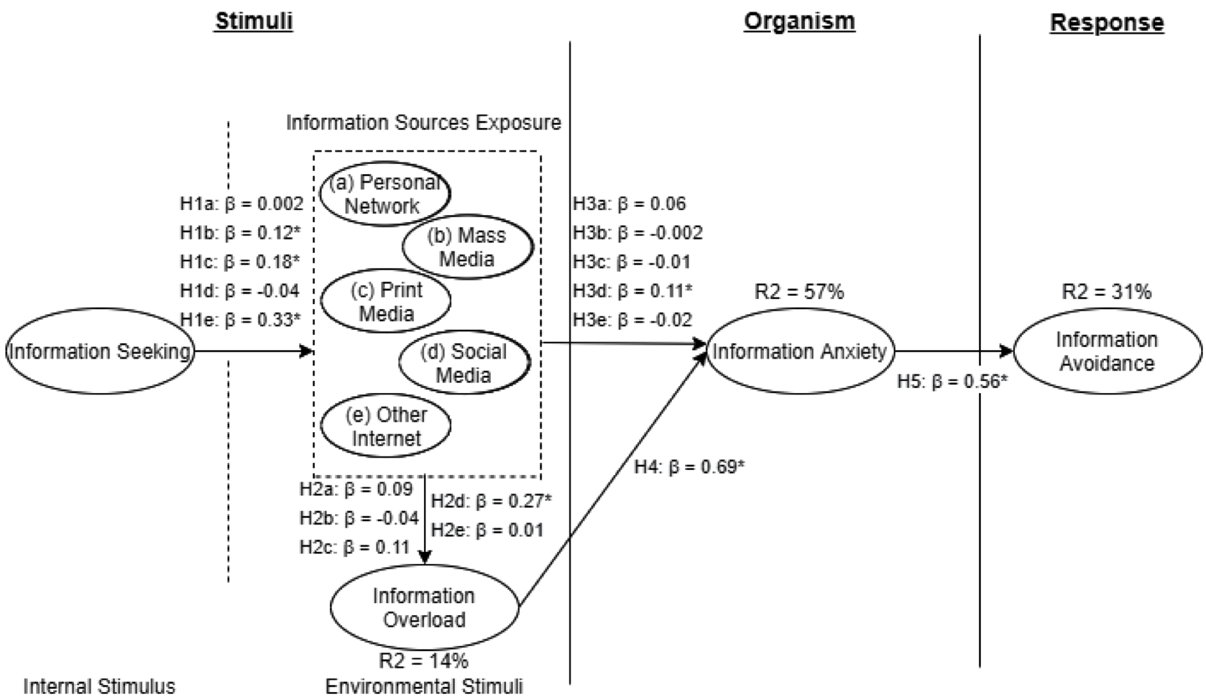

Fig. 4.. Structural Model results showing path coefficients and coefficients of determination for information overload, information anxiety, and information avoidance. All significant results, shown with an asterisk at $p < 0.05$.

insignificant relationship with information overload ($p > 0.05$). Social media exposure accounted for a 14% variance in information overload. Thus, out of five hypotheses between information source exposure and information overload, only one could be substantiated (H_{2d}).

The same results were found when examining the relationship of information source exposure to information anxiety. Out of five, only social media exposure has a significant positive relationship with information anxiety ($\beta = 0.11$, $p < 0.05$) given evidence for supporting hypothesis H_{3d} only. Other hypotheses, H_{2a}, H_{2b}, $H_{2c,}$ and $H_{2e,}$ could not be substantiated. Besides, information overload has a significant positive relationship with information anxiety ($\beta = 0.69$, $p < 0.05$), providing evidence for supporting hypothesis H_4. Social media exposure, together with information overload, accounts for 57% variance in information anxiety.

Lastly, information anxiety significantly predicts information avoidance ($\beta = 0.56$ $p < 0.05$), substantiating hypothesis H_5. Information anxiety accounted for 31% of the variance in information avoidance.

6. Discussion

6.1. Key findings

This study provides several interesting insights related to the information behavior of Finnish people during the Pandemic situation. However, while interpreting the results, we should keep in mind that the respondents were part of a university with some educational qualifications. The results may not be generalized to the whole population.

Firstly, people who wish to learn about Coronavirus (COVID-19) selected traditional information sources such as mass media (including television and radio) and print media (newspapers and magazines). Moreover, when seeking information online, they consulted official websites, such as the government or agencies such as WHO and websites of newspapers. This may be because people in Finland have been found to trust internet-based sources, such as websites, discussion forums, news forums, online newspapers/ magazines, and health portals, for health-related information (Ek, Eriksson-Backa, & Niemelä, 2013). Surprisingly, friends and family (personal network) was not a favorite source for COVID-19 related information. This may be because the COVID-19 situation is new for us, and no one had enough information in a household. It is pertinent to mention here that the COVID-19 situation was developing in Finland at the time of data collection. Further, the information seeker did not prefer social media (Facebook, WhatsApp, Twitter, Instagram, or YouTube) as a source of information. It means traditional media sources and official sources of information were popular among the respondents. Previous research shows that mobile technology and social media usage have become the norm across Finland (more popular among youngsters below age 25) for various purposes such as socialization, hobbies, and information seeking (Koiranen, Keipi, Koivula, & Räsänen, 2019). In this study, we find that social media as a source of health-related information (especially COVID-19) is not a popular medium in Finland. One possible reason for not selecting social media as a source of information for COVID-19 could be that people have concerns about information quality on social media (Zhao & Zhang, 2017), however, this corroboration requires empirical support through a study. The other possible reason is that the current study was conducted during a 'health emergency', therefore, individuals may behave differently compared to a normal situation. They might be more sensitive and cautious in information utilization. Furthermore, health organizations, such as WHO and state information channels, also sensitized people about information credibility.

Secondly, our study identified the exact source that is creating a sense of information overload and information anxiety among the educated people in Finland. We found that social media exposure for information seeking resulted in information overload and information anxiety among the study participants. Previous studies (Bawden, 2001; Cao & Sun, 2018; Edmunds & Morris, 2000; Lee, Kim & Koh, 2016b; Matthews et al., 2020) found that exposure to various information sources creates information overload among people. Moreover, our findings corroborate the results of Farooq et al. (2020) , who found that information overload was higher in the people who used social media as a source of information for COVID-19. Matthews et al. (2020) confirmed that WhatsApp and Youtube are the predictors of perceived information overload. Previously, Balakrishnan and Griffiths (2017) found that YouTube has a positive association with excessive and problematic usage patterns in contexts other than COVID-19. The findings are also in line with another study conducted in the Chinese context, and it proved that information overload is a strong predictor of exhaustion (a psychological state of regret) and as a response, the university students intend to quit the use of social media (Cao & Sun, 2018).

Thirdly, we found that information overload resulted in information anxiety in the context of COVID-19. The findings are consistent with the previous research. Swar et al. (2017) established a negative correlation between perceived information overload and psychological well-being. During the span of the last three decades, the researchers proved that information overload results in cognitive strain Jones (1997); Schick et al. (1990) , stress (Lee, Son & Kim, 2016a), confusion, depressive symptoms (Matthews et al., 2020), anxiety (Bawden & Robinson, 2009), and low motivation (Baldacchino et al., 2002). The current study corroborates the previous findings in an emergency context, that is, COVID-19.

Lastly, we found that the people who felt information anxiety avoided further information related to COVID-19. The findings confirmed the hypothesis that was developed based on the available literature. Case et al. (2005) suggested that individuals avoid the information if there is too much to deal with. Other researchers who worked in the same area also concluded that information overload results in information avoidance (Bawden, 2001; Edmunds & Morris, 2000; Golman et al., 2017). Swar et al. (2017) also reported that online health-related information overload negatively impacts individuals' online health information search behavior.

6.2. Theoretical contributions and practical implications

The study has twofold implications, theoretical and practical. The existing information behavior theories and models explain that several factors shape an individual's information behavior, and the context is one of those factors (Wilson, 1999). The current study explored individuals' information behavior in a particular context, that is, health crisis and the data were collected when the virus was spreading, and the uncertainty among the people was at a peak.

Theoretically, to the best of our knowledge, it is the very first study chalking the extent of information anxiety and information avoidance underpinning the S-O-R framework in the health crisis. The COVID-19 brought uncertainty at the individual as well as the societal level, and people want to know about it to minimize the uncertainty level. Therefore, we proposed the information-seeking behavior as an internal stimulus in our study. Since a wide range of information sources have been used during the COVID-19 pandemic, we focus particularly on the information sources exposure as an external stimulus, rather than the knowledge or awareness accumulated from the sources. The current study expanded the previously proven (Cao & Sun, 2018) effect of information overload on the discontinuation of information source use, along with information overload. We used information seeking as internal and source exposure as external stimuli. The model helped identify the stimuli affecting the cognitive and affective state and individual's actions during a health emergency. By employing the S-O-R framework, the study provides a theoretical lens for model construction, keeping in mind the external environment factors in health information behavior, technostress literature, information seeking discontinuous, and crisis management. The framework will significantly help in understanding the relationship between the aforementioned factors. The study has examined the individual's information behavior to propose a viable set of actions to manage health crisis information behavior.

The study has practical implications as well. The study confirmed that active information seekers were using the sources which were not causing information overload and information anxiety. Therefore, it is suggested that if we want to reduce the information overload, information anxiety, and information avoidance, which are consequences of information overload and information anxiety, there is a need to adopt the strategies to make people active information seekers.

There is a need for public training, helping them learn the criteria to examine the information credibility of social media or any other platform. Mainly three already proven factors, which are, medium credibility (Cooley & Parks-Yancy, 2019 ; Li & Suh, 2015), source credibility (Westerman, Spence, & Van Der Heide, 2014), and message credibility (Li & Suh, 2015) should be a part of these kinds of training. This training could be a part of information literacy programs/health literacy programs at the university level for the student, whereas, for employees, continuous professional development workshops could be arranged to improve information literacy skills, particularly health literacy skills. Health literacy is "the degree to which individuals have the capacity to obtain, process, and understand basic health information needed to make appropriate health decisions" (U.S Health Resources and Services Administration, 2020). It is argued that health literacy is important to develop among all health system stakeholders to cope with the information overload so that they may be able to filter the required information (Klerings, Weinhandl, & Thaler, 2015). Health literacy not only helps individuals to make appropriate health-related decisions but also it has been negatively associated with health-related information overload (Jiang & Beaudoin, 2016) and information avoidance (St. Jean, Jindal, & Liao, 2017). Therefore, it is recommended that health literacy training should be a regular part of public training. Particularly regarding crisis management, extensive training and guidelines should be provided to the public to prepare them for any crises, otherwise, they will have cognitive and affective pressures and most likely will make wrong decisions. Furthermore, social networking sites administrators should develop policies regarding the volume of information sharing (Nawaz et al., 2018), particularly during crises. In the recent past, social bots and cyborg have been used to develop and steer public opinion in a particular direction (Alsmadi & O'Brien, 2020 ; Zhang & Ghorbani, 2020), their use during a pandemic for causing panic cannot be diminished (Paletz, Auxier, & Golonka, 2019). This area also needs special attention from the administrators of social networking sites.

6.3. Limitations and future recommendations

The study is not without significant limitations. For example, we measured single items to measure exposure to information sources such as personal networks, print media, and mass media, which may have limited the predictive validity of the constructs (Diamantopoulos, Sarstedt, Fuchs, Wilczynski, & Kaiser, 2012). Furthermore, we did not use physicians, pharmacists, and nurses as a primary source of information.

To further verify and identify any difference, the model should be tested on different social groups and different contexts. Furthermore, the stimuli other than information source exposure and information overload may also be added as predictors of the 'organism', that is, information anxiety, and similarly for the 'response', that is, information avoidance. The role of moderators, that is, the existing state of knowledge, education level, gender, and context, may also be considered to expand further the model for a comprehensive understanding of information behavior during a health crisis.

One of the study findings that Finnish people used social media less frequently for seeking COVID-19 related information opens the direction to future research. It is imperative to conduct explanatory research to understand the reasons for the low use of social media for health information seeking by Finnish people. Based on the current study, it can be predicted that they may feel overloaded due to the information explosion on social media channels; the other reason may be the credibility and trust issues. However, future research can help to explore the actual causes.

Another future avenue that can be looked into is how the users can be trained to make good use of information sources so that they do not feel overwhelmed. Improving information literacy skills can help in critical evaluation of pieces of information and balanced decision-making, which may reduce information overload and its consequences (Lee, Lee, & Lee-Geiller, 2020). Information literacy skills may involve information acquisition, information evaluation, and information use (Ahmad, Widén, & Huvila, 2020).

7. Conclusion

The purpose of this study was to understand the information behavior (information seeking and information avoidance) during the COVID-19 pandemic in Finland. The study empirically validated the Stimulus, Organism, and Response (S-O-R) framework by identifying that individuals who have more exposure to social media sources were more likely to feel information overload and information anxiety during health crises. The frequency of social media sources exposure and the feelings of information overload affect individual's cognitive and affective state and create information anxiety-causing 57% variance. The cognitive and affective state of people ultimately leads to action, and based on the study findings, it is confirmed that an individual's level of information anxiety has a significant positive impact on the level of information avoidance. We also found that print media, mass media, and other Internet sources such as official websites and the websites of newspapers and magazines were primary sources of information during the COVID-19 pandemic. The study highlights the need that during a situation of uncertainty, particularly a health crisis, individuals should be trained to control the factors that may create information overload. Further, they should be trained to manage information anxiety so that they do not avoid information, as avoiding information during a pandemic may be counter-productive for the preventive measures.

CRediT authorship contribution statement

Saira Hanif Soroya: Conceptualization, Resources, Writing - original draft, Writing - review & editing, Project administration. **Ali Farooq:** Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **Khalid Mahmood:** Supervision. **Jouni Isoaho:** Supervision. **Shan-e Zara:** Conceptualization.

Appendix

Following reflective constructs used in the study were measured on a 5-point scale (1=strongly disagree, 2= disagree, 3= neither agree nor disagree, 4=agree, 5=strongly agree)

Constructs	Item Description	Sources
Information Seeking	IS1 - I have sought out COVID-19 related information.	Yang and Kahlor (2013)
	IS2- I have looked at different information sources to obtain information about COVID-19	Yang and Kahlor (2013)

(*continued on next page*)

(*continued*)

	IS3 - I have paid close attention to COVID-19 related information.	Self-Developed
	IS4 - I have actively searched for COVID-19 related information.	Self-Developed
Information Overload		
	OV1 - I am overwhelmed by the amount of information that I process daily from multiple channels/ sources about COVID-19.	Williamson et al. (2012)
	OV2 - I am often distracted by the amount of information on multiple channels/sources about COVID-19.	Farooq et al. (2020)
	OV3 - There is so much information available to me on the subject of COVID-19 that I have trouble choosing what is important and what's not.	Williamson et al. (2012)
	OV4 - When I search for information on COVID-19, I usually get too much rather than too little information.	Williamson et al. (2012)
	OV5 - I receive too much information regarding the COVID-19 pandemic to form a coherent picture of what's happening.	Farooq et al. (2020)
Information Anxiety		
	IA1 - I feel apprehensive (anxious) due to too much information on COVID-19 around me.	López-Bonilla & López-Bonilla (2011)
	IA2 - Information overload about COVID-19 does not scare me at all.	López-Bonilla & López-Bonilla (2011)
	IA3 - Working with too much information related to COVID-19 make me very nervous.	López-Bonilla & López-Bonilla (2011)
	IA4 - I feel aggressive and hostile towards too much of available information on COVID-19.	López-Bonilla & López-Bonilla (2011)
	IA5 - I get a sinking(unpleasant) feeling when I think of searching for information related to COVID-19	López-Bonilla & López-Bonilla (2011)
	IA6 - I feel stressed about making decisions or choosing the right information on COVID-19.	Self-Developed
Information Avoidance		
	AV1 - I intentionally ignore some information related to COVID-19.	Guo et al. (2020)
	AV2 - I scroll down web pages to avoid COVID-19 related information.	Guo et al. (2020)
	AV3 - I tune out of information about COVID-19.	Hmielowski et al., 2019
	AV4 - I use different means to avoid information related to COVID-19.	Guo et al. (2020)
	AV5 - I unsubscribe/leave the information sharing platforms due to excessive information on COVID-19.	Self-Developed
	AV6 - When it comes to COVID-19, I don't want to know more.	Self-Developed

Information Sources:Information sources constructs were formative measured using a 6-point scale [1 = never, 2 = less than one hour, 3 = 1–2 h, 4 = 3–4 h, 5 = 5–6 h, 6 = more than 6 h]. Each source was presented after the following statement:

"Tell us your daily usage using the following information sources regarding COVID-19 information".

Personal Network	Family, friends, and relatives
Mass Media	Mass media (Television and/or radio)
Print Media	print media (magazine, newspaper, pamphlets, etc.)
Other Internet Sources	
OIS1	University E-mail/communications
OIS2	University Intranet
OIS3	Internet searches, online newspapers, websites
OIS4	Governmental/official websites
Social Media Sources	
SM1	Facebook
SM2	WhatsApp
SM3	Twitter
SM4	Instagram
SM5	YouTube

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