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Understanding the impact of information sources on COVID-19 related preventive measures in Finland

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A R T I C L E I N F O

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A B S T R A C T

The COVID-19 pandemic amplified the influence of information reporting on human behavior, as people were forced to quickly adapt to a new health threatening situation by relying on new information. Drawing from protection-motivation and cognitive load theories, we formulated a structural model eliciting the impact of the three online information sources: (1) social media, (2) official websites, and (3) other online news sources; on motivation to adopt recommended COVID-19 preventive measures. The model was tested with the data collected from university employees and students (n = 225) in March 2020 through an online survey and analyzed using partial least square structural equation modeling (PLS-SEM). We observed that social media and other online news sources increased information overload amongst the online information sources. This, in turn, negatively affected individuals' self-isolation intention by increasing perceived response costs and decreasing response efficacy. The study highlights the role of online information sources on preventive behaviors during pandemics.

1. Introduction

A novel coronavirus disease (COVID-19) was first reported in late 2019 in Wuhan, China, and quickly spread to become a global pandemic. The pandemic was unprecedented in scale and had disruptive impacts across societies and the industry [1,2]. During the pandemic, several negative emergent phenomena related to information technology and its use appeared, for example, cybercrime [3], cyberchondria [4,5], information-specific anxiety [6], and increased general anxiety and depression [7,8]. Besides, not all individuals had the capacity, possibility, or will to follow the recommended health measures [9]. Governments adopted various strategies for curbing the disease, with some countries being stricter than others [10]. Due to the complexity of the situation and fears concerning the actual pandemic and its impact on the production and availability of goods, individuals were at an increased risk of experiencing information overload [5]. From the Information Systems (IS) perspective, an interesting research problem includes the optimal coping strategies in the pandemic situation and what legislators, policymakers, IS system designers, and intervention designers can do to support individuals and boost their adoption of recommended health measures.

Recent IS literature on coping has focused predominantly on technology artifacts' coping behaviors with problematic dimensions [11]. Among the coping behaviors in stressful situations are venting, seeking social support, resistance or avoidance of IS use, and sticking to the minimum required use [11,12], among others. We supplement this body of literature by investigating how individuals' coping appraisal influences two recommended health behaviors during COVID-19: self-isolation and hygienic care. In addition, we contribute to research on information overload by looking at the effects of three types of online information sources on information overload in the context of COVID-19. We propose a structural model that we test with data (N = 225) collected from university employees and students in March 2020, when COVID-19 had just been declared a global pandemic by the World Health Organization (WHO).

The rest of this study is structured as follows. First, we review previous work on human behavior during COVID-19, after which we present the theoretical lens of the current work. We then move to theorize the relationships of our model. Afterward, we describe our research methodology, data collection procedure, and data analysis. We present our findings, which we follow with a discussion section containing key findings, implications, limitations, and future work.

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2. Background

2.1. COVID-19 pandemic and information behavior

What differentiates COVID-19 from other recent pandemics is its enormous scale, impact, and duration [2]. People globally were encouraged to adopt preventive measures, including self-isolation, avoiding public places, good hygienic care [13], and face mask use [14]. Governments, international bodies such as WHO, and similar local authorities used various media sources, including mass media, print media (also referred to as conventional sources), and digital media (including websites and social media), to reach out to the masses, mobilize them and convey measures against the unprecedented situation. Further, given the uncertain situation, people themselves turned to the internet to search for COVID-19 related information [15]. Apart from the conventional sources and peers, social media, internet-based sources (such as search engines and news websites), and official websites (such as of governments' or official bodies' such as UN's or WHO's websites) were used to find COVID-19 information [6,16–18]. Google Trends report also showed a substantial increase of interest in COVID-19 from February 2020, peaking in March 2020, as reported by Ref. [6].

The availability of internet-based information sources (included social media) can be regarded as a double-edged sword. First, we must acknowledge the positive effects, including disseminating valuable COVID-19 related information [16], such as precautionary measures [4]. It also enabled people to compensate for the resulting lack of social interaction by engaging more in online activities such as social media [19], and online gaming [1,5,20–22]. People could seek reassurance and comfort from their peers through online social networks [19] and online peer support group sessions [23] and consequently compensate for the lack of face-to-face interaction during COVID-19. At the time of this uncertainty, financial insecurity, and fear of health hazards, the internet can help alleviate the resulting stress and anxiety [24,25]. Furthermore, through the internet, services such as online psychotherapy, guidance for home-based relaxation techniques, and stress management skills guidance can also be provided [14,23].

On the other hand, the increased use of the internet during COVID-19 had some problematic consequences. First, excessive internet use on itself can create anxiety [26]. Recent studies have shown that internet-based sources negatively impact the masses, both in terms of physical and mental well-being. For example, Farooq et al. [4] showed that information overload and cyberchondria, both are outcomes of Internet-based information sources, negatively impact self-isolation intention. The study showed that information overload was higher among the people who used social media as the source of information. Another study showed that increased engagement with online activities and social media during the COVID-19 pandemic gave rise to anxiety and depression [7,8]. One of the aspects that presumably influenced anxiety, information overload, and overall coping with the situation [11] was the online information sources that people used [6,27]. For example, Youtube was found to have COVID-19 related misinformation in over a quarter of its most viewed videos on the pandemic [27]. COVID-19 related misinformation has been shown to negatively influence the intention to adopt recommended health measures [28]. The spread of misinformation has been attributed to information overload and online source trust [5]. Thus, the online information sources and their accuracy is paramount in motivating people to adopt recommended health behaviors during COVID-19. Another study found that social media sources create information overload and information anxiety among their users, which negatively impacts the user's information behavior, and they start avoiding the information [6].

A review study of digital interventions for combating the COVID-19 pandemic showed that various online interventions were designed, ranging from chatbots to video-consultation [29]. However, it remains unclear to what extent these services were utilized. As the situation is complicated, IS research can contribute by studying the effects of technologies on human behavior during this unprecedented time [30]. Furthermore, while previous research on the topic remains unclear, to what extent it can be applied and generalized to the COVID-19 context. The same applies to the previous research on coping [11,12]. In summary, understanding human online behavior and the impact of engagement with various online services during COVID-19 is relevant but not yet well understood. There is a need to identify the internet-based sources that are doing more harm than good and devise strategies to minimize the adverse effects.

2.2. Theoretical lens of the study

To investigate which of the online sources are doing more harm than good, we use reasoning based on cognitive load theory (CLT) to highlight the negative outcome of being faced with too much new, ill-defined, poorly conceptualized, and ambiguous information. We do this by focusing on information overload. We then link information overload to protection motivation theory (PMT) to understand the influence of information overload on human behavior during COVID-19.

CLT is built on modern neural science, human evolutionary history, and constructivism [31]. It divides cognitive load into (1) intrinsic, (2) extraneous, and (3) germane loads. Intrinsic load refers to individuals' ability to process information and is strongly connected to prior knowledge structures. Extraneous load refers to the cognitive load imposed by the given task, i.e., poorly structured news increases extraneous load. Germane load is related to the processing capacity that translates knowledge from working memory into long-term memory. All three types of cognitive load are modeled to be additive, in that if a person is experiencing germane load, they will have less capacity to deal with intrinsic and extraneous cognitive load. If the addition of the three loads exceeds human mental capacity, cognitive overload occurs [31].

Previous work has discussed different types of overloads, such as information [32] and social overload [33]. The CLT theory has been used widely in learning and can explain human behavior in situations where they need to acquire information on a new topic, such as COVID-19 [5]. In our context, we focus specifically on cognitive overload resulting from the excessive, novel, and poorly conceptualized COVID-19 information, and we discuss this as information overload [32]. To connect information overload to health-related behavior, we turn to PMT.

PMT emerged as a theory to explain motivation based on coping appraisal and threat appraisal [34]. Threat appraisal consists of perceived severity and vulnerability, whereas coping appraisal consists of self-efficacy, response efficacy, and response costs [4,35,36]. Studies have further predicted factors that influence threat and coping appraisal (for example [4,35,36], and behavioral consequences of them and protection-motivation [37]. In the context of COVID-19, PMT has already been used to predict, for example, peoples' self-isolation intention with the finding that both cyberchondria and information overload reduce self-isolation intention [4]. In this work, we focus in particular on people's coping appraisal. We look at the three constructs of (1) self-efficacy, the individual level perception of the capability to carry out desired actions; (2) response efficacy, the belief that the given response results in the desired outcome; and (3) response cost, the perceived costs associated with the given action. PMT posits that these three influence an individuals' protection motivation and, ultimately, health behavior [34]. We look at two health behaviors that were recommended during COVID-19: self-isolation and hygienic care. However, self-reported behaviors are usually prone to social-desirability bias that can impact results [38]. In contrast, intentions are easy to measure through self-reported data [36,39]. Further, as per the theory of planned behavior, intention predicts behavior [40]. To avoid any bias, we focused on self-reported intentions than actual behaviors in this study. Further, as we measure the effects of the coping appraisal constructs on the intentions, we also needed to contextualize the coping appraisal constructs to the specific behavioral actions.

3. Hypothesis and research model

3.1. Effect of online sources

The internet offers an endless amount of information in practice, and people seek this information from varying sources [41]. In addition to the internet, information is still shared through offline social networks and traditional mass media [42]. The use of social media as an information source has been criticized, as laypeople share subjective opinions and occasionally even misinformation [43], which at times can be challenging to distinguish from valid evidence-backed information [44]. During COVID-19, all news sources were further subject to reporting inaccurate information, as they were forced to rapidly produce news reports on a novel topic that was not necessarily previously familiar to them. This leads to disseminating poorly structured information, which may have obfuscated individuals' capability to accurately conceptualize the new status quo [1,5,21,22]. The situation where individuals receive too much information for them to process is referred to as information overload [45].

Information overload is understood through CLT as the outcome of being forced to process information that exceeds the individuals' cognitive capacity [31]. According to Sweller [31]; in addition to the quantity and quality of information, prior knowledge also plays an important role in creating information overload in individuals. Simply being exposed to any kind of news during COVID-19 introduces some cognitive load, which runs the risk of ultimately experiencing information overload [32]. However, the news source's quality in terms of information accuracy and presentation has a major impact. As there is little regulation in social media and online news on what to publish, using these as information sources may increase information overload. On the other hand, as traditional news media are bound to uphold their reputation and follow journalistic ethics and rigor, their reporting may be more accurate and better structured. Thus, we predict traditional online news to have less impact on information overload. Still, the information available even at news websites can increase information overload. [6,18] found that people consulted a variety of sources such as social media, internet-based sources (such as search engines and news websites), and official websites (such as of governments' or official bodies' such as UN's or WHO's websites). Given that dissemination of the same content from various information distributions channels can cause information overload [46], we propose the following three hypotheses:

H1a. Social media relates to information overload.

H1b. Official websites relate to information overload.

H1c. Other internet sources (news websites and search engines) relate to information overload.

3.2. Effects of information overload

Self-efficacy is defined as the individual's ability to carry out actions that result in the desired outcome. The concept of self-efficacy is typically contextualized to see its relationship with corresponding behavioral intention. Accordingly, there is a need to understand and measure self-efficacies corresponding to self-isolation and hygienic care separately. We follow this approach and divide self-efficacy into (1) isolation self-efficacy; and (2) hygienic care self-efficacy (further details in Section 4.1). Using CLT, information overload can be viewed as a state of stress. An individual's cognitive capacity is overloaded, and this impairs their ability to function. Therefore, we postulate the two following hypotheses.

H2a. Information overload negatively relates to self-isolation self-efficacy.

H2b. Information overload negatively relates to hygienic care self-efficacy.

Response efficacy refers to the individuals' perception of the action they take results in the desired outcome. Similarly to self-efficacy, response efficacy is contextualized to specific actions [4,35,36]. In our context, self-isolation response efficacy means an individual believes isolation to be a preferable action for curbing the pandemic and reducing associated risks. While information overload is a stress response, according to CLT, it is specifically caused by having too much information to process [31]. This introduces uncertainty to decision-making and beliefs about response efficacy. With misinformation and inaccurate information circulating online [5] and not having the capacity to process it all, individuals' cannot be sure about the effectiveness of suggested responses. Thus, we postulate the following.

H3a. Information overload negatively relates to self-isolation response efficacy.

H3b. Information overload negatively relates to hygienic care response efficacy.

Continuing with the presumed negative effects of information overload, we look at how it influences response costs. Response costs refer to costs associated with specific behaviors [35,36]. For example, self-isolation response costs could be reduced freedom, reduced social interaction, and having less exercise. Typically almost all actions have response costs, and our behavior is regulated by our appraisal of whether the benefits outweigh the costs. As previously stated, information overload impairs our ability to conceptualize situations and is also associated with stress. This may lead individuals' to perceive response costs as higher than they normally would. Previous work using PMT also indicates that this is the case [4]. Thus, we postulate the following.

H4a. Information overload relates to self-isolation response costs.

H4b. Information overload relates to hygienic care response costs.

3.3. Effects of coping appraisal

As self-efficacy refers to individuals' ability to carry out actions, PMT postulates that it plays a role in behavior. If an individual believes they are unable to carry out an action, or that action has little impact on the surrounding world, they are less likely to do so [47,48]. Studies show that self-efficacy has a significant relationship with corresponding behavioral intentions [35,36] and behaviors [35]. During the COVID-19 pandemic restrictions, self-efficacy may have been lowered by, for example, the need to work socially to make money or not having adequate work peace at home. Hygienic care response efficacy may have been lowered by not being experienced with the recommended hygienic care or not having the proper equipment at home. Self-efficacy is a core component of human motivation and is therefore predicted to have a strong relationship with behaviors [47]. Previous work during pandemics and health risk situations also suggests that self-efficacy increases behavioral intention [49–51] supports this hypothesis. For these reasons, we propose the following.

H5a. Self-isolation self-efficacy relates to self-isolation intention.

H5b. Hygienic measure self-efficacy relates to hygienic care intention.

The role of response efficacy in action is linked to motivation. If an individual believes a certain behavioral response to having a positive or desired effect, they are more likely to carry out that behavior [34]. During COVID-19, official websites, news sites, and several other venues broadcasted the importance of social isolation and hygienic care for curbing the pandemic. It has been found that response efficacy has a significant correlation with COVID-19 preventive behavior among hospital staff [52]. Because of this, we predict that individuals' response efficacy related to these two behaviors will also increase among the people. Thus, we propose two hypotheses:

H6a. Self-isolation response efficacy relates to self-isolation intention.

H6b. Hygienic measure adoption response efficacy relates to hygienic care intention.

In PMT, by definition, response costs have a negative relationship with protection motivation [34]. For example, response costs could manifest as decreased ability to socialize [22] or travel freely. However, the magnitude of response costs varies between activities. As self-isolation is a behavior that radically limits individuals' freedom and alters their lives [4], we predict this behavior to have significant response costs. On the other hand, the hygienic care response costs can manifest as the need to spend money on soap and hand sanitizer. Thus, our final two hypotheses are as follows.

H7a. Self-isolation response costs negatively relate to self-isolation intention.

H7b. Hygienic care response costs negatively relate to the hygienic care intention.

3.4. Research model

The final proposed research model is displayed in Fig. 1. Altogether, we propose 15 hypotheses, which we divide into seven clusters.

4. Methodology

4.1. Survey design and data collection

To test the model given in Fig. 1, an online survey was designed using validated scales from the previous literature related to healthcare and pandemics. The questionnaire began with an introductory paragraph outlining the study's purpose and data handling procedures, followed by an explicit consent to participate in the study. After that, respondents were shown four items related to self-isolation and three items related to hygienic care during the COVID-19 pandemic. These items were adapted from Ref. [53], and we used the statement "I intend to..." before these items. Next, we asked participants about the sources (Four items, Yes/No)) they are used for accumulating information on COVID-19. The sources were 1) online newspapers, 2) Internet searches and websites, 3) social media, and 4) official websites (THL and Finnish government websites). After that, respondents were shown four measures related to self-isolation and asked coping appraisal constructs (response efficacy, response cost, and self-efficacy). Next, three measures related to hygienic care were shown, followed by coping appraisal constructs. In both cases, the same number of items were used to measure response efficacy (2 items), response cost (3 items), and self-efficacy (3 items). Items for self-efficacy were adapted from Ref. [54], whereas items for the other two coping appraisal constructs were adapted from Ref. [55]. After the constructs related to intention and coping appraisal, three items, adapted from Ref. [56], were used to measure information overload (for item description, consult Table 1).

In addition, demographic information such as age, gender, employment status, and living situation was asked at the end of the questionnaire. The questionnaire was uploaded to an online survey tool, Webropol, and the survey link was shared among students, faculty, and employees using email lists at a target University, the best way to reach the target population during the pandemic situation. Furthermore, this highly educated sample arguably has high internet usage, making them suitable for a study involving internet-based information sources. The data collection continued for about two weeks (March 19-30, 2020),

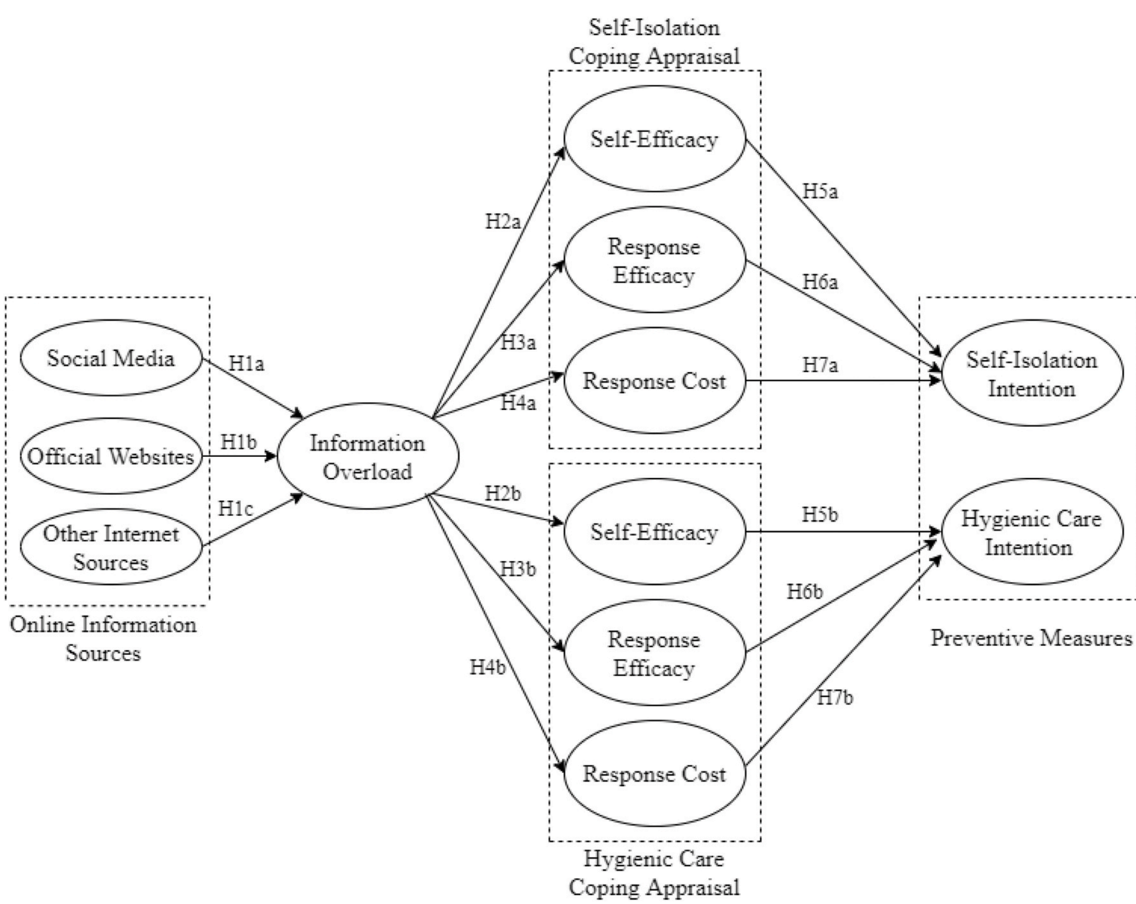

Fig. 1. Research model of the study.

which was the pandemic's peak time in Finland.

4.2. Data analysis

Data was downloaded from the Webropol in CSV and initially examined in SPSS for normality issues. Some items had higher skewness and kurtosis values than the threshold value (0.3) [57], showing a normality issue. Given the normality issue and sample size, we used partial least square structural equation modeling (PLS-SEM) in SmartPLS v3.2 [58]. PLS requires a sample of ten times that of the most complicated multiple regression in the model [32]. Our sample (N = 225) fulfills this criterion. Our study contained both reflective and formative constructs. Information sources exposure/use was measured with four items. For analysis, we treated social media and official websites as single-item constructs. The other internet sources were treated as formative measures consisting of two items ((1) online newspapers, (2) internet searches, and websites). The rationale behind this segregation was to understand the exact source of information overload. All other constructs were treated as reflective constructs.

The PLS-SEM was run in two parts. First, the reliability and validity of the constructs are assessed, also referred to as measurement model testing. For the formative construct, collinearity diagnosis and significance of formative items are checked. Variance inflation factor (VIF) was checked earlier, whereas the stepwise significance of item loadings was also checked as suggested by Hair et al. [58]. For the reflective constructs, the items' internal consistency and items' reliability are used to measure reliability and convergent validity; and discriminant validity is used for validity testing. Internal consistency was conventionally tested using Cronbach's alpha, however, composite reliability is considered a better measure of reliability for PLS-SEM [59], and thus used in this in the study. Item loadings are used for item reliability assessment. Convergent validity is assessed with the help of average variance extracted (AVE), and the HTMT ratio, a new criterion [60], is used for assessing discriminant validity.

In the 2nd part, the relationship between the constructs was examined using Path coefficients (β). The coefficient of determination (R^2) determination, *t-statistics*, and *p-values* were also calculated. This step is referred to as structural model testing. For these steps, we followed the guidelines provided by Refs. [58,61].

5. Results

5.1. Sample characteristics

Out of 225, 65% were female respondents, 32% were males, and the rest preferred not to say their gender. Age-wise, 39% of respondents were less than or equal to 25 years of age, 32% were between 26 and 34, 34% were between 35 and 44, and the rest were 45 years or more. 53% were students while the rest were employed, either faculty member or other supporting staff. In our sample, 54% were living alone while the rest were living in a family household.

5.2. Measurement model testing

In reflective constructs, the composite reliability of all the constructs was above the threshold of 0.7. The AVE was above 0.5, and all the item loadings were above 0.6. Only one item (HC1) from hygienic care intention had an item loading of 0.47 and was removed from further analysis. The mean, standard deviation, item-loading range, composite reliability (CR), and average variance extracted (AVE) for reflective constructs are shown in Table 1:

Table 1
Reliability and convergent validity testing of the constructs involved in the study.

Constructs/Items	IL[a]	CR[b]	AVE[c]
Self-Isolation Intention (Mean:4.30, SD[d]:0.60)			
SI1:Deliberately cancel or postpone a social event, such as meeting with friends, eating out, or going to a sports event	0.77	0.83	0.55
SI2:Reduce using public transport	0.69		
SI3:Avoid going to shops	0.72		
SI4:Stay at home and study/work remotely	0.79		
Hygienic Care Intention (Mean:4.63, SD:0.49)			
HC1:Increase frequency of cleaning or disinfecting things I might touch, such as doorknobs or hard surfaces than usual[e]	0.47	0.78	0.63
HC2:Wash my hands with soap and water more often	0.79		
HC3:Use my arms instead of hands when coughing and sneezing	0.79		
Information Overload (Mean:2.94, SD:0.92)			
IO1– I am often distracted by the excessive amount of information on multiple channels/sources about COVID-19	0.79	0.85	0.67
IO2: I find that I am overwhelmed by the amount of information that I process on a daily basis from multiple channels/sources about COVID-19	0.87		
IO3: I receive too much information regarding the COVID-19 pandemic to form a coherent picture of what's happening	0.78		
Response Cost (Self-Isolation) (Mean:1.77, SD:0.64)			
RC1_SI: The benefits of taking self-isolation measures outweigh the costs	0.72	0.78	0.54
RC2_SI: I am discouraged from taking self-isolation measures as they would impact my work	0.75		
RC3_SI: I am discouraged from taking self-isolation measures because they feel silly	0.73		
Response Cost (Hygienic Care) (Mean:1.48, SD:0.60)			
RC1_HC: The benefits of taking hygienic care measures outweigh the costs	0.67	0.82	0.61
RC2_HC: I am discouraged from taking hygienic care measures as they would impact my work	0.83		
RC3_HC: I am discouraged from taking hygienic care measures because they feel silly	0.84		
Response Efficacy (Self-Isolation) (Mean:4.43, SD:0.58)			
RE1_SI: The self-isolation measures are a good way of reducing the risk of contracting Coronavirus	0.90	0.89	0.80
RE2_SI: The self-isolation measures reduce my chance of catching the Coronavirus	0.89		
Response Efficacy (Hygienic Care) (Mean:4.47, SD:0.55)			
RE1_HC: The hygienic care measures are a good way of reducing the risk of contracting Coronavirus	0.92	0.90	0.82
RE2_HC: The hygienic care measures reduce my chance of catching the Coronavirus	0.89		
Self-Efficacy (Self-Isolation) (Mean:3.99, SD:0.74)			
SE1_SI: I am able to take self-isolation measures if I want to	0.78	0.84	0.64
SE2_SI: Taking self-isolation measures is difficult for me	0.84		
SE3_SI: Self-isolation measures are easy to take	0.78		
Self-Efficacy (Hygienic Care) (Mean:4.34, SD:0.61)			
SE1_HC: I am able to take hygienic care measures if I want to	0.87	0.86	0.68
SE2_HC: Taking hygienic care measures is difficult for me	0.79		
SE3_HC: hygienic care measures are easy to take	0.80		
Social Media Source	1	1	1
Official websites	1	1	1

[a] IL = Item loading.
[b] CR = Composite reliability.
[c] AVE = Average variance extracted.
[d] SD = Standard deviation.
[e] Shows the removed item due to item loading <0.6.

Table 2
Discriminant validity of the constructs using $HTMT_{0.85}$ ratio.

Constructs	1	2	3	4	5	6	7	8	9	10
1. Information overload	0.07									
2. Official websites	0.36	0.04								
3. Response cost (SI[a])	0.53	0.27	0.13							
4. Response cost (HC[b])	0.62	0.14	0.10	0.69						
5. Response Efficacy (SI)	0.50	0.08	0.16	0.73	0.42					
6. Response Efficacy (HC)	0.71	0.13	0.17	0.41	0.59	0.60				
7. Self-Efficacy (SI)	0.16	0.27	0.08	0.79	0.19	0.49	0.18			
8. Self-Efficacy (SI)	0.62	0.09	0.14	0.44	0.63	0.41	0.71	0.31		
9. Self-isolation Intention	0.57	0.09	0.18	0.77	0.36	0.45	0.24	0.50	0.28	
10. Social media	0.17	0.22	0.01	0.07	0.09	0.07	0.02	0.13	0.07	0.07

[a] SI = self-isolation.
[b] HC = Hygienic care.

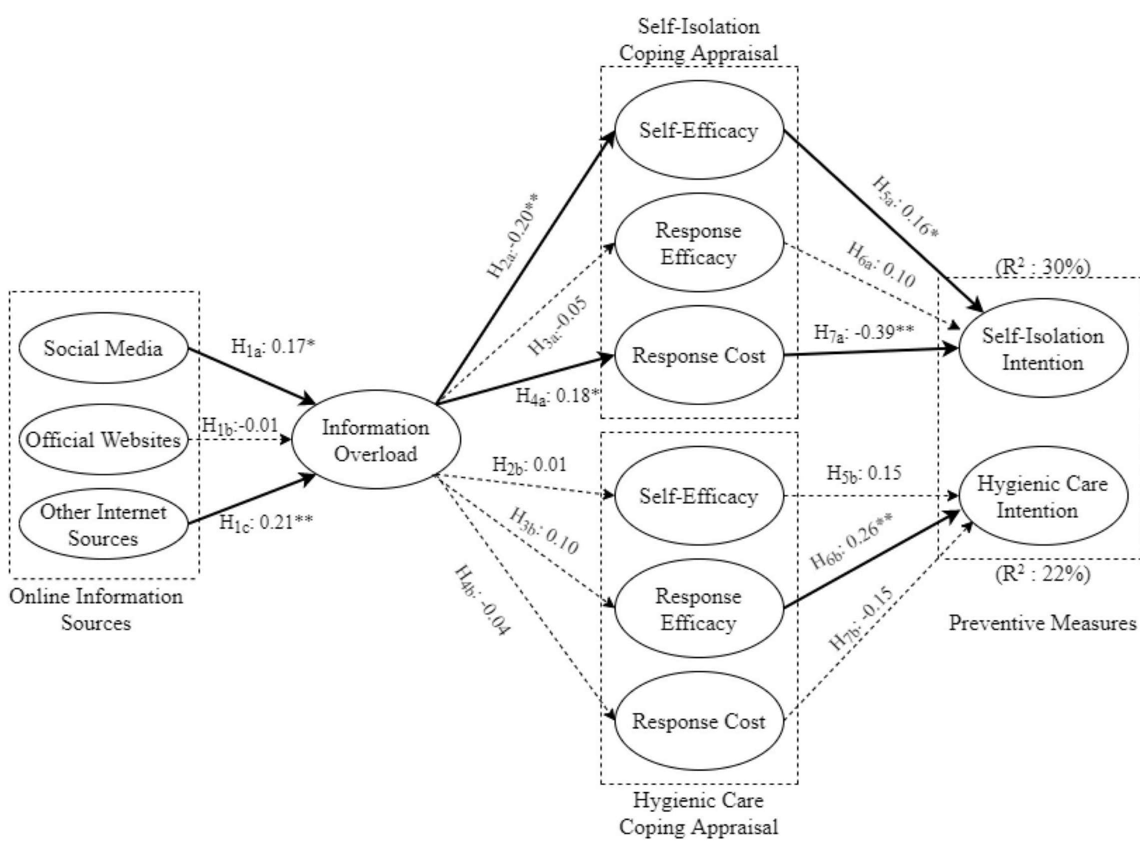

Fig. 2. Structural Model showing significant path coefficients in bold and insignificant relationships in dotted arrows (*p <0.05, ** p < 0.01). Note: The hypotheses not supported are shown in dotted arrows.

For the formative construct, other internet sources, the VIF was 1, and item loadings for both items were 0.79 ($p < 0.05$) and 0.588 ($p < 0.05$), providing evidence for reliability and validity of the formative construct.

The discriminant validity was tested using the HTMT criterion [60] and was found established. Table 2 shows the results of discriminant validity testing.

5.3. Structural model testing

The structural model results are displayed in Fig. 2. Overall, the independent variables explained 30% variance in self-isolation intention and 22% variance in hygienic care intention. Detail statistics of structural model testing are given in Table 3.

The results show using social media ($\beta = 0.17$, $p = 0.01$) and other internet sources ($\beta = 0.21$, $p < 0.01$) as news sources significantly related with information overload. However, official sources did not significant relate with information overload ($\beta = -0.01$, $p = 0.87$). Further, Information overload had a negative significant relation with self-efficacy related to self-isolation $\beta = -0.20$, $p < 0.01$) and positive significant relation with response cost related to self-isolation ($\beta = 0.18$, $p < 0.01$). However, no significant relation was found between information overload and response efficacy of self-isolation ($\beta = -0.05$, $p = 0.43$). With regards to hygienic care, information overload did not significantly relate with any of the coping appraisal construct (Self-efficacy ($\beta = 0.01$, $p = 0.83$), response efficacy ($\beta = 0.10$, $p = 0.11$), response cost ($\beta = -0.04$, $p = 0.54$)).

Further, we found that self-efficacy ($\beta = 0.16$, $p = 0.01$) and response cost ($\beta = -0.39$, $p < 0.01$) significant related with self-isolation intention, however, in case of both these measures did not significant relate with hygienic care intention (self-efficacy ($\beta = 0.15$, $p = 0.06$), response cost ($\beta = -0.15$, $p = 0.05$)). The relationship of response efficacy with corresponding preventive measure intention was different. In the case of self-isolation, the relation of response efficacy was insignificant ($\beta =$

Table 3
Structural model testing results.

Hypotheses	Β	t	p
H1a	0.17	2.51	0.01
H1b	*−0.01*	*0.16*	*0.87*
H1c	0.21	3.15	<0.01
H2a	−0.20	3.07	<0.01
H2b	*0.01*	*0.21*	*0.83*
H3a	*−0.05*	*0.77*	*0.43*
H3b	*0.10*	*1.57*	*0.11*
H4a	0.18	2.62	0.01
H4b	*−0.04*	*0.60*	*0.54*
H5a	0.16	2.36	0.01
H5b	*0.15*	*1.86*	*0.06*
H6a	*0.10*	*1.43*	*0.15*
H6b	0.26	3.01	<0.01
H7a	−0.39	4.81	<0.01
H7b	*−0.15*	*1.96*	*0.05*

Note: The hypotheses not supported are shown in italic.

0.10, $p = 0.15$), whereas, in the case of hygienic care intention, the same relation was significant ($\beta = 0.26$, $p < 0.01$).

6. Discussion

6.1. Key findings

The results from the study show that out of three types of online information sources, only social media (H1a) and other internet sources such as news websites, search engines, and other websites (H1c) create information overload among the people. The official websites' insignificant relationship with information overload (H1b) suggests that information overload is not stemming from the official sources. One possible explanation for this could be that online users can find many posts related to COVID-19 on social media and news websites. The abundance of information combined with a lack of clear conceptualization, structure, and coherence can increase people's cognitive load [21]. By contrast, official websites (THL in Finland, WHO worldwide) provide well-written reports containing unambiguous statistics-based knowledge on the situation aligned with real-world observations. Thus, the quality of the reporting could play a role in reducing information overload. These results suggest that not all online information sources are creating information overload.

The second interesting finding is that information overload significantly relates to coping appraisal constructs (minus response efficacy) of self-isolation behavior, however, no such relationship was found in the case of hygienic care behavior. Regarding self-isolation coping appraisal, the information overload negatively affects self-efficacy, whereas the significant positive relationship with response cost shows that information overload increases perceived response cost related to self-isolation behavior. On the other end, no significant association with the coping appraisal of hygienic care behavior was found.

Thirdly, in the case of self-isolation behavior, both self-efficacy (positively) and response cost (negatively) significantly relate to self-isolation intention, which is as per postulates of PMT. However, no significant relation of response efficacy with self-isolation intention was found. In the case of hygienic behavior, our study does not find a significant relationship with self-efficacy and response cost, unlike we hypothesized. Perhaps the differing relationship between perceived cost and corresponding intentions is because of the magnitude of impact for self-isolation and hygienic care. Self-isolation affected people's lives as they had to forgo many routine tasks, such as going to work, traveling, and even leisure activities. On the other hand, hygienic care required a few more minutes in the lives where one used more soap, applied a hand sanitizer, or used a mask. Opposite to self-isolation behavior, response efficacy was found to have a significant relationship with hygienic care intention.

6.2. Theoretical implications

Topically we contribute to the literature on understanding of human behavior during pandemics such as COVID-19 (e.g. Farooq et al. [4] as well as to the literature on the role of information presentation and information sources in human decision making (e.g. Refs. [6,62]). We extend both these bodies of literature by showing the approximate impact of three online information sources on two recommended health behaviors during COVID-19. Our findings highlight information overload as a key construct when looking at how people behave in novel situations such as the COVID-19 pandemic, and we pinpoint the limited human capacity to process information [31] as a key variable to consider, especially in unprecedented and novel situations.

We also contribute to the PMT literature by suggesting that information overload and information sources are relevant antecedents to coping appraisal. Our differing findings on isolation and hygienic care behaviors demonstrate a need to contextualize coping appraisals in PMT to specific behaviors. We also provide evidence for the feasibility of PMT as a framework for understanding human behavior during the COVID-19 pandemic and other similar situations. The 30% and 22% variance explained (as measured by the R squared values) of our dependent variables could be considered significant, but additional explaining variables are still needed. These variables may be extracted from, for example, the threat appraisal dimension of PMT [34].

6.3. Practical implications

Our empirical results suggest that hygienic care response costs are not a significant predictor of hygienic care intention. By contrast, the response costs of self-isolation are strongly negatively related to self-isolation intention. This implies that not all people experienced isolation to the same degree, even in our sample, where a relatively homogenous sample of university students and personnel was observed. Some experienced high response costs of isolation and were thus less likely to engage in voluntary self-isolation. Such difference was not seen in hygienic care, which may be explained by the low response costs of hygienic care. Taken together, these findings imply that policymakers should take into account the individual differences in the ability to isolate and provide leeway for those who have high response costs for the activity.

Another practical implication of our work relates to the news sources and their impact on behavior. Recent work by Ref. [62] demonstrated that people could be nudged to pay attention to the sources of news they read, which subsequently impacted their perceptions about the material they read. The nudging approach could offer some remedy to the problem of information overload as well, by finding ways to encourage and direct people to read their news in more trustworthy sources. In our case, the governmental sources were the only ones that did not associate information overload. This may be explained by governments outputting well-structured, unambiguous, thought-out information. Thus, similar results could emerge with people reading their news on high-quality news outlets or social media groups where people only post carefully conceptualized information.

6.4. Limitations and future work

Our study has several limitations. First, the collected data were self-reported. Second, we surveyed university teachers and students from a geographically limited area which means the sample consisted of highly educated people. Third, our data were cross-sectional and did not account for any change that may have occurred during the entire duration of the COVID-19 pandemic. Fourth, our study took place in March 2020, a time when COVID-19 was just declared a global pandemic by WHO [5]. While this is not necessarily a limitation per se, it does mean that our findings should be generalized outside the COVID-19 context only with care. Fifth, the study was conducted in a single country where people may have one or very few official websites for COVID-19 related information. Given that official websites can also have issues (for example [63], a multi-country study could provide valuable insights regarding official websites.

Our study encourages further research into the role of information sources in human behavior during pandemics such as COVID-19. To globally curb future pandemic diseases, strong collaboration and compliance with recommended health measures of (1) isolation and (2) hygienic care; is needed. To this end, strategies for keeping people informed while avoiding information overload are needed. While our findings suggest that social media and other internet sources are associated with information overload, the focus should not be on the communication medium (internet) but rather on the content. Official websites typically follow rigorous reporting guidelines. This means that in addition to the information they report being accurate, they also pay attention to presenting the information in an understandable way to the reader. CLT suggests that poorly structured and ambiguous information leads to cognitive overload [31]. Following other recent work, for example [5,6,64], we suggest practitioners focus on the information need of users and information delivery during future pandemic events. Finally, we identify an important avenue for future work to be the longitudinal evaluation of whether people's intention to adopt recommended health measures during COVID-19 has led to significant long-term behavior change. In this study, we measured behavioral intentions in place of actual behaviors. Future studies may collect objective behavior data to test the association between intention and behaviors.

Authors contribution

Ali Farooq: Conceptualization, Methodology, Formal Analysis, Investigation, Data Curation, Writing – original draft, Writing-Review & Editing, Visualization. Samuli Laato: Conceptualization, Writing – original draft, Writing-Review & Editing. A.K.M. Najmul Islam: Conceptualization, Methodology, Investigation, Writing-Review & Editing, Supervision. Jouni Isoaho: Supervision, Writing-Review & Editing.

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