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Article

Measuring information overload and message fatigue toward COVID-19 prevention messages in USA and China

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Summary

COVID-19 prevention messages are a crucial component of disease mitigation strategies and the primary driver of health decision-making during the global pandemic. However, the constant and repetitive nature of COVID-19 messaging may cause unintended consequences. Among the commonly observed phenomena are information overload and message fatigue, which might be experienced differently depending on cultural background. Using measurement invariance testing, this study compared how individuals from two countries—USA ($n = 493$) and China ($n = 571$)—experienced information overload and message fatigue toward COVID-19 prevention messages. Findings revealed that people in China showed significantly lower level of information overload and message fatigue than those in the USA. This study explores the extent of the unintended persuasive effects that people have experienced during the COVID-19 pandemic in different societies, a comparison which has never been studied before, even outside of the context of COVID-19. The study also provides much-needed practical insights to develop public health initiatives that improve COVID-19 prevention communication, which can further reduce these unintended effects in both countries, and has implications for other countries as well.

Key words: COVID-19, prevention messages, information overload, message fatigue, measurement invariance

INTRODUCTION

In December 2019, the first case of the novel coronavirus disease (COVID-19) was detected in Wuhan City of Hubei Province in China. Since this time, COVID-19 has ripped through nearly every country, infecting over 263 million people and killing more than 5.23 million as of 3 December 2021 (World Health Organization, 2021). In doing so, severely crippling the world's economies. Before mass COVID-19 vaccination programs, nonpharmaceutical interventions had been the mainstay to prevent new infections (Baye, 2020). Although a vaccine has been widely available in some countries in the world, the pandemic is not yet under control (Kim and Hong, 2021). Therefore, COVID-19 prevention messages are still crucial public health communication strategies to minimize further disease incidence (Cohen and Kupferschmidt, 2020; Heffner *et al.*, 2021; Su *et al.*, 2021).

Due to the uncertainty and ambiguity around COVID-19, the experts and authorities presented different perspectives of prevention measures and the governmental guidance for prevention also shifted over time in the early stage of the outbreak. Prevention information often contains jargons, which makes it more complicated to understand (Hong and Kim, 2020). Last, the delays in producing effective, evidence-based promotion strategies have further left a vacuum that was quickly filled with misinformation (Adam *et al.*, 2020). Therefore, millions of deceptive and anecdotal preventive strategies appeared on social media platforms during COVID-19.

Information overload occurs when a recipient has insufficient cognitive capacity to handle a large amount of information properly and effectively (Eppler and Mengis, 2004). During COVID-19 pandemic, massive and repeated sharing of COVID-19 prevention information overloaded people's cognitive capacity (Rathore and Farooq, 2020). In turn, lower level of motivation to process COVID-19 prevention messages causes people to experience message fatigue (So and Popova, 2018). It is well-documented that both information overload and message fatigue are unintended consequences of persuasion efforts (So *et al.*, 2017; So and Popova, 2018; Jensen *et al.*, 2020; Reynolds-Tylus *et al.*, 2020). As two responses of information overabundance due to lack of message elaboration, they work together to influence our attitudes and behaviors of COVID-19 prevention messages.

Moreover, these unintended consequences might differ depending on socio-demographic characteristics such as age, gender, education level, income level, and media use, as well as their cultural background, such as residence in different countries (Hong and Kim, 2020). Although all countries have been very much affected by COVID-19, the USA and China have received much significant attention worldwide. China was the first country affected by COVID-19, and the USA is the country with the highest number of infections and deaths in the world (World Health Organization, 2021). Citizens in the USA and China may have had different responses to COVID-19 prevention messages, partly due to previous pandemic experience and different cultural values.

This study aims to compare the degree to which Americans and Chinese experienced information overload and message fatigue toward COVID-19 prevention messages using measurement invariance (MI) testing (Putnick and Bornstein, 2016). With the goals and importance of the study articulated, we begin with a discussion about how information overload and message fatigue may hamper information processing in the era of COVID-19.

This study offers various theoretical and practical insights into the development and delivery of prevention message. First, this study expands the elaboration likelihood model (ELM) by explaining how a large amount of persuasive information can disengage people from message elaboration through information overload and message fatigue. Second, the result of MI tests provides evidence regarding the performance of the adapted measurement of information overload and message fatigue for COVID-19 prevention in the USA and China. Last, this research also provides much-needed practical insights to develop public health initiatives that improves COVID-19 prevention methods, which further avoid these unintended effects in both countries.

Information overload and message fatigue

The ELM was originally developed to explain the underlying psychological mechanisms of attitude change due to different levels of elaboration. ELM conceptualized the processing of persuasive messages into two routes—the central and the peripheral route (Petty and Cacioppo, 1986). The central route involves careful and thoughtful processing of the information presented in support of the advocated behaviors (Petty and Cacioppo, 1986). On the other hand, the peripheral route involves little to no careful thinking, and attitude changes are reliant on simple cues available in the persuasion settings and mental shortcuts (i.e. heuristics; Petty *et al.*, 2009). Since the central route required substantial cognitive efforts, a person's ability and motivation to consider arguments decide whether the central route of persuasion occurs (Petty and Cacioppo, 1986). Hence, the lower level of ability or motivation to process information is associated with less message elaboration. When the amount of incoming information is beyond their information-processing capacity, people might suffer from information overload, which is featured with a state of feeling overwhelmed and confused to handle such a tremendous amount of information properly and effectively (Bawden and Robinson, 2009; Almeida *et al.*, 2016). Aside from ability, a large amount of information can reduce motivation to allocate cognitive efforts by causing message fatigue. In conclusion, information overload and message fatigue are two unintended effects of persuasive messages that lead to less message elaboration during information processing.

Information overload

Information overload arose due to insufficient cognitive capacity to handle a tremendous amount of information properly and effectively (Bawden and Robinson, 2009). Information overload often occurs when too many messages are received from diverse mediated channels and sources (e.g. healthcare providers, social media, everyday conversations with other people) (Eppler and

Mengis, 2004; Bawden and Robinson, 2009). However, they are not able to sufficiently handle a large amount of information (Eppler and Mengis, 2004).

Information overload is evident in many health contexts. For example, cancer patients commonly experience information overload due to the conflicting and uncertain nature of cancer recommendations, complexity of cancer information, and the sheer volume of information present in our ecosystem (Kim *et al.*, 2007; Jensen *et al.*, 2014). As we learned about the characteristics and the effects of COVID-19 prevention information, they were also well-suited to the key components of information overload: First, the information on how to protect ourselves from COVID-19 is expanding and evolving (Seerat and Karthik, 2020). Second, it needs large amounts of cognitive resources for individuals to understand and store the information in memory because of its highly arousing and complex content (Hong and Kim, 2020). Furthermore, it is overwhelming and stressful to keep up with the changing and conflicting information for individuals (Cuan-Baltazar *et al.*, 2020; Gupta *et al.*, 2020).

Message fatigue

Similar to the effects of information overload on ability, message fatigue can reduce message processing motivation. Message fatigue differs from information overload because it not due to the lack of ability to handle overwhelming information. Rather, message fatigue features reduced motivation to allocate cognitive resources due to prolonged and repeated exposures to a class of messages that share a common persuasive goal (So *et al.*, 2017). Four dimensions were included in the conceptual definition of message fatigue: (1) overexposure, which means that that one has been exposed to a class of messages beyond desired frequency (Herbst *et al.*, 2007; Frew *et al.*, 2013), (2) redundancy, means people perceived messages are repetitive and overlapping (Kinnick *et al.*, 1996; Frew *et al.*, 2013), (3) exhaustion, or a feeling of being burned out (Kinnick *et al.*, 1996), and (4) tedium, or lack of enthusiasm (Schumann and Clemons, 1989).

During the ongoing COVID-19 pandemic, constant, daily prevention reminders may result in perceptions of overexposure and redundancy. Consequently, multiple exposures to the same repetitive messages increases the risk of exhaustion and tedium (Koh *et al.*, 2020). With the lockdown during the COVID-19 pandemic, people may feel more depressed, anxious, and powerless, which may increase the extent of message fatigue.

Response to COVID-19 prevention messages in USA and China

It is important to investigate how attitudes and behavioral responses toward prevention messages in a global pandemic differ across countries. Examining the differences between perceived information overload and message fatigue of COVID-19 prevention messages among Chinese and Americans can inform health communication practice and prevention message strategies in both countries (Lu *et al.*, 2021). This study addressed the differences between China and the USA from the individual experience and cultural difference perspectives.

People from different cultural backgrounds are likely to experience the different extent of information overload and message fatigue toward millions of repeated COVID-19 prevention messages. Compared to Americans, the Chinese have had more experience with the pandemic. Many Chinese residents still remember the outbreak of severe acute respiratory syndrome (SARS) in 2003 and the H1N1 influenza pandemic in 2009 (Durham *et al.*, 2012; Dong and Bouey, 2020). They understand the severity of the pandemic and report higher levels of susceptibility after experiencing SARS and H1N1 (Brug, 2009). Previous studies have found that individuals with a high level of susceptibility and perceived severity of a pandemic are more likely to voluntarily adopt prevention information (Duan *et al.*, 2020).

Furthermore, the Chinese government has taken preventive actions such as patient isolation, contact tracing, social distancing, and self-isolation in previous pandemics (i.e. SARS and H1N1). In response to the COVID-19 pandemic, the Chinese government continues advocate people to take these preventive actions. For example, the government announced that all residents in Wuhan city were restricted to stay at home 14 days in self-quarantine to stop the spread of the virus (Du *et al.*, 2020). All large gatherings including the New Year celebrations were also canceled in China. These strict preventive actions have been proved to significantly reduce the spread of the COVID-19 (Liu *et al.*, 2020). Chinese people understand and trust these prevention methods can protect themselves and their families based on these experience (Bruns *et al.*, 2020). Hence, they demonstrated a relatively high level of ability and motivation to enact preventive behaviors during the COVID-19 pandemic.

When considering new diseases, epidemics, and pandemics, we must consider the complicated impact of culture on the effects of health communication (Kahissay *et al.*, 2017; Workneh *et al.*, 2018). The largest cultural difference between China and the USA is collectivism versus individualism (Lu *et al.*, 2021). According to Hofstede's (1980) classification, the USA is an individualistic country, in the sense that individuals are considered independent from one another. In contrast, China is a representative collectivistic country. Collectivist cultures stress the importance of relationships, roles, and status within the social system (Guess, 2004). Individualistic versus collectivistic culture may differentially influence how people perceive pandemic risks and further affect information seeking or avoidance behaviors.

On one hand, individuals with collectivistic orientation reported greater perceived vulnerability than individualistic ones, because they may feel higher interconnection (physical and mental) with others. This may increase the fear and worries of being infected by others. On the other hand, these people always had a strong sense of responsibility toward others and their community (Triandis, 2001; Zhang *et al.*, 2013). Hence, Chinese people may be more willing to take COVID-19 protective measures to protect their families and communities than the Americans.

According to the extended parallel process model (EPPM), people are likely to take self-protective actions when the perceptions of a health risk are strong and perceived levels of efficacy are high (Witte, 1992). People with collectivistic values can perceive more risks than individualistic ones in the face of an observed risk. They also tend to have a higher sense of efficacy than individualistic ones due to their previous pandemic experience and their strong motivation to protect themselves and their communities (Germani *et al.*, 2020). Therefore, the group with collectivistic values are more likely to enact COVID-19 prevention recommendations, and experience lower levels of information overload and message fatigue. According to these different responding of COVID-19 prevention information in the USA and China, the following hypotheses were proposed:

> *H*1: Chinese participants experience a lower level of information overload about COVID-19 prevention information than American.

> *H*2: Chinese participants experience a lower level of message fatigue about COVID-19 prevention information than American.

METHODS

In this study, MI testing was used to compare how American and Chinese people have experienced information overload and message fatigue toward COVID-19 prevention messages using MI. MI testing is based on classical confirmatory factor analysis (CFA) with the maximum likelihood estimation. MI usually involves the testing of four equality constraint levels: configural invariance, metric invariance, scalar invariance, and strict invariance (Widaman and Reiss, 1997). Each of these levels builds upon the previous model by introducing additional equality constraints on model parameters to achieve stronger forms of invariance.

Participants and procedure

In February 2021, participants were recruited from two online platforms: Amazon Mechanical Turk (MTurk) for Americans and Ali Duty for Chinese. MTurk and Ali Duty are crowdsourcing labor markets that allow participants to perform tasks for a nominal amount of compensation. Each participant was paid $0.3 in MTurk/¥2.0 in Ali Duty for completing the questionnaire. Before answering the survey questions, participants were given the consent form, followed by a screening question to identify their nationality. This research protocol was approved by the University Institutional Review Board (IRB).

A total of 625 participants accessed the survey for the USA. There were two attention check questions in the questionnaire. Participants who failed to pass any attention check questions were excluded. The final sample consisted of 493 US participants, ranging from 18 to 75 years old ($M = 35.77$, $SD = 12.17$). Of the participants, 40.8% were female ($n = 201$) and 61.1% were White ($n = 301$). The majority of participants (74.8%) had obtained at least an undergraduate degree, and 32.9% of participants have a previous year's household income equal to or more than $70 000 (the median of the US household income in 2020 is $61 937).

A total of 703 participants accessed the Chinese survey. After removing cases that failed to pass attention check questions, the final sample consisted of 571 participants, ranging from 18 to 73 years old ($M = 29.10$, $SD = 11.866$). Of the participants, 63.9% were females ($n = 365$) and 97.9% were ethnic Han ($n = 559$). Only 43.4% of participants had obtained at least an undergraduate degree and 57.9% had a previous *t* year's household income equal to or more than ¥30 000 (the median of China household income in 2020 is ¥27 540). Demographic information was summarized in Table 1.

Measures

Both measures were adopted from previous studies and adapted to fit the study context of prevention messages in COVID-19. For American participants, the adapted versions were used. Due to the lack of existing questionnaires measuring information overload and message fatigue for Chinese participants, the first author translated

Table 1: Demographics of respondents

Demographic	Number (%) of US respondents ($N = 493$)	Number (%) of China respondents ($N = 571$)
Age		
18–30	225 (45.6%)	365 (%)
31–45	178 (36.1%)	140 (%)
46–60	55 (11.2%)	60 (%)
61–75	35 (7.1%)	6 (%)
Gender		
Female	201 (40.8%)	365 (63.9%)
Male	292 (59.2%)	206 (36.1%)
Education		
No degree	124 (25.2%)	323 (56.6%)
Bachelor's degree	272 (55.2%)	129 (22.6%)
Graduate or professional degree	97 (19.6%)	119 (20.8%)
Income		
Low	136 (27.6%)	132 (23.1%)
Low-Medium	165 (33.5%)	108 (18.9%)
Medium	111 (22.5%)	101 (17.7%)
Medium-High	67 (13.6%)	71 (12.4%)
High	14 (2.8%)	159 (27.8%)
Race/Ethnicity		
Americans (White)	301 (%)	—
Americans (Black)	51 (%)	—
Americans (Hispanic)	9 (%)	—
Americans (Asian)	119 (%)	—
Americans (other)	4 (%)	—
Chinese (Han)	—	559 (97.9%)
Chinese (other)	—	12 (2.1%)

all English survey items into Chinese, which were then back-translated by Chinese master students who major in English. In addition, a convenience sample of 10 Chinese participants completed the survey as a pilot study and provided feedback to improve the Chinese version of survey questionnaires.

Information overload

Information overload was measured using a thirteen-item questionnaire adapted from Jensen *et al.* (2020) cancer information overload scale. All items were measured on 5-point Likert scales ranging from 1 = *strongly disagree* to 5 = *strongly agree*. This questionnaire has been successfully adapted for studying information overload in patients with atrial fibrillation (Obamiro and Lee, 2019), information on healthy diet recommendations (Ramondt and Ramírez, 2019), and sun-safe behavior (Jensen *et al.*, 2020). The sample items included '*There is not enough time to do all of the things recommended to prevent COVID-19*' and '*No one could actually do all of the COVID-19 preventative recommendations that are given*'. For all items, a higher score indicates a higher level of information overload. For the current sample, the reliability measured by Cronbach's alpha was 0.94 for US participants ($n = 493$) and 0.95 for Chinese participants ($n = 571$).

Message fatigue

Message fatigue was measured on a seventeen-item scale, with five items representing perceived overexposure and four items representing each of the other three dimensions of message fatigue, including perceived redundancy, perceived exhaustion, and perceived tedium. All items were measured on 5-point Likert scales ranging from 1 = *strongly disagree* to 5 = *strongly agree* (So *et al.*, 2017). The measurement was developed by So *et al.* (2017) according to the conceptual definition of message fatigue. It has been successfully applied in different health contexts, including safe sex, anti-obesity (So *et al.*, 2017), and COVID-19 prevention messages (Ball and Wozniak, 2021). The sample items include '*I have lost track of the number of times I have heard that COVID-19 is a serious problem* (overexposure)', '*COVID-19 prevention messages rarely provide new* *information* (Redundancy)', '*I am sick of hearing about consequences of not performing COVID-19 preventive behaviors* (Exhaustion)', and '*COVID-19 prevention messages make me want to yawn* (Tedium)' (USA: $\alpha = 0.95$, $M = 3.31$, $SD = 0.96$; CN: $\alpha = 0.96$, $M = 2.23$, $SD = 0.90$). For all items, a higher score indicates a higher level of message fatigue. The measurement models of information overload and message fatigue can be found in online supplementary materials.

Statistical analysis

The data were analyzed using the Statistical Package for Social Sciences (SPSS 26.0) for descriptive analysis and the *Mplus* (version 7.4) for CFA and MI testing. The most basic form of MI is *configural invariance*, which is considered to be the baseline model. The baseline model is fitted to subgroups simultaneously, and the number of factors and the loading patterns are expected to be identical, but other parameters are allowed to vary. *Metric invariance* builds upon configural invariance by requiring that in addition to the constructs being measured by the same items, the factor loadings of those items must be equivalent across constructs. *Scalar invariance* builds upon metric invariance by requiring that the item intercepts also be equivalent across constructs. *Strict invariance*, also called residual invariance, means that the sum of specific variance (of the item that is not shared with the factor) and error variance (measurement error) is similar across groups.

Specifically, the analysis followed two major stages. First, we conducted CFA to test whether the measurements of information overload and message fatigue fit the empirical data from each group. Second, MIs for information overload and message fatigue were hierarchically tested at each of the levels separately (Meredith, 1993; Widaman and Reise, 1997). In comparing the fit of four levels of models, chi-square tests and goodness-of-fit indexes were used. A χ^2/df ratio of 3:1 or less indicates good fit (Carmines and McIver, 1981); the values of the *RMSEA* of 0.05 or less indicate a close fit, and 0.08 or less indicate adequate fit; a value of *SRMR* less than 0.08 indicates a good fit (Browne and Cudeck, 1993); fit is considered adequate if the *CFI* and *TLI* values are >0.90, better if they are >0.95 (Kline, 2015). In addition, the metric, scalar, and residual invariances were evaluated by the significance of the change in χ^2 for two nested models (Marsh and Hocevar, 1985; Byrne *et al.*, 1989; Reise *et al.*, 1993). The traditional criteria of −0.01 for *CFI* and 0.01 for *RMSEA* were used in our analyses.

RESULTS

Descriptive statistics and bivariate correlations

We presented (1) descriptive statistics for each item measuring information overload and message fatigue, (2) a series of independent samples *t*-test comparing item responses between American and Chinese participants, (3) correlations between information overload and message fatigue items in online supplementary materials.

Measurement invariance of information overload between Chinese and American

Results from a CFA showed a good model fit for American {χ^2 (65) = 231.81, $p < 0.05$, RMSEA = 0.07 (90% CI = [0.06, 0.08]), CFI = 0.96, TLI = 0.95, SRMR = 0.03}, and an acceptable model fit for Chinese participants {χ^2 (65) = 586.04, $p < 0.05$, RMSEA = 0.12 (90% CI = [0.11, 0.13]), CFI = 0.91, TLI = 0.89, SRMR = 0.05}. These indicate that the 13 items were valid to measure information overload for both groups.

The second step was to test MI from the configural model to the strict model. To test the configural model, we moved single-group CFA to multi-group CFA to cross-validate the measurement model across the two groups. The configural model provided acceptable fit to the data {χ^2 (130) = 817.85, $p < 0.05$, RMSEA = 0.10 (90% CI = [0.09, 0.11]), CFI = 0.93, TLI = 0.92, SRMR = 0.04}, indicating that the factorial structure of the information overload is equal across groups.

When configural invariance was supported, the factor loadings were then constrained to be equal to test the metric invariance. The metric invariance model also had acceptable fit indices {χ^2 (142) = 891.87, $p < 0.05$, RMSEA = 0.10 (90% CI = [0.09, 0.11]), CFI = 0.92, TLI = 0.92, SRMR = 0.06}. The χ^2 difference test between the configural model and the metric model was significant, $\Delta\chi^2$ (12) = 74.03, $p < 0.001$. Given that the test was based on a large sample size ($n = 493$) and there was no substantial difference in *CFI* (0.93 vs. 0.92), we concluded that there was no appreciable difference in factor loadings between the US and Chinese groups.

The scalar invariance model also provided acceptable fit to the data {χ^2 (154) = 1077.54, $p < 0.05$, RMSEA = 0.11 (90% CI = [0.10, 0.11]), CFI = 0.91, TLI = 0.90, SRMR = 0.08}. The χ^2 difference test between the metric and scalar models was significant, $\Delta\chi^2$ (12) = 185.67, $p < 0.001$. Once again, given that there was no substantial difference in *CFI* (0.92 vs. 0.91), we concluded that there was no appreciable difference in the intercepts of the items across the two groups. Support for scalar invariance indicates that the latent means can be meaningfully compared across groups.

In testing for the strict invariance model, the factor loadings, intercepts, factor variances, and residual variances were constrained to be equal across groups. The strict model provided a poor fit to the data {χ^2 (168) = 1356.04, $p < 0.05$, RMSEA = 0.12 (90% CI = [0.11, 0.12]), CFI = 0.88, TLI = 0.89, SRMR = 0.09}. This result indicates that the factor and residual variances of information overload varied across the two groups. However, this strict model can be optional, as it usually does not add substantive information in applied research (Brown, 2006).

Based on the scalar invariance model, the Chinese participants were found to have a significantly lower level of information overload than the US participants ($M_{\text{diff}} = -0.61$, $SE = 0.06$, $p < 0.001$), thereby supporting *H*1. Table 2 summarizes MI testing results for information overload.

Measurement invariance of message fatigue between Chinese and American

A four-factor measurement model of message fatigue (overexposure, redundancy, exhaustion, and tedium) was used.

The first step was to test whether the four-factor measurement model fits the data from each group. Results showed a good model fit for American {χ^2 (136) = 400.04, $p < 0.05$, RMSEA = 0.07 (90% CI = [0.06, 0.08]), CFI = 0.96, TLI = 0.95, SRMR = 0.04}, as well as an acceptable model fit for the Chinese participants {χ^2 (136) = 734.81, $p < 0.05$, RMSEA = 0.10 (90% CI = [0.09, 0.11]), CFI = 0.93, TLI = 0.92, SRMR = 0.04}. This indicates that the measurement model of message fatigue is valid for both groups. Second, the configural model also provided acceptable fit to the data {χ^2 (226) = 1134.85, $p < 0.05$, RMSEA = 0.09 (90% CI = [0.08, 0.09]), CFI = 0.94, TLI = 0.93, SRMR = 0.04), indicating that the factorial structure of message fatigue is equal across groups.

The metric model also showed acceptable fit indices {χ^2 (239) = 1183.23, $p < 0.05$, RMSEA = 0.09 (90% CI = [0.08, 0.09]), CFI = 0.94, TLI = 0.93, SRMR = 0.05}. The χ^2 difference test between the configural and metric models was significant, $\Delta\ \chi^2$ (13) = 48.38, $p < 0.001$. Given that the test was based on a large sample size ($n = 493$) with substantial difference in CFI (0.94 vs. 0.94), we concluded no appreciable difference in factor loadings between two groups.

Third, the scalar invariance model provided acceptable fits to the data {χ^2 (252) = 1343.65, $p < 0.05$, RMSEA = 0.09 (90% CI = [0.09, 0.10]), CFI = 0.93, TLI = 0.93, SRMR = 0.05}. The χ^2 difference test between the metric model and scalar model was significant, $\Delta\ \chi^2$ (13) = 160.41, $p < 0.001$, but due to no appreciable difference in fit indices, we concluded that the latent means can be meaningfully compared across groups. Last, the strict model of message fatigue also provided a poor fit to the data {χ^2 (288) = 2385.21, $p < 0.05$, RMSEA = 0.12 (90% CI = [0.11, 0.12]), CFI = 0.87, TLI = 0.88, SRMR = 0.11}. This result indicates that the factor variances and residual variances of message fatigue varied across the two groups.

Based on the scalar invariance model, the Chinese participants were found to have significantly lower levels of each subscale (overexposure: $M_{\text{diff}} = -1.04$, $SE = 0.07$, $p < 0.001$; redundancy: $M_{\text{diff}} = -0.58$, $SE = 0.07$, $p < 0.001$; exhaustion: $M_{\text{diff}} = -1.34$, $SE = 0.06$, $p < 0.001$; tedium: $M_{\text{diff}} = -1.20$, $SE = 0.07$, $p < 0.001$), thereby supporting *H*2. Table 3 summarizes MI testing results for message fatigue.

Table 2: Measurement invariance testing of information overload: the USA ($n = 493$) and China ($n = 571$) sample

Models	χ^2	*df*	*p*	RMSEA (90% CI)	CFI	TLI	SRMR	Model comparison	$\Delta\chi^2$	Δdf
Configural model	817.85	130	<0.05	0.100 (0.093, 0.106)	0.929	0.915	0.040	—	—	—
US	231.81									
CN	586.04									
Metric model	891.87	142	<0.05	0.100 (0.093, 0.106)	0.922	0.915	0.062	Metric vs. Configural	74.03	12
US	273.50									
CN	618.38									
Scalar model	1077.54	154	<0.05	0.106 (0.100, 0.112)	0.905	0.903	0.076	Scalar vs. Metric	185.67	12
US	381.50									
CN	696.04									
Strict model	1356.04	168	<0.05	0.115 (0.110, 0.121)	0.877	0.886	0.087	—	—	—
US	476.36									
CN	879.68									

DISCUSSION

This study compared the degree to which Americans and Chinese experienced information overload and message fatigue toward COVID-19 prevention messages using MI testing. The results demonstrated that Chinese participants had significantly lower levels of information overload and each dimension of message fatigue when compared to the US residents. Results of this study have implications for developing and delivering health prevention messages as well as theoretical implications for the literature on overload and fatigue.

Theoretical implications

This research offers a theoretical explanation for how a large amount of persuasive information can disengage people from message elaboration through information overload and message fatigue. Specifically, people may feel overloaded with too many messages, resulting in a reduction in their ability to process (Eppler and Mengis, 2004). Or they may become fatigued from repeated exposure, resulting in a decrease in their motivation to process (So and Popova, 2018). Both the overload and the fatigue responses are responsible for reduced message elaboration, which is expanded the body of ELM (So *et al.*, 2017). In addition, the results of this research proved that the extent of the effects of information overload and message fatigue on information processing differ by the cultural background of the audience.

Second, results of this study have direct theoretical applications for the measurement of information overload and message fatigue. These constructs have largely been considered as individual difference variables but the present investigation suggests that there may be cultural differences present as well. The findings of this study initially revealed how cultural differences influence the extent of perceived information overload and message fatigue. Future research in this area should continue to flesh out these potential cultural differences as measurement is amended and refined.

Third, this research provides some evidence regarding the performance of the adapted measurement of information overload and message fatigue for COVID-19 prevention in the USA and China. In making cross-national comparisons, ambiguity regarding differences in scale score means can be attributed to authentic differences between countries or cross-country measurement differences because of cultural response biases, translation errors, or cultural differences in understanding the underlying construct (Rutkowski and Svetina, 2014). Thus, claims or conclusions regarding comparative differences are necessarily weak without evidence to support MI in different cultures (Horn, 1991; Vandenberg and Lance, 2000). In addition to investigating the comparability of scale scores through MI testing, the present operationalization of message fatigue is fairly new. This research is one of the first studies to contribute to theorizing on message fatigue to flesh out cultural differences.

Last, one interpretation for the differing levels of overload and fatigue is that American and Chinese audiences are at different points in a diffusion of innovation curve of message compliance in response to novel threats, or simply put, these audiences are at different stages of change related to prevention. For example, if Americans were closer to message acceptance we would likely see reduced levels of perceived overload and message fatigue. Chinese people have dealt with previous pandemics and in the case of COVID-19, behavioral enactment at the population level was much faster (Durham *et al.*, 2012; Dong and Bouey, 2020). However, this is the USA's first experience in a 100 years

Table 3: Measurement invariance testing of message fatigue: the USA ($n = 493$) and China ($n = 571$) sample

Models	χ^2	*df*	*p*	RMSEA (90% CI)	CFI	TLI	SRMR	Model comparison	$\Delta\chi^2$	Δdf
Configural model	1134.85	226	<0.05	0.087 (0.082, 0.092)	0.943	0.931	0.041	—	—	—
US	400.04									
CN	734.81									
Metric model	1183.23	239	<0.05	0.086 (0.081, 0.091)	0.941	0.932	0.047	Metric vs. Configural	48.38	13
US	429.11									
CN	754.12									
Scalar model	1343.65	252	<0.05	0.090 (0.086, 0.095)	0.931	0.926	0.052	Scalar vs. Metric	160.41	13
US	509.81									
CN	833.84									
Strict model	2385.21	288	<0.05	0.117 (0.113, 0.121)	0.868	0.875	0.110	—	—	—
US	827.44									
CN	1557.77									

with a pandemic. Future messaging strategies need to be targeted toward populations at different points in the acceptance curve. For example, the stages of change model may need to be applied when confronting novel threats (Prochaska and DiClemente, 2005). Recent study already proved the stages of change model can be used to explain the physical activity and mental health issues for people from different cultures during the COVID-19 (Faulkner *et al.*, 2021).

Practical implications

This study also demonstrates various practical implications. First, USA public health practitioners need to consider the unique informational needs of Americans. For mainstream communities in the USA, beliefs in individualism, autonomy, independence, and freedom are rewarded and respected (Ritter and Graham, 2017). To minimize reactance toward COVID-19 prevention messages, we also want to avoid some message types, like fear appeals, or any messaging perceived as paternalistic in nature. Instead, hope appeals and gain-framed appeals can be used to increase both individual and collective efficacy about vaccination and ending the pandemic. Moreover, all information should be translated into different languages to communicate with each community, especially minority communities. This can enhance the cognitive capacity of minority residents to decrease the probability of perceived information overload.

Limitations and future studies

This study bears a few limitations that merit future studies. First, we recruited the US participants from Amazon Mechanical Turk (MTurk) and the Chinese participants from Ali Duty. Although the data collected on MTurk has been proven to be as reliable as those obtained from traditional survey methods (Buhrmester *et al.*, 2018), it might not represent the socio-demographic characteristics of the population in the USA. The sample collected from Ali Duty has the same issue. Then, the current study only demonstrated the different extent of perceived information overload and message fatigue in the USA and China. However, it did not explore the antecedents (e.g. personal traits, health literacy, fear) resulting in these differences. In addition to these personal characteristics, different sources, channels and the amount of information received also can lead to different degrees of information overload and message fatigue (Mohammed *et al.*, 2021). Future research should extend the current findings of the differences of the unintended effect of COVID-19 prevention messages between the USA and China and examine the reasons of these differences. Last, we also need to explore the extent of perceived information overload and message fatigue among distinct subgroups who are vaccinated at lower rates, especially in some underserved minority groups, such as black and Hispanic populations. It can help the public health practitioners better understand the public's seeking information behaviors and develop appropriate messaging strategies for different groups.

CONCLUSION

The COVID-19 pandemic as a global outbreak has significantly affected the information environment as well as the daily life of people around the world. COVID-19 prevention messages are critical in helping people learn about the disease and the recommendations to prevent infection. However, over time, people who do not have sufficient cognitive capacity may feel overloaded with too many messages from diverse mediated channels and personal sources, (Eppler and Mengis, 2004), or become fatigued from repeated exposure to COVID-19 prevention methods, resulting in a decrease in their motivation to process (So and Popova, 2018). Both overload and fatigue responses are found to be responsible for compromised persuasion effects (Jensen *et al.*, 2020). The extent of these unintended persuasive effects reflected the communication performance of COVID-19 prevention strategies in different countries. Hence, it is meaningful to explore the extent of perceived information overload and message fatigue in the context of COVID-19 in different countries.

Notes on Contributors

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