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Exploring How Social Media Message Modality Influences Information Overload, Effectiveness, and Intention to Follow Healthy Eating Suggestions

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Abstract

Adapting Stephens and Rain's (2011) revised model of complementary Information and Communication Technology (ICT) use, the current study used a 3 (ICT succession: text-only vs. video only vs. combination text and video) x 3 (block repetition) mixed factorial design to examine how different social media modalities (video and text) affect perceived information overload, information effectiveness, attitudes, online engagement intentions, and intention to follow suggestions for healthy eating. A total of 359 participants (Mage = 42.15) were recruited to complete an online experiment. The findings revealed no significant effects of modality succession on information overload, online engagement intention, or behavioral intentions, aligning with some aspects of Stephens and Rains' (2011) ICT Succession Theory but differing in others. Perceived information overload and effectiveness significantly influenced behavioral intentions, particularly when both information overload and information effectiveness shaped attitudes, although attitude alone did not predict online engagement intention. Notably, low information overload enabled participants to follow suggestions even with lower effectiveness, while high overload required high effectiveness for adherence. Unlike prior studies, online engagement intention did not directly influence behavioral intentions but interacted with attitude and effectiveness, highlighting the need for tailored strategies to reduce overload and enhance effectiveness based on specific behavioral goals.

Keywords: healthy eating messages, information effectiveness, information overload, intention to follow suggestions, social media

Introduction

About three in four adults in the United States are considered overweight or obese (Henry Ford Health, 2025). Maintaining a balanced diet by consuming nutrient-dense foods while limiting fat and sugar intake is important for reducing risks of chronic diseases such as cardiovascular disease and obesity (Lichtenstein et al., 2006). Yet, motivating individuals to make healthier food choices remains a critical public health endeavor. The COVID-19 pandemic further exacerbated unhealthy eating patterns, which are thought to extend beyond the pandemic years. Lockdown measures during the pandemic significantly altered eating habits, leading to an increase in unhealthy and snacking behaviors (Ammar et al., 2020; Błaszczyk-Bębenek et al., 2020; Churchill, 2020; Pellegrini et al., 2020; Robinson et al., 2021; Sidor & Rzymski, 2020). About one-third of a large U.S. sample (N = 97,000) reported an increase in snacking, with an average weight gain of seven pounds between March and June 2020 ("Lockdown eating insights: Has the pandemic turned us into a nation of snackers?", 2020).

Although the acute phase of the pandemic has passed, its influence on behavioral patterns, including snacking habits, may persist. A study in Riyadh, Saudi Arabia showed that close to nine out of 10 participants indicated changes in their dietary patterns after the pandemic, with a third reporting higher consumption of fast food, 28.5% reporting increase in consuming sugary foods (e.g., chocolate and paster), thus confirming the potential lasting effects of the COVID-19 pandemic on eating habits (Al-Tannir et al., 2023). Such impact is further facilitated by the continuation and increase in post-pandemic remote work. A fifth of Americans and 28% of workers globally are remote employees (Churchill, 2020, Sherif, 2024, U.S. Bureau of Labor Statistics, 2023), which could explain the continuation of poor eating choices. There is a critical need, among growth of multiple factors contributing to poor eating patterns, to find ways of promoting healthier eating habits.

As social media play a potentially important role in health promotion (e.g., Boulos et al., 2011; Divecha et al., 2012; Donelle & Booth, 2012; Evers et al., 2013; Guse et al., 2012; Pagoto et al., 2014; Weymann et al., 2015), understanding the dynamics of its influence on behavior is critical. Korda and Itani (2013) highlighted the necessities of incorporating theoretical approaches and outcome analysis into social media applications for health promotion. With that in mind, referring to the ICT Succession Theory (Stephens, 2007) and Media Richness Theory (Daft & Lengel, 1986), this study investigates how complementary modality use, specifically the combination of video and text, enhances the effectiveness of healthy eating promotion campaigns, compared to repetitious presentation of the same message in the same modality (video-video and text-text).

Literature Review

Promote Healthy Behaviors on Social Media

Health communication scholars have investigated how websites and social media sites operate in producing and circulating information to promote healthy behaviors (e.g., Evers et al., 2013; Guse et al., 2012; Pagoto et al., 2014; Weymann et al., 2015). Moorhead and colleagues (2013) discussed six benefits of using social media for health communication, including social media's capability to increase interactions with others, the provision of more available, shared, and tailored information, and increased accessibility to health-related information (e.g., Kontos et al., 2010; Kukreja et al., 2011; Scanfeld et al., 2010).

Fighting against unhealthy food and drink marketing on social media is a herculean, especially when health budgets pale compared to global corporations. Dunlop and colleagues (2016) indicated that public health organizations and social marketing campaigns have put significant efforts into promoting healthy eating behaviors through social media. Numerous studies have documented how users, patients, and health professionals leverage social media to communicate about health-related information (e.g., Chen & Wang, 2021; Chou et al., 2009; Gong & Lyford, 2025; Gupta et al., 2022; Han et al., 2021). Small-scale healthy eating promotion campaigns that integrated social media platforms such as Facebook and Twitter have demonstrated high engagement rates among target audiences (George et al., 2016; Tobey & Manore, 2014). Napolitano et al. (2013) designed weight-loss messages delivered via Facebook and text messaging to U.S. college students, which showed preliminary efficacy in weight loss and message acceptance among participants. Additionally, a study of 33 Caucasian women aged 22-73 found that healthy eating blogs written by dietitians provided useful recipe ideas, encouraged lifestyle improvements, and were seen as credible sources of information, facilitating engagement with dietitians (Bissonnette-Maheux et al., 2015).

Social media play a crucial role in promoting healthy behavior by facilitating widespread health communication, increasing user engagement, and enhancing health-related outcomes. Huo et al. (2019) found that individuals increasingly turn to social media for health-related insights. Studies like Rus and Cameron (2016) highlight how specific message features, such as emotional appeals and personal stories, can drive engagement on health-focused pages, particularly in diabetes care (Gong & Lyford, 2025).

Additionally, social influencers have emerged as key players in public health campaigns, effectively shaping attitudes and behaviors through online engagement (Gupta et al., 2022). Social media also benefit older adults by fostering social support and improving health literacy (Han et al., 2021). A systematic review by Chen and Wang (2021) further underscores the potential of social media to enhance health awareness and self-care behaviors. To summarize, social media are effective health promotion tools, capable of reaching diverse audiences and encouraging positive behavioral changes (see Korda & Itani, 2013). However, recent research indicated that because people have limited mental resources and cognitive capacity to process the excessive and often ambiguous information on social media (Islam et al., 2020; Laato et al., 2020; Zheng & Ling, 2021), they may experience social media fatigue, a state of tiredness or exhaustion resulting from social media use (Ravindran et al., 2014). This fatigue can lead to the discontinuation of information searching or processing, particularly regarding health behaviors (Tasnim et al., 2020). Therefore, it is crucial to understand how to design and deliver effective and reliable health messages on social media by considering factors such as content, frequency, and timing. The goal is to reach the right people, in the right place, at the right time. As the availability of online information grows and communicators increasingly employ behavioral targeting and retargeting strategies (Carrascosa et al., 2015; Summers et al., 2016; Yan et al., 2009), this study examines how repeated and sequential exposure to health promotion messages influences communication effectiveness.

Media Richness

Media Richness Theory (Daft & Lengel, 1986), or Information Richness theory (Daft & Lengel, 1984), describes the relative efficiency of different communication media for the purpose of reducing equivocality and enhancing information effectiveness (or communication effectiveness). Equivocality refers to “the degree to which a decision-making situation and information related to it are subject to multiple interpretations” (Walther, 2011, p. 448). Participants perceived health knowledge with clearer expression and higher content richness (e.g., vivid knowledge representation with pictures, cartoons, and videos; Griffith & Neale, 2001; Lan & Sie, 2010) as higher-quality knowledge. People who were exposed to a richer health knowledge presentation tended to gain a deeper cognition and understanding of the knowledge than others (Huo et al., 2018). Research applying Media Richness Theory to promoting physical activity found that media richness influenced participants’ intention to visit a fitness center, while interactivity influenced their intention to recommend it (Lu et al., 2014).

Scholars suggest that online videos incorporating verbal, vocal, and visual elements can effectively reach large audiences due to their interactive features, such as tagging, commenting, and sharing (Chin et al., 2010; Lange, 2007; Keelan et al., 2007; Waters & Jones, 2011). Social media platforms like YouTube and Facebook have expanded access to digital health videos, shifting them from one-way communication on television to interactive engagement (Burgess & Green, 2018; Department of Health, 2010; O'Mara, 2013). While the effectiveness of text-based health messages remains unclear, a meta-analysis of 19 interventions found text messaging-based health promotion to be generally effective (Head et al., 2013). Based on Media Richness Theory and Huo et al. (2018), video-based social media posts, offering higher content richness and clearer expression, are predicted to be more effective than text-based posts. Although rich media content has been found effective in persuasion, message repetition plays a crucial role as it continually reminds individuals of the message and reinforces their attitudes and intentions. In the next section, we review the literature on message repetition.

Message Repetition

Harrison (1977) found that message repetition enhances comprehension and retention, particularly among audiences who are initially unfamiliar with the topic. Similarly, Rogers and Storey (1987) emphasized that repetition is a key component of the diffusion of innovations, facilitating the progression from awareness to adoption stages. In applied contexts, Flora et al. (1997) demonstrated that frequent repetition of public health messages, such as anti-smoking campaigns, improved both message recall and the likelihood of adopting recommended behaviors. Hornik (2002) further argued that successful health communication campaigns rely on repeated exposure across multiple channels to achieve population-level change. However, this body of research also underscores the potential drawbacks of excessive repetition: overexposure may diminish persuasive impact (Cacioppo & Petty, 1979) and, in some cases, lead to message fatigue in mass media campaigns, resulting in audience disengagement or even counterproductive effects on health promotion (So et al., 2017).

Current Study

Information and Communication Technology (ICT) Succession Theory (Stephens, 2007) suggests that multiple modalities (i.e., visual and audio) present when using complementary ICTs may better reinforce message arguments. Complementary ICTs guarantee the second message appears similar but unique and, thus, help retain audiences' attention and ensure they engage with both messages. Although scholars have emphasized the benefits of using multiple media channels to promote health behaviors (Flora et al., 1997; Hornik, 2002; Rogers & Storey, 1987), in practice, most medium- and small-sized businesses rely heavily on social media due to audience preferences and cost concerns (Bandyopadhyay, 2016; Kirtiş & Karahan, 2011; Tsimonis & Dimitriadis, 2014). Because using multiple media channels is sometimes challenging and many businesses are increasingly shifting toward social media platforms, it is essential to understand how repetitive messages within the same platform can remain appealing and attention-grabbing. ICT Succession Theory offers an interesting lens through which to explore this issue. While the theory originally centers on cross-channel transitions, we tentatively propose that it can also be extended to examine how variations in content richness across sequential messages within a single channel influence message processing. Specifically, we argue that repeating the same message using varied modalities, that is, different levels of media richness, will generate more effective persuasive outcomes than repetition using a single, uniform modality.

Promoting healthy eating behaviors involves improving individuals' attitudes toward dietary choices (e.g., Anderson et al., 2005; Kothe et al., 2011; Prelip et al., 2011). An attitude is "a process of individual consciousness which determines real or possible activity of the individual in the social world" (Strauss, 1945, p. 329). Behavioral intention is defined as "the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior" (Warshaw & Davis, 1985, p. 214). Stephens and Rains (2011) suggested that complementary ICT use reduces message-induced information overload and enhances information effectiveness, which positively affect attitudes and behavioral intentions. Information overload refers to situations where individuals have more information than they can process (Eppler & Mengis, 2004). Information effectiveness refers to the formal and informal sharing of meaningful and timely information between a message sender and a receiver (Sharma & Patterson, 1999). In this study, we anticipate that enhanced media richness in repetitive messages will lower information overload and strengthen persuasive effects.

Additionally, this study also highlights the affordances of social media, through the emphasis on an intermediary factor of online engagement intentions, which is thought to influence information processing and persuasiveness of a message shared via social media. Alhabash and colleagues (2015, p. 523) defined online engagement intention as the "desire to enact online behaviors that contribute to a message's virality, such as pressing the like button, sharing the video, and commenting on it." In a study of civic behavioral intention, online engagement intention expressed toward

YouTube videos was the strongest predictor of offline behavioral message adherence intentions (Alhabash et al., 2015). People who are willing to engage in healthy eating related posts on social media are more likely to eat healthy (Krishnan & Zhou, 2019), given social media self-regulatory role and users intentions to harmonize their online and offline personas.

Taken together, the complimentary and sequential use of multiple modalities to communicate the same message and persuasive arguments, specifically within the context of health attitude and behavior change is through to aid the persuasive process (e.g., Flora et al., 1997; Hornik, 2002; Rogers & Storey, 1987). In the current study, we argue that exposure to the same message across two different modalities (text and video) will be superior in terms of persuasive outcomes of reduced information overload, higher information effectiveness, and pro-message attitudes and behavioral intentions – both online and offline. By contrast, we argue that single-modality message exposure would be inferior to multi-modal message exposure. Based on this, we hypothesized:

H1: Participants exposed to both video and text (complementary modalities) will report (a) lower information overload, (b) higher information effectiveness, (c) more favorable attitude toward healthy eating messages, (d) higher online engagement intention, and (e) higher behavioral intention to follow suggestions than those exposed to the video-only and text-only conditions, respectively.

H2: Information overload will be negatively related to (a) attitudes toward the message, (b) online engagement intention, and (c) intention to follow suggestions.

H3: Information effectiveness will be positively related to (a) attitudes toward the message, (b) online engagement intention, and (c) intention to follow suggestions.

A study of 835 young Chinese consumers (*M*age = 21.34) found that positive attitudes toward forwarding entertaining messages predicted their intention to share them as part of online engagement intention (Liu & Hung, 2010). Online engagement intention on social media emerged as a strong predictor of behavioral intentions, such as civic behavioral intention (Alhabash et al., 2015) and intention to maintain a healthy diet (Krishnan & Zhou, 2019). Therefore, we proposed the following:

H4: Information overload has an indirect negative effect on intention to follow suggestions through (a) attitude and (b) online engagement intention in sequence.

Drawing on Stephens and Rains (2011), complementary ICT use can reduce message-induced information overload and enhance perceptions of information effectiveness, which in turn strengthen favorable evaluations and behavioral intentions. Beyond functioning as a downstream consequence of reduced overload, information effectiveness may also serve as a boundary condition that shapes the psychological mechanisms linking overload to engagement and behavior. When individuals perceive information as effective, the negative impact of information overload on attitude is likely attenuated. Even in high-overload environments, effective information may buffer users against cognitive fatigue and ambiguity, enabling them to maintain more positive attitudes. Conversely, when perceived information effectiveness is low, information overload should exert a stronger negative influence on attitudes, cascading through online engagement intention to behavioral intention. Accordingly, information effectiveness is expected to moderate the indirect effect of information overload on behavioral intention through attitude and online engagement intention.

H5: Information effectiveness will moderate the relationship between information overload and (a) attitudes toward the message, (b) online engagement intention, and (c) intention to follow suggestions.

Figure 1 presents the proposed conceptual moderated mediation model.

Method

Stimuli Design and Pretesting

A total of three videos and text-based posts were selected for the study. To select the videos, a pretest (*N* = 55, Age: *M* = 28, SD = 1.80; 66% female; 73% White) was conducted to assess comparability of the three messages promoting healthy eating. A total of five videos related to the topic were identified from YouTube and were transcribed into text through Rev.com. Following transcription, a text-based newsletter social media post was created for each of the five messages. Participants were randomly assigned to view either the video or text-based messages.

Measurement

Information Overload. Participants' perception of information overload was assessed using Stephens and Rains' scale (2011). Participants rated their agreement with six statements on a seven-point Likert-scale ranging from strongly disagree (1) to strongly agree (7). An example question was "The information I received about healthy eating behavior needs too much explanation to be useful". A higher number indicated higher information load. Table 1 presents the items for each variable along with validity and reliability indices from the pretest, while Table 3 lists the items for each variable in the main study.

Information Effectiveness. Participants were asked to evaluate the message they just saw ranging from strongly disagree (1) to strongly agree (7): “This message is effective/detailed/useful/high quality/well supported/weak/uninformative.” (Stephens & Rains, 2011) A higher number indicated greater information effectiveness of the message.

Attitude toward Messages. Adapted from the attitude scale (Stephens & Rains, 2011), participants rated five statements on a seven-point Likert-type scale ranging from strongly disagree (1) to strongly agree (7). An example question was “This message is helpful to my health.” A higher number represented a more positive attitude toward the message.

Intention to Follow Suggestions. Adapted from the scale of Conner et al. (2002), participants rated five statements ranging from strongly disagree (1) to strongly agree (7), definitely do not (1) to definitely do (7), or unlikely (1) to likely (7). An example question was “I intend to follow what the message suggests in next seven days.” A higher number indicated a greater intention to follow suggestions.

Intention to Eating Healthy. Adapted from a previous scale (Conner et al., 2002), participants rated five statements ranging from strongly disagree (1) to strongly agree (7), definitely do not (1) to definitely do (7), or unlikely (1) to likely (7). An example question was “I intend to eat a healthy diet in next seven days.” A larger number indicated a higher intention to eat a healthy diet.

Online Engagement Intention. We adjusted Alhabash and colleagues’ online engagement intention scale (2015) by adding several new items (total 10 items), participants rated their agreement on a seven-point Likert scale ranging from strongly disagree (1) to strongly agree (7). A statement example is “This message is worth sharing with others.”

The pretest study indicated a non-significant interaction effect of repetition and modality on information overload $F(2, 52) = 2.08$, ns, information effectiveness $F(2, 52) = 2.16$, ns, attitude toward the message $F(2, 52) = 2.83$, ns, intention to follow suggestions $F(2, 52) = 1.38$, ns, intention to eat a healthy diet $F(2, 52) = 2.075$, ns, and message comprehension $F(2, 52) = 1.289$, ns for the three selected messages. Following the selection of the stimuli, we referred to the Academy of Nutrition and Dietetics’ Facebook page, “Eat Right Nutrition,” to determine the average number of likes and shares. Using a Facebook post generator, we designed text-based posts that included a video screenshot and transcribed text with mimicked engagement metrics. For the video posts, we incorporated the account name, publication details, and engagement metrics from the text posts into a Qualtrics design, embedding the videos to resemble authentic Facebook video posts.

Main Study

Experimental Design. The current study used a 3 (ICT succession: text-only vs. video only vs. combination of text and video) x 3 (block repetition) mixed factorial design, with modality manipulated between subjects, and block repetition within-subject. ICT succession was manipulated as the exposure to the same message twice, either as both exposure in text format, both exposure in video format, or exposure to both text and video versions of the message in a complementary way (with order counterbalanced). Block repetition referred to health message repetition, where participants were provided with messages related to healthy eating. The inclusion of this repetition factor is necessary to guard against any potential message variability effects (see Thorson et al., 2012 for a more elaborate discussion).

Participants. The sample size of 252 was determined using an a priori power analysis with the following parameters: Effect size (f) = .23, alpha error probability = .04, Power = .95. Taking the response rate into consideration, we oversampled by 30% to 35%. Upon receiving the approval from the Institutional Review Board (IRB), 399 participants were recruited from Amazon Mechanical Turk (mTurk, restricted to Masters with 85% HIT approval rate), with 45 minutes allotted per participant. The study was designed as three conditions (video only, text only, video and text) but four groups. More specifically group 3 and group 4 together were combined into condition 3. Participants who failed the attention check questions or did not complete the survey were removed from the data analysis. The final data analysis included a total number of 359 participants. Overall, participants were nearly equally assigned into Condition 1 (n=124), Condition 2 (n=116), and Condition 3 (n=119). The average age of the sample (N=359) was 42.15 with the standard deviation of 10.98. About 48% of participants were female, while 52% were male. Most participants identified as White (61.9%), followed by Asian (26.9%), Black or African American (6.7%), American Indian or Alaska Native (1.4%), other (0.3%), and mixed races (2.8%). According to the standard weight status categories (CDC, 2020), most participants (42.2%) reported as normal weight or healthy weight (BMI falls between 18.5-24.9), followed by 30% reported as overweight (25.0-29.9), 19% reported as obesity (30.0 and above), and 8.9% reported as underweight (below 18.5). Additional demographic information is provided in Table 1.

Procedure. Participants electronically provided consent.

Participants were randomly assigned to one of three conditions (video only, text only, and video and text), yet in the combinatorial modality condition, order of video and text was counterbalanced, thus the nesting factor of this design. A timer ensured adequate exposure to each stimulus, 15 seconds for text and the full duration for videos before advancing. After each set, participants answered questions for the dependent variables. Finally, participants were thanked, debriefed, and provided code to receive monetary incentive.

Measures

Unless otherwise noted, all dependent variables were measured on a seven-point Likert-type scale as we did for the pretest. Items, reliability and validity are presented in Table 2. Information overload and information effectiveness were assessed using Stephens and Rains' measures (2011). We adapted Stephens and Rains (2011) measure for attitude toward messages. We adapted Conner et al.' (2002) measure for intention to follow suggestions. Finally, we used Alhabash et al.'s (2015) measure for online engagement intentions (OIE). Demographic variables (age, gender, BMI, race, education, marital status, number of dependent, employment status, household income, and health status) were controlled in this study because prior research has demonstrated that individuals differ in their access to, exposure to, and trust in health information based on sociodemographic characteristics. Specifically, Benjamin-Garner et al. (2002) reported significant sociodemographic differences in exposure to health information, suggesting that background characteristics can shape how individuals encounter and process health messages. Similarly, Dutta-Bergman (2003) found that demographic variables such as age, education, and income influence both the sources that individuals rely on for health information and their orientation toward seeking such information online. Therefore, controlling these demographic variables helps ensure that observed effects on message processing, attitudes, and behavioral intentions are not confounded by pre-existing disparities in information access or health communication experiences.

Results

Direct Effects of Modality Succession

Repeated-measures analyses of covariance (ANCOVAs) were conducted to examine the effects of modality succession. The results indicated no significant effects for information overload ($F(2, 343) = 0.92$, *ns*), information effectiveness ($F(2, 343) = 0.49$, *ns*), attitude toward messages ($F(2, 343) = 0.35$, *ns*), online engagement intention ($F(2, 343) = 0.05$, *ns*), and intention to follow the suggestions ($F(2, 343) = 0.18$, *ns*). Therefore, H1a-e were not supported.

Direct Effects of Information Load and Effectiveness

To test H2-5, data were submitted to a moderated mediation analysis using Hayes' (2021) PROCESS macros for SPSS (version 3, Model 92, with 10,000 bootstrap samples). Information overload (IL) was entered as an independent variable, information effectiveness (IE) as a moderator, attitude toward messages (ATT) and online engagement intention (OEI) as mediators, intention to follow suggestions (BI) as a dependent variable, and participants' age, gender, BMI, race, education, marital status, number of dependent, employment status, household income, and health status as control variables.

The final model predicting intention to follow suggestions was significant and explained 64% of the variance (R = .80, R2 = .64, MSE = .71, F(20, 338) = 30.45, p < .001). Table 3 showed that the higher the information overload, the less favorable the attitude toward messages (β = -.23, SE = .11, t = -2.13, p < .05, CILL–UL = -.44 to -.03), thus supporting H2a. However, information overload did not predict online engagement intention (β = -.11, SE = .26, t = -.41, p = .66, CILL–UL = -.62 to .41), therefore H2b was not supported. The higher the information overload, the less the likelihood to follow suggestion (β = -.63, SE = .21, t = -3.03, p < .01, CILL–UL = -1.03 to -.22), thus supporting H2c.

In support of H3a, the higher the information effectiveness, the more favorable the attitude toward messages (β = .88, SE = .05, t = 16.16, p < .001, CILL–UL = .78 to .99). The higher the information effectiveness, the greater the likelihood to engage with the message online (β = -.92, SE = .30, t = -3.01, p < .01, CILL–UL = -1.51 to -.32), supporting H3b. Information effectiveness did not relate to intention to follow suggestions, therefore H3c was not supported.

Interaction Effects

To probe the moderation effects of information effectiveness on the relationship between information overload and intention to follow suggestions (H5), we followed the default pick-a-point approach, where PROCESS estimated the conditional effects at the mean and one standard deviation above and below the mean (Hayes, 2021). The interaction of information overload and information effectiveness positively related to intention to follow suggestions (β = .08, SE = .04, t = 2.38, p < .05, CILL–UL = .01 to .15). In this regard, when information load was low, participants expressed higher behavioral intentions when they perceived the message to be less effective, than moderate, and highly effective, respectively. When information load was perceived moderately, no differences were found across different perceptions of information effectiveness. Finally, when perceived information load was high, participants' behavioral intentions were higher in instances when participants perceived the message to be highly effective, followed by moderate and low effectiveness, respectively (see Figure 2). However, an interaction effect was not found on attitudes or online engagement intention.

Although attitude toward messages did not relate to online engagement intention (β = .13, SE = .24, t = .53, p= .60, CILL–UL = -.34 to .60), the interaction of attitude toward messages and information effectiveness positively related to online engagement intention (β = .17, SE = .05, t = 3.76, p < .001, CILL–UL = .08 to .26). As shown in Figure 3, when participants indicated less favorable attitudes toward the message, no differences were detected in their online engagement intention. However, when they expressed more favorable attitudes toward the message, the perception of high information effectiveness resulted in greater online engagement intention.

The interaction between attitude toward messages and information effectiveness negatively predicted intention to follow suggestions (β = -.13, SE = .05, t = -2.53, p < .05, CILL–UL = -.24 to -.03). In contrast to the interaction between load and effectiveness, when attitude was brought into the mix, participants who expressed less favorable attitudes toward the message expressed higher behavioral intentions when they perceived the message to be highly effective, followed by moderate and low level of information effectiveness, respectively. No differences were detected in behavioral intentions as a function of information effectiveness at moderate levels of attitudes toward the message. Finally, when participants expressed more favorable attitudes toward the message, the highest behavioral intentions were expressed for participants who indicated the lowest level of perceived information effectiveness, followed by moderate and high levels, respectively (see Figure 4). The interaction of online engagement intention and information effectiveness did not relate to intention to follow suggestions.

Results from the PROCESS analyses indicate evidence consistent with a moderated serial mediation model in which information load indirectly influences behavioral intentions through attitudes toward the message and subsequent online engagement intentions, conditional on perceived message effectiveness (Table 4). Although the direct paths from attitudes to online engagement intentions and from online engagement intentions to behavioral intentions were not statistically significant at the unconditional level (Table 3), the bootstrapped indirect effects revealed a significant serial indirect pathway across three levels of perceived message effectiveness.

Specifically, at low effectiveness, the sequential effect was −.02 (SE = .01, 95% CI [−.04, −.002]); at moderate effectiveness, the effect was −.02 (SE = .01, 95% CI [−.04, −.002]); and at high effectiveness, the sequential effect was −.02 (SE = .01, 95% CI [−.04, −.01]). Likewise, the indirect pathway from information load through attitudes alone was significant, whereas the indirect pathway through online engagement intentions alone was not supported. These results suggest that higher information load reduces message attitudes, which in turn dampens online engagement and subsequent behavioral intentions; however, this effect is contingent upon perceived message effectiveness, such that the mediated relationships remain significant at varying levels of effectiveness. Together, these findings support a moderated serial mediation in which perceived message effectiveness conditions how message features shape downstream persuasion processes. Information effectiveness weakens but does not eliminate the negative sequential indirect effect of information overload on intention to follow suggestions through attitude and online engagement intention.

Discussion

Guided by ICT Succession Theory and Media Richness Theory, the current study examines how different modalities (video and text) used on social media affect persuasive outcomes. Specifically, we investigated how repetitive exposure to messages promote healthy eating influence attitudinal and behavioral outcomes and identified the boundary conditions in which successive and multi-modal content presentation affect the persuasive chain of effect leading to desired behavioral change.

Modality Succession

Deviating from previous findings, our findings showed that the modality succession or media richness (video only, text only, video and text combined) did not affect information overload, online engagement intention, or intention to follow suggestions. Per the original premise of ICT Succession Theory, complementary ICT use is defined and operationalized as the repetition of the same message across channels that vary in affordances and the number of cues (e.g., email vs. face-to-face). However, such manipulation is confounded as it does not exhaustively identify whether the effect of ICT succession is the result of channel succession or differences in modalities (media richness). To avoid the confound between modality and channel, the current study only tested content in different modalities on a single channel. It is possible that ICT Succession Theory is more applicable to the combinatorial variability in both channels and modality rather than a test of succession within the same channel. Future research should decipher this effect and isolate its nature in an experimentally valid way. Additionally, our results suggested that video was not more effective than text in lessening information overload, nor improving information effectiveness, attitude toward messages, online engagement intention, or intention to follow suggestions, which did not support findings from Lu et al. (2014). Again, taking the within-channel effects of various modalities, it is plausible that participant's experience of viewing text and/or video messages within a Facebook context did not yield significant variability in any of the outcome variables.

Persuasive Chain

Our study found that perceived information overload and information effectiveness affected behavioral intentions, yet this effect is strengthened if both information overload and information effectiveness influenced attitudes. What is even more interesting is that attitude, on its own, was not a significant predictor of online engagement intention, yet did so by interacting with information effectiveness. So, in essence, the combination of high perceived effectiveness that led to more favorable attitude evoked greater online engagement intention with the message.

The significant two-way interaction between information overload and information effectiveness provides insights regarding cases when participants experienced lower levels of information overload, or perceived the information to be less cognitively demanding, we observed positive effects on behavioral intentions. In fact, the lower information effectiveness positively influenced intention to follow suggestions. On the other hand, when information overload was high, information effectiveness was crucial in determining behavioral intentions, such that to evoke greater adherence to the message, the information should be perceived as highly effective by participants. This effect is a classic example of elaboration likelihood, where the availability of cognitive resources determines the elaborative route taken to process the information (Cacioppo et al., 1996; O'Keefe, 2013; Petty et al., 1992; Petty et al., 1983; Petty & Wegener, 1999). When participants were not overloaded, they processed information superficially through peripheral cues, whereas, when the availability of cognitive resources was low (overload), higher effectiveness was needed to acquire the desired effects on behavioral intentions. This is further illustrated by the two-way interaction between attitude and information effectiveness. For participants who developed less favorable attitude toward messages, it was important to perceive the message as highly effective for that to positively influence behavioral intentions, whereas higher effectiveness worked in opposite direction when attitude toward messages was high. This suggests that the development of positive message attitude, despite perceptions of information effectiveness, is a sufficient condition for influencing behavioral intentions.

The last argument we would make is that information overload, information effectiveness, and their interaction affect attitude, which in turn affects behavioral intentions. Online engagement intention, as a novel variable, is critical to examine here, because it is shown to not be part of the sequential mediation of the effects of information overload and information effectiveness on behavioral intentions, and more importantly, that this effect is pertinent on how attitude and information effectiveness interact to influence it, yet online engagement intention did not directly influence behavioral intentions. Contrary to prior research (e.g., Alhabash et al., 2015; Krishnan & Zhou, 2019), which identified online engagement intention as both a direct predictor of offline behavioral intentions and a mediator between attitudes and behavioral intentions, the present study offers alternative evidence that challenges this pattern.

There are several plausible explanations. First, online engagement intention may function differently from the attitude-behavior relationship, acting as a distinct outcome variable influenced by social media affordances. Second, participants might view positive health messages as normative and engage with them online, but find healthy eating less convenient or attainable offline, highlighting a disconnect between online and offline behaviors. In other words, given the extent behavioral planning involved with changing eating habits, it might be easier for individuals to engage with a healthy eating message online, yet not as easy to follow the persuasive arguments and elevate behavioral readiness for change in eating behavior. Third, differences in how participants allocate cognitive resources could explain varied responses; some may focus on online engagement (slacktivism), while others plan for offline behavior change. More specifically, though the relationship between online and offline behavioral intentions have been well-documented (e.g., Alhabash et al., 2015), in this specific context where planning for health-related behavior change, where the target behavior is socially salient and stigmatized and individually challenging due to its long-term need for compliance to see health benefits, might have elevated the potential that engaging with a message online does not squarely align with enacting offline changes to one's behavior. This suggests individuals may divide their resources based on the context of their intended behavior, warranting further exploration.

Theoretical & Practical Implications

In the original ICT Succession study, Stephens and Rains (2011) manipulated complementary ICT use by repeating the same message either on the same channel (email vs. face to face) or across two channels (email then face-to-face, face-to-face then email). However, such manipulation is confounded as it does not exhaustively identify whether the effect of ICT succession is because of channel succession or differences in modalities, given that face-to-face communication provides more nonverbal cues than email communication. The current study aimed to conduct a theory-driven investigation of the effect of different modalities and their succession (modality followed by a different modality) within a single channel on information overload, information effectiveness, attitude, and behavioral intention change. Results show that different modalities/media richness or succession did not make any difference. It is plausible that the nature of communication in the digital age influenced the presumed effect of ICT succession. In other words, through tremendously valuable and theoretically intriguing, it is possible that the major assumptions of ICT Succession Theory as a legacy communication theory, does not fully translate to the ever-changing, highly dynamic, and tremendously overloaded digital context of social media. To understand the mechanism of ICT Succession Theory, it would be interesting for future research to compare effects of messages in same modality across different channels.

Although the current study did not fully support the ICT Succession Theory or Media Richness Theory, it is worthwhile confirming that information overload negatively predicted attitude toward messages and intention to follow suggestions while information effectiveness positively predicted attitude. To promote people's attitude and behavioral change toward healthy behaviors, health professionals should dedicate their efforts in lessening information overload and improving information effectiveness. Health communicators should define and focus on their target outcomes. Planned behavior should be weighted more heavily when aiming at changing behavior, whereas online engagement intention is more suitable when the goal is to raise awareness.

Another notable finding is the strong influence of information overload on behavioral intentions. This is particularly encouraging, as it suggests that carefully managing the amount and complexity of information presented can significantly impact decision-making and engagement. From a practical standpoint, these findings highlight the importance of designing health promotion messages that are not only clear and concise but also tailored to the audience's cognitive load. For example, segmenting complex information into smaller, digestible parts, using visual aids to simplify key messages, or allowing users to control the pace at which they receive information (e.g., through interactive or layered content) may help reduce overload and enhance message effectiveness. Future campaigns might benefit from user-testing to identify points of overload and optimize content delivery accordingly.

Overall, given that neither modality nor modality succession produced significant differences in outcomes, the findings suggest that message format (e.g., text versus video) may be less important than how effectively the content is structured and delivered. Practitioners should therefore focus on improving message clarity, reducing information overload, and enhancing perceived usefulness rather than investing heavily in specific media types. For example, simplifying key points, using plain language, and organizing information logically can make messages easier to process and more persuasive. In social media contexts, maintaining consistent messaging and limiting unnecessary repetition may help sustain audience engagement without overwhelming users. Overall, these results highlight the importance of optimizing message quality and cognitive accessibility over format variation in the design of health communication campaigns.

Limitation and Future Research

This study has several limitations that future research could address. First, the forced exposure through a timer also affected external validity, and participants spent less time on repeated exposures, potentially reducing the effects of media richness. Additionally, the study’s operationalization of ICT Succession Theory may have weakened its intended effects, as participants were immediately exposed to the same message without contextual separation, which might have altered their perception. The study’s design also made its purpose too obvious, possibly leading to social desirability bias, where participants reported favorable attitudes toward healthy eating regardless of the manipulation. Furthermore, the pretest sample of college students may not have been representative of the main study’s more diverse population, limiting generalizability. Another limitation is the reliance on self-reported measures, which may have introduced common method variance and biased results. Future research should consider in-person experiments for better control over engagement, assess behavioral outcomes such as actual food choices, and explore modality effects across different communication channels to enhance ecological validity.

Another limitation of this study is that participants’ perceptions of the credibility of the stimulus posts may have influenced their attitudes and behavioral intentions. Prior research has shown that messages perceived as more credible are more likely to shape favorable attitudes and increase persuasive outcomes (Hovland & Weiss, 1951; Metzger et al., 2003). Future research should measure perceived credibility to better account for its potential impact on message effectiveness.

Additionally, the study found no significant main effects for modality succession on key outcomes, including information overload, online engagement intention, and behavioral intention. This result diverges from theoretical expectations and may suggest that the manipulation was not sufficiently strong or salient to elicit distinct effects. Future research should incorporate a manipulation check or a measure of perceived media richness to ensure that participants meaningfully differentiated between the text and video formats. Future research could further explore the complementary nature of different communication modalities. It is possible that the effectiveness of combining text and video depends on the complexity of the content being conveyed. For instance, additional text may only enhance understanding when the video message is complex or abstract, and likewise, supplementary video might only be beneficial when the accompanying text presents cognitively demanding information. If the video and text components are merely repetitive and mirror each other exactly, the added value of multimodal presentation may be diminished. Investigating the conditions under which each modality contributes uniquely rather than redundantly could help clarify when and how to design effective multimedia messages.

References

Alam, N., & So, J. (2020). Contributions of emotional flow in narrative persuasion: An empirical test of the emotional flow framework. *Communication Quarterly*, 68(2), 161-182. DOI: 10.1080/01463373.2020.1725079

Alhabash, S., Baek, J. H., Cunningham, C., & Hagerstrom, A. (2015). To comment or not to comment?: How virality, arousal level, and commenting behavior on YouTube videos affect civic behavioral intentions. Computers in human behavior, 51, 520-531.

Al-Tannir, M., AlFayyad, I., Altannir, M., Alosaimi, A., Alonazi, A., & Alqarni, A. (2023). Long-term impact of post COVID-19 pandemic quarantine on eating habits changes among adult residents of Riyadh, Saudi Arabia. Frontiers in Nutrition, 10, 1243288.

Ammar, A., Brach, M., Trabelsi, K., Chtourou, H., Boukhris, O., Masmoudi, L., ... & Hoekelmann, A. (2020). Effects of COVID-19 home confinement on eating behaviour and physical activity: results of the ECLB-COVID19 international online survey. Nutrients, 12(6), 1583.

Anderson, A., Porteous, L., Foster, E., Higgins, C., Stead, M., Hetherington, M., . . . Adamson, A. (2005). The impact of a school-based nutrition education intervention on dietary intake and cognitive and attitudinal variables relating to fruits and vegetables. Public health nutrition, 8(6), 650-656.

Bandyopadhyay, S. (2016). How a cost-effective social media plan can make a difference for small businesses. Journal of the Indiana Academy of the Social Sciences, 19(1), 4.

Benjamin-Garner, R., Oakes, J. M., Meischke, H., Meshack, A., Stone, E. J., Zapka, J., ... & McGovern, P. (2002). Sociodemographic differences in exposure to health information. Ethnicity & Disease, 12(1), 124-134.

Bissonnette-Maheux, V., Provencher, V., Lapointe, A., Dugrenier, M., Dumas, A. A., Pluye, P., ... & Desroches, S. (2015). Exploring women's beliefs and perceptions about healthy eating blogs: A qualitative study. Journal of medical Internet research, 17(4), e87.

Błaszczyk-Bębenek, E., Jagielski, P., Bolesławska, I., Jagielska, A., Nitsch-Osuch, A., & Kawalec, P. (2020). Nutrition behaviors in Polish adults before and during COVID-19 lockdown. Nutrients, 12(10), 3084.

Boulos, M. N. K., Resch, B., Crowley, D. N., Breslin, J. G., Sohn, G., Burtner, R., ... & Chuang, K. Y. S. (2011). Crowdsourcing, citizen sensing and sensor web technologies for public and environmental health surveillance and crisis management: trends, OGC standards and application examples. International journal of health geographics, 10(1), 1-29.

Burgess, J., & Green, J. (2018). YouTube: Online video and participatory culture. John Wiley & Sons.

Cacioppo, J. T., & Petty, R. E. (1979). Effects of message repetition and position on cognitive response, recall, and persuasion. Journal of personality and social psychology, 37(1), 97-109.

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. Psychological Bulletin, 119(2), 197.

Carrascosa, J. M., Mikians, J., Cuevas, R., Erramilli, V., & Laoutaris, N. (2015, December). I always feel like somebody's watching me: measuring online behavioural advertising. In Proceedings of the 11th ACM Conference on Emerging Networking Experiments and Technologies (pp. 1-13).

Centers for Disease Control and Prevention. (2020). About Adult BMI. Retreived from https://www.cdc.gov/healthyweight/assessing/bmi/adult_bmi/index.html

Chen, J., & Wang, Y. (2021). Social media use for health purposes: systematic review. Journal of medical Internet research, 23(5), e17917.

Chin, A., Keelan, J., Tomlinson, G., Pavri-Garcia, V., Wilson, K., & Chignell, M. (2010). Automated delineation of subgroups in web video: A medical activism case study. Journal of Computer-Mediated Communication, 15(3), 447-464.

Chou, W. Y. S., Hunt, Y. M., Beckjord, E. B., Moser, R. P., & Hesse, B. W. (2009). Social media use in the United States: implications for health communication. Journal of medical Internet research, 11(4), e48.

Churchill, F. (2020). Half working from home during lockdown are unhappy with work-life balance, survey finds. People Management.

Conner, M., Norman, P., & Bell, R. (2002). The theory of planned behavior and healthy eating. Health psychology, 21(2), 194.

Daft, R. L., & Lengel, R. H. (1984). Information richness. A new approach to managerial behavior and organization design.

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. Management science, 32(5), 554-571.

Department of Health. (2010) Social Media Action Plan. Department of Health, State Government of Victoria, Melbourne.

Divecha, Z., Divney, A., Ickovics, J., & Kershaw, T. (2012). Tweeting about testing: Do low-income, parenting adolescents and young adults use new media technologies to communicate about sexual health?. Perspectives on sexual and reproductive health, 44(3), 176-183.

Donelle, L., & Booth, R. G. (2012). Health tweets: an exploration of health promotion on twitter. Online J Issues Nurs, 17(4).

Dunlop, S., Freeman, B., & Jones, S. C. (2016). Marketing to youth in the digital age: The promotion of unhealthy products and health promoting behaviours on social media. Media and Communication, 4(3), 35-49.

Dutta-Bergman, M. (2003). Trusted online sources of health information:

differences in demographics, health beliefs, and health-information orientation. Journal of medical Internet research, 5(3), e893.

Evers, C. W., Albury, K., Byron, P., & Crawford, K. (2013). Young people, social media, social network sites and sexual health communication in Australia:" This is funny, you should watch it". International Journal of Communication, 7, 18.

Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines. Information Society, 20, 325-344.

Flora, J. A., Saphir, M. N., Schooler, C., & Rimal, R. N. (1997). Toward a framework for intervention channels: Reach, involvement, and impact. Annals of epidemiology, 7(7), S104-S112.

George, K. S., Roberts, C. B., Beasley, S., Fox, M., Rashied-Henry, K., & Brooklyn Partnership to Drive Down Diabetes (BP3D). (2016). Our health is in our hands: a social marketing campaign to combat obesity and diabetes. American Journal of Health Promotion, 30(4), 283-286.

Gong, Z. H., & Lyford, C. (2025). Using social media for more engaged users and enhanced health communication in diabetes care. American Journal of Lifestyle Medicine, 19(1), 118-128.

Gupta, S., Dash, S. B., & Mahajan, R. (2022). The role of social influencers for effective public health communication. Online information review, 46(5), 974-992.

Guse, K., Levine, D., Martins, S., Lira, A., Gaarde, J., Westmorland, W., & Gilliam, M. (2012). Interventions using new digital media to improve adolescent sexual health: a systematic review. Journal of adolescent health, 51(6), 535-543.

Griffith, T. L., & Neale, M. A. (2001). 8. Information processing in traditional, hybrid, and virtual teams: From nascent knowledge to transactive memory. Research in organizational behavior, 23, 379-421.

Han, M., Tan, X. Y., Lee, R., Lee, J. K., & Mahendran, R. (2021). Impact of social media on health-related outcomes among older adults in Singapore: qualitative study. JMIR aging, 4(1), e23826.

Harrison, A. A. (1977). Mere exposure. In Advances in experimental social psychology (Vol. 10, pp. 39-83): Elsevier.

Hayes, A. (2021). The PROCESS macro for SPSS, SAS, and R. Retrieved from https://www.processmacro.org/download.html.

Head, K. J., Noar, S. M., Iannarino, N. T., & Harrington, N. G. (2013). Efficacy of text messaging-based interventions for health promotion: a meta-analysis. Social science & medicine, 97, 41-48.

Henry Ford Health (2025). American obesity rates are incresing. Here’s how you can maintain a healthy weight. Retreived from https://www.henryford.com/blog/2025/02/american-obesity-rates-are-increasing.

Hornik, R. (2002). Public health communication: Evidence for behavior change: Routledge.

Hovland, C. I., & Weiss, W. (1951). The influence of source credibility on communication effectiveness. *Public Opinion Quarterly, 15*(4), 635–650.

Huo, J., Desai, R., Hong, Y. R., Turner, K., Mainous III, A. G., & Bian, J. (2019). Use of social media in health communication: findings from the health information national trends survey 2013, 2014, and 2017. Cancer Control, 26(1), 1073274819841442.

Huo, C., Zhang, M., & Ma, F. (2018). Factors influencing people's health knowledge adoption in social media: the mediating effect of trust and the moderating effect of health threat. Library Hi Tech.

Islam, A. N., Laato, S., Talukder, S., & Sutinen, E. (2020). Misinformation sharing and social media fatigue during COVID-19: An affordance and cognitive load perspective. Technological forecasting and social change, 159, 120201.

Keelan, J., Pavri-Garcia, V., Tomlinson, G., & Wilson, K. (2007). YouTube as a source of information on immunization: a content analysis. jama, 298(21), 2482-2484.

Kirtiş, A. K., & Karahan, F. (2011). To be or not to be in social media arena as the most cost-efficient marketing strategy after the global recession. Procedia-Social and Behavioral Sciences, 24, 260-268.

Kontos, E. Z., Emmons, K. M., Puleo, E., & Viswanath, K. (2010). Communication inequalities and public health implications of adult social networking site use in the United States. Journal of health communication, 15(sup3), 216-235.

Korda, H., & Itani, Z. (2013). Harnessing social media for health promotion and behavior change. Health promotion practice, 14(1), 15-23.

Kothe, E. J., Mullan, B. A., & Amaratunga, R. (2011). Randomised controlled trial of a brief theory-based intervention promoting breakfast consumption. Appetite, 56(1), 148-155.

Kukreja, P., Sheehan, A. H., & Riggins, J. (2011). Use of social media by pharmacy preceptors. American journal of pharmaceutical education, 75(9).

Krishnan, A., & Zhou, X. (2019). Modeling the effect of health antecedents and social media engagement on healthy eating and quality of life. Journal of Applied Communication Research, 47(4), 365-380.

Laato, S., Islam, A. N., Islam, M. N., & Whelan, E. (2020). What drives unverified information sharing and cyberchondria during the COVID-19 pandemic?. European journal of information systems, 29(3), 288-305.

Lan, Y. F., & Sie, Y. S. (2010). Using RSS to support mobile learning based on media richness theory. computers & education, 55(2), 723-732.

Lange, P. G. (2007). Publicly private and privately public: Social networking on YouTube. Journal of computer-mediated communication, 13(1), 361-380.

Lichtenstein, A. H., Appel, L. J., Brands, M., Carnethon, M., Daniels, S., Franch, H. A., . . . Wylie-Rosett, J. (2006). Diet and lifestyle recommendations revision 2006: A scientific statement from the american heart association nutrition committee. Circulation, 114(1), 82-96. Retrieved from https://search.proquest.com/docview/17263548?accountid=12598

Liu, C., & Hung, K. (2010). Exploring the interactive effects of celebrity endorsement and brand sponsorship on advertising effectiveness. *Journal of Advertising Research, 50*(2), 181-192.

"Lockdown eating insights: Has the pandemic turned us into a nation of snackers?" (2020). Retrieved from https://covid.joinzoe.com/us-post/lockdown-snacking

Lu, Y., Kim, Y., Dou, X. Y., & Kumar, S. (2014). Promote physical activity among college students: Using media richness and interactivity in web design. Computers in Human Behavior, 41, 40-50.

Metzger, M. J., Flanagin, A. J., Eyal, K., Lemus, D. R., & McCann, R. M. (2003). Credibility for the 21st century: Integrating perspectives on source, message, and media credibility in the contemporary media environment. *Communication Yearbook, 27*, 293–335.

Moorhead, S. A., Hazlett, D. E., Harrison, L., Carroll, J. K., Irwin, A., & Hoving, C. (2013). A new dimension of health care: systematic review of the uses, benefits, and limitations of social media for health communication. Journal of medical Internet research, 15(4), e85.

Napolitano, M. A., Hayes, S., Bennett, G. G., Ives, A. K., & Foster, G. D. (2013). Using Facebook and text messaging to deliver a weight loss program to college students. Obesity, 21(1), 25-31.

O'Keefe, D. J. (2013). The elaboration likelihood model. The SAGE handbook of persuasion: Developments in theory and practice, 137-149.

O'Mara, B. (2013). Social media, digital video and health promotion in a culturally and linguistically diverse Australia. Health Promotion International, 28(3), 466-476.

Pagoto, S., Schneider, K. L., Evans, M., Waring, M. E., Appelhans, B., Busch, A. M., ... & Ziedonis, M. (2014). Tweeting it off: characteristics of adults who tweet about a weight loss attempt. Journal of the American Medical Informatics Association, 21(6), 1032-1037.

Pellegrini, M., Ponzo, V., Rosato, R., Scumaci, E., Goitre, I., Benso, A., ... & Bo, S. (2020). Changes in weight and nutritional habits in adults with obesity during the "lockdown" period caused by the COVID-19 virus emergency. Nutrients, 12(7), 2016.

Petty, R. E., Cacioppo, J. T., & Haugtvedt, C. (1992). Ego-involvement and persuasion: An appreciative look at the Sherifs' contribution to the study of self-relevance and attitude change. Social judgment and intergroup relations: Essays in honor of Muzafer Sherif, 147-174.

Petty, R. E., Cacioppo, J. T., & Schumann, D. (1983). Central and peripheral routes to advertising effectiveness: The moderating role of involvement. Journal of Consumer Research, 10(2), 135-146.

Petty, R. E., & Wegener, D. T. (1999). The elaboration likelihood model; Current status and controversies. Dual-process theories in social psychology, 41-72.

Prelip, M., Slusser, W., Thai, C. L., Kinsler, J., & Erausquin, J. T. (2011). Effects of a school-based nutrition program diffused throughout a large urban community on attitudes, beliefs, and behaviors related to fruit and vegetable consumption. Journal of school health, 81(9), 520-529.

Ravindran, T., Yeow Kuan, A. C., & Hoe Lian, D. G. (2014). Antecedents and effects of social network fatigue. Journal of the Association for Information Science and Technology, 65(11), 2306-2320.

Robinson, E., Boyland, E., Chisholm, A., Harrold, J., Maloney, N. G., Marty, L., ... & Hardman, C. A. (2021). Obesity, eating behavior and physical activity during COVID-19 lockdown: A study of UK adults. Appetite, 156, 104853.

Rogers, E. M., & Storey, J. D. (1987). Communication campaigns.

Rus, H. M., & Cameron, L. D. (2016). Health communication in social media: message features predicting user engagement on diabetes-related Facebook pages. Annals of behavioral medicine, 50(5), 678-689.

Scanfeld, D., Scanfeld, V., & Larson, E. L. (2010). Dissemination of health information through social networks: Twitter and antibiotics. American journal of infection control, 38(3), 182-188.

Sharma, N., & Patterson, P. G. (1999). The impact of communication effectiveness and service quality on relationship commitment in consumer, professional services. Journal of services marketing, 13(2), 151-170.

Sherif, A. (2024). Work from home: remote & hybrid work - Statistics & Facts. Statista. https://www.statista.com/topics/6565/work-from-home-and-remote-work/#topicOverview

Sidor, A., & Rzymski, P. (2020). Dietary choices and habits during COVID-19 lockdown: experience from Poland. Nutrients, 12(6), 1657.

So, J., Kim, S., & Cohen, H. (2017). Message fatigue: Conceptual definition, operationalization, and correlates. Communication Monographs, 84(1), 5-29.

Stephens, K. K. (2007). The successive use of information and communication technologies at work. Communication Theory, 17(4), 486-507.

Stephens, K. K., & Rains, S. A. (2011). Information and communication technology sequences and message repetition in interpersonal interaction. Communication Research, 38(1), 101-122.

Strauss, A. (1945). The concept of attitude in social psychology. The

Journal of Psychology, 19(2), 329-339.

Summers, C. A., Smith, R. W., & Reczek, R. W. (2016). An audience of one: Behaviorally targeted ads as implied social labels. Journal of Consumer Research, 43(1), 156-178.

Tasnim, S., Hossain, M. M., & Mazumder, H. (2020). Impact of rumors and misinformation on COVID-19 in social media. Journal of preventive medicine and public health, 53(3), 171.

Thorson, E., Wicks, R., & Leshner, G. (2012). Experimental methodology in journalism and mass communication research. Journalism & Mass Communication Quarterly, 89(1), 112-124.

Tobey, L. N., & Manore, M. M. (2014). Social media and nutrition education: the food hero experience. Journal of nutrition education and behavior, 46(2), 128-133.

Tsimonis, G., & Dimitriadis, S. (2014). Brand strategies in social media. Marketing intelligence & planning, 32(3), 328-344.

U.S. Bureau of Labor Statistics. (2023). One out of five workers teleworked in August 2023. https://www.bls.gov/opub/ted/2023/one-out-of-five-workers-teleworked-in-august-2023.htm

Warshaw, P. R., & Davis, F. D. (1985). Disentangling behavioral intention and behavioral expectation. Journal of experimental social psychology, 21(3), 213-228.

Walther, J. B. (2011). Theories of computer-mediated communication and interpersonal relations. The handbook of interpersonal communication, 4, 443-479.

Waters, R. D., & Jones, P. M. (2011). Using video to build an organization's identity and brand: A content analysis of nonprofit organizations' YouTube videos. Journal of Nonprofit & Public Sector Marketing, 23(3), 248-268.

Weymann, N., Härter, M., & Dirmaier, J. (2015). Quality of online information on type 2 diabetes: a cross-sectional study. Health promotion international, 30(4), 821-831.

Yan, J., Liu, N., Wang, G., Zhang, W., Jiang, Y., & Chen, Z. (2009, April). How much can behavioral targeting help online advertising?. In Proceedings of the 18th international conference on World wide web (pp. 261-270).

Zheng, H., & Ling, R. (2021). Drivers of social media fatigue: A systematic review. Telematics and informatics, 64, 101696.

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Table 1. Descriptive Analysis for Main Study

N	359
Age-M(SD), range	42.15(10.98), 22-75
Sex-(n, %)	
Female	47.8
Male	52.2
Hispanic/Latino	
Yes	4.4
No	95.6
Race/Ethnicity	
American Indian or Alaska Native	1.4
Asian	26.9
Black of African American	6.7
White	61.9
Other	0.3
Mixed Races	2.8
Education-(%)	
Less than high school	0.3
High school graduate	12.2
Some college no degree	13.3
Associate's degree/two-year degree	9.7
Bachelor's degree	48.6
Graduate degree	15
Other	0.8
Marital Status-(%)	
Single, never married	35.3
Married or domestic partnership	55.8
Widowed	0.8
Divorced	6.7
Separated	1.4
Dependent-(%)	
Yes	31.1
No	68.9
Employment Status-(%)	
Employed for wages	66.4
Self-employed	21.4
Out of work and looking for work	2.2
Out of work but not currently looking for work	0.6
A homemaker	4.4
A student	0.6
Military	0.3
Retired	3.3
Unable to work	0.8

Income-(%)	
Less than $10,000	10.3
$10,000 - $24,999	18.3
$25,000 - $49,999	28.1
$50,000 - $74,999	21.4
$75,000 - $99,999	11.1
$100,000 - $ 124,999	5
$125,000 - $149,999	3.3
$150,000 or more	2.5
Health Status-(%)	
Excellent	11.9
Very good	36.7
Good	35.6
Fair	14.7
Poor	1.1
BMI-(%)	
Underweight (below 18.5)	8.9
Normal or healthy weight (18.5-24.9)	42.2
Overweight (25.0-29.9)	30
Obesity (30.0 and above)	19

Table 2. Eigenvalues and Cronbach's for Main Study

Variable Name		Message 1	Message 2	Message 3
Information Overload: The information I received…	Eigenvalue	4.09	4.08	3.90
about healthy eating behavior needs too much explanation to be	% of Var. Exp.	81.85	81.54	77.93
useful.	Cronbach's α	.94	.94	.93
requires me to make too many decisions.				
has too much information.				
is more discussion than I wished.				
is more information than I need.				
Information Effectiveness: This message is…	Eigenvalue	3.71	3.75	4.00
effective.	% of Var. Exp.	74.27	75.06	80.05
detailed.	Cronbach's α	.91	.92	.94
useful.				
in high quality.				
well supported.				
Attitude toward messages: This message is…	Eigenvalue	3.96	3.79	4.04
helpful to my health.	% of Var. Exp.	79.15	75.86	80.78
a valuable resource.	Cronbach's α	.93	.91	.94
important for being healthy.				
a good reference for meal preparation.				
has something positive to me.				
Online engagement intention This message is worth sharing with others.	% of Var. Exp.	76.35	76.14	77.37
I will recommend this message to others.	Cronbach's α	.94	.94	.94
I will press on the "Like" button on Facebook.				
I will press on the "Love" button on Facebook.				
I will "share" this message on Facebook.				
I will "comment" on this message on Facebook.				
Intention to Follow Suggestions from the Message	Eigenvalue	4.49	4.55	4.56
I intend to follow what the message suggests in next seven days.	% of Var. Exp.	89.85	90.90	91.17
I will try to follow what the message suggests in next seven days.	Cronbach's α	.97	.98	.98
I want to follow what the message suggests in next seven days.				
I expect to follow what the message suggests in next seven days.				
How likely is it that you will follow what the message suggests in next seven days?				

Table 3. Moderated Mediation Analysis

Predictor	Attitudes toward Message (ATT)		Online Engagement Intentions (OEI)		Intention to Follow Suggestions (BI)	
	Coeff (SE)	***CI_{LL-UL}***	***Coeff (SE)***	***CI_{LL-UL}***	***Coeff (SE)***	***CI_{LL-UL}***
R (R^2)	.90 (.81)		.79(.62)		.80(.64)	
MSE	.20		1.17		.71	
df	16, 342		18,340		20,338	
F	92.87		31.07		30.45	
p	< .001		<.001		<.001	
(constant)	.42(.49)	-.55,1.38	3.61(1.55)	.56,6.66	-.10(1.27)	-2.59,2.39
Inf. Load (IL)	-.23(.11)*	-.44,-.02	-.11(.26)	-.62,.41	-.63(.21)**	-1.03,-.22
Inf. Effective. (IE)	.88(.05)***	.78,.99	-.92(.30)**	-1.51,-.32	.21(.25)	-.28,.70
Attitudes (ATT)	--	--	.13(.24)	-.34,.60	1.31(.28)***	.79,1.85
OEI	--	--	--	--	-.14(.24)	-.61,.33
IL x IE	.03(.02)	-.01,.06	.03(.04)	-.06,.12	.08(.04)*	.01,.15
ATT x IE	--	--	.17(.05)***	.08,.26	-.13(.05)*	-.24,-.03
OEI x IE	--	--	--	--	.07(.04)	-.01,.16
BMI	.004(.004)	-.004,.01	-.02(.01)	-.03,.001	-.01(.01)	-.02,.01
Age	-.001(.003)	-.01,.004	.02(.01)*	.01,.03	.001(.01)	-.01,.01
Race	-.005(.02)	-.05,.04	-.23(.06)***	-.34,-.12	.03(.04)	-.11,.01
Susceptibility	-.01(.02)	-.04,.03	-.08(.04)	-.09,.07	-.004(.03)	-.07,.06
Anxiety	.02(.02)	-.03,.06	.26(.06)***	.15,.38	.08(.05)	-.01,.17
Education	.005(.02)	-.04,.05	.004(.05)	-.10,.11	.06(.04)	-.02,.14
Marital Status	.003(.03)	-.06,.07	-.03(.08)	-.18,.12	.09(.06)	-.03,.21
Dependents	.02(.06)	-.09,.13	-30(.13)*	-.56,-.03	-.07(.11)	-.28,.14
Employment	.01(.02)	-.02,.04	-.05(.04)	-.13,.03	-.06(.03)*	-.12,-.005
Income	.01(.02)	-.03,.04	.03(.04)	-.13,.03	.07(.03)*	.01,.14
Hispanic	.18(.12)	-.06,.42	-.16(.29)	-.74,.42	.08(.23)	-.37,.53
Gender	.05(.05)	-.05,.15	-.09(.12)	-.15,.33	-.08(.10)	-.27,.11
Health	-.03(.03)	-.09,.03	.03(.07)	-.11,.18	-.06(.06)	-.17,.05

Note: Interaction 1 = IL x IE, Interaction 2 = ATT x IE, Interaction 3 = OEI x IE; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 4. Indirect Effects of Moderated Mediation Analysis

Indirect Effects	IE	Effect	BootSE	$BootCI_{ll-ul}$
IL à ATT à BI	Low (4.47)	-.08*	.03	-.15,-.02
	Moderate (5.47)	-.05*	.02	-.08,-.02
	High (6.40)	-.02*	.01	-.05,-.004
IL à OEI à BI	Low (4.47)	.01	.02	-.03,.04
	Moderate (5.47)	.02	.02	-.01,.05
	High (6.40)	.03	.02	-.01,.08
IL à ATT à OEI à BI	Low (4.47)	-.02*	.01	-.04,-.002
	Moderate (5.47)	-.02*	.01	-.04,-.01
	High (6.40)	-.02*	.01	-.04,-.01

* $p < .05$; ** $p < .01$; *** $p < .001$

Figure 1. Proposed Conceptual Model

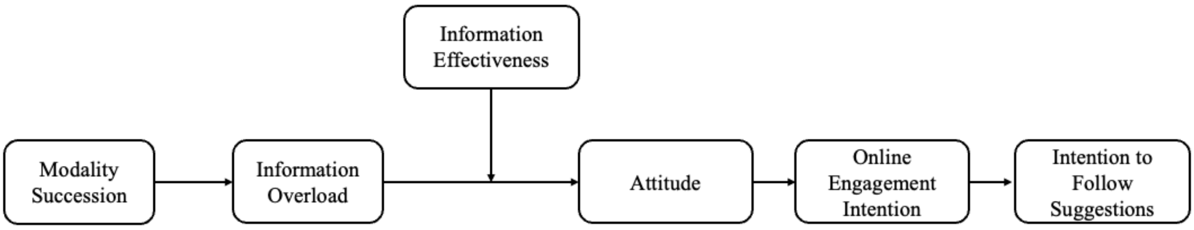

Figure 2. Interaction of Information Overload and Information Effectiveness on Intention to Follow Suggestions

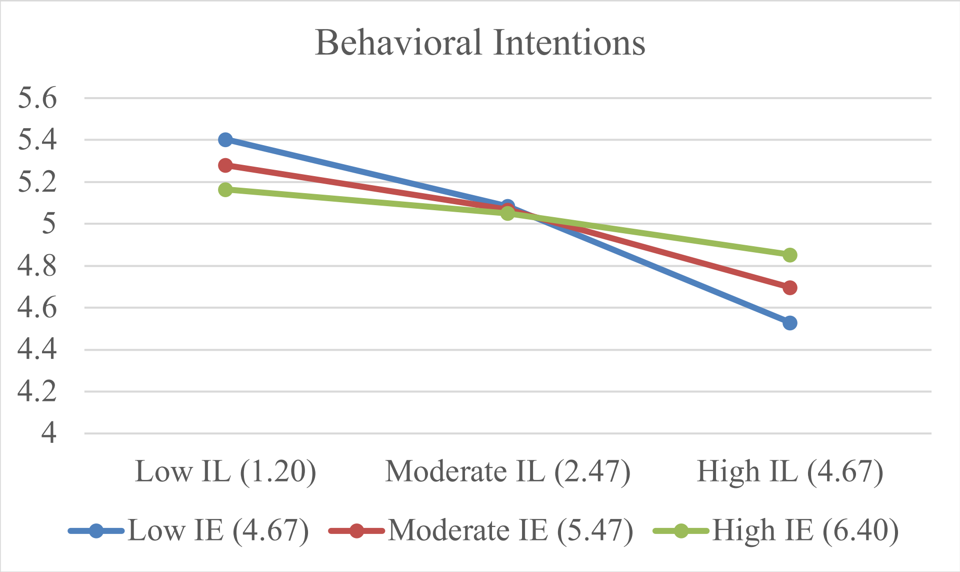

Figure 3. Interaction of Attitude and Information Effectiveness on Online Engagement Intention