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How Interactive Data Visualization and Users' BMI (Body Mass Index) Influence Obesity Prevention Intentions: The Mediating Effect of Cognitive Absorption

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ABSTRACT

The current study examines how interactive data visualization can augment the persuasive potential of health information. In an experiment using an obesity-awareness website (N = 248), we manipulated the level of interactivity in a data visualization tool that featured obesity prevalence in the U.S. and measured participants' absorption into the website, perceived issue severity, content perceptions, and intentions to prevent/treat obesity. Our data demonstrated that lower BMI participants reported greater cognitive absorption when highly interactive data visualization was available on the website. Subsequently, greater cognitive absorption into the website led to higher perceived issue severity, greater content perceptions, and higher obesity prevention intentions among lower BMI participants but not among higher BMI participants.

Health information and trends often involve complex statistics to be reported and delivered. While increasingly more data are available from the health industry and research, data visualization has become a popular approach to engage audience in quickly processing important takeaways from health data. Recent examples include tobacco prevalence and control reports from the Institute for Health Metrics and Evaluation (https://vizhub.healthdata.org/tobacco-control/mexico), or mortality data visualization by the National Center for Health Statistics (https://www.cdc.gov/nchs/data-visualization/index.htm), where various measures of health topics and risks in the United States are visualized in charts and graphs. Especially, journalists and Web designers have embedded on-screen interactive techniques in data visualization to create more interactive user experience (M. L. Young et al., 2018). Whereas literature in data visualization has suggested that applying more interactive features to data visualization can further amplify its communicative effectiveness (e.g., Segel & Heer, 2010; Singer, 2011), very few empirical studies actually examined this question. As a result, the role that interactivity serves in innovative data visualization still remains unclear – does it facilitate the audience to consume the complex health information more easily, fluently, and intuitively? Or, does these stimulating interactive features add additional clutters for readers to process in their cognitive space?

To answer these questions, the present research examines the persuasive effectiveness of interactive data visualization. Specifically, the current study investigates the theoretical mechanism underlying the impact of interactive data visualization in the context of health communication. We argue that the key psychological appeal of interactive data visualization lies in the fact that it enables and encourages user *actions*, such as dragging, zooming, or mouse-hovering, while users digest and interpret complex quantitative data. The degree to which an interface enables users to manipulate its information with a variety of interaction techniques has been defined as *modality interactivity* (Sundar et al., 2015). Modality interactivity has been found to enhance user engagement and shape positive content attitudes (e.g., Beuckels & Hudders, 2016; Oh & Sundar, 2015), but its effectiveness in communicating statistical health information has not been thoroughly investigated.

Filling this gap, the current study applies user engagement models in HCI (human-computer interaction) literature (Oh et al., 2018; Sundar et al., 2015) to explain how cognitive absorption evoked by modality interactivity can augment the persuasive potential of data visualization that portraits the trends in obesity and obesity prevalence in the US. In particular, we are interested in how the level of interactivity in data visualization can influence different audience groups whose health indicators vary, combining the theoretical framework of dual process models (Chaiken, 1980; R. Petty & Cacioppo, 1986) with HCI literature. An obesity-awareness website was constructed for the current study. An experiment was conducted to examine whether cognitive absorption initiated by highly interactive data visualization can enhance the persuasive impact of the obesity-prevalence information featured on the website, and how the impact of interactive data visualization varies depending on participants' BMI scores.

Literature review

The effect of modality interactivity in data visualization on cognitive absorption

Interactive data visualization adds user-controlled tools (e.g., dragging, sliding, clicking, hovering, etc.) to visually present numerical information (e.g., plots, charts, and graphs) (Ward et al., 2010). Current on-screen affordances enable a wide

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variety of user interactions, and different tools can be added based on the nature of data. For instance, users can compare different countries in terms of their social infrastructure by interacting with a spider chart and dragging a slider across a timeline (http://worldshap.in/). Population growth in Europe can be visualized by a color-coded map, and users can hover a mouse over each country to see detailed information (interaktiv.morgenpost.de/europakarte/).

From a human-computer interaction (HCI) standpoint, interactive media content can be communicated through three types of interactivity, including modality, source, and message interactivity (Sundar et al., 2015). Given the nonverbal nature of data visualization, *modality interactivity*, the degree to which users can control visual objects through a variety of interaction techniques such as click, slide, drag, and zoom-in, is considered as the most relevant type of website affordance to enhance user control over complex statistical information (Sundar et al., 2015; Yang & Shen, 2018). As the level of modality interactivity increases, the interface can provide more diverse ways for users to manipulate numerical information and afford greater usability. For instance, a map that has a timeline feature provides much easier ways to understand geospatial and time-oriented data such as population change over time, compared to a click-only website.

Prior literature has identified several defining features of modality interactivity (Sundar et al., 2014, 2015; Wang & Sundar, 2018). Modality interactivity is known to afford more intuitive and natural ways to manipulate the visual elements of the interface (Oh & Sundar, 2015), and be accompanied with richer and more stimulating visual experiences since the user controls the movement of visual elements on the website (Beuckels & Hudders, 2016). Given its ability to influence the way images and visuals are presented on the website, modality interactivity has been also called as *image* interactivity (Cano et al., 2017). Synthesizing the prior literature, we define the immediate perceptual outcome of modality interactivity in data visualization as the degree to which users perceive interface features to allow the user to perform actions on the website content in an intuitive way and simultaneously respond to user actions with richer visual experience.

User engagement models in HCI commonly propose that a prominent feature of modality interactivity is to enhance feelings of immersion and engagement by promoting on-screen actions and thereby elevating the extent of user control (Oh et al., 2018; Sundar et al., 2015). Oh et al. (2018)'s model states that user actions enabled by modality interactivity enhance positive interface perceptions such that the website is natural and intuitive to use, which enhances feelings of absorption into the content that the website delivers. TIME (a theory of interactive media effects; Sundar et al., 2015) also proposes that active use of interactive options on the website leads to greater feelings of absorption due to expanded perceptual bandwidth. According to the model, high modality interactivity permits and encourages users to take advantage of their sensorimotor skills to manipulate website visuals (e.g., drag a slider, hover a mouse on a specific spot, double-click to zoom in, etc.). As human's sensory processing system is inherently responsive to moving objects, users naturally pay more attention to and become more engaged with the website content while they perform actual motions throughout a navigating experience (Reeves & Nass, 2000). As a result, when the movement of objects is controlled by the user, they feel more immersed into the website (Beuckels & Hudders, 2016; Sundar et al., 2015).

Such potential of modality interactivity can be summarized by the unique state of *cognitive absorption*. Former literature has commonly identified several user perceptions that indicate the state of absorption, including heightened immersion, temporal dissociation, enjoyment, control, and intrinsic motivation (Agarwal & Karahanna, 2000; Venkatesh et al., 2012). Especially, studies on human-website interaction have commonly found that when users are cognitively engaged, they demonstrate heightened attention and involvement and fully immerse themselves in performing the task at hands (O'Brien et al., 2018; Saadé & Bahli, 2005). These findings suggest that the dimension of *immersion* is the most relevant to the current study's context – in fact, novelty, esthetic appeal, and usability of interactive system (O'Brien & Toms, 2010; O'Brien et al., 2018; Oh et al., 2018; Sundar et al., 2015), and interactivity of the interface were all found to enhance feelings of immersion in both HCI and communication literature. More importantly, when users feel immersed in the interaction, the experience can positively predict perceived usefulness and perceived ease of use of the system (Agarwal & Karahanna, 2000), as well as greater content perceptions (Oh et al., 2018).

The effect of health indicators: BMI as a moderator

While accumulated findings suggest the positive impact of modality interactivity on user experience, limited literature has illustrated its persuasive potential for health communication. Often, prior studies examined modality interactivity in contexts where the variance in personal involvement is relatively modest. For instance, the majority of former literature empirically examined the effect of modality interactivity in applications of advertising (e.g., Beuckels & Hudders, 2016; Wang & Sundar, 2018) and entertainment (e.g., Corona et al., 2013). In many of these prior studies, sensory-appealing interface design was usually sufficient to draw users' attention to the content. However, cognitive processing of health information is distinct in essence. One's involvement and perception toward a specific health topic is highly dependent on his/her physical condition (Rimer & Kreuter, 2006). In particular, individuals are known to perceive a greater extent of self-relevance if their physical conditions share similarity with what is illustrated under the health topic (Blondé & Girandola, 2018; Rimer & Kreuter, 2006).

To the current study's context, the most relevant health indicator that can influence message processing of obesity data visualization is BMI (Body Mass Index). Statistics related to obesity prevalence are primarily based on the increasing average BMI among the U.S. population (Hales et al., 2020). According to dual process models (Chaiken, 1980; R. Petty & Cacioppo, 1986), elaboration likelihood relies on individuals' motivation to process persuasive messages. Whereas involvement, "the extent to which the attitudinal issue under consideration is of personal importance" (p. 1915; R. E. Petty & Cacioppo, 1979), has been found to predict individuals' motivation to cognitively process persuasive messages in many prior studies (e.g., Briñol & Petty, 2006; Chaiken, 1980; R. Petty & Cacioppo, 1986; Quintero Johnson et al., 2013), health communication researchers have commonly acknowledged the similar role of individuals' physical conditions on message processing and attitude change (Juszczyk et al., 2014; Rimer & Kreuter, 2006; R. Young et al., 2016).

The mechanism by which health conditions influence message processing can be explained by perceived self-relevance or protection motivation (Dinoff & Kowalski, 1999; Petty et al., 2002). Individuals have a tendency to conduct more vigilant cognitive processing when the issue at hand implies a personal threat (Blondé & Girandola, 2018). Prior studies have found evidence that those who feel highly susceptible to health risks engage in more effortful processing of the health message, showing that their attitude change is primarily based on the argument quality (Dinoff & Kowalski, 1999). In contrast, low perceived risk or self-relevance can lead to a state of more convenient cognitive processing, where individuals rely on heuristic cues such as source credibility to quickly process the message (Briñol & Petty, 2006; Quintero Johnson et al., 2013; R. Young et al., 2016). To the current study's context, these studies imply that individuals with higher BMI scores will perceive higher degrees of self-relevance with and susceptibility to the issue of obesity and more likely process obesity-related data in a systematic way compared to those with lower BMI scores.

Then how would BMI scores adjust the impact of *interactive* data visualization that demonstrates trends in obesity and obesity prevalence? Interactivity literature has found that interactive features are often used as convenient heuristic cues that directly inform users of the credibility of the website's content (Metzger et al., 2010; Oh et al., 2019). Consistent with the prediction of dual process models, this tendency has been found to be more prominent among low-involvement users whose cognitive processing is focused on peripheral cues, including website design, layout, and the sheer amount of user actions (Lee & Kim, 2016; Liu & Shrum, 2009; Oh & Sundar, 2015). These findings suggest higher BMI users will be less likely influenced by the peripheral features of the website like the interactivity of data visualization, whereas lower BMI individuals will be more likely to show immediate positive responses to highly interactive data visualization. In other words, whereas highly interactive data visualization would readily capture attention and directly lead to greater feelings of immersion among lower BMI users, its impact on higher BMI users' responses would be minimized or negligible. Thus, we propose:

H1: There will be an interaction effect between participants' BMI scores and interactivity of data visualization on cognitive absorption; highly interactive visualization will enhance feelings of immersion among lower BMI participants but not among higher BMI participants.

The persuasive impact of cognitive absorption

Literature suggests that cognitive absorption, especially the feelings of immersion while performing a task on the website, can increase the impact of the website's messages. Cognitive absorption is indicated by a unique state of immersion, where users extensively focus on the present task performance (Agarwal & Karahanna, 2000; Reychav & Wu, 2015). It is likely that the effect of obesity-related information becomes maximized going through the state of immersion because users allocate additional cognitive resource to information processing when immersed (Léger et al., 2014; Leong, 2011). As users find interactive data about the obesity epidemic in the U.S. as more absorbing, they are likely to perceive the obesity issues as posing greater threat on the public health. The increase in perceived issue severity of obesity should lead to greater intention to prevent or treat obesity issues, as the cumulated literature on the relationship between perceived issue severity and intentions has suggested so far (e.g., Fischhoff, 2012; Rimal & Real, 2003).

In addition, when users feel immersed by highly interactive data visualization, they can develop more positive attitudes toward the interface and its content as well (Oh & Sundar, 2015; Sundar et al., 2015). Former studies in online shopping (Chan et al., 2014) and Internet research (Fan et al., 2017) have shown that cognitive absorption can increase users' trust toward the interface, which positively affects credibility of its content. Therefore, we propose:

H2: Cognitive absorption in the obesity-awareness website, influenced by interactive data visualization, will positively predict participants' perceived issue severity (H2a), content perceptions (H2b), and behavioral intention to prevent/treat obesity (H2 c).

Combining H1 and H2, we also propose:

H3: The increase in absorption among lower BMI participants induced by highly interactive data visualization will lead to greater perceived issue severity (H3a), content perceptions (H3b), and behavioral intention to prevent/treat obesity among them (H3c).

Method

A between-subjects, single-factor experiment was conducted, using an obesity-awareness website where a data visualization tool with two levels of interactivity (high vs. low) was embedded[1].

Participants

A crowdsourcing website, mturk.com was used to recruit participants. Participants received 2.00 USD for their participation. To ensure that participants performed sufficient interaction with the stimulus websites, we applied three strategies simultaneously. First, we recruited participants who currently reside in the US according to their IP addresses, have an approval rate for their past works greater than 99%, and completed at least 500 tasks before. Second, we asked participants to write down any fact or information that they could recall right after they browsed the website. Third, using our log data, we first filtered out participants who did not log in to the stimulus website with given IDs. Then we screened out those

(a) did not slide the interactive timeline at least once, (b) did not click or hover over the interactive map at least once, and (c) did not click or hover over the line graph at least once from the high interactivity condition (see the stimulus section for description). Similarly, we screened out participants who (1) did not click the dropdown menu to view the map by year at least once, (2) did not click on the map and line graph at least once from the low interactivity condition. We also removed those who spent less than 45 seconds on the stimulus website from our sample.

After filtering out disqualified responses, the present experiment used 248 participants' data for analysis. On average, they spent 373.00 seconds (SD = 209.80, Min = 45, Max = 1192) on the stimulus website. All of them correctly identified at least one fact from the website (M = 4.76; SD = 2.73, Min = 1, Max = 20). The result showed that the number of facts recalled was not significantly different across the two conditions, t (247) = 1.31, p = .19. The sample included 87 males (35.1%) and 161 females (64.9%), with an average age of 38.50 (SD = 12.63, Min = 19, Max = 85). The majority of participants were Caucasian (n = 192, 77.4%) and reported speaking English as their first language (n = 240; 96.8%). Median annual household income was between 40,000 USD and 49,000 USD.

Procedure

To ensure all participants browse the website through a consistent layout and presentation, participants who used mobile devices and tablets were screened out first. Qualified respondents continued to fill out a pre-questionnaire, which included an informed-consent form and questions regarding demographic information, BMI, general health, issue involvement, behavioral intention to prevent/treat obesity, and their familiarity with reading and interpreting statistical information. Next, each participant was assigned a username to access the stimulus website. Participants were randomly assigned to one of the two conditions: data visualization with low (n = 125) vs. high interactivity (n = 123). Afterward, participants logged out of the stimulus website and were navigated to complete a post-questionnaire asking their cognitive absorption while browsing the website, perceived susceptibility to obesity, perceived issue severity of obesity, content perceptions, and behavioral intentions to prevent/treat obesity.

Stimulus

The current study constructed a stimulus website collaborating with a Web developer and collected data using the Qualtrics survey tool. The stimulus website was equipped with a system that automatically collected users' log data that tracked their on-screen behaviors in real time. The data visualization tool was designed using information and statistics from a collaborative project of *The Trust for America's Health and the Robert Wood Johnson Foundation* and its existing website, *The State of Obesity* (https://stateofobesity.org/adult-obesity/). Two conditions were created: a data visualization of the United States with either high interactivity or low interactivity.[2] The website included two different tabs: obesity rate and physical inactivity rate in the U.S. For each tab, the data visualization map consisted of two major visual components: (1) a heat map presenting the percentage of obese (or physically inactive) adults in each state, and (2) a line graph visualizing the trend of adult obesity (or physical inactivity) rate from 1990 to 2015 in each state. In the heat map, darker and warmer colors indicated the severity of the obesity or inactivity issue. In the line graph, when a specific state was selected, the corresponding trend line was highlighted.

The high interactivity condition offered three different interactive features in the data visualization feature: slider, clickable heat map, and mouseover on the line graph. First, users were allowed to drag-and-drop an arrow on a slider bar positioned above the map and the line graph. By moving the slider, colors changed from light to dark, which clearly demonstrated that the prevalence of obesity and the rate of physical inactivity in the U.S. rose over the years. In contrast, the low-condition participants were provided with a simple drop-down menu to choose a specific year and a state to search the percentage of obese or physically inactive individuals on the map and the adult obesity/inactivity rates on the line graph, respectively. Therefore, they could not create the continuous change on the map or the line graph over time.

Secondly, in the high interactivity condition, the heat map was clickable. When users clicked on a particular state on the map, corresponding information of the state was highlighted on the line graph as well. Therefore, respondents could freely wander around the map and delve into the states of their interests. In contrast, in the low condition, users were asked to choose a specific state in the drop-down menu to simply observe its color on the heap map.

Third, a mouseover feature was only available in the high interactivity condition. When a participant hovered over a trend line on the line graph, the corresponding state would be highlighted with a black outline on the heat map. Similarly, when a user hovered over a certain state on the heat map, the trend line of the selected state was highlighted on the line graph as well.

Measurement

All items were measured on 7-point scales unless stated otherwise.

Manipulation check

In the high-interactivity condition, participants interacted with the slider, the clickable heat map, and the mouseover feature on the line graph while observing the visual change in colors and graphs. The perceptual outcome of using modality interactivity should include user perceptions of interface features that allow the user to perform actions on the website content in an intuitive way and simultaneously respond to user actions with richer visual experience. Thus, perceived interactivity was measured by five items that asked how much they agreed with that (a) the website was interactive, (b) the website allowed them to perform lots of user actions while browsing it, (c) the website was intuitive, and (d) the website had high-quality visual, and (e) the website had rich visual (M = 5.57, SD = .95, Cronbach's α = .81).

Mediating variable

Cognitive absorption was measured by four items from Agarwal and Karahanna (2000): “I was immersed in the task that I was performing, “I was able to block out most other distractions,” “I was absorbed in what I was doing,” and “My attention did not get diverted” (M = 5.97, SD = 1.02, Cronbach’s α = .86).

Dependent variables

Perceived issue severity was measured by three items, asking how serious obesity is as a national problem, how likely obesity will become a real threat to someone’s health, and how likely the national obesity epidemic in the U.S. will worsen in the future (M = 6.38, SD = .73, Cronbach’s α = .75). Secondly, *content perceptions* were measured by 8 items to capture participants’ evaluation of the information presented on the stimulus website, such as the obesity-related information was believable, objective, informative, useful, important, newsworthy, accurate, and interesting (M = 5.87, SD = 1.04, Cronbach’s α = .93). Finally, participants were asked to report their *behavioral intention to prevent obesity* before and after browsing the website (M = 5.32, SD = 1.30, α = .80). The baseline behavioral intention was measured in the pre-questionnaire and controlled for all analysis that involved the dependent variable. Participants were asked how likely they are to take actions for preventing (or treating) obesity, by doing regular physical exercise, paying attention to obesity information, and talking about obesity issues in the next 3 months (adapted from Wong & Cappella, 2009).

Moderating variable

Participants’ BMI scores were calculated from their self-reported weight and height. After removing univariate outliers whose z-scores were over 3.29, the sample’s average BMI was 27.71 (SD = 7.22, Min = 15.31, Max = 48.26, skewness = .91). The current study proposed BMI as a moderator under the assumption that higher BMI participants will more likely perceive greater self-relevance with obesity information and higher susceptibility to obesity. Thus, the correlations among BMI, issue involvement (to me, information about obesity is unimportant-important, irrelevant-relevant, means nothing to me-means a lot to me, worthless-valuable, not needed-needed, boring-interesting, uninvolving-involving; M = 5.39, SD = 1.39, α = .96), and perceived susceptibility to obesity (“it is likely that I will become overweight or obese,” and “my chances of suffering from obesity are high”; M = 3.53, SD = 1.88, r = .90) were examined. As expected, BMI scores were significantly and positively associated with both issue involvement (r = .34, p < .001) and perceived susceptibility (r = .69, p < .001).

Control variables

Three control variables were used in this study: familiarity with reading and interpreting statistics, age, and sex. Familiarity with statistics was controlled for given the individual difference found in processing numerical information (Jia, 2014). *Familiarity with statistics* was measured using four items, assessing whether a respondent possesses basic understanding in interpreting data and drawing statistical inferences (Jia, 2014), such as “I am familiar with basic terms and ideas related to descriptive statistics” (M = 4.96, SD = 1.40, Cronbach’s α = .95). Participants’ *gender* (87 male and 161 female participants) and *age* (M = 38.50, SD = 12.63) were also controlled for because they both are known to adjust the impact of website interactivity (e.g., Herman & Stachoň, 2018; Lu et al., 2010).

Results

Data analysis

Correlations among all variables were examined first (Table 1). A two-tailed independent sample t-test was conducted for manipulation check. To test our first hypothesis (H1), a general linear model was constructed with the manipulated level of interactivity in data visualization as an independent variable, BMI as a continuous moderator, and participants’ familiarity with statistics, gender, and age as three control variables. A follow-up analysis further probed the interaction effect using the Johnson-Neyman technique. Next, we used Model 7 of PROCESS macro (Hayes, 2013) to examine the moderated mediation as proposed in H2 and H3, which allowed us to assess whether participants’ BMI significantly moderated the indirect effect of interactivity on their perceived issue severity, content perception, and behavioral intention.

Log data

Participants’ log data were automatically recorded to check (a) if they have used at least one available interactive feature (high interactivity condition) or the drop-down menu (low interactivity condition), and (b) if the high interactive condition yielded a higher amount of user actions. Two hundred forty eight participants interacted with the website features as instructed: in the high interactivity condition (n = 125), participants were using the slider 6.33 times (Mdn = 4.00; SD = 8.13), clicking and hovering the map 39.73 times (Mdn = 25.00; SD = 50.85), and clicking and hovering the graph 15.95 times (Mdn = 5.00; SD = 30.92) on average. In the low interactivity condition (n = 123), participants were using the drop-down menu 11.89 times to specify a year (Mdn = 5.00; SD = 19.36) and 5.89 (Mdn = 3.00; SD = 13.98) times to click a state. Participants in the high interactive condition showed greater amount of user actions measured by the number of slides, hovering, and clicks (M = 62.05, SE = 5.74), compared to the total number of clicks on the drop-down

Table 1. Pearson correlation matrix of all variables included in the present study.

	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. Interactivity	1	−.04	.08	.02	.05	.10	−.01	.05	−.01
2. BMI	−.04	1	.10	.23**	.03	.18**	.08	.06	.14*
3. Cognitive absorption	.08	.10	1	.40**	.58**	.33**	.19**	.14*	.19**
4. Perceived issue severity	.02	.23**	.40**	1	.40**	.37**	.10	.16**	.17**
5. Content perception	.05	.03	.58**	.40**	1	.43**	.15*	.09	.13*
6. Behavioral intention	.10	.18**	.33**	.37**	.43**	1	.24**	.11	−.01
7. Familiarity with statistics	−.01	.08	.19**	.10	.15*	.24**	1	−.07	.02
8. Gender	.05	.06	.14*	.16**	.09	.11	−.07	1	−.02
9. Age	−.01	.14*	.19**	.17**	.13*	−.01	.02	−.02	1

*p <.05, **p <.01.

menu in the low interactive condition (M = 17.24, SE = 2.61), t (246) = 7.15, p < .001.

Manipulation check

Manipulation check was conducted by a two-tailed independent sample t-test. The result showed that participants perceived that the website with highly interactive visualization to be more interactive, t (243) = 2.00, p < .05; they perceived it to allow them to perform more actions, be more interactive and intuitive, and had higher-quality and richer visual (M = 5.70, SE = .09) than the website with low-interactivity visualization (M = 5.45, SE = .09). Thus, manipulation check was deemed successful.

The moderating effect of BMI (H1)

General linear model (GLM) analysis was used to test the interaction between interactivity of data visualization and the standardized values of BMI on cognitive absorption. Participants' gender, age, and familiarity with statistics were controlled for. The result confirmed a significant two-way interaction effect between the degree of interactivity in data visualization and the standardized values of participants' BMI on cognitive absorption, $F(1, 238) = 4.01$, $p < .05$, $\eta^2 = .02$.

The two-way interaction effect was further probed by the Johnson-Neyman technique, using PROCESS macro by Hayes (2013). All predictors and the interaction term were first regressed on cognitive absorption. The level of interactivity of visualization, standardized BMI, their interaction term, gender, age, and familiarity with statistics significantly explained cognitive absorption, F (6, 238) = 5.36, p < .001, R^2 = .12. The interaction between interactivity and standardized BMI was significant as hypothesized, $\beta = -.18$, $p < .05$. A Johnson-Neyman plot of the region of significance was generated. The result showed that only among lower BMI participants, those who used highly interactive data visualization reported a higher degree of cognitive absorption than those who were in the low-interactivity condition. Specifically, the difference between high- and low-interactivity conditions became significant for those whose standardized BMI scores were lower than −.40 (i.e., more than .40 SD below the mean), who comprised 39% of our sample. In other words, the highly interactive data visualization could enhance cognitive absorption compared to the low-interactivity condition only for lower-BMI participants, as H1 hypothesized (Figure 1). For average- or higher-BMI individuals whose standardized scores were higher than −.40, the difference between high vs. low conditions was not significant. Thus, H1 was supported.

Gender, age, and familiarity with statistics significantly predicted the level of cognitive absorption as well. Females (M = 6.08, SE = .97) experienced a higher degree of cognitive absorption than males (M = 5.78, SE = 1.09). Elder participants and those who reported higher familiarity with statistics felt more absorbed while they were navigating through the stimulus website (Table 2).

The persuasive impact of interactive data visualizationand the mediating effect of cognitive absorption (H2 and H3)

We used the bootstrapping method proposed by Hayes (2013) to examine H2 and H3. Using PROCESS macro (Model 7; Hayes, 2013), we tested the conditional indirect effects of interactivity on the three dependent variables depending on BMI, with cognitive absorption as a mediator (see Figure 2 for the conceptual model of the analysis). The BMI scores of respondents were standardized, and three control variables (age, gender, and familiarity with statistics) were controlled for all analysis.

Perceived issue severity

Participants' perceived issue severity was significantly predicted by interactivity, BMI, and cognitive absorption, after controlling

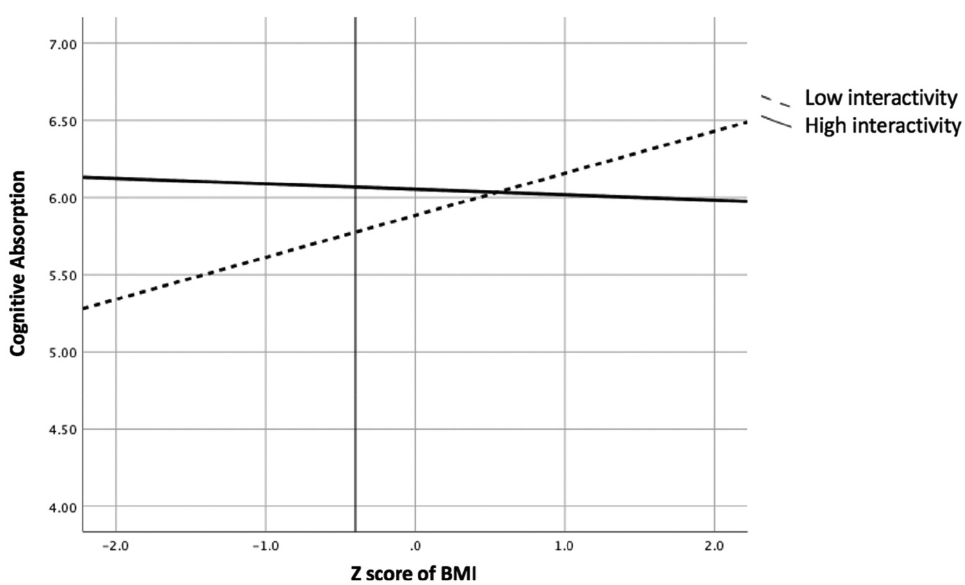

Figure 1. The interaction effect between interactive data visualization and the standardized scores of respondents' BMI on cognitive absorption. *Note*. The black vertical line indicates a significant region (i.e., less than −.40 S.D.) by the Johnson-Neyman technique.

Table 2. The effects of interactivity, BMI, and control variables on cognitive absorption.

	B	β	*p*-Value	Effect size (η^2)
Constant	4.44			
Interactivity	.16	.08	.203	.01
BMI (z-score)	.20	.18	.045	.00
Interactivity X BMI	−.27	−.18	.046	.02
Sex	.33	.15	.013	.03
Familiarity with stats	.14	.19	.002	.04
Age	.01	.18	.005	.03

for age, gender, and familiarity with statistics, $F(5, 239) = 11.01$, $p < .001$, $R^2 = .19$. Cognitive absorption was a significant, positive predictor of perceived issue severity, $B = .25$, $SE = .04$, $p < .001$, supporting H2a. The follow-up bootstrapped analysis showed that for lower BMI subjects (M-1SD), interactivity of data visualization enhanced issue severity through a heightened level of cognitive absorption, $B = .10$, $SE = .06$, 95% C.I. from .01 to .25. As expected, the conditional mediating effect of absorption on issue severity was not significant among participants with average or higher BMI scores (M/M + 1SD). Therefore, H3a was supported.

Content perceptions

Content perceptions were significantly predicted by interactivity, BMI, and cognitive absorption, after controlling for participants' familiarity with statistics, age, and sex, $F(6, 409) = 24.72$, $p < .001$, $R^2 = .34$. Again, cognitive absorption was a significant, positive predictor of content perception, $B = .58$, $SE = .06$, $p < .001$, supporting H2b. The bootstrapped result revealed that lower BMI (M-1SD) participants reported greater content perceptions through a heightened level of cognitive absorption, $B = .24$, $SE = .12$, 95% C.I. from .03 to .49. Cognitive absorption was not a significant mediator among average or high BMI (M/M + 1SD) participants. Therefore, H3b was supported.

Behavioral intention to prevent or treat obesity

We also found behavioral intentions to prevent/treat obesity were significantly predicted by interactivity, BMI, and cognitive absorption, after controlling for subjects' gender, age, and familiarity with statistics, and additionally *baseline behavioral intention* this time, $F(6, 238) = 27.54$, $p < .001$, $R^2 = .41$. Specifically, cognitive absorption was found to be a significant predictor of post-behavioral intention to prevent obesity, $B = .35$, $SE = .07$, $p < .001$, supporting H2 c. The bootstrapped analysis revealed that only those with lower BMI figures (M-1SD) reported a higher degree of behavioral intention to prevent obesity through heightened cognitive absorption, $B = .14$, $SE = .08$, 95% C.I. from .02 to .31. Interactivity in data visualization did not produce any significant conditional effect among average or high BMI (M/M + 1SD) participants. Thus, H3c was also supported.

Summary

Only among lower BMI individuals (below a z-score of −.40), highly interactive data visualization significantly enhanced their cognitive absorption. Follow-up mediation analyses showed that high interactivity of data visualization led to greater cognitive absorption, which resulted in higher perceived issue severity of obesity, greater content perceptions, and higher intention to prevent obesity among lower BMI individuals even after controlling for their baseline intentions. By contrast, the presence of highly interactive data visualization did not yield significant effects on perceptions and behavioral intentions among high- or average-BMI users in our sample.

Discussion

The present research attempted to offer both scholarly and practical contributions by conducting a study that examines the effect of interactive data visualization in the domain of health communication. Combining user interface literature with dual process models, we proposed cognitive absorption and BMI as key predictors that explain the persuasive effects of interactive data visualization assessed by three dimensions, including perceived issue severity, content perception, and behavioral intention. Practically, our results offer guidelines for how interactive data visualization can be applied to different audience groups whose BMI scores vary.

Theoretical implications

Built upon prior literature that has shown the positive impact of modality interactivity on user engagement (Beuckels & Hudders, 2016; Oh et al., 2018; Sundar et al., 2015), our study aimed to reveal the theoretical mechanism by which interactive data visualization persuades users with statistical information

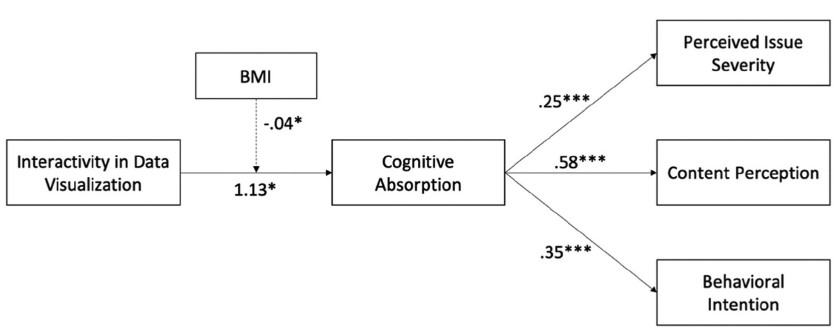

Figure 2. The conceptual model of H2 and H3 with unstandardized path coefficients. *Note*. Solid lines represent the mediating effect of interactivity through cognitive absorption on each of the dependent variables. The dashed line represents the moderating effect of BMI on cognitive absorption (*p <.05, ***p <.001).

about obesity. As hypothesized, highly interactive data visualization enhanced feelings of immersion among lower BMI individuals, which resulted in greater persuasion outcomes. Given that the health information on obesity prevalence remained constant across the high vs. low conditions, the fact that cognitive absorption induced by interactivity of data visualization led to greater persuasion lends additional support to user interface literature that has reported the significant impact of interface features on message perceptions and persuasion (e.g., Metzger et al., 2010; Oh & Sundar, 2015; Wang & Sundar, 2018).

Different from many prior studies in interactivity and user engagement (e.g., Beuckels & Hudders, 2016; O'Brien & Toms, 20108; Van Noort et al., 2012) that have been performed in moderately involving contexts (e.g., online shopping), our study bridges user engagement literature with health communication by incorporating individuals' BMI as a moderator. Whereas prior literature suggested that the mere presence of interactive features provides heuristic cues that directly enhance content credibility and message effectiveness without considering individual characteristics (Metzger et al., 2010; Wang & Sundar, 2018), our results showed no direct effect of the interactivity of data visualization on dependent variables unless individuals' BMI scores were taken into account. Thus, the current results extend the claim of the user engagement models in HCI literature (O'Brien & Toms, 20108; Oh et al., 2018) to a larger domain by demonstrating the conditional impact of interface features and cognitive absorption on persuasion – interface features do not necessarily engage all users; instead, how much action possibilities can encourage cognitive absorption and persuasion relies on individuals' motivation to process the health messages that are conveyed by the interactive features.

Whereas dual process models of persuasion (Chaiken, 1980; R. Petty & Cacioppo, 1986) have shown that involvement predicts effortful processing of persuasive messages, they have not thoroughly explained how significant individual traits in health communication such as physical conditions can be linked to message processing. The current study extends the implication of ELM to health communication by demonstrating that an indicator of one's physical condition such as BMI can also have significant explanatory power in the context of health messaging. For lower BMI users, higher interactivity in the data visualization could easily boost their cognitive absorption given its novel and intuitive nature. For higher BMI users, interactivity of data visualization was not able to sway their cognitive absorption probably because their motivation to process the message content was already set high due to the perceived relevance of the topic and their susceptibility to obesity-related health issues (Chaiken, 1980; Petty et al., 1981). In fact, our result suggests that highly interactive data visualization was almost less engaging for them than the data with simple drop-down menus (Figure 1). Another explanation could be that while using different interaction techniques and striving to understand statistical data, high BMI users were likely to experience cognitive overload, which may have reduced their cognitive absorption. Future studies can examine how health-related indicators can moderate the amount of cognitive resources spent for processing interactive features that deliver relevant health information.

The fact that we only found a small correlation between BMI and issue involvement while BMI was still strongly correlated with perceived susceptibility suggests that an objective indicator like BMI may better gauge the relevance of health information to individuals than does issue involvement. To the literature on dual-process models, our results imply that the function of involvement needs to be further explicated and examined in the domain of health communication. Issue involvement, the perceived personal relevance of the issue, may not be the best predictor of individuals' motivations to process health messages because perceived relevance itself can be influenced by fear or defensive motivations (Petty et al., 2002), which are easily triggered by health messages. Whereas the explanatory power of issue involvement has been largely supported in other domains, health communication research using the framework of dual-process models should consider examining the effects of health-condition variables instead. For instance, smoking status, BMI, and physical illness and symptoms may significantly influence not only the evaluations of health information but also their motivation and ability to process it.

Practical implications

The current study has pushed the boundary of user interface literature and shown a significant potential of interactivity of data visualization in predicting perceived issue severity, content perception, and change in behavioral intentions. Segmenting our target audience with tangible and popular statistics like BMI also enhances the practical implication of our research for health communication literature. Especially, higher cognitive absorption among lower BMI participants led to greater behavioral intentions to prevent obesity, even after controlling for their baseline intentions. Our result suggests that data visualization tools in health websites should afford a higher level of interactivity when targeting users who may not currently have the same health concerns as the data represents but may still be vulnerable to those issues in the future. Another practical implication of our study is applied to news website featuring health information, given that data visualization is a popular tool to foster greater user engagement in journalism. Our findings suggest that highly interactive visualization may further boost the potential of data-driven health news in attracting readers who are not yet involved in the topic.

Limitations and the directions for future research

Our sample, recruited from a crowdsourcing website, had slightly higher BMI scores (27.72) than the US average of 26.5 (CDC, 2017), which may reduce the generalizability of our results. Our sample also included more females than males, and we have used only one type of stimulus website, both of which may also limit the external validity of our study. Future studies should examine the current study's hypotheses with a more representative sample using other health issues, such as alcohol consumption, drug abuse, and more.

The impact of interactive data visualization can be studied from other angles. For instance, visual analytics has been verified to reduce individuals' bias toward a presented subject

(Saket et al., 2018). Whether users' bias toward health-related stigmas can be alleviated by the interactivity of data visualization can be another means to assess its persuasive effectiveness. On the other hand, the aesthetics and experiential quality of data visualization can also be influential in users' information processing and perception toward the content. Therefore, understanding other design components of visualized health data than interactivity can be another stream of future research.

Even though the interaction between interactivity and BMI exerted significant indirect effects on all dependent variables, the effect sizes of interactivity and BMI were very small on cognitive absorption. In order to boost ecological validity, the current study created almost an equally usable control condition where participants had some opportunities to manipulate the data through drop down menus, which created a very conservative condition to test the effect of interactivity in visualization. The nature of health data, which is often not exciting to users, may also have downsized the overall variance we could detect in absorption. Future studies are encouraged to test the moderating effect of BMI in a more highly interactive setting that adds animations and engaging stories to data visualization and reexamine the current study's premises.

Note

1. The current study uses a subsample from a published study (Oh et al., 2018).
2. The images of stimulus are available from the corresponding author.

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