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Picture Yourself Healthy—How Users Select Mediated Images to Shape Health Intentions and Behaviors

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ABSTRACT

Hypotheses on how selective viewing of mediated images may sustain eating habits and aid healthier eating were derived from the Selective Exposure Self- and Affect Management model. The model posits that individuals select to view media to manage their self-concepts—and that this exposure affects subsequent intentions and behaviors. Participants ($N = 265$) selectively viewed Instagram-like postings featuring healthy or unhealthy food imagery. Beforehand, participants reported habits and perceived expert recommendations regarding food intake. After viewing postings, participants chose gift cards representing healthy or unhealthy food purchases and indicated food intake intentions. Results show that existing eating behavior predicts selective exposure to healthy or unhealthy food imagery, which in turn shapes gift card choices and (both healthy and unhealthy) food intake intentions.

Americans access health information frequently online (e.g., Percheski & Hargittai, 2011), and health-focused platforms are increasingly popular (Tucker, 2011). With social media occupying the average American for nearly 2 h a day (Global Web Index, 2016), new opportunities for health communication efforts arise, as pervasive social media use might provide new means to instigate healthier behaviors (i.e., eating habits). Interestingly, posts on social media sites—particularly image-based platforms—prominently feature food-related postings: A recent content analysis suggests that over 10% of postings on Instagram, a popular photo-sharing social media site, depict food (Hu, Manikonda, & Kambhampati, 2014).

Meanwhile, obesity remains a critical health concern in America, with more than a third of adults considered obese (Ogden, Carroll, Fryar, & Flegal, 2015), and increases the risk for many of the leading causes of death (CDC, 2017). Potentially, cues on social media could help to mend this epidemic health concern, as research demonstrates that healthy food cues (e.g., images) can positively influence healthy eating behaviors (Kinard, 2016; Zepeda & Deal, 2008). Hence, the present study investigates how and why individuals access nutrition-relevant information, with a focus on photo-sharing services such as Instagram or Pinterest, because image-based postings may affect health behaviors particularly swiftly (Liu, Agam, Madsen, & Kreiman, 2009). As everyday media environments provide the audience with virtually endless choices of messages, the present study emphasizes the concept of selective exposure and, in methodological terms, draws on the selective exposure paradigm (Knobloch-Westerwick, 2015a). Building on the Selective Exposure Self- and Affect-Management (SESAM) model (Knobloch-Westerwick, 2015b), we will test predictions on how users select content in a photo-sharing social media platform and are, in turn, influenced by this content regarding health behaviors. A previous study examining selective exposure to online health information about food and physical exercise demonstrated that both participants' previous health behaviors and the differences between actual and recommended behaviors resulted in longer selective exposure to health messages, which in turn fostered attitudes regarding recommended behaviors (Westerwick, Johnson, & Knobloch-Westerwick, 2017). The current study employs the SESAM model to further test predictions about social media imagery postings and examines health-relevant messages that users are more likely to encounter in everyday media use than intervention messages commonly studied (see review by Anker, Reinhart, & Feeley, 2011).

Social networking and online health information

Instagram, a social networking site that allows users to easily post, apply various filters, and share photos or brief videos using mobile technology, has pervaded social networking since its launch in 2010. Today, it continues to grow in popularity and currently has more than 600 million active monthly users—more than 400 million of which are active daily (Instagram, 2016). Food-related posts account for more than 10% of posts on Instagram, indicating that food-related content is commonly found on the platform (Hu et al., 2014). Given that mobile users habitually go online, and Instagram users are known to access postings throughout the day (Global Web Index, 2016; Humphreys, Von Pape, & Karnowski, 2013), this channel appears powerful in impacting them regarding eating decisions in their daily lives and

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possibly more effective than traditional mobile-delivered interventions (Nour, Chen, & Allman-Farinelli, 2016). In fact, Kinard (2016) called for research to investigate how interacting with healthy food posts on Instagram and other social media platforms influence individuals' healthy eating decisions.

Compounding the prevalence of food-related posts on Instagram and the platform's great popularity is strong evidence suggesting that images elicit quick reactions. Visual recognition of food—specifically fruit—occurs as quickly as 100 ms, faster than for other categories (i.e., animals, chairs, human faces, and vehicles; Liu et al., 2009). Further, surveys indicate that individuals often recognize and discriminate between nutritionist-classified "healthy" and "unhealthy" foods (Quealy & Sanger-Katz, 2016). One correlational study demonstrated that obese individuals were more likely to share or like an Instagram post depicting a healthy food than normal weight or overweight individuals (Kinard, 2016). Combined, these results suggest that image-based postings not only are prevalent on social networking sites but also they have the ability to affect food-related intentions and behaviors particularly rapidly. Because Instagram offers an enormous wealth of imagery that users can choose from, with over 80 million new postings added each day (Instagram, 2016), the concept of selective exposure is pivotal and will be discussed next based on the SESAM model (Knobloch-Westerwick, 2015b).

## Health information seeking and the SESAM model

Health communication scholars claim that "Arguably, message exposure is the most important issue in persuasion because a person must first be exposed to a message before he or she can be influenced by it" (Pease, Brannon, & Pilling, 2006, p. 235). Hence, ample studies investigated how individuals seek health information, but very few actually observed health information exposure, instead relying on self-reported recall of information seeking (Anker et al., 2011). Recently, investigations indeed observed what health messages individuals attended to (e.g., So, Kuang, & Cho, in press) and examined specifically what characteristics of situations, messages, and recipients foster which health messages are selected for actual consumption (see review by Knobloch-Westerwick, 2015b). In light of the wealth of health information available to individuals, selective exposure is of critical importance.

Selective exposure can be defined as "any systematic bias in audience composition for a given medium or messages, as well as any systematic bias in selected messages that diverges from the composition of accessible messages" (Knobloch-Westerwick, 2015b, p. 3). Historically, the term referenced a bias toward messages consistent with preexisting beliefs (e.g., Stroud, 2008) building on Festinger's (1957) classic cognitive dissonance theory. The theory contends that individuals seek consistency—and avoid inconsistency—between their personal knowledge, beliefs, and behaviors. Once individuals recognize inconsistency, they are thought to experience unpleasant tension known as dissonance and are motivated to diminish it. The theory suggests that individuals avoid messages that challenge their existing attitudes and behaviors to avoid resulting dissonance. Further, individuals may resolve dissonance by changing existing attitudes, beliefs, or behaviors. If individuals address dissonance by altering behavior (e.g., Prochaska & Velicer, 1997), they may then selectively expose themselves to media messages that align with that changed behavior (Knobloch-Westerwick, 2015b).

Based on this foundation, the SESAM model (Knobloch-Westerwick, 2015b; see simplified illustration in Figure 1) posits that individuals expose themselves to media in efforts to regulate certain aspects of their currently salient self-concept, the "working self." Following this selective exposure, individuals experience increased accessibility of a particular aspect of their working self, which, in turn, reinforces congruent behaviors. The model proposes that dynamic changes in the self-concept—which make different facets of the self, affect, behaviors, etc. situationally accessible in the "working self"—both induce and result from selective exposure serving regulation of own behavior. This self-regulation may be motivated by a desire to bolster self-consistency (similar to a confirmation bias, in line with Festinger's (1957); cognitive
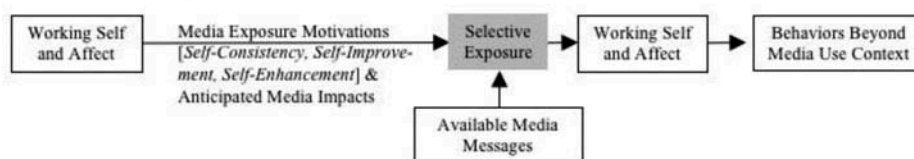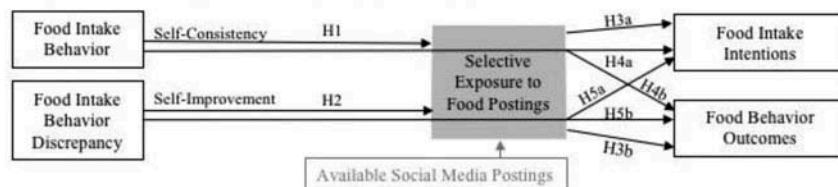

Figure 1. General SESAM model (adopted and simplified from Knobloch-Westerwick, 2015b) and applied SESAM model for food intake regulation.
Note. Selective exposure to food postings inevitably is dependent upon what postings are available. However, availability of postings was not a specific aim of this study.

dissonance theory) or, on the other hand, a desire to change toward self-improvement (the SESAM model also suggests self-enhancement as another motivation, which is not relevant for the present study). For example, an individual who has new year's resolutions to eat healthier might seek out healthy recipes in order to render healthy food self-perceptions salient and build excitement about his or her lifestyle change. The SESAM model also posits that self-discrepancy (a discrepancy between the actual self and an aspirational self by one's own or others' expectations) causes negative affect (Higgins, 1987). As a result, an individual is motivated to selectively attend to content that bolsters *self-consistency* but may also be motivated toward *self-improvement* by attending to messages promoting healthier behaviors.

A recent study (Westerwick et al., 2017) corroborated hypotheses derived from the SESAM model by examining selective exposure to online health information about organic food, coffee, fruit and vegetable consumption, and physical exercise. Participants selectively viewed online health messages about these topics, which either promoted or opposed related health behaviors. Results indicated that both participants' existing levels of health behaviors and their discrepancies (between actual and recommended behavior) led to longer selective exposure to health messages, which in turn fostered attitudes regarding recommended behaviors. In light of these findings for online text articles, the present study employs the SESAM model to further test predictions. By extending the framework to selective exposure to social media imagery postings, the present work examines health-relevant messages that users are more likely to encounter in everyday media use than intervention messages commonly studied (see review by Anker et al., 2011). The flip-side, however, is that such postings could reinforce both healthy and unhealthy behaviors, depending on the content.

Applying the SESAM model to self-regulation via social media use

Social networking sites, though not Instagram specifically, have been linked to the regulation of self-concept and self-presentation among college students (e.g., Schwämmlein & Wodzicki, 2012; Sponcil & Gitimu, 2013; Urista, Dong, & Day, 2009). These studies suggest that social networking sites allow users to assume an "active role" in molding their current self-concept. However, in these studies, self-concept is thought to be most influenced by the number of friends or comments by other users, rather than by self-regulation motivation. In contrast, the SESAM model posits that media users select messages to both reinforce and control their self-concept, as well as their affective and cognitive states and behaviors. Results from a study examining motivations for Instagram use suggest that such users organically browse photos based on their existing preferences (Lee, Lee, Jang Ho, & Sung, 2015). These findings support the notion that Instagram users might adhere to principles within the SESAM model to be tested in the present study. Furthermore, predictions will extend prior work by examining the impacts of selective exposure on health intentions and behaviors.

Current study

Per the self-consistency motivation suggested by the SESAM model, as well as previous findings regarding the notion that Instagram users choose to view content that is consistent, rather than counter to, existing interests, attitudes, and beliefs, the following hypothesis will be tested (see also illustration in Figure 1 for the application of the model):

H1: The more individuals engage in certain health behaviors (i.e., healthy food intake behavior), the more they select messages promoting these health behaviors (selective exposure).

Further, the self-improvement motivation suggested by the SESAM model implies that individuals who perceive themselves as diverging from recommended behaviors will attend more to messages that might aid them in changing towards recommended behaviors. For the following and subsequent hypotheses, this discrepancy was conceptualized as the difference between what individuals actually consume and what they perceive experts recommend they consume. Operationally, the discrepancy variable was calculated by subtracting individuals' current food intake from what they perceive medical experts recommend they eat. Further, what an individual perceives medical experts recommend is distinct from what an individual ideally would consume, because the individual's definition of ideal is highly variable depending on the individual's goals and aspirations. For example, an individual trying to lose weight might view their ideal consumption as distinct from what a medical expert recommends (i.e., medical experts from the Mayo Clinic recommend 225 and 325 g of carbohydrates daily, but some diets, like Atkins, recommend only 20 g of net carbohydrates daily, including those from vegetables; Food Standards Agency, 2009). Given this distinction, the current study will focus solely on what individuals perceive medical experts to recommend. It should be noted that intake behaviors on the one hand and behavior discrepancies on the other hand are not only conceptually different, they also differentiate empirically (detailed in the "Results" section). Using these conceptual and operational definitions, the following hypothesis will be tested:

H2: The more individuals fall short of perceived recommendations for certain health behaviors (i.e., healthy food intake behavior discrepancy), the more they select messages promoting these health behaviors (selective exposure).

Importantly, this hypothesis extends theoretical predictions of classical confirmation bias by examining improvement motivations, rather than focusing solely on maintaining current habits and behaviors. Notably, self-consistency and self-improvement motivations are not mutually exclusive and can co-occur—for example, when a person is eating rather healthy already and wishes to improve further, or when a person wants to largely maintain existing unhealthy habits and aims for only small improvements. Further, selective exposure may then indeed ultimately alter intentions and behaviors in line with the messages that were attended. While previous work (Knobloch-Westerwick, 2015b; Westerwick et al., 2017) yielded impacts from selective exposure, it focused solely on

health attitudes, not intentions and behaviors. Therefore, the present study will extend empirical tests of the SESAM model to intentions and behaviors in the third hypothesis:

H3: Greater selective exposure to messages promoting health behaviors fosters (a) intentions and (b) behaviors in line with these messages.

While H3 focuses on the simple relationship between selective exposure and outcomes, the final hypotheses derive predictions about the entire processes. They focus on mediation impacts, wherein habitual food intake (H4) and discrepancies between actual and recommended behavior (H5) affect intentions and behaviors via selective exposure to Instagram postings. The fourth hypothesis pertains to mediation processes originating in self-consistency motivation. In such cases, individuals might expose themselves to messages promoting behaviors that align with their current behaviors, in an attempt to remain consistent with their self-concept. Conversely, the fifth hypothesis focuses on self-improvement motivation as cause. In this instance, individuals might expose themselves to messages promoting behaviors that do not align with their current behaviors, in an attempt to inspire change.

H4: Engaging more frequently in certain health behaviors (i.e., healthy food intake behavior) increases selective exposure to messages promoting these behaviors and, in turn, fosters (a) intentions and (b) behaviors in line with these messages.

H5: The more individuals fall short of perceived recommended standards for certain health behaviors (i.e., healthy food intake behavior discrepancy), the more they will engage in selective exposure to messages promoting these behaviors, which in turn fosters (a) intentions and (b) behaviors in line with these messages.

The empirical study to test these hypotheses will follow assumptions per the selective exposure paradigm (Knobloch-Westerwick, 2015a): Media users are typically not aware of their motivations for media choice. As a result, they are often unable to recall their selections and motivations in the self-reported, retrospective survey items that are often used in health information seeking research. Concerns regarding social desirability further threaten the validity of these studies. Given these methodological and conceptual limitations, selective exposure research ideally uses unobtrusive, observational measures of selections and subsequent exposure, as the present study will. Further, going beyond prior work that applied the SESAM model to health issues, actual behavior outcomes will be examined.

Method

Overview

In an online procedure, participants (N = 265) indicated current eating habits as well as Instagram use, and perceptions of what medical experts recommend for food intake. Next, participants viewed three sets of three postings that represented either healthy food (i.e., fruit, vegetables, etc.) or unhealthy food (i.e., pizza, burgers, etc.), along with distractors. In each set, they selected a posting they were interested in "following" or seeing more of. In cases where the three selections were distributed across all three postings categories (healthy food, unhealthy food, distractors) such that a preference could not be inferred, participants were shown a fourth set of three postings to determine their preference. Based on participants' choices from the selection task, they then browsed 19 postings: 3 distractor images and 16 images which hinged on their selected postings. After this browsing, participants ranked gift cards—that represented either healthy or unhealthy food purchases—to indicate their preferences. Next, they indicated food intake intentions. Finally, for a stimuli post-test, participants indicated the extent to which postings motivated healthy food intake and completed demographic questions.

Participants

Undergraduate students (N = 265) were recruited from a participant pool at a large Midwestern university in the United States. As incentive, participants received their choice of either course credit or $10. Nearly 46% identified as male and 54% as female. The average age was $M = 20.58$ years (SD = 2.83). The majority were Caucasian/European/White (78.9%), 10.9% were African/African-American/Black, 6.4% Asian/Asian-American, 3% Latino(a), and less than 1% identified with other categories.

Procedure

Baseline measures

Participants completed an online procedure with the following parts. They first completed baseline measures regarding current habitual food intake and perceived recommended food intake, embedded in distractor questions on numerous leisure activities.

Selective exposure task

Then, participants were presented with three postings shown on the same page: one depicting healthy imagery (e.g., salad), one depicting unhealthy imagery (e.g., pizza), and a distractor posting that was neither healthy nor unhealthy (e.g., a landscape or city image). See example screenshot in online appendices at https://osf.io/r98x5/. They were asked to select which type of posting they would like to see more of. This selection task was repeated two to three times with additional sets of three postings (for a total of three selections, or in some cases four selections if the first three choices were not sufficient) to determine preference for viewing healthy food postings, unhealthy food postings, or distractor postings. Next, participants browsed postings in an Instagram-like fashion. Depending on their prior selections, they either saw 16 healthy food postings or 16 unhealthy food postings (always with 3 distractors interspersed) or all distractor postings. The online procedure captured their selections and how much time participants spent on the selection page and on individual pages.

Post-exposure behavior outcomes and intentions

Participants were then presented with four $10 gift card choices and asked to rank them to indicate which they would most like to have. See example page in online appendices at https://osf.io/r98x5/. Next, participants indicated food intake intentions.

Stimuli post-test and behavior outcome measure validation

Finally, for a post-test of stimuli, participants rated two, randomly selected stimuli postings—one from each category (e.g., unhealthy food and healthy food)—regarding how much the postings motivated to eat healthily. For each posting, ratings were obtained from 23 to 28 participants. Further, a subset of participants (11–12 per option) rated one of the four gift card options based on "With the above gift card, I can purchase healthy food items" with 0 = strongly disagree to 5 = strongly agree.

Demographics

Last, participants completed demographic information, including sex, age, race, year in school, and major.

Stimuli postings

Instagram-like platform

In an effort to maximize external validity, stimuli were formatted to resemble Instagram, while removing items that signified the brand itself. For instance, researchers replaced the quintessential Instagram heart with a smiley face graphic and removed the "Instagram" text from the top of the screen. To minimize confounding variables such as sex of the image poster, poster names were chosen using Social Security Administration data indicating gender-neutral names (Baby Names 1000, 2015). Examples include Ashton, Taylor, Alex, and Jesse. These names were pretested for gender neutrality in a previous study (Frampton & Knobloch-Westerwick, 2017). Similarly, photos were devoid of humans to minimize other confounding variables, like race, sex, and physical attractiveness. The number of likes, time of posting, and caption length remained constant among stimuli. To maintain consistency, all captions contained either "you" or "your." In addition, all captions contained a phrase beginning with a hashtag (i.e., #yum). The hashtag also helped reinforce external validity of the study, as the hashtag is a feature central to the Instagram platform.

Healthy and unhealthy food postings

Classification of postings as "healthy" or "unhealthy" was modeled after questionnaire data from both Americans and nutrition experts, as well as after the "Daily Food List" (National Institutes of Health, 2006; Quealy & Sanger-Katz, 2016). For instance, 28% of nutritionists and 29% of Americans agree that hamburgers are unhealthy, and 91% of both groups consider chicken to be healthy. "Healthy" postings included: avocado, egg, apples and other fruit, almonds, oatmeal, kale, lettuce, spinach, and whole grain bread. "Unhealthy" postings included: hamburgers, pizza, cookies, brownies, donuts, bacon, French fries and other fried foods, and cakes. To maximize external validity, when possible, images came from real Instagram accounts, such as Women's Health Magazine and Southern Living Magazine. To ensure validity of "healthy" and "unhealthy" classifications, participants rated postings in a stimulus post-test. For details, refer to stimuli post-test results.

Distractor postings

Distractor postings were chosen to indicate neither healthy nor unhealthy behavior. As such, distractor postings depicted places such as cities, farms, parks, and trails. To maintain external validity and consistency in postings, the majority of these images came from public Instagram accounts and did not show individuals.

Measures

Food intake behavior

To capture actual food intake, participants were asked how many portions of food—taken from the "Daily Food List" (National Institutes of Health, 2006)—they consumed in a typical day or week, respectively. Examples of prompts on that list include "Donuts, Danish, sweet rolls, muffins, dessert breads, or pop-tarts" and "Chicken or turkey." From the responses, two indicators for healthy food intake and unhealthy food intake were computed. For details, see preliminary analyses in the results section.

Perceived recommended food intake

To capture what participants perceived to be expert-recommended food intake, the questionnaire presented the same food items as for food intake but used the following prompt: "How many servings of the following types of food do you think medical experts RECOMMEND?" Two indicators for recommended healthy and unhealthy food intake were computed. For details, see preliminary analyses.

Food intake behavior discrepancy

Behavior discrepancy scores were calculated by subtracting the participants' food intake behavior scores from perceived recommended food intake scores. See details under preliminary analyses.

Selective exposure

To determine which category of postings participants would view (i.e., healthy or unhealthy), they first viewed three selection pages (and in some cases and additional fourth selection page if the first three selections were spread equally across postings categories and thus did not allow to infer a preference) that each contained three postings: one healthy, one unhealthy, and one distractor. The order of postings on each page (i.e., healthy post first vs. unhealthy or distractor post first) was randomized to avoid order effects. Participants were prompted to choose one posting with the following instructions: "Which account would you like to follow or see more of?" Participants repeated this process a total of three times or until a clear preference could be inferred. For 28% of the sample, this required a fourth choice—for instance, if participants had chosen one distractor, one healthy food posting, and one unhealthy food posting, they were directed to a fourth selection page. No participants were randomly

assigned. On average, participants chose $M = 1.27$ (SD = .92) healthy food postings, $M = .90$ (SD = .96) unhealthy food postings, and $M = .48$ (SD = .79) distractor postings. Ultimately, based on their selections, 66% of the sample then browsed the healthy food postings, spending $M = 3.00$ min (SD = 1.41 min) viewing the posts. Further, 19% saw the unhealthy food postings and spent $M = 3.23$ min (SD = 1.36 min) viewing the posts. The remaining 15% had primarily chosen distractor images and spent $M = 3.04$ min (SD = 1.09 min) viewing the posts.

Behavior outcomes

The recruitment offered \$10 as available incentive. After selective exposure, participants were offered four \$10 gift cards and asked to rank them based on what they would most likely to have (see example page in the online appendix at https://osf.io/r98x5/). Two gift cards represented "healthy" food consumption (i.e., *Whole Foods* and *Hello Fresh*) and two represented "unhealthy" food consumption (i.e., *McDonald's* and *Ben & Jerry's*). Average rankings for the gift cards were $M = 1.81$ (SD = .92) for *Whole Foods,* $M = 2.99$ (SD = .93) for *Hello Fresh, M = 2.77* (SD = 1.26) for *McDonald's,* and $M = 2.44$ (SD = .96) for *Ben & Jerry's.* Examination of the correlations among the various pairs of gift cards (that did not represent the same type of consumption) yielded correlations ranging between −.40 and −.60 ($p < .001$), except for the pair of the two gift cards representing "healthy" food consumption and the two gift cards representing "unhealthy" food consumption. Rankings among the two gift cards for "healthy" food consumption were correlated at $r = .23$, $p = < .001$ and thus condensed to a sum score for healthy behavior outcome, with $M = 4.80$ (SD = 1.45). Likewise, rankings among the two gift cards for "unhealthy" food consumption were correlated at $r = −.17$, $p = .006$, and condensed to a sum score for unhealthy behavior outcome, $M = 5.20$ (SD = 1.45).

Food intake intentions

Participants indicated how many portions of food types—per "Daily Food List" (National Institutes of Health, 2006)—they intended to consume. The prompt read, for example: "In the NEXT WEEK, how many TOTAL servings of the following types of foods do you intend to eat?" Based on factor analyses reported in the section on preliminary analyses, two indicators for healthy and unhealthy food intake intentions were computed.

Results

Preliminary analyses can be found in the online appendix at https://osf.io/r98x5/. Mediation analyses with the PROCESS SPSS macro (Hayes, 2013) served to test the hypotheses. The first four analyses used food intake behaviors as independent variables (see Table 1), while a set of additional four analyses employed behavior discrepancies as independent variables (see Table 2). Notably, intake behaviors on the one hand and behavior discrepancies on the other hand were not only conceptually different, they also differentiated empirically (with $r = −.31$, $p < .001$, for healthy food and $r = .60$, $p < .001$, for unhealthy food). Further, separate analyses were run for healthy versus unhealthy food, because the related dimensions are not merely inverse, as people might eat both healthy and unhealthy to a certain extent ($r = .37$, $p < .001$, for healthy and unhealthy food intake). The first analysis will be described in most detail in the text below, whereas the following analyses' details are reported in the tables due to space limitations. (Upon reviewer request, analyses were re-run while including familiarity with Instagram as control variable but yielded the same findings.)

The first mediation analysis tested H1, H3a, and H4a and used healthy food intake behavior as independent variable (X), healthy food intake intentions as dependent variable (Y), and

Table 1. Mediation analysis of food intake behavior impacts via selective exposure on food intake intentions and behaviors.

Related hypothesis	Model path estimates	Model A: Healthy food intake intentions		Model B: Unhealthy food intake intentions		Model C: Healthy behavior outcome		Model D: Unhealthy behavior outcome	
		Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
H1	X to M (a path)	.023***	.008	.023*	.009	.027***	.008	.024*	.009
H3a/b	M to Y (b path)	1.54***	.459	.828***	.240	−.532***	.092	−.602***	.084
	Total X to Y (c path)	.922***	.057	.638***	.037	−.048***	.012	−.032*	.014
	Direct X to Y (c′ path)	.880***	.057	.618***	.036	−.034**	.012	−.018	.013
	Indirect effects	Effect	CI	Effect	CI	Effect	CI	Effect	CI
H4a/b	X to M to Y	.042*	(.014, .084)	.019*	(.003, .040)	−.015**	(−.025, −.006)	−.014*	(−.027, −.003)

Q5

Note. Terms and path labels adopted from Hayes (2013). Coeff. stands for unstandardized coefficient, SE for standard error, and CI for bootstrapped bias-corrected 95% confidence interval. *$p < .05$; **$p < .01$; ***$p < .001$.

Table 2. Mediation analysis of food intake behavior discrepancy impacts via selective exposure on food intake intentions and behaviors.

Related hypotheses	Model path estimates	Model A: Healthy food intake intentions		Model B: Unhealthy food intake intentions		Model C: Healthy behavior outcome		Model D: Behavior outcome	
		Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
H2	X to M (a)	−.025**	.008	−.029*	.012	−.025*	.008	−.028*	.012
H3a/b	M to Y (b)	2.876***	.630	1.211***	.334	−.578***	.093	−.583***	.082
	Total X to Y (c)	−.205**	.082	−.342***	.064	.023	.013	.066***	.017
	Direct X to Y (c′)	−.132	.081	−.308***	.064	.008	.012	.049**	.016
	Indirect effects	Effect	CI	Effect	CI	Effect	CI	Effect	CI
H5a/b	X to M to Y	−.073**	(−.138, −.024)	−.035*	(−.073, −.006)	.015**	(.006, .026)	.016*	(.003, .034)

Q6

Note. Terms and path labels adopted from Hayes (2013). Coeff. stands for unstandardized coefficient, SE for standard error, and CI for bootstrapped bias-corrected 95% confidence interval. *$p < .05$; **$p < .01$; ***$p < .001$.

selective exposure per number of healthy food postings selected as mediator (M). Results are reported in Table 1 under Model A. In line with H1, healthy food intake behavior predicted selective exposure to healthy food postings, coeff. = .023 (SE = .008), p < .001. In line with H3a, this selective exposure predicted healthy food intake intention, coeff. = 1.54 (SE = .459), p < .001. The total effect, coeff. = .922 (SE = .057), p < .001, and the direct effect, coeff. = .880 (SE = .057), p < .001, were significant. More importantly, H4a was supported—the mediation effect via selective exposure was significant because the confidence intervals did not include zero, with a point estimate of .042, and 95% BCa (bias-corrected and accelerated) bootstrap confidence interval of .014–.084. In line with SESAM predictions, healthy food intake behavior shaped selective exposure to healthy food postings, which in turn affected healthy food intake intentions.

The next mediation analysis applied the same logic as above to unhealthy food intake behavior as independent variable (X), unhealthy food intake intentions as dependent variable (Y), and selective exposure per number of unhealthy food postings selected as mediator (M). Results are reported in Table 1 under Model B and essentially mirror the patterns from Model A on healthy food variables. Participants also engaged in selective exposure to bolster unhealthy eating habits and, in turn, reinforced the related future intentions. The effects pertaining to H1, H3a, and H4a were again significant.

A third analysis tested H3b and H4b and used healthy food intake behavior as independent variable (X), healthy behavior outcome as dependent variable (Y), and selective exposure per number of healthy food postings selected as mediator (M). Results are reported in Table 1 under Model C. While this analysis again supports H1, the related coefficient is redundant with Model A. H3b was supported, because the coefficient for impact from selective exposure to behavior outcome was significant, coeff. = −.53 (SE = .092), p < .001. In other words, greater selective exposure to messages promoting health behaviors fostered behaviors in line with the messages participants viewed. Note that the coefficient is negative because lower rankings indicate greater preference for healthy purchases gift cards, as the first rank indicates greatest preference and fourth rank lowest preference. While both the total and the direct effects from healthy food intake behavior (X) to healthy behavior outcome (Y) were significant, the significant indirect effect is of interest. In line with H4b, the indirect effect via selective exposure was significant because the confidence intervals did not include zero. Results indicated that healthy food intake behavior (X) fostered healthy behavior outcome (Y) via selective exposure (M), with a point estimate of −015, and a 95% BCa bootstrap confidence interval of −.025 to −.006. Again, this indirect effect is negative because lower rankings indicate greater preference.

The fourth analysis tested H3b and H4b with unhealthy food intake behavior as independent variable (X), unhealthy behavior outcome as dependent variable (Y), and selective exposure per number of unhealthy food postings selected as mediator (M). Results are reported in Table 1 under Model D. Note that this analysis supports H1, with the related coefficient being redundant with Model C. Again, the findings for unhealthy food variables mirror the patterns from the healthy food variables. Participants selectively attended to postings that bolstered unhealthy eating and, in turn, made unhealthier choices when picking food-related gift cards as behavior outcome. Effects pertaining to H1, H3b, and H4b were again supported with individuals who engage in unhealthy behaviors selecting more unhealthy messages (H1), and this, in turn, influencing their intentions (H3b) and behaviors (H4b) in line with the unhealthy messages.

The second set of mediation analyses—again employing the PROCESS SPSS macro (Hayes, 2013)—used food intake behavior discrepancies as independent variables (see Table 2).

The fifth mediation analysis tested H2 and H5a, employing healthy food intake behavior discrepancies as the independent variable (X), healthy food intake intentions as dependent variable (Y), and selective exposure per number of healthy food postings selected as mediator (M). Full results are reported in Table 2 under Model A. In contrast to the expectation in H2, greater healthy food intake behavior discrepancies did not foster selective exposure to messages promoting these behaviors. The related coefficient was significant, coeff. = −.025 (SE = .008), p = .001, but its direction was the opposite of the impact suggested in H2. Given these results, H5a was also not supported predicting that the more individuals fall short of perceived recommended standards for certain health behaviors, the more they will engage in selective exposure to messages promoting these behaviors and, in turn, fostering intentions in line with these messages; although the mediation effect via selective exposure was significant at a 95% BCa bootstrap confidence level of −.138 to −.024, the effect was not in the anticipated direction, with a point estimate at −.073. Thus, the more individuals fell short of perceived recommendations for healthy eating habits, the fewer times they chose healthy food postings.

The sixth mediation analysis employed identical logic to the fifth analysis, but with unhealthy food intake behavior discrepancy as the independent variable (X), unhealthy food intake intentions as dependent variable (Y), and selective exposure per number of unhealthy food postings selected as mediator (M). Results are reported in Table 2 under Model B. Similar to findings from Model A on healthy food variables, the results were significant, but not in the expected direction for H2, which then leaves H5a unsupported as well.

The next mediation analysis tested H2 and H5b, using healthy food intake behavior discrepancies as the independent variable (X), healthy behavior outcome as dependent variable (Y), and selective exposure per number of healthy food postings selected as mediator (M). Results are reported in Table 2 under Model C. As in the fifth mediation analysis, results were significant, but not in the anticipated direction, coeff. = −.025 (SE = .008), p = .001. As such, H2 was not supported. Because its assumptions depend on a supported H2, the mediation that was tested per H5b did not support the expected process despite being significant at a 95% BCa bootstrap confidence interval of .006–.026, with a point estimate at .015, because the impact from behavior discrepancy on selective exposure was opposite to expectations in H2.

Finally, the last mediation analysis regarding H2 and H5b employed unhealthy food intake behavior discrepancies as the independent variable (X), unhealthy behavior outcome as

dependent variable (Y), and selective exposure per number of unhealthy food postings selected as mediator (M). Results are reported in Table 2 under Model D. Again, H2 and H5b were not supported, although the related effects were significant, as the impact from behavior discrepancy on selective exposure was opposite to expectations in H2 and H5b built on H2.

Discussion

In light of the enormous attraction to social media and its content's relevance to many health issues, the present study examined how social media use can shape health behaviors. Employing a selective exposure approach, and building on the SESAM model (Knobloch-Westerwick, 2015a), the study allowed participants to selectively view postings depicting food.

Results provided support for H1, H3a/b, and H4a/b regarding relationships between current behaviors, selective exposure, and subsequent health intentions and behaviors. Supporting H1, more frequent engagement in certain health behaviors (i.e., healthier food intake) led to more time spent with behaviorally consistent messages in the form of healthy food postings. Yet, this pattern also worked for the unhealthy side of the coin, as people who reported eating unhealthy food items more frequently selected postings with unhealthy foods. Results showed that increased selective exposure to healthy (or unhealthy, respectively) messages fosters both intentions and behaviors that are congruent with health behaviors implied by the messages, lending support for H3a and H3b. Supporting H4, frequent engagement in certain health behaviors did increase selective exposure to messages promoting that behavior, which then fostered congruent intentions and behaviors. For healthy food postings, viewing these messages made people choose gift cards for healthy food and increased intentions to eat healthy; this process originated in the existing eating behavior and was mediated by selective exposure. Again, the same patterns existed for unhealthy food postings, where viewing these messages increased choice of gift cards associated with unhealthy food as well as unhealthy eating intentions. Again, existing behavior led to selective exposure that in turn reinforced unhealthy eating choices and intentions. Overall, these findings strongly support the notion that individuals appear to strive for self-consistency such that existing health behaviors shape selective exposure to health-relevant messages, which then reinforce ongoing behaviors—for better or worse, as it works for both healthful and harmful behaviors. Although previous studies measured behavioral intentions, the present study furthers corroboration of predictions made by the SESAM model by measuring actual behaviors (i.e., gift card rankings) immediately following selective exposure. Thus, the present evidence allows stronger inferences regarding health behavior outcomes.

On the other hand, the notion of self-improvement motivation driving selective exposure did not receive support in the present findings. In contrast to the proposition in H2, greater discrepancy between perceived recommended food intake and actual food intake had a negative impact on selective exposure such that individuals who believed they were not eating as many healthy food items as experts recommend (positive discrepancy) selected fewer healthy food postings. Similarly, for unhealthy food, the more people believed they ate more unhealthy items than medical experts would deem okay (negative discrepancy), the more they chose postings with unhealthy items. These findings contradict H2 and left H5 unsupported, as H5 built on H2.

The lack of support for self-improvement motivation that would stem from a behavior discrepancy and then shape selective exposure diverges from prior research (Westerwick et al., 2017) that found that individuals with greater discrepancies between actual and recommended behavior spent more time on online articles that promoted the related desirable behaviors. Arguably, the present study differs in two important ways from this prior study: It (a) used emotionally appealing imagery, as opposed to pure text messages, and it (b) included messages on what is commonly considered a sensationally pleasant experience (i.e., eating unhealthy items such as donuts, ice cream, etc.), whereas the prior study's messages that opposed healthy behaviors talked about risks such as strain from over-exercising or unjustified cost of organic food, which were not pleasant themselves. It appears that displaying the vivid lure of guilty food pleasures overrode any possible self-improvement motivations, which were apparently more salient and influential in a study context with texts, which appealed more to sensible, rational forms of self-regulation via effortful information processing.

However, we can only speculate here—future research should experimentally induce different self-regulation motivations per self-consistency and self-improvement to rigorously examine their influence. Further, this could help better understand what moderates the extent to which individuals are aware of any self-regulation processes via selective exposure —sometimes individuals may purposefully seek out messages for self-regulation, but oftentimes maintaining habitual behavior will stem from routine selections of messages.

Further, H2, which was unsupported, predicted that the more individuals fell short of perceived expert recommendations for certain healthy behaviors, the more they select messages promoting these health behaviors. Perhaps perceived social norms amongst peers, rather than what medical experts recommend, would induce more powerful discrepancies and motivation for self-improvement, which might lead participants to choose to view healthy imagery in the interest of change. Future research should consider this possibility that more powerful self-discrepancies result from peer norms, compared to expert norms. What triggers a self-improvement motivation is at the heart of any health improvement—hence, examining individuals' image viewing behaviors based on their current stage of change (Prochaska, DiClemente, & Norcross, 1993) regarding healthy eating may also reveal some insights. Individuals in the precontemplation stage with no intent to change a behavior may be more likely to view unhealthy food images compared to individuals in the preparation stage who are already making minor behavior changes. The present study did not ask participants explicitly about their intentions or motivations to change their eating behavior, or "stage of change" (Prochaska et al., 1993), because such questions would sensitize participants to the study's purpose and bias their responses. Thus, there is a

possibility that a preexisting intention to change one's eating behavior influenced the measures on eating intentions beyond the mediated selective exposure impacts.

Limitations of the present study should be acknowledged. Participants completed the research procedure on a desktop computer, rather than using a mobile device, which is different from the typical Instagram use context. Hence, the procedure is an approximation to real world media use. In addition, the present analysis employs controlled images, rather than genuine Instagram posts, and asked users to choose between photos on Instagram, which is not common for the medium. However, the study design allowed users to choose what types of imagery they would view, while also strengthening external validity by employing carefully selected stimuli—which were taken from Instagram itself to maintain ecological validity—and a clean design that emulated Instagram. This online context bolsters its ecological validity, given that social media use occurs exclusively in online contexts. By showing the images in context, this study surpasses previous research, which displays images without any context. Similarly, perceived recommended food intake was measured using a valid and reliable scale—but possibly, an individual's personal goals or perceive norms among peers are more relevant than what experts recommend and might serve better to capture discrepancies between actual and desired behavior in future studies. Further, the current study was not able to capture longer lasting behavior change since there were no delayed measures. However, the authors are designing a future study to examine delayed impacts of exposure to food images on social media platforms.

Although a student sample is often not ideal, it should not be considered a major limitation of the present study, given that students commonly search health information online (Percheski & Hargittai, 2011), just as the general population. Indeed, this group often is targeted with health interventions because it is among the lowest fruit/vegetable consumers (Nour et al., 2016). Further, 59% of Instagram users are between the ages of 18 and 29 (Pew Research Center, 2016). More research with a non-student sample is desirable in future research.

Further, although post-test results corroborated the validity of "healthy" and "unhealthy" gift cards, the gift cards as indicator of behavior have some limitations. For instance, the $10 gift card value might vary across stores (e.g., $10 at McDonalds might provide more than $10 at Whole Foods). This limitation is linked to the online context of the present study, which did not allow to use true food choices as a measure. For instance, while the study measured both intentions and behavioral decisions regarding gift cards, change in actual eating behavior was not measured. However, future research should include such measurement, building on related communication research. For example, Harrison, Taylor, and Marske (2006) presented participants with body ideal imagery and then recorded subsequent eating behavior; findings yielded that exposure to idealized body imagery did influence eating behavior. In another related example, framed norm messages concerning food consumption impacted actual food consumption (Mollen, Holland, Ruiter, Rimal, & Kok, in press). In light of these findings, results from the present study regarding gift card rankings might also extend

to actual eating choices. Further, using actual eating behavior may alleviate the limitations associated with gift card choices. Futures studies should investigate this measuring actual eating behavior (i.e., offering participants healthy or unhealthy foods), rather than using gift cards as an approximation.

While the present analyses focus on eating behavior, further research should extend to the realms of exercise, body image, and mental health. It is of great interest to consider the social processes (e.g., social comparisons) that occur when using social media in health relevant contexts— many social media platforms strongly imply social comparisons regarding health behaviors (e.g., platforms on which people share their running times, weight loss progress, etc., such as Google Fit). Similarly, although the SESAM model considers working self and affect to be central aspect of the model, the present research focused solely on the working self. Given that food imagery can be charged with emotion, it would be useful for studies to consider affect (i.e., guilt, pride) closely related to eating-related postings and choices. Future research should explore effects on social media platforms that are only partially image based, such as Facebook and Twitter. Finally, studies could examine the SESAM model predictions in other media formats including magazines to see if they function in a similar manner.

Together, these present results support self-consistency predictions of the SESAM model (Knobloch-Westerwick, 2015b). They also provide further direction for exploring potential future research using the SESAM model. For instance, future research might further the model by examining what triggers self-improvement motivations. Possible triggers include social norms, stage of change, the impacts of imagery compared to text, or different mechanisms behind impulsive and controlled behaviors. Beyond theoretical implications, the results demonstrate that social media use has health-relevant implications and that social media postings indeed shape eating-related intentions and choices. Although a previous study (Westerwick et al., 2017) examined the effects of selective exposure to online health information in text form, the present investigation examines these effects in a social media context. Given that social media users are inundated with choice of content, and that users spend vast amounts of time on social media, examining previous results in this context is relevant. Further, given that individuals are already using social media, results from the present investigation suggest that natural, selective media use can lead to positive health behaviors, such as healthy eating. Perhaps, these positive effects can be expanded to other positive habits, as well. While exposure to eating-related postings is likely to reinforce positive intentions and choice, it also should be noted that unhealthy behaviors may also be fostered (i.e., through postings featuring junk food). However, these findings present an exciting perspective of communication: self-regulation including health impacts of social media platforms use. Scholars and media alike have long studied and criticized such platforms for their negative effects—linking social media use to increased depression and cyber-bullying, amongst other negative consequences (e.g., Whittaker & Kowalski, 2015). The present study offers an intriguing alternative—and positive—ramification of social media uses.

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