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Assessing the impact of the public nutrition information environment: Adapting the cancer information overload scale to measure diet information overload

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ABSTRACT

Objective: A growing body of research suggests that exposure to too much information – particularly contradictory information that characterizes much health-related information – can lead to feeling overwhelmed. This construct has been conflated with fatalistic beliefs that are negatively associated with preventive behaviors. The objective of this study was to adapt the 8-item Cancer Information Overload (CIO) scale to assess overload of healthy diet information.

Methods: Confirmatory factor analyses with a community sample of rural California adults (n = 290; 75% female; 58% Latino; 46% ≤ H.S./G.E.D.).

Results: Items assessing Diet Information Overload loaded significantly on their relevant factor; factor loadings were acceptable (β ≥ .40). The adapted original scale (CFI = 1.000, RSMEA = .000, SMSR = .022) and a shorter 5-item scale (CFI = .984, RMSEA = .051, SMSR = .026) fit well.

Conclusion: The Cancer Information Overload scale was successfully adapted and shortened to measure perceptions – previously mischaracterized as fatalistic – pertaining to diet information. Improved measures distinguishing between fatalistic beliefs and outcomes of the information environment are critical.

Practice Implications: Understanding information overload is important for shaping prevention messages distinct from those needed to address fatalistic beliefs. Nutrition education efforts should consider the broader – cluttered – information environment in which nutrition education and communication occurs, and public health messages may drown.

1. Introduction

Preventable non-communicable diseases including obesity, cardiovascular disease, cancer, and diabetes account for 70% of deaths worldwide [1]. Communication about diet and nutrition may be a useful population-level intervention approach to reduce the burden of non-communicable diseases [2–5]. Indeed, developments in information and communication technologies in the past two decades substantially increased the amount of health information available to the general public [6]. Individuals may encounter messages from this information environment that affect their behaviors through the course of daily media consumption or they may deliberately seek health information [2,7].

Despite having instant access to this rich information environment, many individuals fail to act on the knowledge available to them – that is, communication often fails to persuade individuals to eat more healthful diets [4]. There are numerous barriers that prevent people from eating a healthy diet, including access to nutritious food, affordability, and knowledge about food preparation [8–12]. Although information alone is often not enough to influence individuals to eat more healthful diets [13], studies have shown that communication about food exerts a powerful influence on dietary behaviors (i.e., marketing, advertising of unhealthy foods) [14]; moreover, that deliberate, well-done strategic communication to encourage healthy diets *can* improve diet [2,4,5,15,16].

However, our understanding of why communication is not always successful is incomplete. Beyond the limitations inherent in communication as information provision, recent research has demonstrated that exposure to too much information – particularly contradictory information that characterizes much cancer-

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and nutrition-related information [4,17–20] – can lead to feeling overwhelmed by the information available [21–23].

Feeling overwhelmed from exposure to contradictory and conflicting messages is not the result of the content of any single specific message, but rather due to the nature of the information environment as a whole. Although a contradictory public information environment may be an accurate reflection of the state of the science of nutrition – and indeed of the nature of science, wherein incremental progress is made non-linearly [19] – the subtleties of scientific studies may be missing from public reporting of the science. Research is full of contradictory findings: a large clinical trial may reach different conclusions compared to a small observational study on the same topic. However, this evolutionary nature of research leads to what Jensen et al. [24] name “the carcinogen of the week” style reporting, with diet related factors often being both being a risk as well as a protective factor [25]. Researchers and health professionals understand the evolutionary nature of research and therefore have the tools to cope with this conflicting environment. However, the public lacks this understanding and may not be able to cope as effectively. In addition, coverage of science often lacks information relevant to facilitate this process [26]. As a result, the public has a hard time making sense of conflicting scientific results [19,27].

Since nutrition and diet are topics of broad interest, food, nutrition science, and dietary advice are frequently covered in the news and broadly disseminated through mass media and social media channels. The lack of concordance in the overabundant information environment may produce information overload, the belief or set of beliefs that there is just too much information, resulting in feeling overwhelmed [24]. Specifically, the model of information overload suggests that as a result of the arousing content in the information environment, additional cognitive resources are necessary to make sense of the content; the resulting strain on capabilities results in information overload [28]. The model further posits that overwhelmed individuals will actively avoid information [28].

Mitigating information overload requires understanding the nature and accurate assessment of this concept. A major challenge has been the conflation of information overload with fatalism [24,29,30]. Incorrectly addressing these beliefs as fatalism, often seen as a cultural trait [29], could hinder efforts to mitigate these beliefs and their adverse effects on health. In an effort to address these issues, Jensen et al. [24] developed and validated a multi-item measure of cancer information overload (CIO). The CIO scale has been validated and assessed in a number of studies examining cancer information behaviors and outcomes [21,23,24,31]. Exposure to the information environment has been shown to predict information overload, with content about cancer causes and uncertainty positively predicting CIO, and content about cancer causes and established prevention information negatively predicting CIO [32]. The CIO scale has been positively associated with information avoidance [31] and negatively associated with preventive behaviors including fruit and vegetable consumption, regular exercise, smoking avoidance [23], and cancer screening [24]. The utility of the CIO scale in understanding negative effects of exposure to the public information environment about cancer suggests opportunities to expand the construct to other contexts that are similarly fraught with misinformation. Thus, the aim of the present study was to extend the construct of information overload to the nutrition and diet information environment context, which, like the cancer information environment, is riddled with misinformation and contradictory advice. Our first goal was to adapt the CIO scale to measure diet information overload (DIO). In addition, we wanted to test the recommendations by Costa et al. [33] to simplify assessment of information overload by removing 3 of the original 8 items. We hypothesized that the best estimates of diet information overload would result from the shortened scale since it includes only the items that precisely capture information overload.

2. Method

2.1. Adaptation of the cancer information overload scale

Diet information overload was adapted from the CIO scale [24] (see Table 1). The scale consists of eight items with five response options (strongly disagree to strongly agree). The adaptation involved replacing “cancer” or “cancer prevention” with appropriate substitutions about “diet” or “eating a healthy diet.” For example, the original item “There are so many different recommendations about preventing cancer, it’s hard to know which ones to follow” was adapted to “There are so many recommendations about eating a healthy diet, it’s hard to know which ones to follow.” The original statement “I feel overloaded by the amount of cancer information I am supposed to know” was adapted to “I feel overloaded by the amount of information about eating a healthy diet I am supposed to know.”

Table 1
Diet Information overload. Respondent scores and confirmatory factor analysis model standardized (β) coefficients (N = 287).

	Items		DIO model 1		DIO model 2		DIO model 3		DIO-SF	
		M (SD)	β	SE	β	SE	β	SE	β	SE
1	There are so many recommendations about eating a healthy diet, it’s hard to know which ones to follow.	2.57 (1.085)	.497*	.056	.497*	.055	.481*	.058	.486*	.063
2	There is not enough time to do all the things recommended to eat a healthy diet.	3.28 (1.122)	.461*	.065	.464*	.065	.390*	.071	–	–
3	It has gotten to the point where I don’t even care to hear new information about eating a healthy diet.	3.55 (1.092)	.514*	.056	.513*	.056	.475*	.062	.531*	.063
4	No one could actually do all of the healthy diet recommendations that are given.	3.33 (1.049)	.062*	.021	–	–	–	–	–	–
5	Information about eating a healthy diet all start to sound the same after a while.	2.75 (1.093)	.619*	.048	.619*	.048	.607*	.052	.656*	.050
6	I forget most information about eating a healthy diet right after I hear it.	3.21 (1.150)	.658*	.047	.657*	.047	.663*	.051	.659*	.055
7	Most things I hear or read about eating a healthy diet seem pretty far-fetched.	3.32 (1.061)	.621*	.056	.621*	.056	.607*	.059	–	–
8	I feel overloaded by the amount of information about eating a healthy diet I am supposed to know.	3.16 (1.141)	.714*	.041	.713*	.041	.741*	.043	.695*	.053

DIO = Diet Information Overload scale, DIO model 1 = CIO model adaptation, DIO model 2 = DIO scale minus item 4, DIO model 3 = DIO scale minus item 4 and including error correlations, DIO-SF = Diet Information Overload scale Short Form (1 = strongly agree to 5 = strongly disagree), * $p < 0.05$.

In their comments on the original CIO scale, Costa and colleagues [33] argued that three of the eight items could be omitted since they deviate from the definition offered by Jensen et al. [24]: “feeling overwhelmed by the amount of cancer-related material in the information environment”. Specifically, they recommended removing the item, “Most things I read or hear about cancer seem pretty farfetched” since it addresses the quality of the information instead of the quantity. Second, they recommended removing the item, “No one could actually do all of the cancer recommendations that are given” since it is not capturing perceptions about the respondents own psychological response. Lastly, they recommended removing, “There is not enough time to do all of the things recommended to prevent cancer,” as time is a barrier to action and not a feeling about the information environment. We therefore compared performance of the adapated DIO with the original eight items as developed by Jensen et al. [24] with the shorter five item scale as recommended by Costa et al. [33].

Additionally, the scale was adapted into Spanish using standard procedures to ensure equivalence. Additional details about the process are provided in another publication [blinded for review].

2.2. Sample and procedure

Data were collected from a community sample in rural Central California (N = 290) as part of a larger community health partnership program. A stratified sampling approach by ethnicity was utilized to reflect the population of the county [34,35]. Participants were recruited at a variety of public places, including local parks, and supermarkets. Surveys were verbally administered in person or by phone. Participants were eligible to participate if they were over 18 years of age, were proficient enough in English or Spanish to complete the survey, and worked or lived in the county where the data was collected. Three participants did not complete the DIO scale, resulting in a final sample of 287 participants. Almost 20% of the sample (N = 56) completed the survey in Spanish. The majority of the sample was female (74.9%). Age was distributed as follows: 18–24 (16.4%), 25–34 (28.9%), 35–44 (23.7%), 45–64 (23.0%), and 65+ (7.3%). Most participants identified as Hispanic/Latino (57.7%), 22.4% identified as White/Caucasian, 10.8% Hmong and 9.1% identified themselves as other than the above three ethnicities. Education was measured by asking about the highest level of education completed (from 0 = No formal education to 21 = graduate or professional degree, Mean = 13.84, SD = 4.67). A little over 20% (N = 58) of the participants did not receive a high school degree, 25.7% did receive a high school degree, 37.7% received some college, and 16.2% received a bachelor degree or higher. We used food assistance as an additional indicator of socioeconomic status and proxy for household income: Over 43% of the sample (N = 122) received food assistance in the past year.

2.3. Analyses

Consistent with Jensen and colleagues’ [24] original approach, assessment of the factor structure of the DIO and DIO-SF was examined through a confirmatory factor analysis (CFA) in order to determine if the adapted questions had the same underlying construct. We used a regression model to investigate the relationship between diet information overload and our socio-demographic characteristics. Descriptive statistics, the regression analysis, and Cronbach’s α were conducted with IBM SPSS Statistics 24.0. CFA were conducted using Mplus version 7.31 [36]. The amount of missing data was low (<.0001%) and missing completely at random [37]; Mplus defaults were used for missing data imputation [36]. Items with non-significant factor loadings and loadings below .3 were not considered salient [38] and were compared based on fit indices with models omitting these items. Modification indices were inspected for improvement, with values of 3.84 or greater indicating significant model improvements [38]. However, we only employed modifications if there was an underlying substantive basis for doing so, as is recommended by Brown (2015). To assess the model fit of the models, we computed and compared the comparative fit index (CFI), the root mean square error of approximation (RMSEA), the standardized root mean squared residual (SRMR), and the chi-square (χ^2). The CFI is a measure of model fit ranging from 0 to 1 where larger values (closer to 1) indicate better fit [39]. The RMSEA is a measure of model misfit where values of .05 or lower indicate excellent fit, values <.8 indicate fair fit and values >.1 indicate unacceptable fit [39,40]. Standardized root mean squared residual (SRMR) indicates good fit at .08 or lower [39]. A significant χ^2 test indicates a poorly fitting model [41]. In addition, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC) were used to directly compare models; lower scores indicate better fit [42].

3. Results

3.1. Confirmatory factor analysis - DIO

The full adaption of the CIO (DIO model 1) (M = 3.14, SD = .71) to diet demonstrated good reliability, α = .80. However, the model showed unsatisfactory fit (see Table 2), X^2 = 41.066, $p < .001$, CFI = .942, RMSEA = .061 (CI = .034–.087), SMSR = .044, AIC = 9074.036 and BIC = 9161.864. Item 4, “No one could actually do all of the healthy diet recommendations that are given” (see Table 1) had a low factor loading (β = .062, SE = .021) and was removed.

The DIO model with item 4 removed (i.e. DIO model 2), showed improvements (AIC = 5718.771 and BIC = 5796.621). The CFI (.956) showed good fit, and the SMSR (.040) was excellent. However, the RMSEA (.060, CI = .027–.092) was fair and the X^2 test was still significant (X^2 = 28.492, p = .011). Modification indices indicated

Table 2
Fit indices.

Fit indices.		DIO model 1	DIO model 2	DIO model 3	DIO-SF
Absolute fit					
	CFI	.942	.956	1.000	.984
	RMSEA	.061 (.034-.087)	.060(.027–.092)	.000 (.000–.053)	.051 (.000–.106)
	SRMR	.044	.040	.022	.026
	X^2	41.066*	28.492*	9.152	8.669
Comparison					
	AIC	9074.036	5719.771	5700.150	4123.938
	BIC	9161.864	5796.621	5787.977	4178.830

DIO = Diet Information Overload scale, DIO model 1 = CIO model adaptation, DIO model 2 = DIO scale minus item 4, DIO model 3 = DIO scale minus item 4 and including error correlations, IO-SF = Diet Information Overload scale Short Form, CFI = Comparative Fit Index, RMSEA = Root Mean Error of Approximation, SRMR = Standardized Root Mean Square Residual, AIC = Akaike Information Criterion and BIC = Bayesian Information Criterion, *p < 0.001.

that correlating the item errors between several items would significantly improve the model. We identified three pairs of dyads that can be related to each other beyond the information overload construct: Items 1 and 2 both relate to efficiency, items 2 and 7 both relate to disinterest, and items 3 and 5 both address backlash. Since these dyads may be related to each other beyond information overload, their error terms were allowed to correlate. With these additional adjustments, the model (DIO model 3) (M = 3.12, SD = .73) showed excellent fit, X^2 = 9.152, p = .608, CFI = 1.000, RMSEA = .000 (CI = .000–.053), SMSR = .022, AIC = 5700.150 and BIC = 5787.977. This model demonstrated good reliability, α = .78.

3.2. Confirmatory factor analysis – DIO-SF

The shorter version of the scale (i.e. DIO-SF) (M = 3.05, SD = .78) demonstrated good reliability, α = .74. and showed excellent fit, X^2 = 8,669, p = .123, CFI = .984, RMSEA = .051 (CI = .000–.106), SMSR = .026, AIC = 4123.938 and BIC = 4178.830. Given the excellent fit of the model, no post hoc modifications were applied.

3.3. Predicting DIO-SF

Education significantly predicted diet information overload. Participants with more education were more likely to feel overloaded by diet information (B = .025, SE = .012, p = .045). The only other significantly predictor, receiving food assistance, negatively predicted diet information overload (B = –.225, SE = .098, p = .023). Age, gender, ethnicity and completing the survey in Spanish were not found to be significant predictors in the model.

INSERT Table 3 HERE

4. Discussion and conclusion

4.1. Discussion

Communication about diet and nutrition can be a useful tool for health promotion, but too much information, particularly when much of it is contradictory, can have adverse effects [22]. In growing recognition of the complexity of public health communication, prior studies have attempted to characterize the information environment directly [27]. However, there was not previously a way to assess audiences' perceptions of the diet information environment. In this study, we successfully adapted the cancer information overload scale to measure diet information overload, providing a tool for assessing patients' perceptions of the diet information environment.

In addition to validating the original 8-item information overload scale, we found that a shortened 5-item version suggested by Costa and colleagues (2015) demonstrated better fit. For theoretical, statistical, and practical reasons, we recommend using the shorter version. First, from a theoretical perspective, the short form more precisely represents information overload, since it explicitly excludes items that do not fit the formal information overload definition. Statistical analyses support the short version: Comparison indices suggested that the DIO-SF fit the data better. In addition, the shorter version addresses the limitation brought up in the original article and comment [24,33] about the post hoc adjustments to the scale. Adjustments based on modification indices capitalize on chance in small sample sizes [43,44] and MacCallum et al. [44] suggest that constructing an alternative a priori model is a more appropriate way to deal with imperfect model fit. Lastly, practically: a shorter version of the scale is less of a burden on patients and the general public.

In contrast to many of the cancer-related studies [24,45–47], in this study, more education predicted *more* diet information overload. While this may seem paradoxical, it is possible that differences in information access may explain these findings. That is, with increased education comes increased access to information, health information seeking behaviors, and in general the skills to make sense of retrieved information [2,7]– but not necessarily the skills to *cope* with too much information. As such, those with lower education may lack access to the full scope of the public nutrition information environment, but this lack of access may be protective, buffering from potential negative consequences such as information overload [48]. Surprisingly, our other indicator of socioeconomic status – the proxy for income – was related differently to information overload: Receiving food assistance in the past year negatively predicted information overload. This finding may be due to the comprehensive services offered by food assistance agencies. For example, in California, recipients of the federally-funded nutrition assistance program often take advantage of nutrition education classes [49–51]. These classes may increase participants' baseline levels of knowledge about nutrition guidelines, which could help cut through the clutter of the public information environment.

A strength of this study was the diverse sample, reflecting an ethnically diverse, low income, low education, and rural population. The diverse community sample used in this study addresses an important limitation that surrounds previous information overload work, the potential bias and inequalities introduced by only sampling highly educated, Caucasian participants [21,23,24,52]. However, a corresponding limitation is that the study did not randomly sample from the U.S. population as a whole and therefore may not be generalizable nationwide. Similarly, the inclusion of diverse samples and multiple languages, as is the case in this study, calls for validation of measurements for non-Caucasian and non-English speakers. Although this study included a substantial proportion of Spanish speakers, it was underpowered for an appropriate test for structural invariance. Measurement invariance of the DIO or DIO-SF should be assessed in future studies. In addition, while the diet information overload scale was adapted from cancer, certain reliability questions still need to be answered, including test-retest reliability.

Lastly, it is important to note that regression model explained only a small part of the variance in diet information overload. The included demographic variables are not sufficient to explain the complex process underlying diet information overload. Future research should consider the driving factors, including access to health information, related to exposure to too much dissonant healthy diet information, and variables moderating the subsequent diet information overload.

4.2. Conclusion

The information environment can contribute to troubling beliefs – previously characterized as fatalistic – that may affect preventive behaviors. The information overload scale was successfully adapted from the cancer context to measure perceptions

Table 3
Regression predicting DIO using the DIO-SF.

Fit indices.	B (SE)	P
Age	–.001 (.003)	.766
Female	.086 (.110)	.431
Ethnicity		
Hispanic/Latino	–.075 (.126)	.552
Hmong	.049 (1.26)	.785
Other	–.193 (.193)	.318
Education	.025 (.012)	.045*
Survey in Spanish	.040 (.146)	.785
Food assistance	–.225 (.098)	.023*

R^2 = .062, *p < 0.05.

of the information environment specific to healthy diet information, and validated in a diverse community sample.

4.3. Practice implications

The nutrition information environment is cluttered and often conflicting; this results in confusion and information overload among the general public, which can have negative effects on preventive behaviors. This study provides a tool for assessing patients' perceptions of the diet information environment. Nutrition education efforts should take into account the broader – cluttered – information environment in which nutrition education and communication occurs, and public health messages may drown.

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References

[1] WHO, Noncommunicable Diseases, WHO, 2017. (Accessed September 26, 2017) http://www.who.int/mediacentre/factsheets/fs355/en/.
[2] A.S. Ramirez, D. Freres, L.S. Martinez, N. Lewis, A. Bourgoin, B.J. Kelly, C.-J. Lee, R.H. Nagler, J.S. Schwartz, R.C. Hornik, Information seeking from media and Family/Friends increases the likelihood of engaging in healthy lifestyle behaviors, J. Health Commun. 18 (2013) 527–542, doi:http://dx.doi.org/10.1080/10810730.2012.743632.
[3] M.H. Fernstrom, K.A. Reed, E.B. Rahavi, C.C. Dooher, Communication strategies to help reduce the prevalence of non-communicable diseases: proceedings from the inaugural IFIC Foundation Global Diet and Physical Activity Communications Summit, Nutr. Rev. 70 (2012) 301–310, doi:http://dx.doi.org/10.1111/j.1753-4887.2012.00480.x.
[4] B.A. Hornick, N.M. Childs, M. Smith Edge, W.R. Kapsak, C. Dooher, C. White, Is it time to rethink nutrition communications? A 5-year retrospective of Americans' attitudes toward food, nutrition, and health, J. Acad. Nutr. Diet. 113 (2013) 14–23, doi:http://dx.doi.org/10.1016/j.jand.2012.10.009.
[5] M.A. Wakefield, B. Loken, R.C. Hornik, Use of mass media campaigns to change health behaviour, Lancet 376 (2010) 1261–1271, doi:http://dx.doi.org/10.1016/S0140-6736(10)60809-4.
[6] K. Viswanath, R.H. Nagler, C.A. Bigman-Galimore, M.P. Mccauley, M. Jung, S. Ramanadhan, The communications revolution and health inequalities in the 21st century: implications for cancer control, Cancer Epidemiol. Biomark. Prev. 21 (2012) 1701–1708, doi:http://dx.doi.org/10.1158/1055-9965.EPI-12-0852.
[7] B. Kelly, R. Hornik, A. Romantan, J.S. Schwartz, K. Armstrong, A. Demichele, M. Fishbein, S. Gray, S. Hull, A. Kim, R.H. Nagler, J. Niederdeppe, A.S. Ramirez, A. Smith-Mclallen, N. Wong, Cancer information scanning and seeking in the general population, J. Health Commun. 15 (2010) 734–753, doi:http://dx.doi.org/10.1080/10810730.2010.514029.
[8] D. Chen, E.C. Jaenicke, R.J. Volpe, Food environments and obesity: household diet expenditure versus food deserts, Am. J. Public Health 106 (2016) 881–888, doi:http://dx.doi.org/10.2105/AJPH.2016.303048.
[9] K. Glanz, M. Basil, E. Maibach, J. Goldberg, D. Snyder, Why Americans eat what they do: taste, nutrition, cost, convenience, and weight control concerns as influences on food consumption, J. Am. Diet. Assoc. 98 (1998) 1118–1126, doi:http://dx.doi.org/10.1016/S0002-8223(98)00260-0.
[10] N.I. Larson, C.L. Perry, M. Story, D. Neumark-Sztainer, Food preparation by Young adults is associated with better diet quality, J. Am. Diet. Assoc. 106 (2006) 2001–2007, doi:http://dx.doi.org/10.1016/j.jada.2006.09.008.
[11] N.I. Larson, M.T. Story, M.C. Nelson, Neighborhood environments: disparities in access to healthy foods in the U.S, Am. J. Prev. Med. 36 (2009) 74–81, doi:http://dx.doi.org/10.1016/j.amepre.2008.09.025.
[12] Z. Valdez, Community perspectives on access to and availability of healthy food in rural, low-resource, Latino communities, Prev. Chronic Dis. 13 (2016), doi:http://dx.doi.org/10.5888/pcd13.160250.
[13] M. Fishbein, J.N. Cappella, The role of theory in developing effective health communications, J. Commun. 56 (2006) 1–17, doi:http://dx.doi.org/10.1111/j.1460-2466.2006.00280.x.
[14] G. Cairns, K. Angus, G. Hastings, M. Caraher, Systematic reviews of the evidence on the nature, extent and effects of food marketing to children. A retrospective summary, Appetite 62 (2013) 209–215, doi:http://dx.doi.org/10.1016/J.APPET.2012.04.017.
[15] S.M. Curtis, M.S. Willis, "Are you eating healthy?" Nutrition discourse in Midwestern clinics for the underserved, Patient Educ. Couns. 99 (2016) 1641–1646, doi:http://dx.doi.org/10.1016/j.pec.2016.04.011.
[16] J. Wardle, K. Parmenter, J. Waller, Nutrition knowledge and food intake, Appetite 34 (2000) 269–275, doi:http://dx.doi.org/10.1006/appe.1999.0311.
[17] J.N. Clarke, M.M. Everest, Cancer in the mass print media: fear, uncertainty and the medical model, Soc. Sci. Med. 62 (2006) 2591–2600, doi:http://dx.doi.org/10.1016/j.socscimed.2005.11.021.
[18] E.A. Gill, A.S. Babrow, To hope or to know: coping with uncertainty and ambivalence in women's magazine breast cancer articles, J. Appl. Commun. Res. 35 (2007) 133–155, doi:http://dx.doi.org/10.1080/00909880701263029.
[19] J.P. Goldberg, S.A. Sliwa, Communicating actionable nutrition messages: challenges and opportunities, Proc. Nutr. Soc. 70 (2011) 26–37, doi:http://dx.doi.org/10.1017/S0029665110004714.
[20] R.J. Hurley, K.A. Kosenko, D. Brashers, Uncertain terms: message features of online cancer news, Commun. Monogr. 78 (2011) 370–390, doi:http://dx.doi.org/10.1080/03637751.2011.565061.
[21] J.D. Jensen, M. Pokharel, C.L. Scherr, A.J. King, N. Brown, C. Jones, Communicating Uncertain science to the public: how amount and source of uncertainty impact fatalism, backlash, and overload, Risk Anal. 37 (2017) 40–51, doi:http://dx.doi.org/10.1111/risa.12600.
[22] R.H. Nagler, Adverse outcomes associated with media exposure to contradictory nutrition messages, J. Health Commun. 19 (2014) 24–40, doi:http://dx.doi.org/10.1080/10810730.2013.798384.
[23] J. Niederdeppe, T. Lee, R. Robbins, H.K. Kim, A. Kresovich, D. Kirshenblat, K. Standridge, C.E. Clarke, J.D. Jensen, E.F. Fowler, Content and effects of news stories about uncertain cancer causes and preventive behaviors, Health Commun. 29 (2014) 332–346, doi:http://dx.doi.org/10.1080/10410236.2012.755603.
[24] J.D. Jensen, N. Carcioppolo, A.J. King, C.L. Scherr, C.L. Jones, J. Niederdeppe, The cancer information overload (CIO) scale: establishing predictive and discriminant validity, Patient Educ. Couns. 94 (2014) 90–96, doi:http://dx.doi.org/10.1016/j.pec.2013.09.016.
[25] J.D. Schoenfeld, J.P. Ioannidis, Is everything we eat associated with cancer? A systematic cookbook review, Am. J. Clin. Nutr. (2012), doi:http://dx.doi.org/10.3945/ajcn.112.047142 ajcn.047142.
[26] W.Y.Y. Lai, T. Lane, Characteristics of medical research news reported on front pages of newspapers, PLoS One 4 (2009) e6103, doi:http://dx.doi.org/10.1371/journal.pone.0006103.
[27] R.H. Nagler, R.C. Hornik, Measuring media exposure to contradictory health information: a comparative analysis of four potential measures, Commun. Methods Meas. 6 (2012) 56–75, doi:http://dx.doi.org/10.1080/19312458.2011.651348.
[28] J.D. Jensen, N. Carcioppolo, A.J. King, J.K. Bernat, L. Davis, R. Yale, J. Smith, Including limitations in news coverage of Cancer research: effects of news hedging on fatalism, medical skepticism, patient trust, and backlash, J. Health Commun. 16 (2011) 486–503, doi:http://dx.doi.org/10.1080/10810730.2010.546491.
[29] A.S. Ramirez, Fatalism and cancer risk knowledge among a sample of highly acculturated latinas, J. Cancer Educ. 29 (2014) 50–55, doi:http://dx.doi.org/10.1007/s13187-013-0541-6.
[30] S. Ramondt, A.S. Ramirez, Fatalism and Exposure to information from the media: examining the evidence for causal influence, Ann. Int. Commun, Assoc. 41 (2017) 298–320, doi:http://dx.doi.org/10.1080/23808985.2017.1387502.
[31] J. Chae, Who avoids Cancer information? Examining a psychological process leading to cancer information avoidance, J. Health Commun. 21 (2016) 837–844, doi:http://dx.doi.org/10.1080/10810730.2016.1177144.
[32] J. Niederdeppe, T. Lee, R. Robbins, H.K. Kim, A. Kresovich, D. Kirshenblat, K. Standridge, C.E. Clarke, J. Jensen, E.F. Fowler, Content and effects of news stories about uncertain cancer causes and preventive behaviors, Health Commun. 29 (2014) 332–346, doi:http://dx.doi.org/10.1080/10410236.2012.755603.
[33] D.S.J. Costa, A. Ben Smith, B.T. Lim, J.E. Fardell, Simplifying the assessment of cancer information overload: a comment on Jensen et al. (2014), Patient Educ. Couns. 98 (2015) 1450, doi:http://dx.doi.org/10.1016/j.pec.2015.04.020.
[34] U.S. Census Bureau, State & County QuickFacts, Merced County, California, 2015.
[35] American FactFinder - Results Race Reporting for the Asian Population, (n.d.). https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=DEC_10_SF1_PCT5&prodType=table (Accessed May 22, 2018).
[36] L.K. Muthén, B.O. Muthén, Mplus User's Guide, Muthén & Muthén, Los Angeles, CA, 1998.
[37] P.D. Allison, Missing Data, Sage, Thousand Oaks, CA, 2002.
[38] T.A. Brown, Confirmatory Factor Analysis for Applied Research, 2nd ed., Guilford Press, New York, 2015.
[39] L. Hu, P.M. Bentler, Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives, Struct. Equ. Model. Multidiscip. J. 6 (1999) 1–55, doi:http://dx.doi.org/10.1080/10705519909540118.
[40] R.C. MacCallum, K.F. Widaman, K.J. Preacher, S. Hong, Sample size in factor analysis: the role of model error, Multivar. Behav. Res. 36 (2001) 611–637, doi:http://dx.doi.org/10.1207/S15327906MBR3604_06.
[41] P.M. Bentler, D.G. Bonett, Significance tests and goodness of fit in the analysis of covariance-structures, Psychol. Bull. 88 (1980) 588–606, doi:http://dx.doi.org/10.1037//0033-2909.88.3.588.

[42] H. Akaike, Factor analysis and AIC, Psychometrika 52 (1987) 317–332, doi: http://dx.doi.org/10.1007/BF02294359.
[43] P.M. Bentler, SEM with simplicity and accuracy, J. Consum. Psychol. Off. J. Soc. Consum. Psychol. 20 (2010) 215–220, doi:http://dx.doi.org/10.1016/j.jcps.2010.03.002.
[44] R.C. MacCallum, M. Roznowski, L.B. Necowitz, Model modifications in covariance structure analysis: the problem of capitalization on chance, Psychol. Bull. 111 (1992) 490–504.
[45] J. Chae, C. Lee, J.D. Jensen, Correlates of Cancer information overload: focusing on individual ability and motivation, Health Commun. 31 (2016) 626–634, doi: http://dx.doi.org/10.1080/10410236.2014.986026.
[46] P.K.J. Han, R.P. Moser, W.M.P. Klein, E.B. Beckjord, A.C. Dunlavy, B.W. Hesse, Predictors of perceived ambiguity about Cancer prevention recommendations: sociodemographic factors and mass media exposures, Health Commun. 24 (2009) 764–772, doi:http://dx.doi.org/10.1080/10410230903242242.
[47] K. Kim, L.M.A. Lustria, D. Burke, N. Kwon, Predictors of cancer information overload: findings from a national survey, Inf. Res. (2007) 12.
[48] A.S. Ramírez, Fatalism and cancer risk knowledge among a sample of highly acculturated latinas, J. Cancer Educ. 29 (2014) 50–55, doi:http://dx.doi.org/10.1007/s13187-013-0541-6.
[49] Calfresh, Calfresh. (2017). http://mycalfresh.org/.
[50] Supplemental Nutrition Assistance Program Education (SNAP-Ed), (2017). https://www.fns.usda.gov/snap/supplemental-nutrition-assistance-program-education-snap-ed.
[51] Supplemental Nutrition Assistance Program - Education, (2017). http://www.cdss.ca.gov/inforesources/CalFresh/Supplemental-Nutrition-Assistance-Program-Education.
[52] J.D. Jensen, M. Liu, N. Carcioppolo, K.K. John, M. Krakow, Y. Sun, Health information seeking and scanning among US adults aged 50-75 years: testing a key postulate of the information overload model, Health Informatics J. 23 (2016) 96–108, doi:http://dx.doi.org/10.1177/1460458215627290.