Health Marketing Quarterly

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/whmq20

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HEALTH MARKETING QUARTERLY
2021, VOL. 38, NO. 4, 223–237
https://doi.org/10.1080/07359683.2021.1989746

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The importance of personally relevant knowledge for pandemic risk prevention behavior: A multimethod analysis and two-country validation

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ABSTRACT
Pandemics threaten world stability; however, spread is mitigated with prevention behaviors. We introduce "personally relevant knowledge" to explain the knowledge–behavior gap (i.e., objective and subjective knowledge on information acquisition and behavioral change). Hypotheses are derived from prior knowledge literature, economic psychology, and relevance theory. Multimethod analysis (survey data, partial least squares structural equation path modeling [PLS-SEM], and an asymmetric information theoretic statistical analysis) is applied to H1N1 data from the USA and Australia. Personally relevant knowledge is an important addition to prior knowledge conceptualizations, and information theory uncovers asymmetric variable relationships concerning the knowledge–behavior gap, not captured by PLS-SEM.

KEYWORDS
Asymmetric measurement; disease prevention behavior; information acquisition; information theory; prior knowledge; relevance theory

Introduction

People are mobile and diseases travel with them. This is exemplified by COVID-19, the current pandemic disease caused by the SARS-CoV-2 virus. Starting in November 2019 in China, by July 3, 2020, it spread to 216 counties, infecting 10,719,946 and killing 517,337 (World Health Organization [WHO], 2020). In addition to mortality and morbidity, economic consequences are significant. COVID-19 produced a global recession due to preventative lockdown measures.

The WHO recommends mitigating disease spread through behavioral change: regular hand washing, maintaining distance between people, avoiding crowds, staying home, and self-isolating (WHO, 2020). Given the need for the public to engage in appropriate prevention behavior to attenuate

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Supplemental data for this article can be accessed here disease spread, experts benefit by better understanding what motivates individuals to seek prevention information (which can change as understanding of the virus evolves) and behaviorally act on information in pandemics.

Knowledge learned is not necessarily knowledge used, and marketers struggle to motivate consumers to acquire information and use it for behavioral change (Pan & Meng, 2015; Raymond et al., 1998; Tweneboah-Koduah et al., 2012). Knowledge research often focused on nutrition (e.g., Moore & Lehmann, 1980; Moorman et al., 2004) and largely ignored relationships between prior knowledge and disease prevention (Manika et al., 2017). This knowledge–behavior gap (information known and not acted on) hinders prevention. Thus, understanding the role of prior knowledge in information acquisition and prevention behavior is critical in pandemics.

The first motivation behind this research is to expand existing prior knowledge conceptualizations, namely objective (information stored in memory; Russo & Johnson, 1980) and subjective knowledge (self-perceptions of individual knowledge; Park & Lessig, 1981). Here we add a third construct, personally relevant knowledge, from economic psychology. We empirically investigate these different knowledge types' effects on pandemic risk prevention behavior. Verelst et al. (2016) reviewed behavioral change models for infectious disease transmission (2010–2015) and discussed distinguishing how information translates into preventive actions. We extend that discussion to incorporate relevant knowledge constructs.

Using data from the most recent (2009 H1N1) pandemic, we investigate the roles of prior knowledge (objective and subjective) and personally relevant knowledge as drivers of information acquisition and pandemic prevention behavior. Specifically, we address: "How does the perceived relevance of a piece of information impact behavior?" This is important for pandemic response.

Second, this research responds to a call for a shift in marketing and consumer research from symmetric to asymmetric thinking (Woodside, 2013) by incorporating an asymmetric analysis as part of our multimethod data analysis. Multimethod analysis provides validation and robustness benefits as discussed in Hausman (2000) and Xu and Albarracín (2016). Here we use both partial least squares structural equation path modeling (PLS-SEM) and asymmetric information theoretic statistics to analyze H1N1 pandemic data. Information theory provides asymmetric statistics measuring the proportion of information that one set of variables (Y) explains about another set of variables (X). It provides asymmetric information complementing commonly used symmetric statistical information. It is asymmetric because the impact of attitude for behavior, for example, may differ from the impact of behavior for attitude.

Last, this research informs policymakers about effectively using prior knowledge for educating about COVID-19 and pandemic disease prevention. The research builds on existing prior knowledge concepts, applying them to data collected during the H1N1 pandemic. Conclusions are validated using two countries (USA and Australia). Prior knowledge research in marketing focuses almost exclusively on the USA. Since pandemics are multinational, validating prior knowledge constructs outside the USA is important for designing effective prevention information communication. We addresses whether prior knowledge constructs function similarly in other countries, using Australia to externally validate results from the USA.

Advancing prior knowledge literature in consumer research

The relevance of prior knowledge is well known (e.g., Alba & Hutchinson, 2000; Carlson et al., 2009; Moorman et al., 2004). Research has focused on (1) attribute importance (Park & Lessig, 1981; Raju et al., 1995), (2) quality and content of product information (Alba, 1983; Cordell, 1997), (3) information search (Johnson & Russo, 1984; Moore & Lehmann, 1980), (4) information processing and decision-making (Alba, 1983; Johnson & Russo, 1984; Raju et al., 1995), and (5) tangible and intangible products (e.g., Hadar et al., 2013; Donoghue et al., 2016). This research has not investigated prior knowledge in relation to disease prevention behavior—something very important today.

Although studies operationalize prior knowledge constructs differently, all agree that *objective knowledge* is "what is actually stored in memory" (Brucks, 1985, p. 2). The literature treats *subjective knowledge* as "what individuals perceive they know" (Brucks, 1985, p. 2), sometimes including the individual's level of confidence in their knowledge. According to Moorman et al. (2004), *subjective* and *objective knowledge* are distinct constructs with unique measures and unique influences on search and choice behavior.

In economic psychology, Frey and Foppa (1986, p. 147) present the concept of personal (relevant) knowledge as, "what a particular individual takes to apply to himself, and which is therefore taken into consideration for his own behavior." Although a person might be knowledgeable about an issue, product, or action, they may not apply that knowledge personally or take objective (testable) known knowledge into account for personal decision-making. What knowledge a person applies personally is important in understanding the knowledge–behavior gap (e.g., knowing that wearing face masks in public statistically reduces COVID-19 transmission, but going maskless anyway). The knowledge–behavior gap may exist because the person believes the danger is "not going to happen to me" (i.e., is not personally relevant). This gap is especially important in a pandemic context where personal actions effect both personal and community risks.

Here we introduce *personal knowledge relevance* as an additional dimension to the literature's prior knowledge constructs (objective and subjective). Here "(personally) *relevant knowledge*" is the knowledge a person views as relevant to him/herself for action. This construct is supported by relevance theory (Sperber & Wilson, 2006; Wilson & Sperber, 2012).

Relevance theory appeared as a "cognitive psychological theory" in the pragmatics literature (Sperber & Wilson, 2006, p. 625) based on the *cognitive principle of relevance*, that "[h]uman cognition tends to be geared towards the maximization of relevance" (Sperber & Wilson, 2006, p. 255). That is, the cognitive system's mental mechanisms and biases allocate attention to information/inputs having the greatest expected relevance and, it processes them in a relevance-enhancing way (Allott, 2013; Wilson, 2010). Relevance theory has not been previously presented in marketing or disease prevention literatures.

Similar to the thesis of relevance theory, this study posits personal knowledge relevance is central to behavioral decision-making and information acquisition in a disease context like COVID-19. The individual emphasizes using personally relevant information over other information not so perceived (see Supplement 1 on how this concept is different from involvement).

Hypotheses development

We investigate, within a pandemic context, the impact of prior knowledge on two outcomes: disease prevention information acquisition and behavior. Objective and subjective prior knowledge influences behavior (Brucks, 1985; Moorman et al., 2004), and we examine the role of relevant knowledge as a mediator between prior knowledge and behavior (using PLS-SEM).

Prior knowledge is positively and significantly related to information search, as using prior knowledge makes information processing easier (Johnson & Russo, 1984). Moore and Lehmann (1980) find a negative relationship between prior knowledge constructs and information processing, and Brucks (1985) finds a significant positive relationship between objective knowledge and information processing and information search variability (nutrition context). In an AIDS disease context, Stanaland and Golden (2009) show a positive and significant relationship between objective knowledge and information receptivity.

The activity of seeking information is "one step in health behavior change, but more focused on the decision-making steps" (Freimuth et al., 1989, p. 6). Thus, it is hypothesized that objective, subjective, and also relevant prior knowledge all influence disease prevention information acquisition and behavior.

H1. Within a pandemic context, *objective* knowledge is significantly and positively related to (a) disease prevention information acquisition and (b) disease prevention behavior.

Prior literature demonstrates a strong link between subjective knowledge and information acquisition (Brucks, 1985), information search (Raju et al., 1995), and search selectivity (Moorman et al., 2004). Individuals who self-perceive being highly knowledgeable may desire to control or prevent an event through further knowledge acquisition and/or prevention behavior. That is, knowledge often begets knowledge (Stanaland & Golden, 2009). In addition, according to a meta-analysis by Carlson et al. (2009), objective knowledge and subjective knowledge tend to be positively correlated.

H2. Within a pandemic context, *subjective* knowledge is significantly and positively related to (a) disease prevention information acquisition and (b) disease prevention behavior.

H3. Within a pandemic context, objective knowledge and subjective knowledge are significantly and positively correlated.

We also add relevant knowledge to these prior knowledge constructs. According to Frey and Foppa (1986), the greater the relevant "personal knowledge" (the degree that someone regards an idea as relevant and personally applicable), the more likely is action on that information. Consistent with this expectation, and guided by relevance theory, it is proposed that the more a person perceives prevention information as personally relevant, the more s/he will engage in prevention behavior. Prior knowledge should also affect relevant knowledge, as relevance is judged through cognitive effects, as previously discussed.

H4a. Within a pandemic context (disease prevention information acquisition and behavior), *relevant knowledge* mediates the positive effect of *objective* knowledge on behavior.

H4b. Within a pandemic context (disease prevention information acquisition and behavior), *relevant knowledge* mediates the positive effect of *subjective* knowledge on behavior.

Finally, from consumer behavior and relevant disease prevention research (Yang, 2012), a positive and significant relationship between disease prevention information acquisition and behavior is expected.

H5. Within a pandemic context, disease prevention information acquisition is significantly and positively related to behavior.

Methodology

Phase 1: qualitative and quantitative measurement development

To develop the prior knowledge construct scales, we reviewed literature in consumer behavior (Brucks, 1985; Moorman et al., 2004), disease prevention (Durodie, 2011; Yang, 2012), and recognized news sources. We generated an item pool for each construct. Empirical studies were the basis for initial development of scales and measures of the prior knowledge constructs for the H1N1 pandemic.

To develop scales, we first used qualitative data techniques involving a series of structured in-depth interviews and an hour-long group discussion to develop relevant specifics of prior knowledge in the infectious disease prevention context, using a class from a large USA university. Following this qualitative stage, we refined scales and questions and developed additional questions. Next, we pretested the instrument on a convenience sample of 29 students and professors at a large USA university. Surveys were used for initial psychometric scale development, ultimately expanded, and finalized (for the final scales, see Supplement 2). All constructs were measured using multiple items on a 7-point semantic differential scale, and all constructs' Cronbach's alpha scores were $\geq$.80.

For the measure of objective knowledge a comprehensive review of the literature and popular press identified relevant H1N1 issues, and expert knowledge sources (medical professionals, government websites) and known facts. The objective knowledge measure was created assessing an individual's knowledge relative to an external "known true" knowledge standard. A health professional approved test questions and correct answers before data collection. Objective knowledge (see Supplement 3) was measured using a 15-item summation of right answers.

Phase 2: internet survey development and administration (USA and Australia)

Most prior knowledge research uses only USA data, so we collected data in a second country (Australia) to externally validate hypothesized model performance as exhibited in the USA. The USA and Australia share language with similar culture, and the topic and constructs were relevant for both countries in this pandemic. We used an Internet survey, so panel respondents were computer-literate. Commonalities between countries reduced or eliminated potential administrative procedure method bias (van de Vijver & Leung, 1997).

A commercial panel firm provided email addresses (matched to general public characteristics) for the USA and Australia. The same questionnaire was administered, via Qualtrics, during the same period of the pandemic. Data quality assurance measures were implemented to eliminate cheaters and ensure that respondents were reading and paying proper attention to survey questions (Smith et al., 2016).

To minimize potential common method bias effects, we assured respondent confidentially and randomized scales during administration (Podsakoff et al., 2003). Harman single-factor test results, assessed through principal component analysis without rotation, showed that one factor explains only 37.96% (USA) and 32.55% (Australia) of sample variance (i.e., <50%). This compares with four factors with eigenvalues greater than 1 explaining 71.31% (USA) and four factors explaining 65.29% (Australia) of the sample variance.

The final sample was 453 USA and 490 Australian geographically and demographically diverse respondents. USA respondents were 47% female, average age 46 years ($SD = 14.9$), 61.4% married or living together, 45% with no children, 24.3% completed high school only, and 62.2% had some college education or higher. Australian respondents were 51.6% female, average age 39 years ($SD = 13.6$), 66.5% were married or living together, 26.5% had no children, 29.4% completed high school only, and 27.5% had some college education or higher. The average objective knowledge score for the USA was 11.49 ($SD = 1.72$), ranging from 5 to 15 (out of 15 possible). For Australians, the average score was 11.61 ($SD = 1.62$), ranging from 6 to 15.

Results: PLS-SEM (method 1)

We implemented PLS-SEM using SmartPLS 3.0 (Hair et al., 2016) with 5,000 bootstrap resamples for testing both measurement and structural models. We checked the variable-to-sample ratio for the USA and Australia separately, before implementing the analysis procedure suggested by Hair et al. (2016) and Fornell and Larcker (1981) for assessing convergent and discriminate validity in each sample. For both countries, every multi-item construct had Cronbach's alpha $\geq .72$, composite reliability $\geq .84$, and average variance extracted (AVE) $\geq .56$. Correlations between any construct items were ≤ 0.85, and values for the Fornell–Larcker criterion were acceptable (AVE $> (r)^2$) for all multi-item scales, confirming discriminant validity (for means, standard deviations, correlations, and Fornell–Larcker criterion see Supplement 4). We also checked the heterotrait-monotrait ratio (Henseler et al., 2015) for all latent variables in both countries. We found no collinearity between the variables (variance inflation factor [VIF] ≤ 1.6 for each variable for both countries). Thus, the measurement model performed appropriately in both countries.

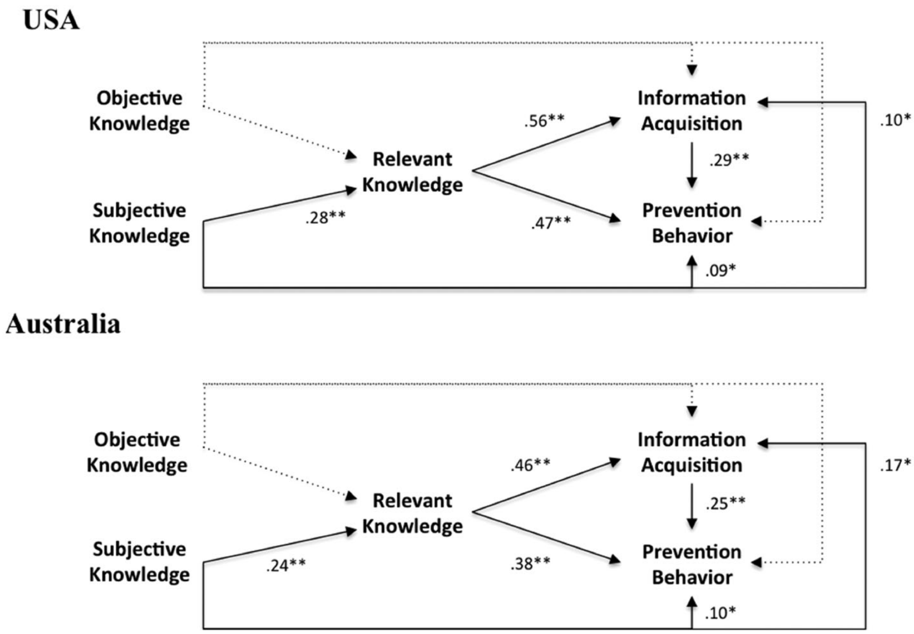

Figure 1. PLS-SEM Results. Dotted lines tested but not significant. *Significant at the 0.05 level; **Significant at the 0.01 level; H3 and H4b not tested via PLS-SEM were also supported; H4a was not supported.
PLS-SEM = partial least squares structural equation path modeling.

We also used the measurement invariance of composite models (MICOM) evaluation procedure (Henseler et al., 2015) to test measurement invariance. Partial measurement invariance was established for all constructs (Step 2 of MICOM), suggesting that standardized path coefficients can be compared across the two samples. We then tested the USA and Australia models separately using PLS bootstrapping and blindfolding techniques.

Structural model quality was assessed in both countries (blindfolding procedure in SmartPLS; Hair et al., 2016) using cross-validation communality and redundancy indices. All Stone–Geisser Q^2 values are strictly positive (USA, .05–.46; Australia, .03–.27), confirming the predictive relevance of the model for all latent constructs. The USA model explained 36% of the variance in disease prevention information acquisition and 51% of the variance in behavior; in Australia the explained variances were 26% and 34%, respectively. Figure 1 presents PLS-SEM results.

Hypotheses results were consistent across the USA and Australia. Objective knowledge did not affect either outcome (disease prevention information acquisition or behavior); hence, H1a and H1b were not supported. On the other hand, subjective knowledge did have a small to moderate positive and significant effect on disease prevention information acquisition and behavior, in support of H2a and H2b.

PLS-SEM does not directly allow testing H3 (the relationship between objective knowledge and subjective knowledge), so this was tested using SPSS. Data for both countries indicate a positive and significant relationship between objective and subjective knowledge (USA, $r = .21$, $p < .05$; Australia, $r = .26$, $p < .05$). Thus, H3 is supported.

To examine important mediation effects of relevant knowledge postulated in H4, we used an ordinary least squares regression approach to path analysis (Hayes, 2013). Using the average scores of the latent constructs, we estimated indirect effects using PROCESS and calculated 95% confidence intervals (CIs) via bias-corrected and accelerated bootstrap with 10,000 resamples (Hayes, 2013).

All positive indirect effects are consistent with the hypotheses tested through PLS-SEM and indicate relevant knowledge partially mediates the links between subjective knowledge and the outcomes (information acquisition: USA, $\beta = .17$, 95% CI, .11 to .24; Australia, $\beta = .11$, 95% CI, .06 to .17; prevention behavior: USA, $\beta = .19$, 95% CI, .12 to .26; Australia, $\beta = .14$, 95% CI, .08 to .21). Relevant knowledge does not, however, mediate the links between objective knowledge and the outcomes. These results support H4b but not H4a. Results confirm the importance of relevant knowledge for disease prevention information acquisition and behavior.

Finally, a moderately positive relationship between disease prevention information acquisition and behavior was evidenced, in support of H5. Thus, when people search for prevention information, they also tend to engage in prevention behavior. Information acquisition also mediated the relationship between relevant knowledge and prevention behavior (USA, $\beta = .18$, 95% CI, .11 to .25; Australia, $\beta = .13$, 95% CI, .07 to .20).

Results: information theory analysis (method 2)

Information is fundamental to consumer research, and understanding informational relationships among variables is required to comprehend disease prevention activity. The most common quantification used for information is the inverse of the variance (univariate) or the inverse of the variance–covariance matrix (multivariate). Variance–covariance measures are symmetric, $\text{Cov}(X,Y) = \text{Cov}(Y,X)$; however, variable relationships can be asymmetric (X may supply a larger percentage of information about Y than Y supplies about X; Golden et al., 1990). Covariance-based analysis does not provide asymmetric insights into the information content one variable may hold concerning the other. PLS-SEM provided information on strengths of relationships in one direction, whereas information theory is bidirectional and asymmetric. By combining both symmetric and asymmetric analyses, we gain a more complete perspective on the data (for more on the mathematics of information theoretic analysis see the Supplement 5).

The goal is to determine the percentage of information about H1N1 disease prevention behavior explained by knowing the individual's levels of objective knowledge, subjective knowledge, relevant knowledge, and information acquisition behavior. We also analyze the percentage of information about H1N1 information acquisition behavior explained by observing levels of H1N1 objective and subjective knowledge, prevention behavior, and relevant knowledge. Results from the USA and Australia indicate that these variables provide excellent prediction of prevention behavior (USA explained, 80.2%; Australia, 78.2%). Similarly, the set of variables provides 86.4% (USA) and 80.4% (Australia) of the information for knowing information acquisition.

These results indicate that relevant knowledge explains a larger percentage of information than any other single predictive variable about both disease prevention information acquisition and behavior for Australia. For the USA, relevant knowledge explains more information about information acquisition than any other predictive variable; however, it is second to information acquisition for supplying information about prevention behavior. A summary of the information explained by all possible combinations of variables of interest related to disease information acquisition and prevention behavior is in Supplement 6, along with the directionality in the information supplied by one variable about another (information asymmetry). For example, prevention behavior supplies more information about information acquisition (USA, 17.9%; Australia, 11.9%) than vice versa (USA, 16.8%; Australia, 10.6%). The degree of asymmetry can also be expressed in percentage terms. For example, Australia data indicate that prevention behavior supplies 12% (= [11.9–10.6]/10.6) more information about information acquisition than information acquisition supplies about prevention behavior.

Figure 2 graphically presents Chi-square significant asymmetric informatic relationship percentages between all variable pairs. For each pair, the number on the arrow gives the percentage of information the arrow tail variable supplies about the arrow head variable. For example, in Australia relevant knowledge supplies 13.5% of the information about information acquisition, whereas information acquisition supplies only 12.9% of the information about relevant knowledge. For both countries, the relationship between relevant knowledge and prevention behavior is significant ($p <$ .01), while the relationship between objective knowledge and prevention behavior is not significant. The shared information between objective and subjective knowledge for the USA is significant at .05.

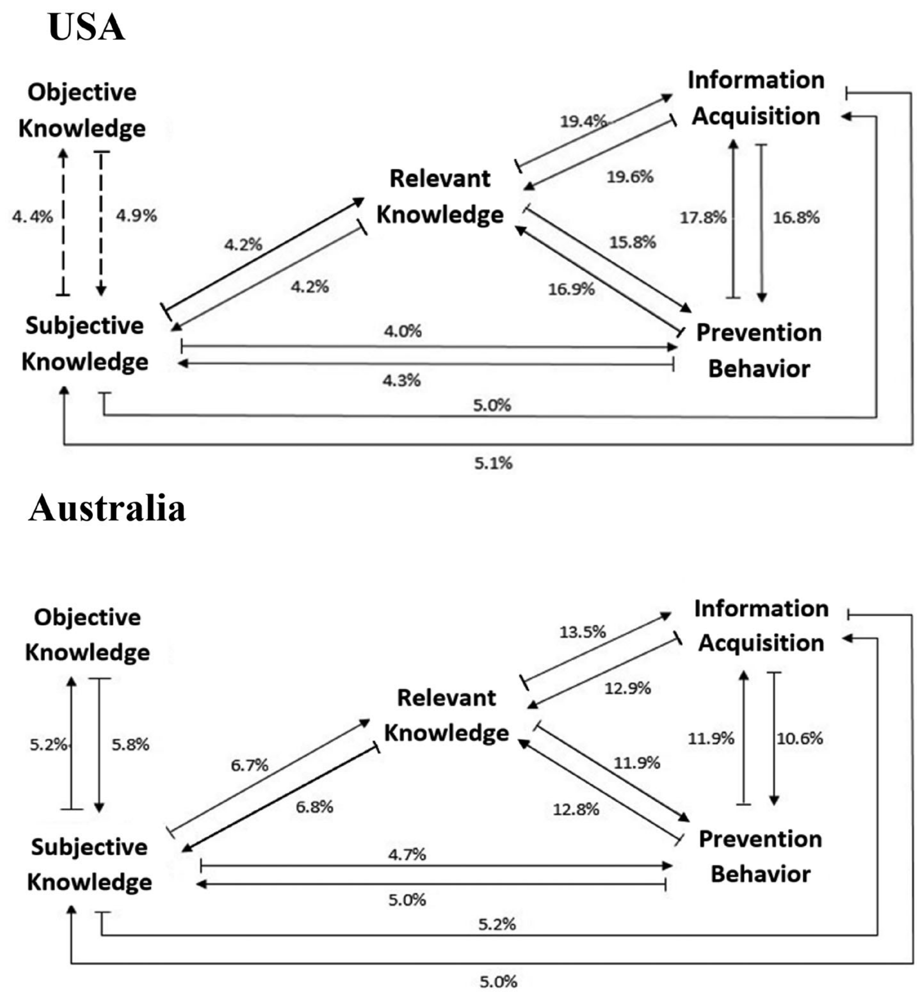

Figure 2. Diagram of bivariate asymmetric percentage of information explained for statistically significant entropic relationships between each pair of variables ($p \leq .01$)*.
*A solid line indicates a significant relationship at $p \leq .01$. A dashed line represents statistical significance relationship $\leq .05$. No line between variables indicates no statistical significance. The percentages on the arrows give the percent of information the variable at the arrow tail supplies about the variable at the arrow head.

The significance of relationships between the variables assessed via information theoretic analysis (Figure 2) reinforces those relationships uncovered as significant via PLS-SEM (Figure 1). This concordance of multimethod analyses provides validation and enhances the credence of using these results for public policy directives.

Discussion, limitations, and future research

This research examines a topic at the intersection of public health interests and consumer research: the relationships among information search, personal knowledge relevance, and objective and subjective knowledge and their effects on disease prevention information acquisition and behavior within a pandemic context. Relationships are examined for two countries using data collected during an actual pandemic (H1N1). Personal knowledge relevance introduced here has not appeared in prior knowledge consumer research and is the most import knowledge construct for disease prevention information acquisition and behavior.

Combining insights from asymmetric and symmetric statistical modeling approaches, this research shows that relevant knowledge is important for removing uncertainty about an individual's disease prevention information acquisition behavior and disease prevention behavior. This result is externally validated (USA and Australian results are concordant), and results are consistent across multiple methods (PLS-SEM and informational theoretic).

An important conclusion here is that in a pandemic disease context, contrary to results in prior consumer research, *objective* knowledge did not influence disease prevention information acquisition or prevention behavior. Disease prevention may require more personal actions than those required in previous researched contexts (where positive health changes were related more to acquisition, e.g., whiter teeth, fewer pounds). The lack of a statistical relationship between objective knowledge and prevention behavior is consistent with the transtheoretical model in health communications, positing that individuals may not be motivated to take prevention measures even when they are knowledgeable about the topic or risk (Prochaska et al., 2002). This suggests that cognitive knowledge is not necessarily connected to action tendencies. In pandemics, knowledge acquisition and disease prevention behavior are also related to avoidance of risk. The knowledge–behavior gap may increase in certain contexts (like pandemics), creating more barriers to be overcome to achieve desired actions (wearing of masks, avoiding large gatherings, etc.). Reinforcing knowledge so it becomes internalized as relevant is the key here.

Prior consumer research findings show that objective knowledge is significantly related to *past* information search dimensions (Brucks, 1985). However, the context of an ongoing pandemic is temporally different—*current and future* information acquisition—and there we find no support for the impact of stored information on current or future information acquisition. What is known now does not necessarily lead to current and future information acquisition activity. During a pandemic, objective information evolves, requiring new information acquisition activity (e.g., masks first deemed unnecessary, and later prescribed; gatherings of more than 50 first banned, then lowered to 10; etc.). A task during pandemics is motivating current (and future) information acquisition.

Given competing information from multiple forums (including misinformation), the need to appropriately leverage information acquisition is critical. Relevance of knowledge is an important knowledge conceptualization with implications for eliciting preventive behavior in pandemics. Relevant knowledge was shown to have the strongest behavioral influence, and prevention communications should provide information that accentuates personal relevance.

Objective and subjective knowledge were found to be positively and significantly correlated, a result consistent with the consensus of consumer behavior prior knowledge research (Brucks, 1985; Carlson et al., 2009; Raju et al., 1995). We also find that subjective knowledge is significant for disease prevention information acquisition, as well as for prevention behavior, which has not been empirically tested previously.

Health marketers designing public service announcements should focus on creating campaigns that (1) motivate information acquisition through health education using *relevant knowledge* points and (2) motivate prevention behavior by using knowledge that is *personally relevant*. Conveying personally relevant knowledge is crucial to influencing prevention behavior within the context of COVID-19 and future pandemics (e.g., G4 EA H1N1; Berkeley, 2020).

Funding

This work was supported by a grant from the Center for Risk Management and Insurance Research at the University of Texas at Austin.

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