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Check (it) yourself before you wreck yourself: The benefits of online health information exposure on risk perception and intentions to protect oneself

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ABSTRACT

The current study contributes to a better understanding of health information acquisition (HIA) and ongoing public policy debates about the usefulness of online health information. We distinguish between types of health knowledge (i.e., objective vs. subjective knowledge) and health information sources (information on the Internet vs. information from a Health Professional's office visit), to examine risk perceptions and health behavior outcomes (i.e., health information seeking intentions, general prevention intentions, and vaccination intentions). Using the human papillomavirus, one of the most common sexually transmitted diseases in the US among men and women aged 18–26 years, as the health context, field survey data were collected through a US online consumer panel and analyzed via structural equation modeling. We find that factually correct health information acquired by a health professional's office visit (rather than the Internet) leads to reduced risk perceptions, with potentially detrimental effects on health behavior change outcomes. Conversely, perceptions of knowledge acquired through the Internet (rather than information from a health professional's office), leads to enhanced risk perceptions with positive impacts on health behavior change outcomes. We discuss how this discrepancy can lead to a conundrum for public policy and efforts to effectively communicate health risks to individuals.

1. Introduction

Even though people often turn to the Internet to inform themselves about the risks and consequences of diseases and health issues (Lee and Lee, 2018; Manika et al., 2018; Morrison, 2020; Myrick, 2017), and organizations use Internet-based technology tools to improve their health care service provision (Almobaideen et al., 2017; Gastladi et al. 2018; Wang et al., 2018; Wang, Gupta and Ozdemir 2019), online health information is often criminalized (Betsch et al., 2010). Frequently described as "unreliable" (Gottlieb, 2000), health information on the Internet may mislead, misinform, and deceive. For example, some online sources actively discourage protective health behavior by providing "harsh criticism against vaccinations" (Betsch et al., 2010, p.447). But at the same time, due to the emotionally-charged content with visuals, personal stories and interactive content (Manika, Gregory-Smith and Antonetti 2017), the Internet is considered a highly influential source of health information for behavior change. From a public policy perspective, using online health information is in line with strategic considerations to stem the massive costs of health care and associated health problems (Keller and Lehman 2008); which is the reason for the upsurge of research on forms of communicating health information and its association with health behavior (Bostrom 1997; Downs, Bruine de Bruin and Fischhoff 2008; Betsch et al., 2012; Deng et al., 2015; Morgan and Trauth 2013; Mou et al., 2016; Redmond et al., 2010).

In the current study, we expand on this body of literature, and health information acquisition models in particular, by distinguishing between types of health knowledge (i.e., objective vs. subjective knowledge) and health information sources (information on the Internet vs. information from a Health Professional's office visit) to examine risk perceptions and health behavior outcomes (i.e., health information seeking intentions, general prevention intentions, and vaccination intentions). Objective knowledge refers to the accuracy of one's knowledge stored in memory, while subjective knowledge is the perceived amount of knowledge one thinks he/she has, irrespective of whether it is accurate or not (Manika et al., 2018). The differentiation between these two types of knowledge is noteworthy (Ran et al., 2016), as it can have different effects on health

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behavior (Alba and Hutchinson, 2000). Past health information acquisition models do not distinguish between these two types of knowledge, but often rely on subjective perceptions of knowledge adequacy (Health Information Acquisition Model; Freimuth et al., 1989), or information insufficiency (Risk Information Seeking and Processing Model; Griffin et al., 1999) as a predictor of additional information seeking behavior.

In relation to the health information source, we contribute to ongoing debates about the usefulness of health information on the Internet for behavior change and present a public-policy conundrum: We find that factually correct health information (i.e., objective knowledge), connected to exposure to information from a health professional's office visit (rather than the Internet), can lead to reduced risk perceptions, with detrimental effects on health behavior change outcomes; while perceptions of knowledge (i.e., subjective knowledge), connected to information exposed on the Internet (rather than information from a health professional's office), lead to enhanced risk perceptions with a positive impact on health behavior change outcomes. Given that the behavioral outcome is the ultimate goal, one may wonder whether it is better to engage in public health communications that increase subjective or objective knowledge.

We conducted a field survey that examines how past exposure to sources of health information (e.g. from the Internet, from a health professional's office visit, and no exposure) affects people's health knowledge types and, in turn, their risk perceptions and disease prevention intentions. Our results show that knowledge type depends on past exposure. Exposure to information, whether from the Internet or from a health professional's office visit, leads to higher objective and subjective knowledge compared to no exposure at all. Moreover, information exposure from a health professional's office visit (versus from the Internet), leads to higher objective knowledge but not subjective knowledge. In our data, higher objective knowledge is related to lower risk perceptions whereas higher subjective knowledge is related to higher risk perceptions. Finally, we find evidence for risk perceptions mediating the knowledge-behavior relationship, such that subjective knowledge increases risk perceptions, which in turn are related to higher intentions to seek further health information. These results allow insights into the psychological processes of preventative health behavior and the role of the Internet in health information acquisition. Based on these findings, we argue that health information from the Internet should not be criminalized per se. While acknowledging that individuals make health care decisions dependent on a multitude of information and sources, we provide recommendations to policy makers and contribute to ongoing debates about the usefulness of Internet-based health information.

2. Literature review

2.1. Health information seeking and knowledge acquisition

Research highlights that people often engage in information-seeking activities to improve their health (Brashers et al., 2002; Deng et al., 2015; Freimuth et al., 1989; Kahlor 2010; Manika et al., 2018; Mou et al., 2016; Myrick, 2017; Rains, 2008). The goals for these information-seeking activities may range from understanding a health diagnosis to considering treatments and taking control over one's own health and/or lives (Palsdottir, 2010). Health knowledge is a result of past information exposure and also determines how people seek, encounter, and avoid information (Kahlor, 2010; Manika and Golden, 2011; Stanaland and Golden 2000; Wilson, 2000). The interconnected process between knowledge and information seeking underscores the complexity of health decision-making where knowledge is dynamic and competing goals may interfere with translating knowledge into behavior (Manika et al., 2018).

Several models have been proposed to describe and explain when and why health risk information is sought. For example, the Health Information Acquisition Model (HIAM; Freimuth et al., 1989), and the Risk Information Seeking and Processing Model (RISP, Griffin et al., 1999) posit that perceived information insufficiency acts as a trigger for the need to obtain further information. The notion of information insufficiency relies on subjective perceptions similar to the concept of (i.e., "subjective knowledge"). If one thinks he/she has a sufficient amount of health knowledge, he/she is less likely to continue seeking health information. However, the HIAM and RISP models do not take into account the factual correctness of the current information (i.e., "objective knowledge").

Based on previous models, this perceived information insufficiency, in turn, has been linked to risk perception. Thus, these models suggest that individuals form the intention to seek further information if they consider their current level of knowledge to be inadequate or insufficient and perceive a health risk. In an extension to the RISP model, Kahlor, (2010) proposed the Planned Risk Information Seeking Model (PRISM), which also incorporates aspects of several other models, such as the Theory of Planned Behavior (TPB; Ajzen, 1991), Health Information Acquisition Model (HIAM; Freimuth et al., 1989), and the Comprehensive Model of Information Seeking (CMIS; Johnson and Meischke, 1993), among others. According to PRISM, the intention to seek information depends directly on subjective norms, attitudes, control (including whether information is available), and affective reactions to risk. While these models contribute to our understanding of health information acquisition, and the mediating psychological mechanism of risk perceptions between knowledge adequacy/insufficiency and health behavior, they do not distinguish between types of health knowledge (i.e., objective vs. subjective knowledge) and health information sources to examine risk perceptions and health behavior outcomes. The current study proposes a model which addresses this gap in the literature (see Fig. 1) and thus contributes to information acquisition theories as well as public policy debates on effective health communication.

2.2. Online health information sources: curse or blessing?

Health information can be acquired through a multitude of sources (e.g., TV, radio, magazines, newspapers, the Internet, health professionals, doctors, fellow patients, family, and friends; Fox, 2011). The advantages of using Internet-based health information sources have been well-documented in prior literature, which might explain why public-policy makers are still using the Internet as one of the main sources for health information dissemination. Online sources are immediately accessible, widespread, practical for younger adults, low-income, less educated and minority groups and allow for privacy, anonymity and variety of opinions (Cotton and Gupta, 2004; Fox, 2011; Jacobs, Amuta, and Jeon 2017). On the other hand, offline sources like print media, friends and family, and health professionals are more associated with health behaviors than other sources of information (Redmond et al., 2010). Most individuals compare Internet-based health information through a variety of sources (Dutta-Bergman, 2004), given the associated lower trust in online information compared to information from health professionals (Fox 2011). However, Internet information can promote better physician-patient interactions offline (Seckin 2014) and virtual one-to-one consultations with health professionals, which offer convenience to both patients and doctors (Greenhalgh et al. 2016).

While a plethora of research has debated the negative and positive aspects of using Internet-based health information, online health information is often criminalized (Betsch et al., 2010) due to its unreliability (Gottlieb, 2000) and resulting negative associations with health behavior (Bostrom, 1997; Downs, Betsch et al., 2012; Deng et al., 2015; Morgan and Trauth 2013; Mou et al., 2016; Redmond et al., 2010). In contrast, information acquired via a health professional's office visit is considered more trustworthy (Fox 2011). We compare these two types of health information because health professionals are more associated with health behavior than any other source of information (Redmond et al., 2010). This may be due to people being more receptive to health

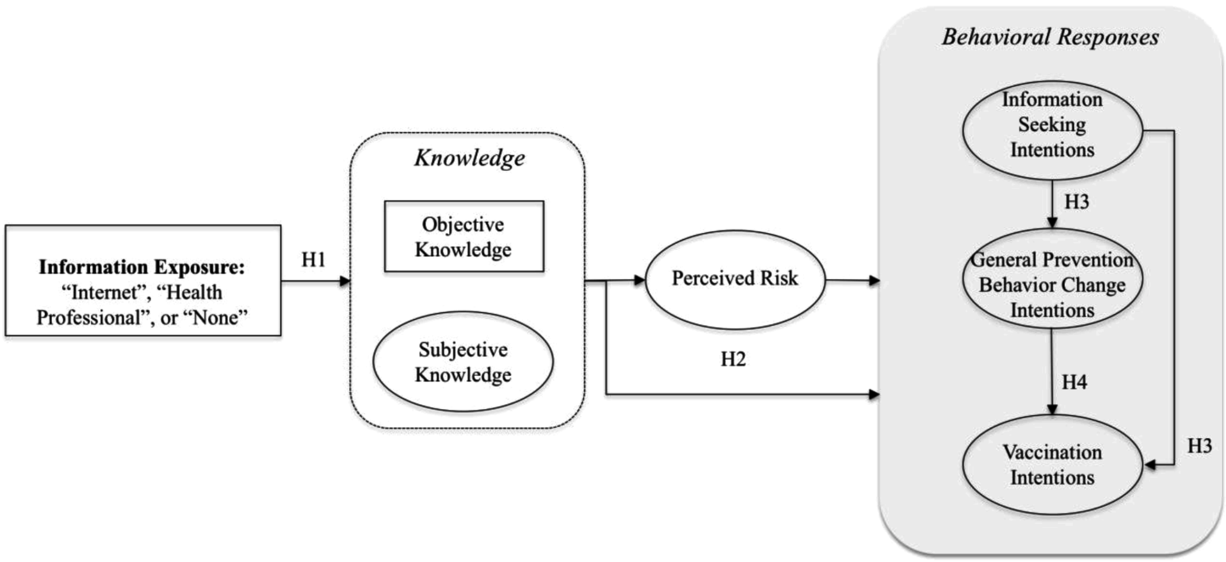

Fig. 1. Hypothesized model.

information during a health professional's office visit, paying more attention to that information, as well as comprehending information better, all of which could contribute to greater objective knowledge acquisition. Conversely, Internet-based health information might make individuals less inclined to process information deeply in the first place. Finally, regardless of whether exposure to health information is Internet-based or via a health professional's office visit, individuals are more likely to have increased health knowledge compared to those not exposed to any information.

2.3. Objective and subjective health knowledge

The influence of prior knowledge on information processing and decision-making is well documented (e.g., Alba and Hutchinson, 2000; Hadar et al., 2013; Lee, 2016; Lee and Koo, 2012), including health-related contexts (e.g., Brucks 1985; Manika and Golden 2011; Rudell 1979; Stanaland and Golden 2000; Manika et al., 2018; Moorman et al., 2004). Knowledge can influence people's comprehension and adoption of a new product (e.g. such as a prevention vaccine) as well as perceptions of its advantages and risks (Moreu et al., 2001). At the same time, health knowledge can also determine future information-seeking behaviors (Kahlor 2010; Moorman et al., 2004) and affects disease prevention behavior in general (Manika and Golden, 2011). However, simply increasing knowledge accuracy about health threats and related issues (i.e., objective knowledge; Brucks, 1985) sometimes is not enough to elicit behavior change. Objective knowledge may be misperceived or rejected (Fessenden-Raden et al., 1987) leading to misconceptions of one's subjective extent of health knowledge.

Generally, subjective knowledge has been found to affect behavior more than objective knowledge (Schneider et al., 2016). Objective and subjective knowledge are unique constructs with unique measures (Park, Motherbaugh and Feik 1994); they have unique influences (Bettman and Park, 1980; Brucks, 1985; Moorman et al., 2004; Rudell 1979), unique antecedents (Park, Mothersbaugh and Feik, 1994) and varying correlations (Carlson et al., 2009; Raju et al., 1995). Studies which have explored these knowledge types provide support for their relevance in understanding health behaviors (Brucks, 1985; Stanaland and Golden, 2009; Manika and Golden, 2011; Moorman et al., 2004). It is still unclear, however, how exposure to various sources of health information may affect objective and subjective health knowledge, and in turn how this new knowledge may lead to risk perceptions and behavioral responses.

In the current study, based on the aforementioned literature we hypothesize that past exposure to health information from any source will lead to greater knowledge, than not being exposed to any information. Even though this seems intuitive, no prior research has examined this hypothesis based on the distinction between objective and subjective knowledge. When exposed to health information, people may know more (i.e., higher objective knowledge) and think they know more (i.e., higher subjective knowledge) - even if that knowledge is not factually correct -compared to no exposure at all (H1a). In relation to H1b, health information from a health professional's office visit is considered more trustworthy from an expert source of information, compared to health information on the Internet (Fox, 2011); hence it is more likely that health information from a health professional's office visit will lead to greater knowledge (objective and subjective) compared to health information on the Internet. In regards to subjective knowledge, it might be that just the exposure itself increases perceptions of subjective knowledge, while the actual truth content of that information is less relevant. The same relationship is being proposed for objective and subjective knowledge due to the absence of literature on how knowledge types are affected by sources of past health information exposure. Hence, in summary we hypothesize the following relationships (see Fig. 1):

H1: *(a) Past exposure to health information leads to greater health knowledge (*i.e., *objective and subjective health knowledge) than not being exposed to health information; while (b) past exposure to health information from a health professional's office visit leads to greater health knowledge (*i.e., *objective and subjective health knowledge) than health information exposure from the Internet.*

2.4. Risk perceptions and health behavior

For health information to be relevant for people's health behavior, it needs to communicate both the information that leads to knowledge as well as motivate to act (Fischoff, 1995; Bostrom, 1997). One way how knowledge can motivate health behavior is through informing about risks of contracting a disease and related preventative behaviors.

The study of risk perception provides a basis for understanding public responses to health threats and improving the communication of risk information for the general public (Bruine de Bruin and Bostrom 2013; Slovic et al., 1982). Research on the mental-models approach for communicating risk information (e.g. Bostrom, 1997; Jungermann et al., 1988) suggests that next to identifying the knowledge needed for making informed decisions, policy makers should also identify what people already know, compare lay decision models with expert models, and test the effectiveness of their communication content. Recipients of health information communications need to identify the potential threat, assess their own likelihood of contracting a specific disease, and identify means by which to protect themselves. The assessment of risk often includes judgments of severity (e.g., how deadly a certain virus is) as well as judgments of the probability of this outcome (Slovic et al., 2004). Both types of judgment are often driven by affective interpretations (i.e., risks are deemed higher if the consequences are severe; Dickert et al., 2015; Keller et al., 2006; Slovic, 2010).

Prior research has proposed risk perceptions as mediators to the knowledge-behavior gap within health-related contexts (Klerck and Sweeney 2007; Bolton et al. 2008) but largely ignored the distinction between objective and subjective knowledge and their effects on the disease prevention behavioral responses examined in the current study. . More specifically, while extensive research has been conducted on the cognitive and affective underpinnings of risk assessments (e.g., Siegrist et al., 2005; Slovic 1999; Slovic et al., 2007), the role of objective and subjective knowledge in driving risk perceptions is not entirely clear. It is possible that objective knowledge is linked to more cognitive processes of risks while subjective knowledge is related to affective processes underlying risk perceptions. This could be the case because objective knowledge of health risks is often communicated by abstract numerical facts (e.g., the risk of becoming infected with HIV while using condoms is less than 0.05%), whereas subjective interpretations of these facts carry more affective meaning and evoke stronger mental imagery, both of which are linked to stronger emotional reactions (Slovic et al., 2004). Research on decision making and risk perception suggests that abstract numerical facts (such as percentages) can be difficult to mentally represent and are thus less likely to motivate action (Slovic et al., 2007). Conversely, using more concrete representations of risks (e.g., using frequency formats) can increase risk perceptions, particularly for people with low numerical skills (Keller and Siegrist, 2009; Peters, Hart and Fraenkl 2011; Peters et al., 2006).

Thus, we argue that greater knowledge can affect the perceived risk (in both directions, such that knowledge about the negative consequences of infection increases perceived risk and knowledge about the actually low probability of contracting the disease can decrease perceived risk), and higher perceived risk should increase preventive behaviors and further information search. Therefore, we propose that:

***H2**: Perceptions of risk mediate the effects of health knowledge (objective and subjective knowledge) on behavioral responses.*

As per previous health information acquisition models, such as PRISM, we suggest that the motivation to search for more information can be interpreted as a motivation to find ways of protecting oneself. Therefore, we assume that search intentions are a precursor to general prevention as well as specific vaccination intentions.

***H3**: Health information seeking intentions are positively related to general prevention behavior change intentions, and vaccination intentions.*

Finally, general intentions to protect against infection should predict specific intentions to get vaccinated, as that is one of the more prominent ways of avoiding infection (Manika et al., 2017). In this paper we distinguish vaccination intentions from general prevention measures due to the fact that vaccinations sometimes meet staunch opposition on specific websites on the Internet (Betsch et al., 2010) whereas general prevention behavior seems to be regarded favorably for the most part. This also allows us to re-examine the relationship between specific and general prevention behaviors in relation to types of information source and objective vs. subjective knowledge.

***H4**: General prevention behavior change intentions are positively related to vaccination intentions.*

3. Methods

3.1. Research context, design and sampling frame

Human papillomavirus (HPV) is one of the most common sexually transmitted diseases in the United States, estimated to cause 30,700 cancers in men and women every year (CDC, 2018). The HPV vaccine is the first cancer-related prevention vaccine available since 2006 (Fayed, 2008). Google Trends show that HPV has been a popular search term online since 2004 in the U.S., with spikes in popularity in 2007 when the HPV vaccine started to gain significant attention due to its aggressive promotion to the public through direct-to-consumer (DTC) advertising, and more recently in 2016 because of the increasing number of debates regarding HPV-related legislation in some U.S. states (Google Trends, 2018; NCSL, 2017). The frequent news coverage, and aggressive promotion through DTC pharmaceutical advertisements in the USA, both through the Internet and health professionals, make HPV an appropriate and topical health issue for our study.

For the data collection, a self-administered online Internet survey was created, pretested and administered using e-mail addresses rented from a U.S. online Internet consumer panel (Qualtrics), to men and women aged 18–26 years old; who have never been diagnosed with or vaccinated against HPV. The sampling frame was selected on the basis that young adults aged 18–26 years have the highest rates of HPV infection (Bosch and De Sanjose 2007) and therefore represent a specific target group for public health management. Participants who were exposed to both health information from a health professional's office visit and the Internet were excluded from our sampling frame – even though that can happen in reality – as the aim was to compare the two sources and their effects on objective and subjective knowledge. Data was collected before the Covid-19 pandemic. Our sample was representative of the target group and geographically dispersed.

3.2. Sample characteristics and survey measures

To investigate whether objective and subjective health knowledge differs based on the source of information exposure, we assessed the self-reported[1] source of past health information exposure to categorize participants into one of the three groups i.e., those who had only been exposed to HPV information from the Internet (which could include for example websites, social media, newspapers read online, etc.), those who had only been exposed to HPV information from a health professional's office visit (health professionals could include printed materials in a clinic, aside from personalized health advice from an expert), and those who had not been exposed to any HPV information.

Out of the 261 participants (m_{age} = 22; 64% female), 38.7% participants had been exposed to HPV information from a health professional's office visit, 23.4% had been exposed to HPV information from the Internet, and 37.9% of them had not been exposed to HPV information. Almost half of the sample (41.4%) attended "some college but had no degree". The largest group of the sample classified themselves as "Anglo American" (36.4%), had an average income of $25,000 to $34,999 (18.8%), and self-described their health status as "good" 37.9%) or "very good" (35.6%).

After assessing past exposure to HPV information, the survey measured participants' objective HPV knowledge based on the HPV objective knowledge scale by Manika et al., (2017), which included 15 multiple-choice questions about HPV. The sum of correct answers formed the composite test score of participants' objective HPV knowledge (M = 8.41, SD = 3.92, Range = 0–15). Subjective HPV knowledge, risk perceptions, information seeking intentions, general prevention behavior change intentions and vaccination intentions were also based on existing 7-point rating scales. Table 1 provides details on the multi-item measures for subjective knowledge (M = 4.12, SD = 1.79) adapted from Burton et al., (1999); perceived risk (M = 2.55, SD = 1.42) based on Rosenstock, (1974); and information-seeking intentions (M = 3.88, SD = 1.63) adapted from Kahlor, (2010) and Manika and Golden,

[1] (binary: yes or no; respondents who were not sure were allowed to select "not sure" and were subsequently removed from the final sample)

Table 1
Multi-item Scales.

Constructs	Loadings	
Subjective knowledge		
In general, how much do you think you know about HPV?[a]	.86**	C.R. = 0.90
In general, how much do you think you know about how to protect yourself from HPV?[a]	.91**	AVE = 0.70
In general, how much do you think you know about the potential health consequences of having HPV?[a]	.89**	
Perceived risk		
To what extent do you personally feel you are at risk of being infected with HPV?[b]	.77**	C.R. = 0.85
Do you actively engage in any behaviors that might put you at risk of getting HPV?[c]	.77**	AVE = 0.66
I believe I am personally at risk for getting infected with HPV[d]	.89**	
Information-seeking intentions		
I intend to seek HPV-related information[e]	.86**	C.R. = 0.89
I intend to actively search for information about HPV[e]	.87**	
I intend to actively seek information on how to prevent myself from getting infected with HPV[e]	.84**	AVE = 0.73

**p<.01; AVE = Average Variance Extracted; C.R. = Construct Reliability
[a]7-point bipolar adjective scale (1 = Nothing, – 7 = *A* Lot)
[b]7-point bipolar adjective scale (1 = At no risk – 7 = At great risk).
[c]7-point bipolar adjective scale (1 = Not at all severe – 7 = Very severe).
[d]7-point bipolar adjective scale (1 = At no risk – 7 = At great risk).
[e]7-point bipolar adjective scale (1 = Strongly Disagree – 7 = Strongly Agree).
**p = .00.

(2011). Most scales were adapted from health-related studies to ensure context relevance.

The two behavioral intentions measures employed (i.e., general prevention behavior change intentions and specific vaccination intentions) were measured via single-item measures ranging from 1 = Strongly Disagree to 7 = Strongly Agree: "I will change my behavior to try to avoid getting infected with HPV" (M = 4.60, SD=1.90) and "I intend to get vaccinated against HPV in the next 6 months" (M = 3.54, SD = 2.11), respectively. We chose single items to measure general and specific prevention behaviors because these measures benefit from simplicity, cost, ease of interpretation, ease of collection (DeSalvo et al., 2005), and are commonly used in health research (Bowling, 2005; DeSalvo et al., 2005). In fact, Fuchs and Diamantopoulos, (2009) note that single-item measures are increasingly accepted in the academic literature and are appropriate under certain conditions such as in the measurement of behavioral outcomes.

3.3. Confirmatory factor analysis and common method bias

A confirmatory factor analysis was conducted using Mplus to test the reliability and validity of the hypothesized model constructs. All multi-item scales had significant factor loadings above 0.77 and were highly reliable and valid, with construct reliabilities above or equal to 0.85 and average variance extracted (AVE) scores above or equal to 0.66 (Fornell and Larcker, 1981). The measurement model demonstrated a theoretically and statistically good overall fit [$\chi^2_{(24)}$ = 40.01, p = .02; Comparative Fit Index (CFI) = 0.99; Tucker Lewis Index (TLI) = 0.98; Standardized Root Mean Square Residual (SRMR) = 0.03]. Table 2 shows the inter-item correlations, with none exceeding 0.59, thus indicating discriminant validity. The Fornell and Larcker criterion [AVEv>(r)^2] indicated that the AVEs for each construct were greater than the square of the correlation estimates. The authors also confirmed that the data were normally distributed by calculating z-scores for skewness and kurtosis for each variable with SPSS. All were between -3 and +3, which are considered acceptable (Field, 2005). There were also no signs of extreme multicollinearity as indicated by the Variance Inflation Factor (VIF) (VIF < 1.97) and tolerance (tolerance > 0.50) levels for each construct (Hair et al., 1998).

To minimize potential common method bias (CMB), all scales were randomized and participants were reminded frequently of the anonymity and confidentiality of their responses (Podsakoff et al., 2003). Results of a Harman single factor test, assessed through a principal component analysis with no rotation, showed that one factor explains 32.4% of the variance in the sample. This compares to two factors explaining 60.98% of the variance. This analysis suggests that CMB is not a threat in the interpretation of the results.

4. Results

4.1. Structural equation model results

We used orthogonal contrasts to create two dummy variables (Dummy 1: No exposure versus Exposure, and Dummy 2: Internet vs. health professional's office visit), which were subsequently used in the structural equation modeling analysis.

The structural equation model was tested with Mplus and had statistically acceptable model fit [$\chi^2_{(63)}$ = 176.95, p < .01; CFI = 0.94; TLI = 0.91; SRMR = 0.07], accounting for 42% of the variance in vaccination intentions, 34.8% in general prevention intentions, and 22.2% in information-seeking intentions. Table 3 shows the SEM results for the hypothesized relationships and Fig. 2 depicts the significant relationships only.

Whether individuals have been exposed to information or not (i.e., Dummy 1) and whether individuals have been exposed to information from the Internet versus a health professional's office visit (i.e., Dummy 2) has implications for health knowledge. Results show that exposure to information leads to higher objective and subjective knowledge compared to no exposure at all. Moreover, information exposure from a health professional's office visit (versus the Internet) leads to higher objective knowledge, but not higher subjective knowledge. In turn, these health knowledge types are related to risk perceptions and information seeking intentions. However, objective health knowledge has a negative relationship and subjective health knowledge a positive relationship with risk perceptions and information seeking intentions. Neither knowledge nor risk perceptions directly influence general prevention behavior change intentions or vaccination intentions. Only information seeking intentions influence these latter behavioral response variables positively (supporting H3). Lastly, general prevention behavior change intentions positively relate to vaccination intentions (supporting H4).

Thus, the SEM results support both H3 and H4. Even though the SEM

Table 2
Correlations.

Constructs	Correlations & square root of average variance extracted							
Dummy 1 information exposure (No exposure versus exposure)	**1**							
Dummy 2 information exposure (internet vs. health professional's office visit)	n/a	**1**						
Objective knowledge	.47**	.37**	**1**					
Subjective knowledge	.41**	-0.01	.59**	**.84**				
Perceived risk	.01	-0.18*	-0.05	.13*	**.81**			
Information-seeking intentions	.01	-0.09	-0.10	.14**	.30**	**.85**		
General prevention intentions	.08	-0.04	.01	.17**	.13*	.53**	**1**	
Vaccination intentions	-0.02	-0.12	-0.06	.15*	.23**	.55**	.49**	**1**

N = 261; * p ≤ .05; ** p≤ .01; Bold diagonal illustrate the square root of average variance extracted.

Table 3
Structural equation model results.

Relationship	Estimate	S. E.
Dummy 1 Information exposure (no exposure vs. exposure) → objective knowledge	.43**	.05
Dummy 1 information exposure (no exposure vs. exposure) → subjective knowledge	.43**	.05
Dummy 2 information exposure (internet vs. health professional's office visit) → objective knowledge	.23**	.05
Dummy 2 information exposure (internet vs. health professional's office visit) → subjective knowledge	−0.01	.06
Objective knowledge → perceived risk	-0.18*	.08
Objective knowledge → information seeking intentions	-0.21**	.07
Objective knowledge → general prevention behavior change intentions	.01	.07
Objective knowledge → vaccination intentions	-0.06	.06
Subjective knowledge → perceived risk	.21*	.01
Subjective knowledge → information seeking intentions	.26**	.07
Subjective knowledge → general prevention behavior change intentions	.09	.07
Subjective knowledge → vaccination intentions	.08	.06
Perceived risk → information seeking intentions	.29**	.06
Perceived risk → general prevention behavior change intentions	-0.08	.06
Perceived risk → vaccination intentions	.05	.05
Information seeking intentions → general prevention behavior change intentions	.59**	.05
Information seeking intentions → vaccination intentions	.42**	.07
General prevention behavior change intentions → vaccination intentions	.23**	.06

**$p \leq .01$, *$p \leq .05$; Coding Dummy 1: No exposure = -2 versus Exposure (whether from the Internet or from a health professional's office visit) = 1; Coding Dummy 2: Internet = -1 versus Health professional's office visit = 1).

results also provide initial partial support for both H1 and H2, to examine these hypotheses in more detail we conduct *t*-tests using the orthogonal contrasts and the use of the PROCESS macro by Hayes, (2013) to perform a mediation analysis.

4.2. Differences based on information exposure

Objective and subjective HPV knowledge significantly differed for participants who were exposed to information compared to those who were not ($t_{(259)} = -8.64$, $p < .01$ and $t_{(257)} = -7.15$, $p < .01$ for objective and subjective knowledge, respectively). Participants exposed to information had higher objective ($M = 9.85$, SD = 3.11) and subjective ($M =$ 4.69, SD = 1.51) knowledge than those who were not exposed to information at all (Objective knowledge: $M = 6.04$, SD = 3.97 and Subjective knowledge: $M = 3.18$, SD = 1.83). When comparing individuals who had been exposed to information from the Internet versus a health professional's office visit, only objective knowledge differences were found ($t_{(160)} = -5.04$, $p < .05$), with participants who had been exposed to information from health professionals having greater objective knowledge ($M = 10.75$, SD = 2.68) than those exposed to online information ($M = 8.37$, SD = 3.24). No differences were found for subjective knowledge. These results confirm the aforementioned SEM results and partially support H1.

Even though no differences were found in risk perceptions and behavioral outcomes based on comparing those who had and had not been exposed to information (i.e., Dummy 1), results indicated that risk perceptions did differ between those who had been exposed to information from the Internet versus a health professional's office visit (Dummy 2: $t_{(157)} = 2.32$, $p < .05$). Specifically, participants who had been exposed to online information had higher risk perceptions ($M =$ 2.90, SD = 1.42) than those who were exposed to information from a health professional's office visit ($M = 2.36$, SD = 1.41).

4.3. Mediation results

To probe the mediations postulated by the model in regards to H2, an OLS regression approach to path analysis was adopted (Hayes 2013) to estimate the indirect effects for all dependent variables. Table 4 presents the results of indirect effects estimated using PROCESS and the calculation of 95% confidence intervals with bias-corrected and accelerated bootstraping with 10,000 resamples (Hayes 2013). The mean average of the scales is used for the analysis. All direct relationships were mostly consistent with those found in the SEM model (slight differences were observed because average scores are used in the mediation analysis,

Table 4
Mediation results testing H2.

Mediation	Result
Objective knowledge → risk perception → information seeking intentions	b = -0.01, 95% C.I. [-0.02 to 0.01]
Subjective knowledge → risk perception → information seeking intentions	b = 0.03, 95% C.I. [.01 to 0.08]
Objective knowledge → risk perception → general prevention behavior change intentions	b = -0.01, 95% C.I. [-0.01 to 0.01]
Subjective knowledge → risk perception → general prevention behavior change intentions	b = 0.01, 95% C.I. [-0.00 to 0.04]
Objective knowledge → risk perception → vaccination intentions	b = -0.01, 95% C.I. [-0.02 to 0.01]
Subjective knowledge → risk perception → vaccination intentions	b = 0.03, 95% C.I. [.01 to 0.08]

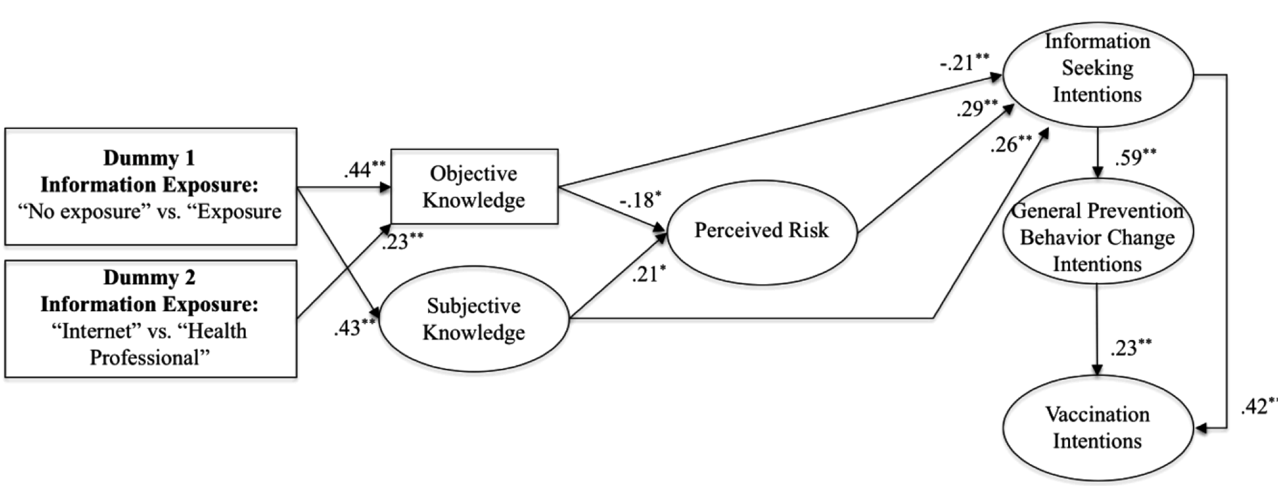

Fig. 2. SEM results. **$p \leq .01$, * $p \leq .05$; Coding Dummy 1: No exposure = -2 versus Exposure (whether from the Internet or from a health professional's office visit) = 1; Coding Dummy 2: Internet = -1 versus Health professional's office visit = 1).

while in the SEM the variables may be also affected by the additional variables simultaneously included in the model).

Based on the mediation results, risk perceptions mediated the relationship between subjective knowledge and information seeking intentions, and between subjective knowledge and vaccination intentions. More specifically, as subjective knowledge increased, so did risk perceptions, which in turn led to higher information seeking intentions and vaccination intentions. However, risk perceptions did not mediate the subjective knowledge and general prevention behavior change intention relationship. Additionally, risk perceptions did not mediate any relationship between objective knowledge and behavioral responses. Thus, H2 is supported for subjective knowledge only.

5. Discussion

Turning knowledge into behavior has been a challenge for health information campaigns for decades (Atkin and Rice, 2013). The health-related knowledge-behavior gap has been examined within both online (Faith et al., 2016; Myrick, 2017; Taiminen, 2016; Lowe et al., 2015; Manika et al., 2018; Woolley and Peterson, 2012) and offline contexts (Berger and Rand, 2008; Bolton et al., 2007; Bolton, Bhattacharjee and Reed, 2015; Gomez et al., 2017; Guthrie et al., 2015; Hansen and Thomsen, 2013; Rogers and Gould, 2015; Spiteri Cornish and Moraes, 2015). Past studies also suggest that the distinction between objective and subjective health knowledge is important for health behaviors (Brucks, 1985; Gomez et al., 2017; Manika and Golden, 2011; Moorman et al., 2004), while perceived risks have been found to mediate the knowledge-behavior gap (Klerck and Sweeney, 2007; Bolton et al. 2008). However, to date Health Information Acquisition models often ignore the distinction between objective and subjective health knowledge. The current study was designed to address this research gap and further our understanding on how health information from the Internet versus a health professional's office visit can help people's information acquisition processes and influence prevention choices.

5.1. Theoretical contributions

Our results support a conceptual model in which exposure to sources of health information affects people's objective and subjective knowledge differently. It further provides supporting evidence for risk perception as a mediator of the knowledge-behavior gap (Klerck and Sweeney, 2007; Bolton et al., 2008).

However, our findings add two additional layers in understanding this mediating relationship. First, we found that objective and subjective health knowledge have different effects on risk perceptions and, second, these risk perceptions, in turn, are associated with higher intentions to seek further health information but not other behavioral responses (general prevention behavior change intentions and vaccination intentions).

While subjective knowledge is related to increased risk perceptions, objective knowledge is related to lower risk perceptions. In other words, this suggests that the more someone thinks he/she knows the more likely he/she is to perceive a health issue as risky. Additionally, we found that risk perception only mediated the effects of subjective knowledge, but not of objective knowledge. We interpret these findings to be in line with affective accounts of risk (e.g. Loewenstein et al., 2001, Slovic et al., 2004), which highlight the importance of subjective risk perception (Slovic, 1999). Underlying this perspective is the observation that people generally find risks meaningful if they "feel" them. Although in our model we do not equate subjective knowledge to subjective risk perception, we do note that they share a common underpinning: both are subjective perceptions of reality and likely linked to affective reactions to the information exposed to.

However, the opposite seems to be the case for high objective knowledge. The more factually correct information an individual has about a health issue, the less likely he/she will perceive a high risk. This contradicts popular health theories postulating that knowledge positively impacts risk perceptions (Glanz et al., 2008). However, past research has mostly ignored the difference between an individual's accuracy of knowledge and an individual's perceptions of his/her knowledge for risk perceptions. Individuals with higher objective knowledge scores may well know how to protect themselves from a disease and hence may perceive a lower personal risk than those with lower objective knowledge scores. Conversely, those who report higher subjective knowledge may perceive a greater risk because of an increased exposure to disease-related information. In turn, we found that greater perceived risk is related to greater likelihood to seek further health information, in part supporting prior literature (e.g. Kahlor, 2007; Glanz et al., 2008). It should be noted, though, that in our study objective and subjective knowledge correlated positively, such that participants who possess factually correct knowledge also generally perceive themselves to be more knowledgeable. Still, these two types of knowledge are related to risk perceptions differently.

Finally, although our study was on protective health behavior, some of our findings can be extrapolated to other models of risk perception. For example, research on climate change suggests that people's attitudes are influenced by psychological and experiential factors, including affect, imagery, and values (Leiserowitz, 2006). All of these can be related to subjective knowledge of the causes for climate change, which might influence environmental protective behavior by increasing risk perception. Similarly, research also has shown that people do not have accurate objective knowledge about how long air pollutants (e.g., carbon dioxide) stay in the atmosphere and that this (inaccurate) knowledge was not related to support taking action to counter climate change (Dryden et al., 2018). Thus, it is possible that subjective knowledge is a better predictor for environmental protective behavior as well.

5.2. Implications for practice and public policy

Our results showed that individuals exposed to health information had both higher objective and subjective knowledge than those not exposed to information at all. This is good news for health communication strategists, as exposure indeed influences both factual as well as perceived knowledge in the population at risk. However, individuals exposed to information at a health professional's office had more factually correct information than those exposed to information online, while the information source did not matter for how much someone thinks he/she knows. These results indicate that the choice between health information sources has implications for the accuracy of individuals' knowledge (i.e., objective knowledge), but not for perceptions of knowledge (i.e., subjective knowledge).

In combination, these findings indicate that health information campaigns should not only be concerned about message content and differences between lay and expert mental models, but also about the source type. Even though past research and public policy recommendations note the importance of objective health knowledge in encouraging health behavior, our results suggest that this advice needs a more nuanced elaboration. Individuals may become less receptive to new information as a result of higher factually correct knowledge, as they may already have the necessary expertise and accurate knowledge on how to protect themselves from a disease. In contrast, individuals who think they know a lot may be more likely to seek additional information. Hence, health campaigns aiming to motivate the public to seek more information should try to increase subjective rather than objective health knowledge.

Lastly, even though neither knowledge nor risk perceptions directly impacted general prevention behaviors and vaccination intentions, higher intentions to seek further health information was found to be positively related to both general as well as specific prevention intentions. This finding illustrates that the likelihood of engaging in one health behavior increases the probability of engaging in another. Thus, health campaigns should focus at least on one specific health behavior, as then individuals are more likely to engage in more behaviors to prevent a disease. Motivating information seeking intentions may be the way forward through exposure to information, which aims to increase individuals' subjective knowledge.

The relationship between health knowledge and health behavior is a cornerstone of behavior change and health communications, however our results indicate not only that objective and subjective health knowledge have different effects on information seeking intentions, but also that neither directly impacts general prevention behavior change and vaccination intentions. Our results further indicate that even though one behavior can lead to another, not all behavioral responses should be treated the same in communication campaigns. It is important to understand the effect of information exposure on knowledge and behavior, in order to devise effective health information campaigns. Effective health campaigns need to strike a balance between increasing objective knowledge about a disease and motivating people to acquire further information. One way to do this seems to be to increase people's subjective knowledge.

5.3. Limitations, further research and conclusion

In this study we sought to address an important research gap and provide novel findings in regards to the knowledge-behavior relationship and the impact of sources of information exposure to advance information acquisition literature and contribute to ongoing public-policy debates on the usefulness of Internet-based health information. In evaluating the data and overall results, however, several limitations should be considered.

First, we used a correlational / quasi-experimental design, based on field data, which does not allow drawing definite causal conclusions. This also relates to the fact that individuals may be exposed to health information via a combination of sources. Future research should address this with either a true experimental design, which considers the multitude sources and combinations of health information exposure. A combination of exposure types would probably further increase objective and subjective knowledge, although it is not clear how risk perceptions and behavioral responses would be influenced. In our study, using field data increased external validity, but it did not permit controlling for the similarity of the information content across sources of health information exposure nor could we control for the self-selection of participants' exposure type (e.g., people with higher risk perceptions may have preferred online information because of accessibility).

Furthermore, HPV is often sexually transmitted and potentially a private matter for the target group. This could have influenced their choice of information sources. Additionally, with advances in technology it is possible to have one-on-one virtual consultations online via the internet or other telecommunications. Similarly, health information exposure from a health professional's office visit does not necessitate speaking to a nurse or doctor and can include printed material. We note, however, that the prevalence of face-to-face interactions is higher in the health professional context and interpret our results such that a major difference between information acquired via this source versus health information from the Internet is the interpersonal interaction with a person versus the anonymity (and potentially less reliable information) online.

Our study did not measure source credibility and hence future research should take into account source credibility as a moderator for the knowledge-risk-behavior relationships posed in this research. The current study also did not measure real behavior and focuses instead on behavioral intentions. Although intentions are often a good predictor for actual behavior, future research could address these limitations by using a true experimental design while keeping constant the information provided and using actual behavioral responses.

Furthermore, this study also looked at perceived risks without distinguishing between performance, psychological and physical risks (Klerck and Sweeney, 2007). Exploring how each of these risk types may be impacted by objective and subjective knowledge may lead to additional insights. Various mediators aside from risk perceptions have also been proposed as explanations for the knowledge-behavior gap, such as self-efficacy (Bolton et al., 2007), unhealthy-equals-tasty intuition (Mai and Hoffmann, 2015), motivation and ability (Bolton, Bhattacharjee and Reed, 2015), including skepticism (based on persuasion knowledge; Manika et al., 2018) and digital health technologies readiness and willingness to pay to adopt medical advice (Lowe et al., 2015), among others. Future research on the knowledge-behavior gap could explore how these mediators may be impacted by the distinction between knowledge types and behavioral responses.

Lastly, data was collected before the Covid-19 pandemic and was based on a consumer panel. Hence, more research is required on the current health information environment – during and after Covid-19, with a representative sample of the entire population and taking into account whether or not the participants have medical insurance; as in the US the HPV vaccine would not be covered by any medical insurance. Relevant to the data collection also, we did not include a marker variable for checking CMV although does note its consideration in future data collections.

In conclusion, our findings present a conundrum to public policy, as policy makers want to correctly inform people of objective risks, and thereby increase protective behavior. However, in our study objective knowledge was not positively related to any of the behavioral protective measures we examined. Subjective knowledge seems to be a better motivator for people to seek more information on health issues, and subsequently form behavioral intentions to protect themselves. Moreover, using the Internet as a communication channel of health information may present a cost-efficient way of information dissemination, yet it is possible that this does not increase objective knowledge. It does, however, help increase subjective knowledge and, via increased risk perception, contribute to health protection behavior indirectly.

CRediT authorship contribution statement

Danae Manika: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Funding acquisition. **Stephan Dickert:** Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Linda L. Golden:** Conceptualization, Investigation, Funding acquisition.

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