



Article The Effects of Knowledge Types on Consumer Decision Making for Non-Toxic Housing Materials and Products

Hyun Joo Kwon ^{1,*}, Mira Ahn ² and Jiyun Kang ³

- ¹ Department of Interior & Environmental Design, Pusan National University, Busan 46241, Korea
- ² School of Family and Consumer Sciences, Texas State University, San Marcos, TX 78666, USA; ma32@txstate.edu
- ³ Division of Consumer Science, School of Hospitality and Tourism Management, Purdue University, West Lafayette, IN 47907, USA; jiyunkang@purdue.edu
- Correspondence: hyunjookwon@pusan.ac.kr

Abstract: This study explored how different types of consumer knowledge (exposure, subjective knowledge, and objective knowledge) predict perceptions (benefits, severity, and barriers) and behavioral intention to choose non-toxic housing materials and products based on the extended health belief model (HBM). The target population was people 18 years or older living in the U.S. A total of 1050 valid responses were collected through an online survey. Structural equation modeling was used to test the model via AMOS version 24. Results show that the prediction of exposure, subjective knowledge, and objective knowledge for behavioral intention is mediated by health belief perceptions in different ways. Exposure had a significant impact on perceived benefits and perceived severity but not on perceived barriers. Subjective knowledge on the HBM elements were significant. Significant indirect effects of exposure and subjective knowledge on behavioral intention were found; the indirect effects of objective knowledge on behavioral intention were insignificant. By adopting the extended HBM, this study contributes to a better understanding of the link among knowledge types and perceptions of non-toxic housing materials and products, and behavioral intention to choose them.

Keywords: exposure; subjective knowledge; objective knowledge; non-toxic housing materials and products; behavioral intention; health belief model

1. Introduction

Most people spend about 90% of their time indoors and approximately 70% of that time at home [1]. Key determinants of indoor environmental quality in a residential environment are housing materials and products [2]. The use of non-toxic housing materials and products reduces the amount of indoor air contaminants and improves the quality of indoor air, both of which improve residents' health and quality of life [3]. According to the U.S. Environmental Protection Agency, building products containing toxic contaminants, such as volatile organic compounds (VOCs) and formaldehyde, can cause irritation, respiratory disease, or nasal cancer [4–6]. A review of 50 research articles from 1985 to 2015 revealed that exposure to VOCs is a biomarker of lung cancer [7]. As these negative health consequences have been confirmed through reliable empirical studies, consumers' interest in a healthy home environment is growing, along with concern about the use of harmful materials [8,9].

Consumers' intentions to use health-related products and services can be motivated and influenced by health concerns [10], perceptions [11], or consumer knowledge [10,12]. Consumer knowledge is a significant predictor of the consumption of health-related products and services, in addition to environmentally conscious behavior [13–15]. The



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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). amount [16,17] and type of knowledge [18,19], affect consumers' perceptions and decisions. However, there is limited research on how different types of knowledge influence consumers' perceptions and decisions about health-related products. This study began with a question developed based on a recent study [10], which indicated knowledge, along with health concerns, affected the consumption of healthy housing materials: What type of consumer knowledge most influences consumers' perceptions and purchase decisions regarding non-toxic housing materials? To deepen the understanding of consumer knowledge and its role in predicting consumer decision making for more sustainable options, this current study highlights the three types of consumer knowledge, that is, consumers' exposure to information, subjective knowledge, and objective knowledge of non-toxic housing materials and products.

In addition to consumer knowledge, perceived benefits, severity, and barriers have been revealed as preconditions for behavioral change—e.g., [20–23]. To incorporate these components into our proposed research model, the health belief model (HBM) [24] was adopted as a theoretical framework for this study. The model explains the health-related decision-making process based on one's perception of health-related behavior.

The purpose of this study was to explore how different types of consumer knowledge constructs affect perceptions of and behavioral intention to use non-toxic housing materials and products based on the theoretical framework of an extended HBM [24]. Three dimensions of consumer knowledge were considered from existing studies [17–19,25]: exposure, subjective knowledge, and objective knowledge. Based on the HBM, the research team identified three perceived components of non-toxic housing materials and products: perceived benefits, perceived severity, and perceived barriers. Those components were examined as mediators between dimensions of consumer knowledge and the intention to choose non-toxic housing materials and products.

2. Literature Review

2.1. Consumer Knowledge

Consumer knowledge is important to theoretical models of consumer behavior and marketing practices. It has been researched in terms of product-related experience, subjective and objective knowledge, familiarity, and expertise. Brucks [25] described three categories of consumer knowledge: product-related experience, subjective knowledge, and objective knowledge. This framework has been used and adapted by many scholars [19]. According to Flynn and Goldsmith [19], product-related experiences include various types of exposure to products and are considered as the most comprehensive level. They include exposure to advertising, information searches, communication with salespeople, experiences with decision making, and product use.

There is a conceptual distinction between subjective and objective knowledge. Subjective knowledge is "what we think we know"; objective knowledge is "what we actually know" [19] (p. 57). Even though both are shaped by consumers' experiences, each has a different effect on behavior [25]. Subjective knowledge differs from objective knowledge under a condition where individuals are over- or under-confident in their actual (objective) knowledge [17]. It is suggested that subjective knowledge is a stronger motivation than objective knowledge, especially with product purchases, supporting the notion that each domain of consumer knowledge has a unique role in consumer behavior [19].

Similarly, Alba and Hutchinson [18] proposed familiarity and expertise to explain consumer knowledge. Product familiarity is generally associated with consumer expertise. Familiarity is the amount of product-related experiences a consumer has accumulated. The operationalization of product familiarity has embraced both subjective and objective knowledge [16]. In the meantime, expertise is a consumer's ability to successfully perform product-related tasks [18]. There are two ways to operationalize and measure product "familiarity": the extent to which a consumer actually knows about the product and the extent to which a consumer thinks they know about it [18]. Product familiarity can be considered the knowledge structure of the consumer's long-term memory. It can be

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measured with the consumer's self-reported belief on how much he or she knows about the product [26]. Based on the previous consumer knowledge literature, the research team adopted three categories of knowledge constructs for the current study: exposure to information as a prior experience, subjective knowledge, and objective knowledge. This study included an exposure construct in our research model as a separate knowledge component since the research team expects this inclusive type of knowledge type to have a unique role in health-related products and services. The hypotheses regarding this relationship are presented in the methods part.

2.2. Health Belief Model

According to the health belief model, if a health-related behavior is perceived to have a significantly positive or negative effect on a person's health, he or she will intend to do the behavior [24]. Since the HBM was introduced in the 1950s by researchers in the U.S. General Health Service [27], it has been used to understand prevention of severe diseases, such as cancer or infectious diseases—e.g., [28–30]. As people become more interested in health and quality of life in daily living and surrounding environments, the HBM has been applied to areas such as nutrition—e.g., [31], tourism— e.g., [32], environmental science—e.g., [33], and interior design—e.g., [10]. Even though the HBM is useful to predict health-related behaviors and explain the process of interventions changing behaviors, few studies have examined moderator or mediator effects of the HBM elements [27].

The model includes four perceptions, cues to action and self-efficacy [27], which are perceived benefits; severity; barriers; and susceptibility. According to the model, if people believe that a particular health-related behavior has strong benefits for their health, they are more inclined to engage in that behavior. For example, college students who believe that eating vitamin supplements and having breakfast will improve their health will do so [34]. The model also posits that people will try to adopt healthy behavior if they perceive severe health outcomes if they do not. One study about breast self-examinations of university female students for breast cancer prevention revealed that those students who perceived breast cancer as a serious illness were more likely to do regular self-examinations than students who did not [35]. People are unlikely to adopt a health-related behavior when they perceive strong barriers, such as costs, time, and effort. A study of the self-care behavior of people with diabetes found that people who did not see barriers to self-care were more inclined to practice it [36]. Lastly, if people believe they are susceptible to certain fatal health outcome, they will be more likely to do their best to avoid it [37]. Sim et al. [38] found that people are more likely to use facemasks when they feel vulnerable to contracting respiratory diseases.

This study included three HBM perceptions—perceived benefits, severity, and barriers—to our proposed research model. The research team excluded perceived susceptibility based on previous research that reported no relationship between perceived susceptibility and behavioral intention [39].

2.3. Interior Materials and Health

It is evident that interior materials impact the health of residents [40]. Consumers are more interested than ever in a healthy home environment [8,9]. A study about young adults' perception of interior materials that contribute their health and well-being found that young consumers believe wooden materials have positive health impacts [41]. In addition, for better indoor air quality, people avoid harmful products and materials or choose natural or organic ones [3]. If consumers suspect these materials and products are dangerous, or if they perceive poor indoor air quality as a possible cause of health problems, they would choose non-toxic housing materials and products that do not include certain toxic chemicals or that have earned environmental performance certifications. These include low VOC paints, non-toxic adhesives, and formaldehyde-free plywood [2,6].

The use of non-toxic housing materials and products can reduce air contaminants and enhance indoor air quality, eventually improving residents' health [3]. Most internationally

built environment rating systems that focus on energy saving and residents' health include non-toxic interior materials and products. Leadership in Energy and Environmental Design (LEED) includes a materials and resources category. The Well Building Standard and Building Research Establishment Environmental Assessment Method (BREAM) contains a materials category. In rating systems, materials and products, such as Greenguard and Green Seal, meet a standard of minimum toxicity level and earn a better level of building certification.

2.4. Hypotheses

To test the proposed research model, hypotheses were developed and are presented in Figure 1.



Figure 1. Conceptual model for intention to choose non-toxic housing materials and products.

Hypothesis 1 (H1). Three types of knowledge significantly predict HBM elements.
Hypothesis 1-1a (H1-1a). Exposure to information significantly predicts perceived benefits.
Hypothesis 1-1b (H1-1b). Exposure to information significantly predicts perceived threats.
Hypothesis 1-1c (H1-1c). Exposure to information significantly predicts perceived barriers.
Hypothesis 1-2a (H1-2a). Subjective knowledge significantly predicts perceived benefits.
Hypothesis 1-2b (H1-2b). Subjective knowledge significantly predicts perceived threats.
Hypothesis 1-2c (H1-2c). Subjective knowledge significantly predicts perceived barriers.
Hypothesis 1-3a (H1-3a). Objective knowledge significantly predicts perceived benefits.
Hypothesis 1-3b (H1-3b). Objective knowledge significantly predicts perceived benefits.
Hypothesis 1-3c (H1-3c). Objective knowledge significantly predicts perceived benefits.
Hypothesis 1-3a (H1-3a). Objective knowledge significantly predicts perceived benefits.
Hypothesis 1-3c (H1-3c). Objective knowledge significantly predicts perceived benefits.
Hypothesis 2 (H2). Three types of knowledge significantly predicts perceived barriers.
Hypothesis 2 (H2a). Exposure to information significantly predicts behavioral intention.
Hypothesis 2 (H2b). Subjective knowledge significantly predicts behavioral intention.
Hypothesis 2 (H2c). Objective knowledge significantly predicts behavioral intention.

Hypothesis 3 (H3). *Three types of knowledge indirectly predict behavioral intention, mediated by HBM elements.*

Hypothesis 3a (H3a). *Exposure to information indirectly predicts behavioral intention, mediated by HBM elements.*

Hypothesis 3b (H3b). *Subjective knowledge indirectly predicts behavioral intention, mediated by HBM elements.*

Hypothesis 3c (H3c). *Objective knowledge indirectly predicts behavioral intention, mediated by HBM elements.*

3. Method

3.1. Data Collection and Sample

The research team administered an online survey to collect data for our study. To enhance the generalizability of our model testing results, this study used a random sample of U.S. residents who were adults (18 years or older), who the research team recruited from Qualtrics. The research team increased the representativeness of our sample by ensuring that distributions across age, gender, and ethnicity were as close as possible to the proportions of the U.S. national population. The research team also ensured the quality of responses, by screening out invalid responses using an attention filter and a speed checker. Only high-quality data were retained for analyses. There were 1050 final valid responses. Table 1 details those respondents' demographics and residential specifications.

Table 1. Demographics and housing specifications of final valid respondents.

Demographics and Housing Specifications	n	%
Gender		
Male	501	47.7
Female	534	50.9
Race		
White	468	44.6
Hispanic	176	16.8
Other	94	9.0
Marital Status		
Married	490	46.7
Other ^a	560	53.3
Work Status		
Full time ^b	392	37.3
Part time ^c	133	12.7
Not working ^d	525	50.0
Education		
High school or lower	333	31.7
College or higher	717	68.3
Annual Household Income		
Less than \$25,000	252	24.0
\$25,000-\$49,999	309	29.5
\$50,000-\$99,999	322	30.6
\$100,00-\$149,000	110	10.5
\$150,000 or more	57	5.4
House Type		
Single family home	698	66.5
Other ^e	352	33.5
Location		
Rural areas	244	23.2
City suburb	500	47.6

Demographics and Housing Specifications	n	%
Urban areas	206	20.1
Tenant Type	300	29.1
Own	646	61.5
Rent	404	38.5
Length of Residency		
Less than 10 years	562	53.5
11–20 years	248	23.6
21–30 years	142	13.5
More than 30 years	98	9.3
Total Valid Responses	1050 ^f	100.0

Table 1. Cont.

^a Separated/Divorced/Widowed/Never married/Living together, but not married. ^b Employed or self-employed full time. ^c Retired and employed (or self-employed) part-time/Employed or self-employed part time. ^d Retired and not working/Unemployed. ^e Single family townhouse or duplex/Multi-family building (low-rise or high-rise apartment/condominium)/Mobile home. ^f Median age = 50 (18 to 88 years old).

3.2. Instruments

As Table 2 shows, the instrument contained knowledge types (exposure, subjective knowledge, and objective knowledge), HBM elements (perceived benefits, severity, and barriers), and behavioral intention. Each construct was measured based on the established scale of previous studies. Before starting the survey, respondents were given descriptions of non-toxic housing materials and products.

For knowledge types, exposure was measured with two items modified from Vaske et al.'s [42] study. The first item consisted of seven types of information channels with information about non-toxic housing materials and products. They were measured by either yes (1 point) or no (zero points). Sum of the total score (between 0 and 7) was used for further analysis. The second item asked, "How often did you see or hear about non-toxic housing materials and products within the last year?" It was measured along a five-point Likert scale. Subjective knowledge was measured with five items modified from the literature [19,43]. Lastly, objective knowledge was measured with seven items drawn from the three studies [19,43,44]. The seven items were selected and modified from a green building qualification exam book [45]. The research team assumed that these seven items should be known to the public through marketing or advertising. It should be noted that objective knowledge was measured by seven statements with yes or no answers. For example, one of the statements was "chemical cleaning products may affect indoor air quality and health." The correct answer earned 1 point and an incorrect answer received none. The total number of correct responses, ranging from 0 to 7, were summed and treated as the measure for final objective knowledge. In terms of the HBM elements, perceived benefits are the presumably positive aspects of choosing non-toxic housing materials and products. It was measured with three items modified from Lindsay and Starthman [46]. Perceived severity is the perception of negative results related to residents' health when one does not choose non-toxic housing materials and products. It was measured with five items modified from two studies [46,47]. Perceived barriers, the perception of obstacles, such as costs, product options, and design quality when choosing non-toxic housing materials and products, was measured with 10 items adapted from three studies [47–49]. Behavioral intention was measured with four items modified from three studies [50–52]. All HBM items were measured using a five-point Likert scale.

Table 2. Instruments.

Construct (Scale)
Fynosure
EXPOSITE EI1 Lhave heard and/or read about non-toxic housing materials and products from (you can choose more than one answer)
Print news articles or magazines
TV
Radio
Internet
Friends and family
Organizations
Sales person
EI2. How often did you see or hear about non-toxic housing materials and products within the last year? $(1 = never: 5 = very often)$
Subjective Knowledge (1 = strongly disagree; 5 = strongly agree)
SN1. I feel comfortable purchasing non-toxic housing materials and products due to my prior knowledge. *
SN2. Compared to others, I think I know less about non-toxic housing materials and products. (R) **
SN3. When it comes to non-toxic housing materials and products, I don't know a lot. (R) *
SN4. I am knowledgeable about how to evaluate the quality of non-toxic housing materials and products.
SN5. People who know me consider me as an expert in non-toxic housing materials and products.
Objective Knowledge (0 = All incorrect; 7 = All correct)
ON1. I have heard about Sick Building Syndrome. (1 = Yes; 0 = No)
ON2. Carpet adhesives may contain toxic chemicals. $(1 = \text{Yes}; 0 = \text{No})$
ON3. Chemical cleaning products may affect indoor air quality and health. $(1 = \text{Yes}; 0 = \text{No})$
ON4. Low-emitting housing materials should be used rather than conventional products because of their reduced off-gassing with
narmful contaminants. $(1 = 165; 0 = N0)$
ON6. A charter is a root building material related to health $(1 - No; 0 - Vec)$
ON7 VOCs (Volatile organic compounds) are toxic building materials (1 – Yes: 0 – No)
Perceived Renefits
PBN1. To what extend to do you think using non-toxic housing materials and products is good for your health? (1 = not at all good:
5 = extremely good
PBN2. To what extend to do you think using non-toxic housing materials and products is good for your quality of life? (1 = not at
all good; 5 = extremely good)
PBN3. I think I could save on medical expenses if I choose non-toxic housing materials and products. (1 = strongly disagree;
5 = strongly agree) *
Perceived Severity (1 = strongly disagree; 5 = strongly agree)
PS1. How severe would it be to your health if you do not use non-toxic housing materials and products in your house? (1 = not at
all severe; 5 = extremely severe)
PS2. I will have long-lasting effects.
PS3. I will be bed-ridden for a long time. *
PS4. I will have high medical expenses.
PS5. It will be narmful for my family life.
PBR1 Lthink there are enough options of non-toxic housing materials and products for my house. (P) **
PBR2 I think most non-toxic housing materials and products look good (R)*
PBR3 I think non-toxic housing materials and products have poor brand images
PBR4. I think it would take too much time choosing non-toxic housing materials and products. *
PBR5. I think it would take too much effort to choose non-toxic housing materials and products.
PBR6. I think choosing non-toxic housing materials and products would be too expensive.
PBR7. I don't expect non-toxic housing materials and products to be cost-effective.
PBR8. Due to lack of information, it is hard to choose non-toxic housing materials and products. *
PBR9. Even though there are non-toxic housing materials and products information, it is hard to believe the
labeling/measurement standard. *
PBR10. It is hard to believe the performance of the non-toxic housing materials and products.
Behavioral Intention
INIT. I intend to choose non-toxic housing materials and products in the future. $(1 = \text{definitely do not}; 5 = \text{definitely do})$
IN12. I want to choose non-toxic housing materials and products in the future. (1 = strongly disagree; 5 = strongly agree) *
IN 15. 1 am determined to choose non-toxic nousing materials and products in the future. $(1 = \text{very unlikely}; 5 = \text{very likely})$
1×1^{-1} . How likely is it that you will choose non-toxic nousing materials and products in the future? (1 = very unlikely; 5 - very likely)
Note. (R) Reverse coded. * Removed due to high MI and low representativeness. ** Removed due to low confirmatory factor loadings.

3.3. Data Analysis

Structural equation modeling (SEM) via AMOS version 24 was used to test the model. SEM was selected as the main analysis method in this study since SEM enables a simultaneous test of our conceptual model that has multiple mediators denoting complex relationships among constructs, allowing measurement errors while inferring casual effects of variables. The recommended two-step procedure for SEM was followed: measurement model testing and then structural model testing [53]. The procedure is detailed in the Results section.

4. Results

4.1. Measurement Model Testing

The research team began by estimating a measurement model and testing it with confirmatory factor analyses (CFAs) to ensure the reliability and validity of the measures. Through a series of CFAs, several items were removed to improve model fit. Before any deletion, the research team carefully considered if items that showed low confirmatory factor loading (<0.50) multiple high modification index (MI) scores, very low representativeness for its corresponding domain, or overly high similarity to other items in the same latent variable, following the recommended guideline [54]. Table 2 notes the items that have been removed along with the reasons. The final measurement model offered a good fit to the data: χ^2 (df = 188) = 513.55, CFI = 0.96; NFI = 0.94; TLI = 0.95; RMR = 0.04; RMSEA = 0.04. Table 3 includes the specific estimates from the final measurement model. Results of descriptive statistics of constructs in the final measurement model are as follows. Mean value of the first exposure item E11 was 1.80 (SD = 1.16) out of seven and the second item E12 was 2.34 (SD = 1.00) out of five, both of which were fairly low. Two items were included for subjective knowledge and mean value was 2.97 (SD = 1.19) out of five. Mean value of objective knowledge was 5.19 (SD = 1.26) out of seven. Mean value of perceived benefits was 3.92 (SD = 0.97), perceived severity was 3.30 (SD = 1.12), and perceived barriers value was 2.99 (SD = 1.03) out of five. Mean value of behavioral intention was 3.87(SD = 0.97) out of five.

Table 3. The final measurement model properties.

Construct/Items	М	SD	CFA Loading	α	Composite Reliability	AVE
Exposure				0.63	0.66	0.50
EI1	1.80	1.16	0.56			
EI2	2.34	1.00	0.83			
Subjective Knowledge	2.97	1.19		0.79	0.79	0.65
SN4	3.08	1.14	0.79			
SN5	2.37	1.25	0.82			
Objective Knowledge					N/A	N/A
ON	5.19	1.27	N/A	N/A		
Perceived Benefits	3.92	0.97		0.89	0.89	0.80
PBN1	3.93	0.98	0.89			
PBN2	3.92	0.96	0.90			
Perceived Severity	3.30	1.12		0.79	0.80	0.51
PS1	3.20	1.12	0.54			
PS2	3.50	1.00	0.67			
PS4	3.07	1.14	0.79			
PS5	3.44	1.12	0.82			

Construct/Items	Μ	SD	CFA Loading	α	Composite Reliability	AVE
Perceived Barriers	2.99	1.03		0.78	0.79	0.43
PBR3	2.85	0.96	0.52			
PBR5	2.67	1.10	0.77			
PBR6	3.28	1.06	0.69			
PBR7	3.09	1.04	0.59			
PBR10	3.09	0.99	0.66			
Behavioral Intention	3.94	0.97		0.92	0.92	0.80
INT1	3.94	0.94	0.83			
INT3	3.80	1.00	0.93			
INT4	3.88	0.98	0.92			

Table 3. Cont.

The research team then examined the reliability and validity of the measurements cf. [55]. Each of the multi-item measures showed adequate reliability based on Cronbach's alpha (α), which ranged from 0.63 to 0.92, and composite reliability ranged from 0.66 to 0.92. The convergent validity the multi-item measures were established based on item confirmatory factor loadings, which ranged from 0.52 to 0.93, with t-values all significant at p = 0.01 level, and the average variance-extracted estimates (AVEs), of which, all except one exceeded the recommended 0.50 thresholds. One construct, perceived barriers, showed an AVE that was slightly low (0.43), however, it was considered still valid since all of its items' t-values were significant, and their factor loadings were high enough. Lastly, the research team ensured discriminant validity based on the matrix of the AVEs and squared correlations—none of the AVEs were smaller than any of squared correlations between paired constructs (see Table 4).

Table 4.	Discri	ninant	validity	testing	matrix.
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Construct	1	2	3	4	5	6	7
1 = Exposure	0.50						
2 = Subjective Knowledge	0.15	0.65					
3 = Objective Knowledge	0.01	0.00	N/A				
4 = Perceived Benefits	0.04	0.00	0.05	0.80			
5 = Perceived Severity	0.04	0.03	0.01	0.10	0.51		
6 = Perceived Barriers	0.00	0.00	0.01	0.01	0.00	0.43	
7 = Behavioral Intention	0.10	0.10	0.02	0.12	0.18	0.05	0.80

Note. Italicized numbers in the diagonal line are the average variance-extracted estimates. Others represent squared correlations between latent variables.

4.2. Structural Model Testing

Given that this study ensured reliability and validity of all measurements, the research team ran a structural modeling test. Following the conceptual modeling, along with our hypotheses, the research team specified exposure, subjective knowledge, and objective knowledge as exogenous variables, while treating perceived benefit, perceived severity, and perceived barriers as mediators, and behavioral intention as the ultimate endogenous variable. The structural model demonstrated a good fit to the data: GFI = 0.95; AGFI = 0.92; CFI = 0.95; RMR = 0.07; RMSEA = 0.06.

4.2.1. Direct Effects

The research team examined the direct effects of knowledge types on the HMB elements (H1) and behavioral intention (H2). The significance of the effects was tested at a *p*-value of 0.01, and specific estimates are presented in Figure 2. The effects of exposure were significant on perceived benefits and perceived severity but not perceived barriers, by which H1-1a and H1-1b were accepted and H1-1c was rejected. None of the effects of subjective knowledge on HBM elements were significant, rejecting H1-2. At the same time, all of the effects of objective knowledge on the HBM elements were significant, which caused H1-3 to be accepted. The effects of exposure and subjective knowledge on behavioral intention were both significant. However, the effects of objective knowledge on behavioral intention were found to be insignificant. Therefore, H2a and H2b were accepted but H2c was rejected.



Figure 2. Structural equation modeling results.

4.2.2. Indirect Effects

To examine the indirect effects of knowledge types on behavioral intention (H3), the research team used a decomposition test via a bootstrapping method (Hays, 2009). The results showed the significant indirect effects of exposure ($\beta = 0.12$, p < 0.05) and objective knowledge ($\beta = 0.10$, p < 0.01) on behavioral intention, while the indirect effects of subjective knowledge on behavioral intention were insignificant ($\beta = -0.02$, p = 0.68). Therefore, H3a and H3c were accepted and H3b was rejected. These results provide evidence that exposure and objective knowledge indirectly affect behavioral intention, mediated by HBM elements.

5. Discussion

Our results indicate that the proposed model can predict the behavioral intention to purchase non-toxic housing materials and products. Knowledge constructs affected behavioral intention mediated by the HBM elements, while demonstrating different impacts based on knowledge type. This model indicated that exposure had a direct positive association with the behavioral intention. Although mean value of exposure was quite low according to our results, exposure showed the strongest association with the behavioral intention among the three knowledge types. This result is supported by previous studies that found that an increase in exposure to a product is related to purchases of that product [56,57]. Meanwhile, exposure affected the perceived benefits and perceived severity but not perceived barriers. This missing association could be the content of advertising which usually emphasizes product benefits for consumption more than other kinds of related information.

One interesting result pertains to subjective knowledge. This knowledge type was revealed to have a direct positive association with behavioral intention, whereas it did not affect any of the three HBM components. Subjective knowledge is based on self-judgment and can be more relevant to consumers' decision-making strategies [16]. However, this study indicated that this knowledge does not need to be associated with the product's benefits, barriers, or severity. Considering that consumers who are confident with their subjective knowledge about a new product are less likely to search for external information about the product [17,25,58], this relationship is fairly well explained. On one hand, consumers who think they know about the product would not need to conduct additional research about the product; rather they are more likely to use stereotypical information based on their knowledge. On the other hand, this result could be a consequence of the product category, as non-toxic housing materials and products are fairly new. Results showed that mean value of subjective knowledge was slightly lower than median value. Consumers could be either under- or over-confident about what they think they know, so their subjective knowledge of the three HBM components might not be meaningfully translated.

In terms of objective knowledge, our study showed that this knowledge construct did not affect behavioral intention, but it did have a significant influence on all three elements of HBM. Insignificant direct impact of the objective knowledge to the behavioral intention is supported by previous research, which reported objective knowledge was a weaker motivation than subjective knowledge [17,43]. The significant association between objective knowledge about non-toxic housing materials and products and all three HBM elements revealed that consumers are sufficiently aware of the benefits, severity, and barriers of the product beyond simple product-related experience [59].

Perceived benefits, perceived severity, and perceived barriers all mediated behavioral intention. This indicates that HBM elements can predict an inclusive range of health-related behaviors. Consumers who perceived greater benefits and severity and fewer barriers were more likely to intend to adopt non-toxic materials and products. Although mean value of perceived benefits was higher than their perceived severity, perceived severity was revealed to be a stronger indicator of behavioral intention than perceived benefits. According to Carpenter's [39] meta-analysis, perceived barriers was a stronger predictor of behavioral intention when the consumption was for the purpose of prevention rather than treatment. Based on this meta-analysis, we might be able to categorize the purpose of non-toxic materials and products consumption for something other than prevention. However, we believe that it would be too early to know the purpose of non-toxic housing materials and products and suggest testing more similar materials and products for future studies.

6. Implications and Limitations

This study confirmed that exposure, subjective knowledge, and objective knowledge play different roles mediated by the HBM elements in making decisions about non-toxic housing materials and products. Understanding the intricate relationships between knowledge constructs and perceptions on the non-toxic housing materials and products will better prepare professionals in terms of marketing and communication strategies. This study recommends putting more effort into increasing consumers' subjective knowledge through effective exposure channels. According to the literature reviewed earlier, subjective knowledge is primarily shaped by consumers' prior experience with the product [59]. Creating more opportunities for either actual or virtual experience with non-toxic products would, therefore, be helpful. As all three HBM elements are associated with the intention to purchase, the provision of sufficient, relevant information regarding benefits, severity, and barriers during the initial and repeated experiences for consumers would be desirable.

This study confirmed the efficacy of the HBM applications to consumer behavior fields. Also, this study contributes to advancing the more effective use of the model by identifying the mediator effects of the three HBM elements [27]. However, several limitations related to the modeling need to be addressed. Firstly, the association of personal and housing variables with the intention to purchase non-toxic housing materials and products should be investigated. As people are spending more time at home, especially because of the COVID-19 pandemic [60], they are expected to be more mindful of the quality of their

indoor environment. In future studies, additional physical housing attributes, such as house size, location, or type, should be incorporated into the model to see its significance. Inclusion of demographic variables, such as gender or age, is also recommended.

Future studies should consider using refined measures for the information search and other product-related experiences. This study was limited to types of exposure. However, some exposures to media would be more closely related to information searches. For example, once we search for a product online, we continue to see information not only for that product but also for similar products. Although investigating these algorithms for social media is outside the scope of our research, this topic has meaningful implications for both consumers and marketers.

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References

- Klepeis, N.E.; Nelson, W.C.; Ott, W.R.; Robinson, J.P.; Tsang, A.M.; Switzer, P.; Engelmann, W.H. The National Human Activity Pattern Survey (NHAPS): A resource for assessing exposure to environmental pollutants. *J. Expo. Sci. Environ. Epidemiol.* 2001, 11, 231–252. [CrossRef] [PubMed]
- 2. U.S. Green Building Council. *Green Building 101: What Is Indoor Environmental Quality?* Available online: https://www.usgbc. org/articles/green-building-101-what-indoor-environmental-quality (accessed on 25 August 2021).
- 3. Spiegel, R.; Meadows, D. Green Building Materials: A Guide to Product Selection and Specification; John Wiley & Sons: New York, NY, USA, 2010.
- 4. American Lung Association. Where VOCs Come from. Clean Air. Available online: https://www.lung.org/clean-air/at-home/ indoor-air-pollutants/volatile-organic-compounds (accessed on 25 July 2020).
- 5. Manuel, J. A healthy home environment? Environ. Health Perspect. 1999, 107, A352–A357. [CrossRef]
- 6. United States Environmental Protection Agency. *Technical Overview of Volatile Organic Compounds. Indoor Air Quality.* Available online: https://www.epa.gov/indoor-air-quality-iaq/technical-overview-volatile-organic-compounds (accessed on 25 July 2021).
- 7. Saalberg, Y.; Wolff, M. VOC breath biomarkers in lung cancer. Clin. Chim. Acta 2016, 459, 5–9. [CrossRef]
- 8. Ade, R.; Rehm, M. Home is where the health is: What indoor environment quality delivers a "healthy" home? *Pac. Rim. Prop. Res. J.* **2020**, *26*, 1–17. [CrossRef]
- 9. Sundell, J. On the history of indoor air quality and health. Indoor Air 2004, 14, 51–58. [CrossRef] [PubMed]
- 10. Kwon, H.J.; Ahn, M. Boomers' Intention to Choose Healthy Housing Materials: An Application of the Health Belief Model. *Sustainability* 2019, 11, 4869. [CrossRef]
- 11. Suki, N.M. Green products purchases: Structural relationships of consumers' perception of eco-label, eco-brand and environmental advertisement. *J. Sustain. Sci. Manag.* **2013**, *8*, 1–10.
- 12. Wunderlich, S.; Gatto, K.; Smoller, M. Consumer knowledge about food production systems and their purchasing behavior. *Environ. Dev. Sustain.* **2018**, *20*, 2871–2881. [CrossRef]
- 13. Cook, L.A. Health Belief Model and healthy consumption: Toward an integrated model. *J. Food Prod. Mark.* **2018**, *24*, 22–38. [CrossRef]
- 14. Hornik, J.; Cherian, J.; Madansky, M.; Narayana, C. Determinants of recycling behavior: A synthesis of research results. *J. Socio-Econ.* **1995**, *24*, 105–127. [CrossRef]
- 15. Yoon, H.J.; Kim, Y.J. Understanding green advertising attitude and behavioral intention: An application of the health belief model. *J. Promot. Manag.* **2016**, *22*, 49–70. [CrossRef]
- 16. Lee, J.K.; Lee, W.-N. Country-of-origin effects on consumer product evaluation and purchase intention: The role of objective versus subjective knowledge. *J. Int. Consum. Mark.* **2009**, *21*, 137–151. [CrossRef]

- Park, C.W.; Lessig, V.P. Familiarity and its impact on consumer decision biases and heuristics. J. Consum. Res. 1981, 8, 223–230.
 [CrossRef]
- 18. Alba, J.W.; Hutchinson, J.W. Dimensions of consumer expertise. J. Consum. Res. 1987, 13, 411–454. [CrossRef]
- 19. Flynn, L.R.; Goldsmith, R.E. A short, reliable measure of subjective knowledge. J. Bus. Res. 1999, 46, 57–66. [CrossRef]
- 20. Bandura, A. Health promotion by social cognitive means. *Health Educ. Behav.* 2004, 31, 143–164. [CrossRef] [PubMed]
- Hazavehei, S.; Sharifirad, G.; Mohabi, S. The effect of educational program based on health belief model on diabetic foot care. *Int. J. Diabetes Dev. Ctries.* 2007, 27, 18–23. [CrossRef]
- 22. Sharifirad, G.; Entezari, M.H.; Kamran, A.; Azadbakht, L. The effectiveness of nutritional education on the knowledge of diabetic patients using the health belief model. *J. Res. Med. Sci. Off. J. Isfahan Univ. Med. Sci.* 2009, 14, 1–6.
- 23. Shojaeizadeh, D.; Hashemi, S.Z.; Moeini, B.; Poorolajal, J. The effect of educational program on increasing cervical cancer screening behavior among women in Hamadan, Iran: Applying health belief model. *J. Res. Health Sci.* **2011**, *1*, 20–25.
- 24. Janz, N.K.; Becker, M.H. The health belief model: A decade later. Health Educ. Q. 1984, 11, 1–47. [CrossRef]
- 25. Brucks, M. The effects of product class knowledge on information search behavior. J. Consum. Res. 1985, 12, 1–16. [CrossRef]
- Lichtenstein, S.; Fischhoff, B. Do those who know more also know more about how much they know? *Organ. Behav. Hum. Perform.* 1977, 20, 159–183. [CrossRef]
- Skinner, C.S.; Tiro, J.; Champion, V.L. The Health Belief Model. In *Health Behavior and Health Education: Theory, Research, and Practice*; Glanz, K., Rimer, B.K., Viswanath, K., Eds.; John Wiley & Sons: New York, NY, USA, 2008; pp. 75–94.
- Chen, M.-F.; Wang, R.-H.; Schneider, J.K.; Tsai, C.-T.; Jiang, D.D.-S.; Hung, M.-N.; Lin, L.-J. Using the health belief model to understand caregiver factors influencing childhood influenza vaccinations. J. Community Health Nurs. 2011, 28, 29–40. [CrossRef]
- 29. Wong, L.P.; Alias, H.; Wong, P.-F.; Lee, H.Y.; AbuBakar, S. The use of the health belief model to assess predictors of intent to receive the COVID-19 vaccine and willingness to pay. *Hum. Vaccines Immunother.* **2020**, *16*, 2204–2214. [CrossRef]
- 30. Yarbrough, S.S.; Braden, C.J. Utility of health belief model as a guide for explaining or predicting breast cancer screening behaviours. *J. Adv. Nurs.* 2001, 33, 677–688. [CrossRef] [PubMed]
- Abood, D.A.; Black, D.R.; Feral, D. Nutrition education worksite intervention for university staff: Application of the health belief model. J. Nutr. Educ. Behav. 2003, 35, 260–267. [CrossRef]
- 32. Huang, X.; Dai, S.; Xu, H. Predicting tourists' health risk preventative behaviour and travelling satisfaction in Tibet: Combining the theory of planned behaviour and health belief model. *Tour. Manag. Perspect.* **2020**, *33*, 100589. [CrossRef]
- 33. Msengi, I.G. Development and evaluation of innovative recycling intervention program using the health belief model (HBM). *Open J. Prev. Med.* **2019**, *9*, 29–41. [CrossRef]
- 34. Kim, H.-S.; Ahn, J.; No, J.-K. Applying the Health Belief Model to college students' health behavior. *Nutr. Res. Pract.* 2012, *6*, 551–558. [CrossRef] [PubMed]
- 35. Didarloo, A.; Nabilou, B.; Khalkhali, H.R. Psychosocial predictors of breast self-examination behavior among female students: An application of the health belief model using logistic regression. *BMC Public Health* **2017**, *17*, 861. [CrossRef] [PubMed]
- 36. Ayele, K.; Tesfa, B.; Abebe, L.; Tilahun, T.; Girma, E. Self care behavior among patients with diabetes in Harari, Eastern Ethiopia: The health belief model perspective. *PLoS ONE* **2012**, *7*, e35515. [CrossRef]
- 37. Rosenstock, I.M. Why people use health services. *Milbank Q.* 2005, 83, 94–124. [CrossRef]
- 38. Sim, S.W.; Moey, K.S.P.; Tan, N.C. The use of facemasks to prevent respiratory infection: A literature review in the context of the Health Belief Model. *Singap. Med. J.* 2014, *55*, 160–167. [CrossRef] [PubMed]
- 39. Carpenter, C.J. A meta-analysis of the effectiveness of health belief model variables in predicting behavior. *Health Commun.* **2010**, 25, 661–669. [CrossRef]
- Loftness, V.; Hakkinen, B.; Adan, O.; Nevalainen, A. Elements that contribute to healthy building design. *Env. Health Perspect.* 2007, 115, 965–970. [CrossRef] [PubMed]
- 41. Häyrinen, L.; Toppinen, A.; Toivonen, R. Finnish young adults' perceptions of the health, well-being and sustainability of wooden interior materials. *Scand. J. Res.* 2020, *35*, 394–402. [CrossRef]
- 42. Vaske, J.J.; Needham, M.D.; Stafford, N.T.; Green, K.; Petchenik, J. Information sources and knowledge about chronic wasting disease in Colorado and Wisconsin. *Hum. Dimens. Wildl.* **2006**, *11*, 191–202. [CrossRef]
- 43. Pieniak, Z.; Aertsens, J.; Verbeke, W. Subjective and objective knowledge as determinants of organic vegetables consumption. *Food Qual. Prefer.* **2010**, *21*, 581–588. [CrossRef]
- 44. House, L.O.; Lusk, J.; Jaeger, S.R.; Traill, B.; Moore, M.; Valli, C.; Yee, W. Objective and subjective knowledge: Impacts on consumer demand for genetically modified foods in the United States and the European Union. *AgBioForum* **2004**, *7*, 113–123.
- 45. Cottrell, M. Guide to the LEED Green Associate Exam; John Wiley & Sons: New York, NY, USA, 2010; Volume 17.
- 46. Lindsay, J.J.; Strathman, A. Predictors of recycling behavior: An application of a modified health belief model 1. *J. Appl. Soc. Psychol.* **1997**, *27*, 1799–1823. [CrossRef]
- 47. Deshpande, S.; Basil, M.D.; Basil, D.Z. Factors influencing healthy eating habits among college students: An application of the health belief model. *Health Mark. Q.* 2009, *26*, 145–164. [CrossRef] [PubMed]
- 48. Gadenne, D.; Sharma, B.; Kerr, D.; Smith, T. The influence of consumers' environmental beliefs and attitudes on energy saving behaviours. *Energy Policy* **2011**, *39*, 7684–7694. [CrossRef]
- 49. Häkkinen, T.; Belloni, K. Barriers and drivers for sustainable building. Build. Res. Inf. 2011, 39, 239–255. [CrossRef]
- 50. Ajzen, I. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 1991, 50, 179-211. [CrossRef]

- 51. Conner, M.; Norman, P.; Bell, R. The theory of planned behavior and healthy eating. Health Psychol. 2002, 21, 194–201. [CrossRef]
- 52. Wiles, J.L.; Leibing, A.; Guberman, N.; Reeve, J.; Allen, R.E. The meaning of "aging in place" to older people. *Gerontologist* **2012**, 52, 357–366. [CrossRef]
- 53. Kline, R.B. Principles and Practice of Structural Equation Modeling; Guilford Publications: New York, NY, USA, 2015.
- 54. Nunnally, J.C. Psychometric Theory, 3rd ed.; Tata McGraw-Hill Education: New York, NY, USA, 1994.
- 55. Fornell, C.; Larcker, D.F. Evaluating structural equation models with unobservablevariables and measurement error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
- 56. Anwar, K.; Climis, R. Analyzing the relationship between types of advertisement and customer choice: A study of retailer stores in erbil. *Int. J. Acc. Bus. Soc.* 2017, 25, 43–52. [CrossRef]
- 57. Kim, Y.J.; Yoon, H.J. Predicting green advertising attitude and behavioral intention in South Korea. *Soc. Behav. Personal. Int. J.* **2017**, *45*, 1345–1364. [CrossRef]
- 58. Fredrica, R. Consumer Food Selection and Nutrition Information; Praeger: New York, NY, USA, 1979.
- 59. Park, C.W.; Mothersbaugh, D.L.; Feick, L. Consumer knowledge assessment. J. Consum. Res. 1994, 21, 71–82. [CrossRef]
- 60. Lee, M.; Zhao, J.; Sun, Q.; Pan, Y.; Zhou, W.; Xiong, C.; Zhang, L. Human mobility trends during the early stage of the COVID-19 pandemic in the United States. *PLoS ONE* **2020**, *15*, e0241468. [CrossRef] [PubMed]