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A qualitative comparison study of information search behavior in online distribution

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Abstract

Purpose: This study offers suggestions to e-commerce companies for increasing shoppers' repurchase intention by considering the effect of distribution information in online shopping. It applies complexity theory to incorporate habitual information search behavior and shopper characteristics into the Stimulus-Organism-Response model and indicates how these complex factors work together in online shopping. **Research design, data, and methodology:** This study used an interview survey of 158 Vietnamese consumers with an experience of online shopping. A fuzzy-set Qualitative Comparative Analysis (fsQCA) was used to examine the relationship between antecedents and outcomes depending on complex conditions in the given contexts. **Results:** The results (1) indicate the importance of observing information search patterns and investigating their influence on online distribution, and (2) clarify what kind of configurations, under what conditions, predict a high or low outcome; this provides evidence and hints for the development of frameworks for future studies. **Conclusions:** The findings suggest that shoppers' unconscious, habitual behavior can work with conscious attitude factors, such as satisfaction, to increase their repurchase intention. Hence, e-commerce companies should consider how to present useful distribution information and create functions that allow shoppers to engage with a variety of information while increasing their repurchase intention on the site.

Keywords: online shopping, repurchase intention, habitual information search behavior, complexity theory, distribution science

JEL Classification Code: M31, M15, L86

1. Introduction

Although electronic commerce (e-commerce), a crucial distribution channel, has created numerous benefits for companies and consumers, it still faces some obstacles. For example, successfully offering a well-designed shopping site that meets consumers' needs and gains their trust and loyalty relates to a company's ability to deal with cultural differences (Fleenor & Raven, 2011) as well as to demographic and psychological factors (Carpenter & Baliya, 2010). Additionally, online shoppers cannot touch or feel products directly, as they would in physical stores; therefore, companies must offer all the information required to make a purchase, especially for markets with less experience in online shopping (Ashraf, Thongpapanl, & Auh, 2014). Moreover, online shoppers prefer accessing different shopping sites to compare products or prices before purchasing from the website that best meets their requirements, instead of shopping at one site only (Ansari, Mela, & Neslin, 2008). Ease of access and low switching costs contribute to low customer loyalty in e-commerce, thereby calling into question the association between online store characteristics and satisfaction and loyalty in online shopping.

Marketing research has investigated this issue from various aspects, for example, how distribution information should be effectively presented on websites to enhance customer conscious attitudes using the Stimulus-Organism-Response (SOR) model, the Technology Acceptance

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Model, and the Information Systems (IS) continuance theory. These models have established a foundation to understand online distribution science—specifically, what factors influence shoppers' repurchase intention (RI)—and examined the significance of the correlation between attitudes and behaviors in online shopping (e.g., Groß, 2015; Hubert, Blut, Brock, Backhaus, & Eberhardt, 2017). This study combines the SOR model with complexity theory to develop an understanding of how conscious and unconscious factors work together under certain circumstances, focusing on explaining the complex relationships that exist among variables not necessarily related to behavior or attitudes.

Complexity theory is used to predict complex relationships and situations that result in a specific outcome (Woodside, 2014; Woodside, Nagy, & Megehee, 2018). This study aims to examine the relationship between online store design, satisfaction, and RI by applying complexity theory, as such a relationship could be triggered by complex circumstances and moderators in e-commerce context. One of these moderators is habit. Habit is an unconscious response stimulated by an environmental cause, or a conscious mental process formed by the learned association between satisfaction and behavior (Chiu, Hsu, Lai, & Chang, 2012; Hsu et al., 2015), and can influence decision-making (Wood, Quinn, & Kashy, 2002). Some shopping-related habitual activities could eventually influence shopping decisions (e.g., a habit of searching for product information in certain ways). This study chooses to investigate four types of habitual information search behaviors and their possible effects: (1) browsing for information on websites; (2) looking up information via social media; (3) contacting friends for advice; and (4) visiting offline stores.

This study intends to answer two online shopping -related issues: (1) Do online shoppers make all their decisions based on conscious attitudes (i.e., satisfaction) that have been presented in the relevant literature? Despite e-commerce companies' attempts to offer a lower price and greater variety of merchandise to increase customers' RIs, we are skeptical about how shoppers actually react to these store characteristics; and (2) do unconscious behaviors influence shoppers' satisfaction and RIs? We believe that testing these habitual behaviors can not only develop the understanding of designing distribution information in online shopping, but also explain how conscious and unconscious factors jointly influence online shopping.

Considering that habit could be formulated differently depending on the development of e-commerce in a market (Ashraf, Thongpapanl, Menguc, & Northey, 2017), this study chooses to survey a developing e-commerce market, Vietnam. According to the Statista Research Department, the Vietnamese e-commerce market, given its rapid development, was ranked fourth in Asia for online shopping, recording 11.8 billion US dollars in sales in 2020. Even though Vietnamese consumers have gradually accepted online shopping, e-commerce has not yet widely penetrated the national market (Ho & Chen, 2014). This could be due to two reasons. First is the importance of personal relationships in Vietnam (VECITA, 2019), where people prefer face-to-face communication and shopping over online contact (Kshetri, 2007). Second is finding the best price, which is one of the biggest goals of online shopping for Vietnamese consumers (Ho & Chen, 2014). Although offering lower prices can always attract more customers, this study points to the significant potential for e-commerce companies to engage shoppers in areas other than price, such as offering shopping-related information based on shoppers' characteristics.

The results gained by applying complexity theory via fuzzy-set Qualitative Comparative Analysis (fsQCA) offer different configurational models of factors and conditions, which not only indicate interactions between online shopping and information search but also provide specific strategic implications for e-retailers to target different shoppers based on their information engagement.

2. Literature Review

This study applies complexity theory because unique tenets cannot be gained by applying a single theory via null hypothesis significance testing (NHST) (i.e., correlation, regression) (Trafimow, Hyman, Kostyk, Wang, & Wang, 2021). The limitation of the NHST is that it overlooks or over rejects results and makes studies barely identify and explain complex relationships existing among variables that are not necessarily related to outcomes (Woodside, 2019). The advantage of applying complexity theory is that we can gain multiple solutions (configurations) for predicting the same outcome equally and effectively, depending on the effects of variables, complex conditions, and context settings (Pappas & Woodside, 2021).

As one tenet of complexity theory described by Woodside (2014, 2019), the same antecedent (satisfaction, in our case) can significantly and insignificantly affect outcomes because the relationship between the antecedent and outcome depends on complex conditions and the given contexts (i.e., consumer demographics and shopping conditions). Unlike applying a single theory (i.e., the SOR model) via NHST that only reports significant directional relationships in designed models, complexity theory provides causal mechanisms by identifying combinations of multiple antecedents that lead to specific outcomes (Brenes, Ciravegna, & Woodside, 2017; Trafimow et al., 2021; Woodside, 2019; Woodside et al., 2018).

In online distribution science, the SOR model has been considered as the appropriate framework to study repurchase behavior (Brunner-Sperdin, Scholl-Grissemann, & Stokburger-Sauer, 2014; Pereira, Salgueiro, & Rita, 2016; Liu, Chu, Huang, & Chen, 2016). However, there are still concerns regarding developing an understanding of online purchase intentions based on complex contexts such as shoppers' ages and online shopping experiences. Notably, all these factors appear as visible information on a shopping site; however, purchase decisions are based on not only the information shown on the shopping sites but also on the information with which shoppers personally engage. Thus, this study focuses on the configurations among all the factors that could directly or indirectly and positively or negatively influence RI, applying complexity theory via asymmetric testing via fsQCA.

3. Conceptual Framework and Research

The conceptual model based on SOR model shown in Figure 1 includes four parts that indicate potential causal configurations (solutions) predicting a high score for the outcome—RI. Along with online store characteristics and shoppers' satisfaction, four types of habitual information search patterns and shoppers' characteristics are added to the causal patterns of factors predicting RI.

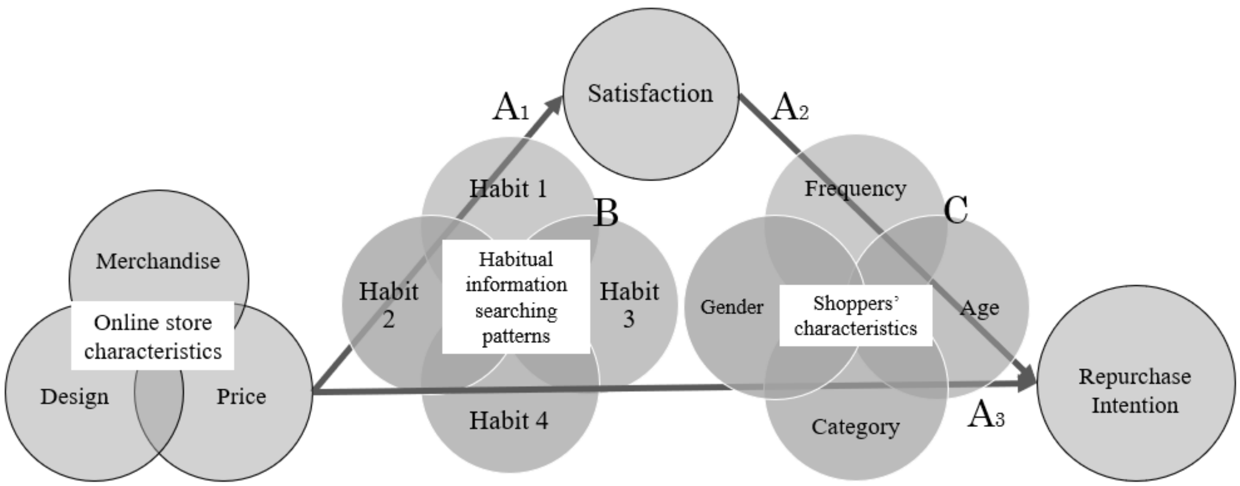

Figure 1: Conceptual model

3.1. The S, O, and R in the SOR model

In e-commerce studies, the SOR model has explained how online factors—such as design, merchandise assortment, and price—stimulate consumers' affective and cognitive states, and then increase behavioral responses, such as patronage of, and repeat visits to, online stores (Brunner-Sperdin et al., 2014). This study adopted satisfaction and RI as the O and R, respectively, in the SOR model. RI is the patronage intention toward a particular shopping site. Satisfaction provided by a shopping site is one of the crucial attitudinal variables that engenders shoppers' confidence in their purchase and increases the possibility of a repurchase at the same site (Srinivasan, Anderson, & Ponnavolu, 2002; Pereira et al., 2016).

Among the various online store factors that have been studied in previous research, we choose website design, merchandise assortment, and price as the three main factors representing online store characteristics. These three factors are considered the most important drivers in the developing e-commerce markets, such as the Vietnamese market that we study in this paper. Particularly, purchasing unique products at the best price is the biggest goal of online purchase for Vietnamese consumers (Ho & Chen, 2014). Additionally, since website design has been analyzed as an important factor for inducing consumers' trust (Gao & Koufaris, 2006; Hasan, 2016), it could significantly influence Vietnamese shoppers who are seriously concerned about the reliability of online shopping (Ho & Chen, 2014). Although many studies have shown the correlations between these online store factors and RI, it is important to highlight how these characteristics can be effectively converted into on-screen information (Kim & Srivastava, 2007; Lee & Bell, 2013).

Based on the first tenet of complexity theory, "a simple antecedent condition may be necessary but a simple antecedent condition is rarely sufficient for predicting a high or low score in an outcome condition" (Woodside, 2014), we assume that although online store characteristics and satisfaction could be the main antecedents predicting high RI (Arrows A1, A2, and A3 in Figure 1), it is unlikely that shoppers' attitudes influence RI independently.

3.2. The influence of habitual information search behavior on online shopping

Although the intimate correlation between satisfaction and RI has been shown by many e-commerce studies (Eroglu, Machleit, & Davis, 2003; Kim & Lim, 2010; Pereira et al., 2016), the influence of satisfaction relies on other factors, such as shoppers' own experiences (Lai & Hitchcock, 2017), perception and expectations (Ren, Qiu, Wang, & Lin, 2016), and habitual behaviors (Amoroso & Lim, 2017).

For example, recent studies have found that the information offered by online stores—as well as the type of information in which shoppers prefer to engage—influence their purchase decisions (e.g., Bhatnagar & Papatla, 2019). Furthermore, depending on the frequency and prior experiences of information search, consumers' search behavior may gradually become habitual or automatic, and may potentially influence their purchase decisions every time they shop. This confirms the importance of incorporating information search behavior into online store design and e-commerce marketing (Dutta & Das, 2017).

In technology use, habit is viewed as a behavior resulting from the feedback from previous experiences (Kim & Malhotra, 2005); it is also measured as the extent to which an individual believes the behavior to be automatic (Limayem, Hirt, & Cheung, 2007). In e-commerce studies, habit was found to directly induce RI (Wood, et al., 2002) and influence it through satisfaction (Khalifa & Liu, 2007; Limayem et al., 2007). For example, some studies found a negative moderating effect of habit. As shoppers become familiar with a shopping process and environment, they may develop a habit of shopping in that environment. In this case, habit may reduce the need for extensive reasoning and conscious attention, thereby limiting the power of conscious drivers on purchase or usage decisions (Limayem et al., 2007; Hsu et al., 2015).

Furthermore, RI may be contingent upon the development of habits regarding performance of certain activities, particularly information-related activities (Fuentes & Svingstedt, 2017). For example, e-window-shopping and social media interaction help consumers gain useful and trustworthy information that can influence their online purchase (Hamilton, Kaltcheva, & Rohm, 2016; Wang, Yang, & Brocato, 2018); information from an offline social interaction (i.e., participating in a local community, chatting with friends) could enhance online purchase intention (Lee & Bell, 2013; Kim, Kim, Choi, & Trivedi, 2017). This effect could be due to the information from friends or community being considered more reliable than online information (Sinha & Swearingen, 2001), encouraging shoppers to subsequently consider online shopping more positively.

These findings indicate that the information content, as well as how consumers practically engage with the information, could influence their purchase decisions. Based on the studies on information in e-commerce (i.e., Bhatnagar & Ghose, 2004), we classify information into online and offline channels by considering the way consumers may engage with the channels. Additionally, online shopping has been observed to be influenced by interaction-based information, such as sharing shopping experiences via social media (Bhatnagar & Papatla, 2019) and participating in a local community (Lee & Bell, 2013; Kim et al., 2017). We classify information search behavior into four patterns based on online and offline channels: (a) browsing for information on websites, (b) looking up information via social media, (c) contacting friends for advice, and (d) visiting offline stores. The first two patterns are classed as online, while the latter two are classed as offline.

Thus, we assume that when the information search behavior becomes a habit, it increases the engagement with certain types of information which may influence shoppers' evaluation of a shopping site and their RI toward it. Despite there being little academic evidence showing that habit can enhance satisfaction, we believe that habit may have an influence on satisfaction by changing the way a consumer perceives online store characteristics. This is because the way shoppers search for information is based on their shopping motives and attitudes, which may change their conscious evaluation of the products or stores at which they consider purchasing (Liu & Forsythe, 2010).

As a result, as shown as B in Figure 1, the information gained can influence shoppers' confidence in the online store, and then influence their RI.

3.3. Complex conditions in online shopping

As the fifth tenet of complexity theory found in Woodside (2014) states, the same individual feature in a configuration can contribute either positively or negatively to a specific outcome depending on the presence or absence of the other ingredients and conditions in the recipes. Consumers' choice of online shopping can be influenced by culture (Van Slyke, Lou, Belanger, & Sridhar, 2010), consumer demographics (Carpenter & Balija, 2010), and shopping situations (Basu, Guin, & Sengupta, 2014). Much e- or m-commerce research has found that RI can be influenced significantly by a direct effect or moderating effect of demographics (Loureiro & Roschk, 2014), shopping frequency, and product category (Sohn, 2017). Furthermore, because habit is predicted by prior experiences, online shopping experiences, frequency, and expenses may influence the effect of habit on purchase (Lai & Hitchcock, 2017).

Thus, all the relationships shown as A1, A2, A3 and B may differ depending on shoppers' gender, age, online shopping frequency, and categories of the products they purchase (shown as C in Figure 1).

4. Research Methodology

4.1. Data collection and sample

The framework is examined by surveying Vietnamese shoppers who have often purchased apparel or electronic goods at online shopping websites. The respondents were asked to answer all questions based on their experiences of online shopping for all types of devices. A local survey company translated all questions into Vietnamese, and we used 10 local people to assess the questions for any confusing expressions.

Table 1: Characteristics of the sample

Sample profile (Valid N = 158)	Number	Sample %
Gender		
Male	67	42.4
Female	91	57.6
Age (years)		
Under 20	64	40.5
21–30	86	54.4
31–40	8	5.1
Frequency of online shopping		
1–2 times per year	23	14.6
Once every 3–4 months	53	33.5
Once per month	59	37.3
Over 3 times per month	23	14.6
Average shopping expense per event		
Less than 50 US dollars	91	57.6
51–100 US dollars	52	32.9
101–150 US dollars	11	7.0
More than 150 US dollars	4	2.5
Product category		
Apparel	92	58.2
Electronics	66	41.8

From November 20 to December 5, 2019, the survey was randomly sent to 1,000 online shoppers who had registered as volunteers willing to participate in an online questionnaire survey followed by a telephonic interview. The survey included two parts. The first was an online survey with questions on shoppers' personal characteristics and questions measuring the five variables. In the second part, we hired four local survey assistants to conduct a telephonic interview with respondents. To standardize the interview, we prepared a guideline that explained the interview construct and content in the Vietnamese language, including the definition of habit and descriptions of the four habitual information search patterns. The four survey assistants interviewed the respondents following the guidelines, by presenting scenarios for the four habits. For example, we demonstrated habit 1 as "when I want to purchase an apparel (or electronic) product online, I usually browse a variety of information on websites immediately without thinking. I do this automatically as a habit before making a purchase online. I keep doing it almost every time when I intend to buy that type of product online." Respondents needed to answer if this fit their own situation (1=least like me; 2=a little like me; 3=neutral; 4=usually like me; 5=most like me). Similarly, we demonstrated the other three patterns, namely, habit 2 (looking up information on social media, such as some influencers' and other shoppers' reviews and recommendations of the product); habit 3 (contacting a friend or relative for advice about the purchase that was being considered); and habit 4 (visiting a physical (offline) store to look up the product that was being considered for purchase).

Table 2: Habitual information search patterns

Four patterns of habits	Mean	Number (%)
Habit 1 (Browsing a variety of inf ormation on websites)	4.24	
Least like me		3 (1.9)
A little like me		10 (6.3)
Neutral		12 (7.6)
Usually like me		54 (34.2)
Most like me		79 (50.0)
Habit 2 (Looking up information via social media)	4.22	
Least like me		2 (1.3)
A little like me		12 (7.6)
Neutral		16 (10.1)
Usually like me		48 (30.4)
Most like me		80 (50.6)
Habit 3 (Contacting friends for ad vice)	3.89	
Least like me		4 (2.5)
A little like me		12 (7.6)
Neutral		32 (20.3)
Usually like me		59 (37.3)
Most like me		51 (32.3)
Habit 4 (Visiting a physical store)	3.36	
Least like me		7 (4.4)
A little like me		27 (17.1)
Neutral		53 (33.5)
Usually like me		44 (27.8)
Most like me		27 (17.1)

In the first survey, we collected 396 valid answers (valid response rate: 39.6%); however, only 158 out of 396 respondents participated in the interview; they were selected as our final sample. The survey offered respondents who participated in the interview a coupon (about two US dollars) for a shopping site. The sample (Table 1) consisted of 42.4% males and 57.6% females; 94.9% of shoppers were under 30 years of age. More than half of the respondents (51.9%) shopped online every month, and 90.5% of them usually spent less than 100 US dollars per purchase. Of the frequently purchased goods, apparel and electronic products accounted for 58.2% and 41.8%. respectively. The sample's information search patterns are described in Table 2.

4.2. Measurements and data analysis

The data analysis consisted of four steps: (1) measurement model testing, (2) correlation and cross-tabulation, (3) fsQCA, and (4) predictive validity. First, a Likert-type scale, ranging from 1 (strongly disagree) to 5 (strongly agree), was used for multi-item variables. The different scale items for the main five constructs are described in Table 3. SPSS Amos 26.0 was used to test the structural model based on confirmation factor analysis (CFA). The measurement model with all 18 items produced the following fit statistics: x2(df) = 279.042 (124); p = .000; GFI, NFI, IFI, TLI, and CFI, are .92, .91, .93, .93, and .92, respectively; RMSEA and SRMR are .084 and .044, respectively. The model exhibited a good fit to the data (Hu & Bentler, 1999). The composite reliabilities of constructs ranged from .85 to .91, which suggest a good convergence for these constructs. Further, all items exhibited each construct's average variance extracted (AVE) as greater than .67.

Table 3: Constructs and measurement assessment

Constructs and scale items	Loading	Cronbach's Alpha	CR[a]	AVE[b]
Design (Kim et al., 2007)		0.69	0.86	0.76
The color schemes on this site are attractive.	0.835			
The interface of this site makes it easy to browse the desired product.	0.908			
The styles and fonts of this site are well designed.	0.738			
Merchandise assortment (Kumar & Kim, 2014)		0.77	0.85	0.68
This shopping site carries a wide selection of merchandise.	0.839			
This shopping site provides many of my favorite products.	0.815			
The merchandise on this shopping site is attractive.	0.82			
Price (Moriuchi & Takahashi, 2016)		0.76	0.89	0.80
The discount and promotional activities on this site are attractive.	0.89			
The prices on this site are reasonable.	0.842			
The prices on this site are attractive.	0.907			
Satisfaction (Pereira et al., 2016; Srinivasan et al, 2002)		0.88	0.91	0.67
My choice for this site was right.	0.805			
Shopping at this site always meets my expectations.	0.773			
When shopping on this website, I feel the excitement of exploring.	0.844			
Overall, I am satisfied with this site.	0.869			
This site is my first choice when I intend to purchase the same cate gory products.	0.81			
Repurchase Intention (Kim et al., 2007)		0.86	0.91	0.71
I intend to visit this website in the future.	0.798			
If I could, I would like to continue using this site to purchase products.	0.898			
In the future, I would be very likely to shop at this site.	0.803			
I would patronize this shopping site.	0.859			

Notes: [a]CR, composite reliability; [b]AVE, average variance extracted

Since the collected samples were cross-sectional and a self-report method was used, common method bias (CMB) may mislead the empirical results (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). CMB was assessed by Harman's single factor test using exploratory factor analysis. The result showed that no single factor (the first/largest factor = 27.1%) accounted for most of the covariance in our data (MacKenzie & Podsakoff, 2012).

Second, SPSS 26.0 was used to test means and correlation. Table 4 shows that the three online store characteristics, satisfaction, and habits 1, 2, and 3 have significant and positive correlations with RI, while merchandise and price have significant and positive correlations with the four habits as well. Except for age, demographic and shopping situation variables are significantly relevant to certain variables. Further, all correlations are less than the square root of AVE for each factor. Thus, the results indicate an acceptable level of discriminant validity (Hair, Ringle, & Sarstedt, 2011).

Table 4: Descriptive statistics and correlation matrix

	Mean	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Design	3.48	.87a												
2 Merchandise	3.76	.38[a]	.82b											
3 Price	3.45	.29[a]	.43[a]	.89c										
4 Satisfaction	3.44	.46[a]	.37[a]	.43[a]	.82d									
5 RI	3.71	.42[a]	.56[a]	.42[a]	.57[a]	.84e								
6 Habit 1	4.24	.28[a]	.37[a]	.29[a]	.39[a]	.40[a]	1.0							
7 Habit 2	4.22	.24[a]	.25[a]	.32[a]	.32[a]	.31[a]	.77[a]	1.0						
8 Habit 3	3.89	.19[a]	.26[a]	.32[a]	.27[a]	.29[a]	.64[a]	.67[a]	1.0					
9 Habit 4	3.36	.11	.16[a]	.21[a]	.14	.13	.39[a]	.36[a]	.47[a]	1.0				
10 Age	1.65	-.03	-.05	.05	-.13	-.09	.04	.06	-.04	-.06	1.0			
11 Gender	1.58	.15	.12	.12	.13	.09	.11	.26[a]	.30[a]	.18[a]	-.17[a]	1.0		
12 Frequency	2.52	.24[a]	.16	.13	.21[a]	.23[a]	.002	.07	.15	.09	-.05	.11	1.0	
13 Category	1.42	.05	-.05	-.19[a]	-.001	.06	.06	.01	-.06	-.20[a]	.14	-.13	.05	1.0

Notes: [a]p < .05; a, b, c, d, e are the square roots of the AVE of each factor.

Table 5: Cross-tabulation of satisfaction and RI

Satisfaction (Cramer's V =.207, Phi=.41, p< .05)	**Repurchase Intention**					**Total**
	Very low	Low	Neutral	High	Very high	
Very low	0	0	1	3	1	5
Low	0	8	10	8	1	27
Neutral	1	5	24	28	4	62
High	0	3	17	28	6	54
Very high	0	0	0	8	2	10
Total	1	16	52	75	14	158

Although the significant and positive correlations between satisfaction and RI were tested as a symmetric correlation (Phi = .41, Cramer's V =.207), Table 5 contains an example showing that the correlation is not necessarily symmetrical in all cases. In the crossover between satisfaction and RI, as shown in the dotted bordered box, a total of 13 cases with a low level of satisfaction have high RI scores (8.23% of the total sample) and a total of three cases with a high level of satisfaction have low RI scores (1.9% of the total sample). Thus, symmetric tests would not be an appropriate way for presenting the outcome that results in high or low scores, with particular conditions and particular configurations.

4.3. Calibrations

Before predicting the outcome, all scale values were converted into membership scores by calibration via fsQCA. For multi-item scales, we computed the mean of all the items of each variable to gain one single value per variable. By following a recent guideline for fsQCA mentioned in Pappas and Woodside (2021), we adopted a direct calibration for setting three breakpoints corresponding to full-set membership, full-set non-membership, and intermediate-set membership, respectively. We used the percentiles 95%, 50%, and 5% as the three memberships to compute our measures via fsQCA. The details of data calibrations are presented in Table 6.

Table 6: Calibrations using percentiles

		Design	Merchandise	Price	Satisfaction	Repurchase
Percentiles	5	2.00	2.00	2.00	2.00	2.25
	50	3.50	4.00	3.50	3.40	3.75
	95	4.50	5.00	5.00	5.00	5.00

For single-item measures such as online shopping frequency, we used 1 (1–2 times per year), 3 (once per month), and 4 (over 3 times per month) to code membership scores; for the four types of habits, we used 1, 3, and 5 to convert membership scores. For gender, male and female were converted as 0.00 and 1.00. For age, under 20 years old, 21–30 years old, and 31–40 years old were converted as 0.00, 0.05 and 1.00. For product category, apparel and electronic were converted as 0.00 and 1.00.

Based on this calibration, we coded these variables and renamed them to highlight the different conditions that would occur in the causal models. They are “well designed,” “attractive merchandise,” and “strong price performance” as high scores for online store factors; “high satisfaction,” four “strong habit” variables (1–4), “female” as a high score in gender, “older shopper” as a high score in age, “high frequency” as a high score in online shopping frequency, and “electronics” as a high score in product category. When a condition “~high satisfaction” (for example) appeared in a causal model, it represented a negation of high satisfaction, which means a low level of satisfaction; when a condition “~electronic” appeared, it represented the opposite of the condition, which means apparel.

5. Results of Configurational Model

A truth table via fsQCA presents all combinations of causal conditions (solutions) in predicting the outcome. According to Ragin (2008) and Woodside et al. (2018), “consistency index” indicates the accuracy of antecedents in predicting outcomes under certain conditions, and “coverage index” measures the ratio of the number of high cases in the outcome condition to all cases. A useful model that has been suggested in current research should have a consistency above 0.80 and a coverage greater than 0.01 (Woodside et al. 2018). As our sample (158) is larger than 150 cases, we set the frequency at 3, and an acceptable cutoff for consistency at 0.80 (Pappas & Woodside, 2021).

First, configurational models with only three online store characteristics and satisfaction to predict a high RI are presented in Table 7. To produce a high RI score, a high level of satisfaction was absent in two models (models 2 and 4). This indicates that satisfaction is a sufficient but not a necessary factor for predicting a high RI. When at least one online store condition is highly evaluated, satisfaction does not influence RI independently. Among online store factors, attractive merchandise appeared the most often, in three out of the four models (models 1, 2, and 4).

Table 7: Configurations predicting high score of RI with main factors

Variables	Models (solutions)			
	1	2	3	4
Well designed		~	~	●
Attractive merchandise	●	●		●
Strong price performance		~	~	●
High satisfaction	●		●	
Raw coverage	0.67	0.35	0.37	0.41
Unique coverage	0.24	0.02	0.03	0.05
Consistency	0.91	0.88	0.87	0.86

Overall: solution coverage=0.79, Solution consistency=0.83
Notes: “●” indicates presence of antecedent condition in the model; “~” indicates negation of the antecedent condition in the model; blank space indicates absence of the antecedent condition in the model.

Second, by incorporating shoppers’ information search patterns and characteristics including gender, age, shopping frequency, and purchase product category into the model, configurations indicated seven specific solutions for predicting a high level of RI (Table 8, left side). Overall, only habit 3 (contacting friends for advice) appeared in all the models, while habit 2 (looking up information via social media) and habit 4 (visiting a physical store) appeared in five models. Satisfaction only appeared in three models, along with strong price performance and well-designed website (models 2, 4, and 6). Among online store factors, strong price performance appeared in six out of seven models.

Table 8: Configurations predicting high score of RI including habitual behaviors and shoppers' characteristics

Variables	Models for high score of RI							Models for negation of RI		
	1	2	3	4	5	6	7	1	2	3
Well designed	~	●	~	●	~	●	●	~	●	●
Attractive merchandise	●	~	~	~	●	●	~	~	~	~
Strong price performance	●	●	~	●	●	●	●	~	~	~
High satisfaction		●	~	●	~	●	~	~	~	~
Strong habit 1		~	●	●		●	~	●	~	~
Strong habit 2	●	●	~	●	~	●	●	~	~	●
Strong habit 3	●	●	●	●	●	●	●	●	~	~
Strong habit 4	●		●	~	●	●	●	●	~	~
Female	●	●	~	~	~	~	●	~	●	~
Older shopper	~	~	~	~	●	~	~	~	~	~
High frequency	●	~	~	~	~	~	●	~	●	●
Electronics	~	●	~	●	●	~	●	~	●	●
Raw coverage	0.13	0.17	0.04	0.05	0.04	0.07	0.09	0.05	0.10	0.04
Unique coverage	0.01	0.04	0.01	0.03	0.02	0.04	0.02	0.02	0.10	0.02
Consistency	0.96	0.98	0.83	0.94	0.83	0.93	0.83	0.97	0.89	0.95

Overall: models for high score of RI: solution coverage=0.48, solution consistency=0.88; models for negation of RI: solution coverage=0.20, solution consistency=0.91

Notes: "●" indicates presence of antecedent condition in the model; "~" indicates negation of the antecedent condition in the model; blank space indicates absence of the antecedent condition in the model.

Table 9: Model for high score of RI for subsamples 1 and 2

Model for subsample 1	Raw coverage	Unique coverage	Consistency
~welldesigned*bigmerchandise* strongpriceperformance *stronghabit1* stronghabit2*stronghabit3*stronghabit4*female*~highfrequency* ~oldershopper*~electronics	0.308563	0.102377	0.875410
Model for subsample 2	**Raw coverage**	**Unique coverage**	**Consistency**
~welldesigned*bigmerchandise* strongpriceperformance*stronghabit1* stronghabit2*stronghabit3*stronghabit4*female*~highfrequency* ~oldershopper*~electronics	0.275096	0.077222	0.939189

More specifically, for younger female shoppers with high shopping frequency, merchandise, price, and habits 2–4 predicted high RI in case of apparel products (model 1), while well-designed website, strong price performance and habits 2 and 3 predicted a high RI in case of electronics (models 2 and 7). For younger male shoppers with low shopping frequency, when they purchased electronics online, strong habits 1 (browse information on websites), 3 and 4 were the necessary conditions (models 3 and 6); however, when they purchased apparel products, online store factors, satisfaction and strong habits 1, 2, and 3 become the conditions predicting high RI (model 4). For older male shoppers with low shopping frequency purchasing electronics, attractive merchandise, strong price performance, and strong habits 3 and 4 were the conditions predicting high RI (model 5).

In negation of RI (Table 8 right side), three combinations are suggested. Weak merchandise, weak price performance, low satisfaction, and younger shoppers appeared in all models. All types of habits appeared at a low level in two out of three models. A high level of a condition such as habit 3, which necessarily predicted high RI, also predicted the negation of RI depending on how other factors and conditions worked in this configuration.

Finally, regarding the importance of predictive validity among different samples (Brenes et al. 2017), we split the sample into two subsets. We first tested subsample 1 followed by its configurational model by using subsample 2. Table 9 demonstrates an example that indicates a high RI score with all variables and consumer conditions. A model with 11 variables for subsample 1 is similar to the results for the total sample (Table 9). Similarly, we used subsample 2 to test the model in subsample 1. The results prove the ability of the model to predict outcome conditions with different datasets.

6. Discussion and Conclusion

6.1. Implications for theory and practice

This study applied complexity theory to deepen the understanding of online distribution science by examining (1) the potential effect of habitual information search behavior on online shopping and (2) how online store factors and satisfaction influence RI differently depending on shoppers' information search patterns, demographics, and shopping situations. We chose to combine complexity theory with SOR because it can supplement the existing research in this field by highlighting how conscious and unconscious factors work together under complex conditions.

For example, a recent habit-related study by Amoroso and Lim (2017) reported a mediating effect of habit in relationship satisfaction–continuance intention toward a mobile technology, and another study by Hsu et al. (2015) reported a negative effect of habit on the association between satisfaction and repeat purchase in online shopping. Both these studies provided evidence for the asymmetric relationship between conscious attitude and behavioral outcome. However, we wonder what kind of habitual activities could affect the relationship and why habit has both positive and negative influences on the relationship depending on the research setting.

Some online distribution-related studies have applied complexity theory via fsQCA and thereby have presented the advantages of using fsQCA, which can propose integrated models by combining factors from different perspectives and with different consumer characteristics (Fang, Shao, & Wen, 2016; Pappas, 2018). The results also overcome the limitation of requiring symmetric relationships between variables and outcomes (Liu, Chu, Huang, & Chen, 2016).

Based on previous findings, the present study contributes to online distribution marketing theory in two ways: (1) it incorporates an unconscious factor—habit—into the SOR model via fsQCA to supplement previous research by examining all correlations in a specific context, and (2) it examines the impact of both conscious and unconscious factors on RI by studying four information search patterns of online shopping. Based on the findings, we also offer several practical implications for e-commerce firms.

First, consistent with the implications of Amoroso and Lim (2017), this study proves that online shopping is not influenced by satisfaction alone. The greater the number of specific conditions added to the causal models, the more the potential interactions between online store factors, satisfaction, and habitual information search behavior with respect to RI were seen in the results. When information search habits are strong enough, the effect of satisfaction on RI is not that necessary or sufficient. This may be because the information shoppers search for habitually can support their repurchase decisions without the need for conscious attention and, as a result, eventually reduce the dependence of RI on satisfaction (Anderson & Srinivasan, 2003; Limayem et al., 2007; Hsu et al., 2015). In our case, a strong habit of contacting friends for advice (habit 3) was a necessary condition predicting RI in all solutions. The reliable information the shoppers gained unconsciously somehow supplanted the value they received from a shopping site. This confirmed the importance of personal relationships in Vietnam, where people prefer face-to-face communication and offline shopping over shopping online (Kshetri, 2007).

Furthermore, the results regarding online store factors showed that for female shoppers, a high score on price performance is a sufficient and necessary condition predicting high RI, over website design and merchandise. This finding shows that a good price is still the biggest goal of online shopping for Vietnamese consumers (Ho & Chen, 2014). However, a well-designed shopping site and a strong price performance positively influence RI only for shoppers who have strong habits of looking up information via social media (habit 2) and contacting friends (habit 3). It indicates that offering information via social media, including various product- and distribution-related information, and influencers' and other shoppers' recommendations and reviews, can help shoppers trust the product and the shopping site being used by them, in turn reducing the sensitivity of price and encouraging their repeat purchase at the same site.

Second, consistent with Bhatnagar and Papatla (2019) regarding the potential habitual behavior in e-commerce, we found some differences among the four habitual information search patterns. Based on these differences, e-commerce companies can reconsider how to offer effective information on their shopping sites. For example, the habit of browsing various information (habit 1) only affect younger male shoppers with low shopping frequency. E-commerce companies can simplify the information search process by adding some information resource links or information comparing products' functions and prices to those of the products that young male shoppers often purchase.

The habit of looking up information via social media (habit 2) worked for all types of younger female shoppers. It is because the information shoppers gain via social media is not only about products but also interactive information from other shoppers' recommendations and reviews. Additionally, females are more likely to develop a habit of interacting on social media during shopping (Kuo, Hu, & Yang, 2013; Anshari, Alas, Hardaker, Jaidin, Smith, & Ahad, 2016). E-commerce companies should consider creating a functional social media link that allows shoppers to interact with their social network and their friends during online shopping, which can conveniently assist them in choosing products and induce them to stay longer at the shopping site, as a result increasing RI toward the site.

The habit of contacting friends for advice (habit 3) is the most effective behavior seen in online shopping in Vietnam. It worked for all situations and conditions in our results. The reason may be the rudimentary stage of e-commerce development and the comparatively limited experience of Vietnamese people in online shopping. Companies can make use of these characteristics to engage their customers. For example, they can offer some coupons or special promotional events to people who introduce their shopping sites to their friends. They can also add a convenient feature to their sites which allows shoppers to share links of the products they purchase with their friends via email or social media.

A strong habit of visiting physical stores (habit 4) worked for both male and female shoppers, particularly for older male shoppers with low shopping frequency purchasing electronics at the same shopping site visited previously. The reason may be the risk of purchasing an electronic product, which is usually expensive and requires a rich product description including maintenance and after-sale service-related information. Physical stores, in effect, support older shoppers who intend to confirm the product they are considering to purchase. Once they visit the physical store and decide on the product they want, they may come back to the shopping site and purchase it online for convenience and better cost performance. Thus, we suggest that e-commerce companies provide easy-to-understand introductions for electronic products, such as posting videos to introduce the characteristics of a product, which can support older shoppers in choosing the product and encourage them to repurchase from those stores. Additionally, because online stores may not be able to offer some features that physical stores can, such as enjoyment and entertainment via window-shopping and social interaction (Kotzé, North, Stols, & Venter, 2012), this implies the relevance of interaction in offering information through both online and offline distribution channels on online purchase behavior (Gallino & Moreno, 2014). E-commerce operations should, thus think about how to collaborate with offline stores.

6.2. Limitations and future research

This study has few limitations that need to be addressed in future research. First, the effect of other conscious attitudes, such as trust, should be tested to develop an understanding of the role of habits in online shopping (Chiu et al., 2012; Hsu et al., 2015) because habitual behavior could reduce the uncertainty of repeat behavior and, as a result, reduce the influence of trust on purchase intention.

Second, the results could be different depending on the devices shoppers use for shopping and seeking information, which was not tested in this study. For example, due to the convenience of a mobile phone, shoppers who use mobile shopping apps may develop the habit of interacting on social media more than shoppers who use laptops (Fuentes & Svingstedt, 2017).

Third, our data collection is limited to the self-report method, which differs from experimental settings suggested in habit-related research (Lin & Lekhawipat, 2014). By developing the measurement of habit, our results could be clarified.

Finally, culture is an important driver that influences habit development (Ashraf et al., 2014). Additionally, shoppers' experience and technology adoption also influence their online shopping attitudes and information search habit development (Ashraf et al., 2017). This study is the first step toward conducting cross-cultural research to better understand the effects of habit(s) under different circumstances and reflecting different cultural values.

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