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Customer Involvement Facets Stimulating Customers' Intention to Use Internet-Only Bank Services in China:

The Extension of Perceived Risk-Value Model

Mei-Lan Li, Sanming University, Sanming, China
Shu-Ping Lin, CTBC Business School, Tainan, Taiwan
Ya-Hui Chan, CTBC Business School, Tainan, Taiwan
Chia-Huei Wu, Minghsin University of Science Technology, Xinfeng, Taiwan
https://orcid.org/0000-0001-6399-2113

ABSTRACT

In this study, the authors extended the perceived risk-value model to include customer involvement to conceptualize an adoption intention model in the context of internet-only bank services (IOBSs). Hypotheses were tested using survey data collected in China. A total of 252 valid questionnaires were returned. Structural equation modeling was used to test two models, an antecedent model, and moderating model, constructed by assuming that customer involvement affects the perceived risk-value model in different ways. The findings verified that the perceived value could explain customers' intention to adopt IOBSs, whereas the influences of perceived risk were discovered to be nonsignificant, reducing the fitness of the perceived risk-value model. However, the opposite result was obtained when customer involvement was considered to exert a moderating effect rather than an antecedent effect. The implications of this research for IOBS service operators are discussed, and suggestions for future research are provided.

KEYWORDS

Adoption Intention, Customer Involvement, Internet-Only Bank, Moderating Effect, Perceived Risk, Perceived Value, Structural Equation Modeling

INTRODUCTION

The global financial technology ecosystem continued to grow rapidly during 2018. Because of the rise of open banking thinking, financial business is no longer limited to taking place in traditional financial institutions. The technology, retail, and telecom industries, among others, have joined the financial technology market under the trend for supervision regulation of open banking, which is maturing worldwide. Financial technology was thus promoted into the era of Internet-only bank services (IOBSs), which began in 2019.

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IOBSs use various new types of financial technology to create a better experience for users; however, the essence of an IOBS remains the "bank," and the business content is similar to that of a traditional bank. Therefore, whether IOBSs can change the behavior of customers by providing financial services is a topic worthy of attention. Additionally, regarding the definition of Internet-only banking, financial services are always conducted through the internet and using automated processes; services thus have to be reliable interaction or communication patterns between the service provider and requester (Bhadoria & Chaudhari, 2019). Nevertheless, IOBSs have a higher risk than traditional bank services, because business-related conversation occurs between service providers and clients in financial services and IOBSs rely heavily on the Internet and automated processes. Therefore, understanding how associated risks affect customers' perceptions of the value of IOBSs is also critical.

Although extant IOBS service operators provide numerous benefits to attract and retain customers, most are still failing to create continuous and organic user-scale growth. The reason may be that superior services have become a basic threshold that is no longer sufficient to motivate customers to make a change; because the benefits of the system are explicit, competitors can easily imitate them. Therefore, the perceived value perspective plays an essential role but can only partially explain the cause of customers' adoption intention.

In the 2010s, the perceived value perspective was extended to include the perceived risk perspective to enhance the understanding that consumers' adoption intention has a spectrum, regardless of whether an independent (e.g., Wessels & Drennan, 2010; Wu & Wang, 2005) or dependent (e.g., Featherman, Miyazaki, & Sprott, 2010; Gupta & Kim, 2010; Kim & Gupta, 2009; Mutahar, Daud, Ramayah, Isaac, & Aldholay, 2018) viewpoint is adopted. Perceived risk must be included because IOBSs are provided on the basis of a high degree of cross-domain data exchange and are being developed within mobile applications that can be used at any time and in any place; thus, extensive information communication occurs in the online or digital environment, and the resultant risks strongly influence transactions between supply and demand sides. If customers discover a difference between their actual experience and their expectation during service delivery, they perceive the risk of using the service to be higher, and that risk is dependent on the degree of customers' subjective uncertainty regarding the outcomes (Alalwan, Dwivedi, Rana, & Algharabat, 2018; Bauer, 1960; Cox, 1967; Kesharwani & Bisht, 2012). Because the perceived risk–value model has been employed in various service domains, such as mobile banking (Featherman et al., 2010; Mutahar et al., 2018) and online commerce (Gupta & Kim, 2010; Kim & Gupta, 2009), it is regarded as the foundation of the IOBS adoption intention model in the present study.

In accordance with the definition of perceived risk as the potential for loss when pursuing a desired outcome and because perceived risk may negatively affect perceived value, discovering the potential antecedents of perceived risk is a vital task. In accordance with research that has emphasized the necessity of understanding customer behavior through a cross-theory approach, the present study considered customer involvement theory in the social psychology perspective, because this theory was demonstrated to enhance understanding of changes in customer behavior through individuals' psychosocial phenomena (Chen, Wang, Cheng, & Kuntjara, 2008; Houston & Rothschild, 1978; Hynes & Lo, 2006; Laurent & Kapferer, 1985; Mittal & Lee, 1989; Sherif & Cantril, 1947; Zaichkowsky, 1985). Customer involvement theory is proposed in the persuasive communication literature, and the social judgment–involvement approach has been used to explain attitude and attitude change (Michaelidou & Dibb, 2008; Varki & Wong, 2003). However, no researchers appear to have explored the role played by customer involvement in the perceived risk–value model. Thus, the research question of this study was how customer involvement influences the perceived risk–value model to change customers' judgment of the adoption of IOBSs.

In summary, this study aimed to construct a hybrid model of customers' intention to use IOBSs through the following: (1) investigating how perceived risk and perceived value influence customers' decision processes regarding IOBS adoption and (2) extending the perceived risk–value model to include customer involvement theory (stated in the social psychology perspective) for empirically examining changes in customers' intention to use IOBSs.

In the following sections, we first explore how other studies and theories have examined perceived value, risk, and customer involvement. Subsequently, we propose our hypotheses and explain the methodology used, after which the results are presented. Finally, we conclude this paper with a discussion identifying the implications and limitations of our study as well as possible directions for future research.

LITERATURE REVIEW: THEORETICAL BACKGROUND

Perceived Value

Customers' motivation to perform a behavior is mainly determined by their perception of the associated benefits of that behavior. When customers are unfamiliar with a new service or product, are inexperienced, or lack knowledge, subjective value judgment is the basis of their decision making. According to Porter and Donthu (2006), the system-specific and personality-specific paradigms are the two paradigms that have been employed in recent research, and both paradigms offer explanations for why customers accept or adopt information technology services. The system-specific paradigm explains how the features of technology influence how customers perceive that technology, whereas the personality-specific paradigm examines the use and acceptance of new information technology services from the perspective of customers' personal traits including insecurity, discomfort, optimism, and innovativeness.

For the system-specific paradigm, the theoretical basis most commonly adopted by scholars is the technology acceptance model (TAM) introduced by Davis (1989). This model explains customer behavior regarding the adoption of new information systems by using the ideas of perceived usefulness and perceived ease of use. Perceived usefulness is the degree to which customers believe their work efficiency can be enhanced if they use the information system. In recent years, many researchers have reported that perceived usefulness can be the key factor leading to differentiation, and perceived usefulness has often been demonstrated to be the most crucial factor in perceived value models (e.g., Godoe & Johansen, 2012; Lee, Park, Chung, & Blakeney, 2012; Rahman & Sloan, 2017).

Perceived ease of use refers to the degree to which an individual believes that using a particular information system will be free of effort. When customers consider an information system to be easy to use, their efficiency is improved. Especially in e-services, technology functions must fulfill the tasks that customers use them for and provide customers with appropriate feedback and assistance while being continually accurate (Ivanaj, Nganmini, & Antoine, 2019). Unlike perceived usefulness, the effects of which have been strongly supported by most studies, findings are inconsistent regarding the influence of perceived ease of use in different service contexts. However, both perceived usefulness and ease of use were included in the present study to conceptualize perceived value.

Perceived Risk

Bauer (1960) defined perceived risk as uncertainty and unfavorable consequences associated with customers' expectations. Perceived risk thus originates from customers' beliefs about the likelihood of gains and losses. It reflects customers' perceptions of the uncertainty of outcomes and primarily pertains to the prepurchase behavior of searching for and selecting a product or service before making any purchasing decision (Cox, 1967). More specifically, aspects related to perceived risk have been widely regarded as crucial negative determinants of customer intention to adopt an information technology service (Alalwan et al., 2018).

Researchers have agreed that perceived risk is a multidimensional construct. For example, Cunningham (1967) identified two major categories of perceived risk: performance risk and psychological risk. Performance risk was later divided into four facets—performance, financial, time, and safety risk—whereas psychological risk was divided into social and psychological risk. Studies have recently suggested that safety risk should be replaced with security or privacy risk, because security and privacy concerns are increasingly pertinent in investigations of information technology services (e.g., Featherman et al., 2010; Khedmatgozar & Shahnazi, 2018). Dowling and Staelin (1994) proposed a risk model that encompasses three components of risk: inherent risk, handled risk, and acceptable risk. Their study was the first to assess the level of risk that customers were willing to accept during a purchase decision and indicated that risk acceptance may vary depending on product or service attributes (Bruwer, Fong, & Saliba, 2013).

The present study referred to Cunningham's typology to conceptualize perceived risk, because this typology has been employed in a rich stream of the literature for understanding customers' intention to adopt innovative services and their associated behaviors (Antioco & Kleijnen, 2010; Featherman & Pavlou, 2003; Khedmatgozar & Shahnazi, 2018).

Customer Involvement

Involvement theory was first proposed in the social judgment theory of Sherif and Cantril (1947). This theory emphasizes the concept of "ego involvement." Ego involvement can be used to explain the process of change in an individual's attitude and judgment. The more an individual is involved in an incident, the less likely they will accept an opinion opposite to their own and the more likely they will amplify the negative explanation of this opposing opinion. Conversely, when an individual encounters an opinion that is the same as their own, the more they become involved, the more they accept the opinion, and the more likely they are to amplify the positive explanation of this opinion. Being highly involved and making extensive inputs to the service production and delivery process modify a customer's beliefs, and this modification results in valuable and marketable outcomes for a business (Mustak, 2019).

The concept of customer involvement has been commonly used to enhance various customer behavior models; however, its typologies are diverse. For example, Houston and Rothschild (1978) classified consumer involvement into situational, enduring, and participation involvement. Situational involvement emphasizes that an individual's involvement is affected by the context; enduring involvement emphasizes individual factors such as individual subjective value systems and experience; and finally, participation involvement emphasizes the opinions of others or responses to customers.

Zaichkowsky (1985) defined consumer involvement as "a person's perceived relevance of an object based on inherent needs, values, and interests" and reported that involvement is based on personal demands, values, and interests, which dictate the importance of an item. Zaichkowsky divided involvement into product, commercial, and purchasing decision involvement. Similarly, Mittal and Lee (1989) considered involvement to be the mental status in which considerable attention is paid to an incident or event. Customer involvement can thus be defined as personal investment and effort, including that of time and money, regarding personal needs, values, and interests.

From another perspective, Laurent and Kapferer (1985) defined involvement as an individual difference variable that causes or motivates a customer's purchase and communication behavior. They developed the customer involvement profile (CIP) scale, which has five facets: importance, risk probability, symbolism, pleasure, and interest. In the present study, we employed the CIP to explore customers' involvement in IOBSs, because this scale has received considerable attention and been extensively used and tested (Chen et al., 2008; Hynes & Lo, 2006; Parihar, Dawra, & Sahay, 2018).

RESEARCH HYPOTHESES

Perceived Value and Adoption Intention

The TAM is a powerful model designed to predict information technology acceptance and usage. Numerous studies employing the TAM have emphasized the importance of perceived value and its role in predicting the service usage and acceptance of customers. For example, Godoe and Johansen (2012) analyzed why users reject a system even if they are positive toward the technology in general and concluded that low perceived ease of use and perceived usefulness contributed to users' rejection of the system despite their optimistic attitude. Lee et al. (2012) proposed a unified model that included technology value perceptions, technology-specific perceptions, user characteristics, and task-user characteristics to discuss customers' intentions to use mobile financial services. They reported that both perceived usefulness and perceived ease of use significantly affected intention to use mobile financial services, and both variables mediated the relationship between other factors and adoption intention.

Yen and Wu (2016) proposed an extended model based on the TAM to predict the adoption of mobile financial services. The findings revealed that perceived mobility, personal habit, perceived usefulness, and perceived ease of use constitute the major antecedents that influence continued usage intention toward mobile financial services. In their study conducted in Bangladesh, Rahman and Sloan (2017) identified perceived usefulness as the determinant of users' adoption of mobile commerce and concluded that companies should continue to optimize their technologies and services to help users meet the demands of their modern evolving lifestyle. The TAM was considered a good theoretical model for explaining the acceptance of new information technology; however, whether the TAM can be applied to all cases of IOBS adoption remains debatable. Incorporating findings from more than a decade of information technology service research, we hypothesized that the TAM would be appropriate for modeling adoption intention in the IOBS context. Hence, the following hypotheses were proposed:

H1: Perceived usefulness positively affects customers' intention to employ IOBSs.
H2: Perceived ease of use positively affects customers' intention to use IOBSs.
H3: Perceived ease of use positively affects customers' perception of the usefulness of IOBSs.

Perceived Risk and Adoption Intention

Service providers must enhance consumers' confidence and reduce their risk-related concerns to ease their anxiety when they conduct transactions through information technology. Featherman and Pavlou (2003) extended the positive utility approach to include measures of negative utility (i.e., potential losses) attributable to e-service adoption. Drawing from perceived risk theory, six risk facets were operationalized and empirically tested within the TAM, resulting in an e-service adoption model. Their results indicated that e-service adoption is adversely primarily affected by performance risk, whereas psychological risk, concerning the loss of current social status, was not discovered to have a significant influence. Lee (2009) synthesized perceived risk theory, five specific risk facets—financial, security or privacy, performance, social, and time risk—the TAM, and the theory of planned behavior to propose a theoretical model that explains users' intention to use online banking. Their results indicated that intention to use online banking was adversely affected by security or privacy risk and financial risk, whereas it was indirectly affected by performance risk and time risk through users' positive attitude.

In a study investigating barriers to customers' adoption of technological innovations under "lack of content" and "presence of content" contingencies, Antioco and Kleijnen (2010) discovered that the barriers posed by financial and performance risk were negatively related to adoption intention. More recently, Khedmatgozar and Shahnazi (2018) investigated the effects of performance, privacy, security, financial, time, and social risk on bank clients' intention to adopt corporate internet banking. The results indicated a significant relationship between all the types of risk and adoption intention, and performance and privacy risk were the two facets that reduced the clients' intention the most. Because the present study employed Cunningham's typology to conceptualize perceived risk into six risk facets—performance, financial, time, safety, social, and psychological risk—the following hypothesis was proposed:

H4: Perceived risk negatively affects customers' intention to use IOBSs.

Perceived Risk–Value Relationship

Many researchers have suggested that perceived risk can reduce the value perceived by customers. Thus, when a customer's concern regarding risk outweighs the value of a service, the customer's intention to use the service may be adversely affected, and the customer may even reject the service or cease to use it continually. Shamdasani, Mukherjee, and Malhotra (2008) integrated the self-service quality framework and TAM to investigate internet banking. They empirically tested their comprehensive model in which service quality, perceived risk, perceived value, and perceived satisfaction were hypothesized to predict customers' continued adoption. Their results indicated that perceived service quality, perceived value, and satisfaction were critical predictors of continued adoption, whereas perceived value played a pivotal role in the full mediated relationship between perceived risk and continued adoption. Kim and Gupta (2009) examined differences between potential and repeat customers on the basis of mental accounting theory and information processing theory. They discovered that for potential customers, the perceived value of online transactions, as an overall judgment for decision making, was more strongly influenced by nonmonetary (perceived risk) factors than monetary factors (perceived price); for repeat customers, however, perceived value was more strongly influenced by monetary factors.

In a survey of customers' online-purchase decision making in which the value perspective was employed on the basis of mental accounting theory, Gupta and Kim (2010) discovered that the monetary construct (perceived price) affected online purchase decisions directly and indirectly though perceived value; by contrast, the nonmonetary construct (perceived risk) affected online purchase decisions indirectly through perceived value. Featherman et al. (2010) discussed how to reduce privacy risk and its effects for the purpose of enhancing adoption of an online bill paying service. They found that security and reliability concerns were the causes of customers' perceived risk, and perceived usefulness was affected by this risk, with higher perceived risk resulting in lower adoption likelihood. More recently, Mutahar et al. (2018) examined the effect of perceived risk and awareness as external factors on the TAM to obtain understanding of intention to use mobile banking. Their results revealed that perceived risk had major negative effects on perceived ease of use and perceived usefulness. Hence, this study proposed the following hypotheses:

H5: Perceived risk negatively affects customers' perception of the usefulness of IOBSs.
H6: Perceived risk negatively affects customers' perception of the ease of use of IOBSs.

Alternative Roles of Customer Involvement in the Perceived Risk–Value Model

When discussing customers' intention to adopt information technology services, few studies have included customer involvement in the perceived risk–value model to enable an extended discussion. Thus, no consensus has yet been reached on the direct and indirect influences of customer involvement, perceived risk, and perceived value. Some scholars have regarded customer involvement to be an antecedent of perceived risk. For example, Venkatraman (1989) considered perceived risk to be a consequence of product involvement and argued that products in which customers become highly involved have higher perceived performance, financial, and physical risk, causing customers to actively search for more information. Similarly, in a study discussing how customer involvement influences the search for information when considering a product purchase, Chaudhuri (2000) concluded that compared with the hedonic dimension of involvement, which directly influenced information searching, perceived risk fully mediated the effect of the importance dimension of involvement on information search. Recently, Hong (2015) examined the relationship among individual risk facets, situational involvement, and trust expectation to understand the process through which customers select online merchants. His results revealed that situational involvement not only positively affected all five types of perceived risk but was also positively related to consumers' trust expectation.

By contrast, some studies have suggested that the involvement construct has a moderating effect on various consumer decision-making processes. For example, Xue (2008) investigated the moderating role of product involvement when predicting the effects of self-concept and consumption situation on consumers' situational decision making. They conducted an experiment with a two (self-concept) × two (consumption situation) between-group design, and the results suggested that for consumers who were highly involved with the product, self-concept and consumption situation were both determinants in situational brand choices. Given that involvement is a significant precursor to customer loyalty, Sanchez-Franco (2009) explored and confirmed the various moderating effects of customer involvement on the satisfaction–trust–commitment model of e-banking services. However, regarding the moderating effect of customer involvement on the perceived risk–value relationship, researchers have failed to confirm that this effect exists.

Accordingly, two alternative roles of customer involvement in the perceived risk–value model were explored in this study. Because the CIP scale was used to measure the degree of customer involvement, the following hypotheses were proposed:

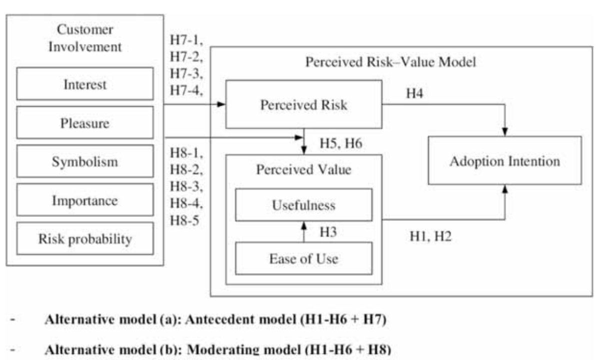
H7: Customer involvement (interest: H7-1; pleasure: H7-2; symbolism: H7-3; importance: H7-4; and risk probability: H7-5) negatively affects customers' perceptions of the risk of IOBSs.
H8: Customer involvement (interest: H8-1; pleasure: H8-2; symbolism: H8-3; importance: H8-4; and risk probability: H8-5) moderates the relationship between customers' perceptions of the risk and value of IOBSs.

Figure 1 displays the two models based on extending the perceived risk–value model to include customer involvement theory.

RESEARCH METHODS

The objective of this study was to understand customers' intention to use IOBSs by extending the perceived value–risk model to include customer involvement theory within the customer social psychology perspective. Structural equation modeling (SEM) was employed to test the antecedent and moderating models. Multiple-item measurement was used to assess the various constructs. A questionnaire was employed to obtain primary data; it comprised 45 items measured on a 7-point Likert scale (1 = *strongly disagree*, 2 = *disagree*, 3 = *somewhat disagree*, 4 = *neither disagree nor agree*, 5 = *somewhat agree*, 6 = *agree*, and 7 = *strongly agree*). The data were collected using the

Figure 1. Conceptual model of adoption intention in the IOBS context



- **Alternative model (a): Antecedent model (H1-H6 + H7)**
- **Alternative model (b): Moderating model (H1-H6 + H8)**

online sampling method in China, and 252 valid questionnaires were obtained. Of the respondents, 62% were female, and 37% were younger than 20 years, whereas 40.5% were aged 21–30 years. Most of the respondents had a college education (66%).

Because there is no single correct or universally accepted calculation approach or method for determining the ideal sample size for SEM, researchers tend to rely on rules of thumb. Most researchers recommend that the *N*:*q* ratio of observations to estimated parameters be 10:1 (Schreiber, Nora, Stage, Barlow, & King, 2006) or 5:1 (Bentler & Chou, 1987), depending on model complexity. In this study, the ratio of 5:1 was adopted because no data were missing and the latent constructs could be explained through multiple indicators (Bentler & Chou, 1987). According to the judgment criteria proposed by Hair, Black, Babin, Anderson, and Tatham (2006), the internal consistency of latent constructs, factor loading of observed items, and average extracted variance (AVE) are the main methods used to evaluate reliability and validity. Cronbach's α and composite reliability (CR) are used to represent the internal consistency of latent constructs. Higher CR indicates the percentage of true variance (i.e., the variance of latent variables) that accounts for the total variance, and CR should be higher than .6. The square of the factor loading of each observed item can be used to represent the power that the latent constructs have to explain the observed item and is the basis of evaluation of convergent validity; it should have a value higher than .7. The AVE is the total power that the latent constructs have to explain the observed items. According to Fornell and Larcker (1981), if the AVE is higher than .5 and higher than the degree of association between the latent constructs, the measured variables have adequate discriminant validity.

RESULTS

Reliability and Validity Analysis

Table 1 presents the reliability statistics. The values of Cronbach's α for the latent constructs were between .813 and .966, and all the CR values were higher than .83. All factor loadings of the measured latent constructs were higher than .67, and all values were higher than .622 and larger than the square of the correlation coefficients between latent constructs (Table 2), confirming the convergent and discriminant validity of the measurement.

Confirmatory factor analysis was additionally employed to construct a measurement model by using the maximum likelihood method in LISREL 8.13. In our measurement model, chi-squared was 1915.12 ($df = 854$, $p < .0001$). Because the χ^2 test is known for its sensitivity to sample size (Hair et al., 2006), four additional fit indexes were employed to test the fit of the model: the χ^2 ratio (χ^2/df), goodness-of-fit index (GFI), comparative fit index (CFI), and root-mean-squared error of approximation (RMSEA). The guidelines on which values for these indices indicate satisfactory fit are as follows: $\chi^2/df \leq 5$, GFI and CFI $\geq .9$, and RMSEA $\leq .1$. The values obtained for the measurement model satisfied all these criteria: $\chi^2/df = 2.24$, GFI = .75, CFI = .98, and RMSEA = .07. Therefore, the measurement model had adequate goodness of fit.

Structural Model Analysis

Perceived Risk–Value Model Testing

SEM was first used to interpret the effects in the perceived risk–value model (Figure 1) as the basis for alternative model testing. According to results displayed in Table 3, the overall fit indices of the model were all within the acceptable range, suggesting that the model favorably fit the data. The R^2 of the perceived risk–value model for adoption intention was .52 with significance, indicating the high power of the model to explain intention to adopt IOBSs.

The standardized path coefficients displayed in Table 3 revealed that four of the six hypotheses in the perceived risk–value model were supported. First, two hypotheses regarding the influences of perceived value on adoption intention were supported: H1 (perceived usefulness → adoption intention;

Table 1. Measurement and reliability statistics

Measurement	Cronbach's α	CR	AVE	Means	Factor Loading
Perceived Value					
Perceived usefulness (PU)	.966	.966	.803	5.209	
(PU1) Using an IOBS improves my quality of life.				5.194	.86
(PU2) Using an IOBS enables me to more quickly complete a financial transaction.				5.508	.89
(PU3) Using an IOBS increases my productivity in financial transactions.				5.064	.90
(PU4) Using an IOBS improves my performance in dealing with financial transactions.				5.048	.89
(PU5) Using an IOBS enables me to complete more financial transactions than other people.				5.095	.88
(PU6) Using an IOBS increases my effectiveness in dealing with financial transactions.				5.262	.94
(PU7) Generally, I think an IOBS helps me deal with the financial transactions I need to make.				5.294	.91
Perceived ease of use (PEOU)	.943	.943	.806	5.163	
(PEOU1) Learning to use an IOBS is easy for me.				5.254	.87
(PEOU2) I think it is simple to complete my financial transactions through an IOBS.				5.254	.94
(PEOU3) The interaction operation of IOBSs is clear and stable.				4.933	.87
(PEOU4) I think IOBSs are user friendly in general.				5.258	.91
Perceived Risk					
Finance risk (PFR)	.813	.830	.622	4.075	
(PFR1) IOBSs cause me financial loss.				3.667	0.78
(PFR2) IOBSs expose me to potential financial fraud.				4.103	0.90
(PFR3) IOBSs increase the likelihood of incurring nonessential expenses.				4.456	0.67
Performance risk (PPR)	.917	.919	.693	3.939	
(PPR1) IOBSs do not function normally and undermine my credibility.				4.064	0.82
(PPR2) IOBSs do not function normally and lead to the mishandling of financial transactions.				3.944	0.86
(PPR3) IOBSs do not function normally and lead to the delay of financial transactions.				4.183	0.89
(PPR4) The security systems of IOBSs are not substantial enough to secure my financial transactions.				3.976	0.80
(PPR5) IOBSs are often problematic or do not function normally.				3.528	0.79
Privacy risk (PVR)	.874	.875	.700	4.294	
(PVR1) I lose control of the privacy of my financial transactions if I use an IOBS.				3.976	.84
(PVR2) My privacy is violated when I use an IOBS because my personal information is used without my knowledge.				4.437	.85

continued on following page

Table 1. Continued

Measurement	Cronbach's α	CR	AVE	Means	Factor Loading
(PVR3) Using an IOBS increases the probability that internet hackers will gain control of my financial transactions.				4.468	.82
Psychology risk (PYR)	.904	.906	.828	3.325	
(PYR1) Using IOBSs causes psychological loss because they do not match my self-image or self-concept.				3.361	0.90
(PYR2) Using IOBSs causes psychological loss because they do not match my habits.				3.290	0.92
Social risk (PSR)	.944	.944	.893	3.208	
(PSR1) Using IOBSs negatively influences how people think of me.				3.135	0.95
(PSR2) Using IOBSs causes social loss because my friends and relatives have low opinions of IOBSs.				3.282	0.94
Time risk (PTR)	.903	.907	.766	3.631	
(PTR1) When starting to use an IOBS, I waste a lot of my time in preliminary work such as registration and opening a bank account.				3.814	.79
(PTR2) Using IOBSs wastes a lot of my time because I must resolve mishandled financial transactions.				3.536	.92
(PTR3) Using IOBSs wastes a lot of my time because I must learn its regulations and how to use it.				3.544	.91
Customer Involvement					
Interest (INT)	.943	.943	.847	4.718	
(INT1) The IOBS I use is very important to me.				4.778	.92
(INT2) I am really interested in IOBSs.				4.690	.94
(INT3) I am concerned about IOBSs.				4.687	.90
Pleasure (PLE)	.912	.912	.837	4.641	
(PLE1) I really like to use IOBSs.				4.766	0.93
(PLE2) To me, using an IOBS is a pleasure.				4.516	0.90
Symbolism (SYM)	.928	.928	.865	4.135	
(SYM1) I think using IOBSs indicates who you are.				4.155	0.94
(SYM2) I think using IOBSs reflects who I am.				4.115	0.92
Importance (IMP)	.860	.862	.757	4.474	
(IMP1) I feel upset when discovering I have not used an IOBS correctly.				4.440	0.89
(IMP2) I feel upset when discovering I made an incorrect choice during the use of an IOBS.				4.508	0.85
Risk probability (RP)	.890	.892	.734	3.970	
(RP1) I am not always sure which IOBS provider I should choose.				4.075	.87
(RP2) When I use an IOBS, I am not always sure whether I am using it correctly.				4.016	.86
(RP3) Choosing an IOBS is difficult.				3.817	.84

continued on following page

Table 1. Continued

Measurement	Cronbach's α	CR	AVE	Means	Factor Loading
Adoption Intention (AI)	.943	.945	.810	4.778	
(AI1) If I could gain access to an IOBS,				4.627	.87
(AI2) If I could gain access to an IOBS, I might try to use it.				4.841	.91
(AI3) Because I have access to an IOBS, I will continue to use it.				4.766	.93
(AI4) I am willing to recommend my IOBS to others.				4.877	.89

Table 2. Discriminant validity analysis

	PU	PEOU	PFR	PPR	PVR	PYR	PSR	PTR	INT	PLE	SYM	IMP	RP	AI
PU	(.803)													
PEOU	.784	(.806)												
PFR	.029	.031	(.622)											
PPR	.021	.021	.517	(.693)										
PVR	.057	.063	.422	.495	(.700)									
PYR	.000	.001	.250	.411	.347	(.828)								
PSR	.004	.001	.209	.377	.266	.823	(.893)							
PTR	.000	.000	.351	.432	.384	.658	.644	(.766)						
INT	.398	.406	.014	.016	.037	.008	.000	.000	(.847)					
PLE	.381	.396	.010	.011	.017	.009	.002	.002	.782	(.837)				
SYM	.241	.239	.046	.063	.017	.095	.075	.052	.454	.557	(.865)			
IMP	.198	.187	.051	.045	.034	.062	.025	.044	.374	.362	.336	(.757)		
RP	.039	.035	.088	.180	.109	.331	.298	.271	.087	.068	.190	.342	(.734)	
AI	.409	.382	.034	.025	.037	.006	.002	.006	.542	.553	.266	.288	.057	(.810)

Note: The numbers in the lower triangular matrix are the squared correlations; the numbers in parentheses are AVEs.

Table 3. SEM results obtained for the perceived risk–value model

Path (hypothesis)	Standardized path coefficient	Significance (t value)	Hypothesis testing
H1: PU→AI	0.43*	3.25	Supported
H2: PEOU→AI	0.30*	2.22	Supported
H3: PEOU→PU	0.92*	18.05	Supported
H4: RISK→AI	0.09*	2.00	Opposite result obtained
H5: RISK→PU	0.00	−0.13	Rejected
H6: RISK→PEOU	0.01	0.21	Rejected
Fit indices of SEM χ^2/df = 4.3; RMSEA = .10 (.09; .11); RMR = .078; CFI = .96; NFI = .95; GFI = .76			

Note: *p < .05

path coefficient = 0.43) and H2 (perceived ease of use → adoption intention; path coefficient = 0.30). Therefore, perceived value played a crucial role in predicting customers' intention to use IOBSs. Second, H3 was supported, revealing that perceived ease of use positively affected perceived usefulness (path coefficient = 0.92). Notably, H4 (risk → adoption intention) was significantly rejected (path coefficient = 0.09), with the opposite result as was hypothesized. In addition, the influences of perceived risk on perceived usefulness and perceived ease of use were nonsignificant, rejecting the mediating role of perceived value between perceived risk and adoption intention. Thus, some external constructs may exist and were needed to enhance the perceived risk–value model.

Modeling Customer Involvement as an Antecedent in the Perceived Risk–Value Model

Based on the results for the perceived risk–value model, used to explain customers' adoption intention in the IOBS context, this study then regarded customer involvement as a potential external construct and, on the basis of the first stream of hypotheses proposed in the reviewed literature, examined whether customer involvement was an antecedent in the perceived risk–value model and could increase the explanatory power of the overall model. SEM was also employed for antecedent model testing [Figure 1(a)]. According to results shown in Table 4, the overall fit indices of the model were all within the acceptable scope, suggesting that the model favorably fit the data. However, the R^2 of the perceived risk–value model was .52, the same as that of the original perceived risk–value model. Therefore, considering customer involvement as a potential antecedent failed to increase the power of the model to explain customers' adoption intention in the IOBS context.

Some findings are notable. As indicated in Table 4, all four hypotheses were again supported in the perceived risk–value model. However, only two out of five hypotheses regarding the relationship between customer involvement and perceived risk were supported: H7-4 (importance → risk) and H7-5 (risk probability → risk). Therefore, the importance and risk probability aspects of customer involvement negatively affected the perceived risk of adopting IOBSs (path coefficients = −0.36 and

Table 4. SEM results obtained for the antecedent model

Path (hypothesis)	Standardized path coefficient	Significance (t value)	Hypothesis testing
H1: PU→AI	0.43*	3.25	Supported
H2: PEOU→AI	0.30*	2.23	Supported
H3: PEOU→PU	0.92*	18.05	Supported
H4: RISK→AI	0.09*	2.02	Opposite result obtained
H5: RISK→PU	0.00	-0.08	Rejected
H6: RISK→PEOU	0.01	0.23	Rejected
H7-1: INT→RISK	−0.35	-1.07	Rejected
H7-2: PLE→RISK	0.28	0.67	Rejected
H7-3: SYM→RISK	0.20	1.41	Rejected
H7-4: IMP→RISK	−0.36*	-2.82	Supported
H7-5: RP→RISK	−0.80*	-6.13	Supported
Fit indices of SEM χ^2/df = 3.8; RMSEA = .099 (.094; .10); CFI = .96; NFI = .95; GFI = .73 Explanatory power R^2 for AI is .52; R^2 for RISK is .47			

Note: *p < .05

0.80, respectively), and no other direct influences of facets of customer involvement on perceived risk existed. The results correspond to the nonsignificant increase in the explanatory power of the antecedent model.

Modeling Customer Involvement as a Moderator in the Perceived Risk–Value Model

The moderating effect of customer involvement in the perceived risk–value model was next examined [Figure 1(b)]. This study classified customer involvement into five facets—interest (H8-1), pleasure (H8-2), symbolism (H8-3), importance (H8-4), and risk probability (H8-5)—and examined the thesis hypotheses separately to clarify whether customer involvement moderated or mitigated the influences of perceived risk on perceived value and intention to use IOBSs. Because customer involvement is a multiple and continuous construct, the significance of moderating effects was determined by creating an interaction (new additional latent construct). This approach was proposed by Holmbeck (1997), who indicated that to examine moderating effects with continuous constructs, all possible products of the measured items can be computed and assumed to represent the latent constructs and thus the interaction effects. Joreskog and Yang (1996) further reported that the main measured items must be extracted when computing products, and multiple interaction effects must be considered to comprehensively understand the significance of moderating effects.

This research followed the suggestions of these researchers (Holmbeck, 1997; Joreskog & Yang, 1996), creating the interaction effects and examining their significance to clarify the moderating effects in the perceived risk–value model. First, we selected the measurement item with the largest factor loading from each customer involvement facet (latent construct) and multiplied it by each measured item of the latent construct (perceived risk) to create multiple interaction effects. The interaction effects were then tested using SEM to confirm the moderating effects. The results are presented in Tables 5–9.

Table 5. Moderating effects of customer involvement: interest-based interaction effect

	Model 0	Model 1	Model 2	Model 3	Model 4
Path (hypothesis)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)
H1: PU→AI	0.43* (3.25)	0.37* (2.78)	0.50* (3.97)	0.39* (2.91)	0.32* (2.64)
H2: PEOU→AI	0.30* (2.22)	0.37* (2.73)	0.22 (1.72)	0.21 (1.61)	0.17 (1.42)
H3: PEOU→PU	0.921* (18.05)	0.92* (18.06)	0.91* (17. 62)	0.92* (18.04)	0.88* (16.41)
H4: RISK→AI	0.09* (2.00)	0.11* (2.57)	0.11* (2.47)	−0.59* (−6.24)	−0.56* (−5.61)
H5: RISK→PU	0.00 (−0.13)	0.00 (−0.06)	−0.16* (−2.68)	0.00 (−0.04)	−0.10 (−1.51)
H6: RISK→PEOU	0.01 (0.21)	−0.88* (−7.63)	0.05 (0.78)	0.05 (0.80)	−0.84* (−7.28)
H8-1a: INT×RISK→PEOU		1.06* (8.90)			1.01* (8.55)
H8-1b: INT×RISK→PU			0.18* (3.08)		0.12 (1.65)
H8-1c: INT×RISK →AI				0.82* (8.27)	0.77* (7.19)
R^2 for AI	0.52	0.53	0.51	0.56	0.64
The difference in chi-square		142.38*	5.76*	38.83*	193.6*

Note: *p < .05

Table 6. Moderating effects of customer involvement: pleasure-based interaction effect

	Model 0	Model 5	Model 6	Model 7	Model 8
Path (hypothesis)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)
H1: PU→AI	0.43* (3.25)	0.37* (2.77)	0.49* (3.84)	0.42* (3.14)	0.36* (2.90)
H2: PEOU→AI	0.30* (2.22)	0.37* (2.77)	0.23 (1.81)	0.18 (1.34)	0.14 (1.09)
H3: PEOU→PU	0.921* (18.05)	0.92* (18.04)	0.91* (17.66)	0.92* (18.06)	0.89* (16.20)
H4: RISK→AI	0.09* (2.00)	0.11* (2.55)	0.11* (2.45)	−0.59* (−5.97)	−0.56* (−5.31)
H5: RISK→PU	0.00 (−0.13)	0.00 (−0.12)	−0.14* (−2.25)	0.00 (−0.06)	−0.08 (−1.10)
H6: RISK→PEOU	0.01 (0.21)	−0.94* (−7.94)	0.05 (0.80)	0.05 (0.82)	−0.90* (−7.64)
H8-2a: PLE×RISK→PEOU		1.12* (9.20)			1.08* (8.89)
H8-2b: PLE×RISK→PU			0.16* (2.56)		0.09 (1.16)
H8-2c: PLE×RISK→AI				0.81* (7.93)	0.77* (6.78)
R^2 for AI	0.52	0.53	0.52	0.55	0.63
The difference in chi-square		138.34*	2.74*	43.36*	190.52*

Note: *p < .05

Table 7. Moderating effects of customer involvement: symbolism-based interaction effect

	Model 0	Model 9	Model 10	Model 11	Model 12
Path (hypothesis)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)
H1: PU→AI	0.43* (3.25)	0.38* (2.85)	0.50* (3.93)	0.38* (2.80)	0.32* (2.53)
H2: PEOU→AI	0.30* (2.22)	0.35* (2.64)	0.22 (1.33)	0.26 (1.89)	0.23 (1.81)
H3: PEOU→PU	0.921* (18.05)	0.92* (18.09)	0.91* (17.62)	0.92* (18.03)	0.88* (16.54)
H4: RISK→AI	0.09* (2.00)	0.11* (2.50)	0.11*(2.44)	−0.52* (−5.05)	−0.49* (−4.50)
H5: RISK→PU	0.00 (−0.13)	0.00 (−0.07)	−0.19* (−2.94)	0.00 (−0.04)	−0.13 (−1.85)
H6: RISK→PEOU	0.01 (0.21)	−0.94* (−7.42)	0.05 (0.75)	0.05 (0.77)	−0.90* (−7.09)
H83a: SYM×RISK→PEOU		1.09* (8.48)			1.05* (8.13)
H83b: SYM×RISK→PU			0.21* (3.30)		0.15* (1.98)
H83c: SYM×RISK→AI				0.71* (6.77)	0.67* (5.84)
R^2 for AI	0.52	0.53	0.52	0.53	0.63
The difference in chi-square		99.79*	4.86*	27.78*	138.74*

Note: *p < .05

Table 8. Moderating effects of customer involvement: importance-based interaction effect

	Model 0	Model 13	Model 14	Model 15	Model 16
Path (hypothesis)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)
H1: PU→AI	0.43* (3.25)	0.39* (2.95)	0.48* (3.69)	0.41* (3.06)	0.37* (2.91)
H2: PEOU→AI	0.30* (2.22)	0.34* (2.56)	0.24 (1.90)	0.25 (1.83)	0.22 (1.73)
H3: PEOU→PU	0.921* (18.05)	0.92* (18.04)	0.91* (17.81)	0.92* (18.05)	0.90* (17.00)
H4: RISK→AI	0.09* (2.00)	0.11* (2.47)	0.11* (2.42)	−0.45* (−4.55)	−0.42* (−4.13)
H5: RISK→PU	0.00 (−0.13)	0.00 (−0.08)	−0.13* (−1.98)	0.00 (−0.02)	−0.08 (−1.13)
H6: RISK→PEOU	0.01 (0.21)	−0.79* (−6.28)	0.05 (0.75)	0.05 (0.77)	−0.76* (−6.00)
H8-4a: IMP×RISK→PEOU		0.93* (7.31)			0.90 (7.01)
H8-4b: IMP×RISK→PU			0.14* (2.22)		0.09 (1.22)
H8-4c: IMP×RISK→AI				0.64* (6.26)	0.60* (5.58)
R^2 for AI	0.52	0.53	0.52	0.53	0.59
The difference in chi-square		115.79	6.02	31.7	148.61

Note: *p < .05

Table 9. Moderating effects of customer involvement: risk-probability-based interaction effect

	Model 0	Model 17	Model 18	Model 19	Model 20
Path (hypothesis)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)	Path coefficient (*t* value)
H1: PU→AI	0.43* (3.25)	0.41* (3.09)	0.46* (3.51)	0.41* (3.07)	0.39* (2.99)
H2: PEOU→AI	0.30* (2.22)	0.32* (2.39)	0.27* (2.03)	0.29* (2.15)	0.27* (2.13)
H3: PEOU→PU	0.921* (18.05)	0.92* (18.05)	0.92* (17.93)	0.92* (18.04)	0.91* (17.61)
H4: RISK→AI	0.09* (2.00)	0.10* (2.32)	0.10* (2.31)	−0.31* (−3.04)	−0.28* (−2.83)
H5: RISK→PU	0.00 (−0.13)	0.00 (0.01)	−0.10 (−1.56)	0.00(0.05)	−0.08 (−1.04)
H6: RISK→PEOU	0.01 (0.21)	−0.56* (−4.19)	0.04 (0.64)	0.04(0.65)	−0.53* (−3.97)
H8-5a: RP×RISK→PEOU		0.66* (4.95)			0.63* (4.70)
H8-5b: RP×RISK→PU			0.11 (1.75)		0.08 (1.15)
H8-5c: RP×RISK→AI				0.45* (4.50)	0.43* (4.18)
R^2 for AI	0.52	0.53	0.52	0.53	0.56
The difference in chi-square		66.52*	2.22	3.97*	63.47*

Note: *p < .05

The interest-based interaction effect moderated the effects of perceived risk on perceived value and adoption intention, with all differences in chi-square being significant to support H8-1 (Table 5). Concerning the influence of perceived risk on perceived ease of use, when the effect of customer involvement on the perceived risk–value model was not considered (Model 0), perceived risk had no significant influence on perceived ease of use. However, when the interest-based interaction effect was included (Model 1), the influence of perceived risk on perceived ease of use was significantly negative (path coefficient = −0.88), and the interest-based interaction effect significantly and positively intervened the relationship between perceived risk and perceived ease of use (path coefficient = 1.06); specifically, greater interest suggests a weaker negative influence of perceived risk on perceived ease of use.

The observation regarding the direct influence of perceived risk on perceived usefulness (Model 0) also indicated the absence of a significant effect. However, when the interest-based interaction effect was included (Model 2), the influence of perceived risk on perceived usefulness was significantly negative (path coefficient = −0.16), and the interest-based interaction effect significantly and positively intervened in the relationship between perceived risk and perceived usefulness (path coefficient = 0.18); thus, greater interest was associated with a weaker negative influence of perceived risk on perceived usefulness. Furthermore, Model 0 revealed that perceived risk had a significant positive effect on adoption intention. Nevertheless, when the interest-based interaction effect was included (Model 3), the influence of perceived risk on adoption intention was significantly negative (path coefficient = −0.59). The interest-based interaction effect also significantly and positively intervened in the influence of perceived risk on adoption intention (path coefficient = 0.82). Greater interest resulted in a weaker negative influence of perceived risk on adoption intention.

The present study employed the same analytical process to examine the interference effects of the other four facets of customer involvement (i.e., pleasure, symbolism, importance, and risk probability) on the perceived risk–value model. In terms of individual effects on perceived ease of use, when different facets were included in Models 5, 9, 13, and 17 to obtain an interactive effect, perceived risk negatively influenced perceived ease of use in all models (path coefficients = −0.94, −0.94, −0.79, and −0.56, respectively). In addition, the different interaction effects all significantly and positively intervened in the relationship between perceived risk and perceived ease of use (path coefficients = 0.16, 0.21, 0.14, and 0.66 respectively). Greater pleasure, symbolism, importance, and risk probability thus resulted in a weaker negative influence of perceived risk on perceived ease of use.

The individual effects on perceived usefulness revealed that for Models 6, 10, and 14, which included different facets separately for interaction effects, perceived risk had a negative influence on perceived usefulness (path coefficients = −0.14, −0.19, and −0.13, respectively). The different interaction effects all significantly and positively intervened in the relationship between perceived risk and perceived usefulness (path coefficients = 0.16, 0.21, and 0.14, respectively). Nevertheless, for Model 18, which included the risk-probability-based interaction effect, perceived risk did not significantly influence perceived usefulness and did not significantly intervene in the relationship between perceived risk and perceived usefulness. Accordingly, the pleasure, symbolism, and importance aspects of customer involvement all indicated that greater customer involvement resulted in a weaker influence of perceived risk on perceived usefulness.

Results obtained for Models 7, 11, 15, and 19 demonstrated that perceived risk significantly and negatively affected adoption intention (path coefficients = −0.59, −0.52, −0.45, and −0.31, respectively). The different interaction effects significantly and positively intervened in the relationship between perceived risk and adoption intention (path coefficients = 0.81, 0.71, 0.64, and 0.45, respectively). Therefore, greater pleasure, symbolism, importance, and risk probability indicated a weaker influence of perceived risk on adoption intention.

In summary, the analysis revealed that in the perceived risk–value model, the relationship among perceived risk, perceived value, and adoption intention was clearer when intervention effects were considered, which would reduce misjudgments of customer behavior. According to results obtained for Models 4, 8, 12, 16, and 20, the R^2 of the overall model increased from 0.52 to 0.64, 0.63, 0.63, 0.59, and 0.56 (all significant differences in the chi-square test) when interest-, pleasure-, symbolism-, importance-, and risk-probability-based interaction effects were included, respectively. This indicated that customer involvement mediated the relationships of perceived risk with perceived value and adoption intention; customer involvement improved the overall explanatory power of the model. Therefore, H8-2, H8-3, H8-4, and H8-5 were supported.

DISCUSSION AND IMPLICATIONS

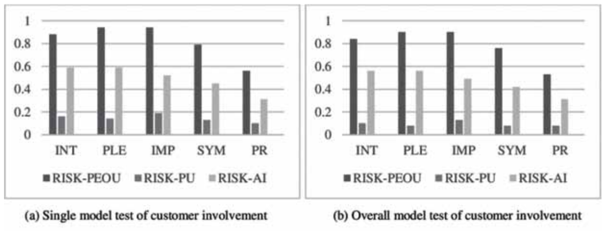
This study extends the knowledge on the relationship between customer involvement and the perceived risk–value model. Although customer involvement has been widely investigated in the customer social psychology domain, to the best of our knowledge, this study is the first to explore its potential effects on the perceived risk–value model in the customer marketing domain and context of IOBSs. Establishing this link is crucial, because adoption intention is the most widely used indicator of customers' rejection or adoption behavior in marketing systems, and perceived risk and perceived value explain customers' adoption intention to a high degree. The findings of this study therefore provide some confidence that it is valuable to attempt to understand the facets of customer involvement and monitor the status of those with perceived risk when attempting to increase customers' adoption intention through perceived value. Such empirical knowledge is critical to the development of effective marketing designs that are capable of improving service diffusion.

More precisely, through conceptualization and testing of two customer involvement–based alternative models that have not been previously examined, this study made findings that contribute new insights into the relationship described by the perceived risk–perceived value model. First, customer involvement was assumed to have an antecedent effect on the perceived risk–value model. However, the results revealed that this antecedent model failed to increase the understanding of customers' adoption intention in the IOBS context. The effects of only two facets of customer involvement—importance and risk probability—on perceived risk were supported. This result responds to the nonsignificant increase in explanatory power of the antecedent model. This study thus concludes that regarding customer involvement as an antecedent is not a favorable method of understanding the intention of customers to use IOBSs; other roles played by customer involvement must be explored.

Second, this study assumed that customer involvement had a moderating effect on the perceived risk–value model. Interestingly, this study corrected the inconsistent arguments about the relationship among perceived risk, perceived value, and adoption intention in the literature. For example, that customers' perceived risk reduces perceived value and affects customers' adoption intention has been widely proven (e.g., Featherman et al., 2010; Gupta & Kim, 2010; Kim & Gupta, 2009; Mutahar et al., 2018; Shamdasani et al., 2008), but this argument was not supported in the current study regarding IOBSs. An exception to the rule that perceived risk positively affects perceived value has thus been identified. When the intervention effect of customer involvement was included, we discovered that the phenomenon was reversed (from positive to negative), obtaining results that agreed with those in the literature. Given that customer involvement significantly influences adoption intention, the present study explored and explained the importance of customer involvement in the IOBS context. In particular, customer involvement has an intervention effect on the relationships of perceived risk with perceived value and adoption intention, and this intervention effect cannot be neglected when a business is aiming to increase customers' willingness to adopt a product or service.

By testing the moderating effects at the facet level rather than the construct level, the present study provides more detailed empirical implications than other studies. Figure 2 displays a comparison of Tables 5–9. The results demonstrate the factors (y-axis) affecting perceived ease of use (Models 1, 5, 9, 13, and 17), perceived usefulness (Models 2, 6, 10, 14, and 18), and adoption intention (Model 3, 7, 11, 15, and 19) when single model or overall model tests (Models 4, 8,812,16, and 20) are employed and interaction effects are included. According to results obtained when including the

Figure 2. Comparison of the intervention effect concerning the different customer involvement facets



interaction effects, pleasure and importance were the facets of customer involvement that most strongly weakened the negative influences of perceived risk on perceived ease of use, followed by symbolism. The importance facet weakened the negative effect of perceived risk on perceived usefulness to the greatest degree, followed by the interest facet. The interest and pleasure facets had the strongest weakening effects and importance the second strongest weakening effect on the negative influence of perceived risk on adoption intention. These results revealed that the order of importance of the facets concerning customer involvement was as follows: importance, pleasure, interest, and symbolism, with risk probability being the least essential facet. Accordingly, we propose three practical suggestions.

First, if service operators are to change or reduce the influence of customers' perceived risk on perceived value and adoption intention, the most crucial is to increase customers' reliance on IOBSs and the importance of IOBSs to this group. Service operators should attempt to enhance customers' internalization of IOBSs and strengthen the connections of IOBSs with customers' life and work; when customers are highly familiar with the content and procedure of the IOBS, the probability of incorrect use or choice and subsequent negative influences can be reduced. This suggestion is similar to the claim of Roger (1962) regarding the innovation acceptance model; Roger stated that compatibility is a determinant of innovation diffusion. Because compatibility expresses the degree to which an innovation is perceived as being consistent with an individual's values, experiences, and needs, scholars have demonstrated that the more mobile banking is perceived as being compatible with a person's values, experiences, and needs, the better the attitude of that person toward mobile banking (e.g., Püschel, Mazzon, & Hernandez, 2010; Veríssimo, 2016). Therefore, when service operators are designing IOBSs, they should not only accentuate the effectiveness of the system's functionality but also understand customers' lifestyles or work styles to reduce the possibility of unexpected conflict during IOBS use. This would help overcome obstacles to IOBS adoption and eventually transform customers' selective behavior into habitual behavior.

Second, service operators should continually strengthen their communication with customers through service experiences and enhance customers' emotional connection to the service. This could be achieved by creating fun for customers, enabling them to enjoy and be impressed by the service experience, shortening the cycle of service updates, and establishing a comprehensive message delivery or announcement system to maintain the topicality and popularity of the service and keep customers interested. Services have become more transparent in the information environment. IOBSs are affected by the negative influence of information transparency despite being in the development stage. Hence, if service operators cannot rapidly improve and differentiate their product or maintain close communication with customers, they cannot continually gain the favor of their customers.

The same findings were obtained by Parihar et al. (2018), who investigated the role of customer engagement in the involvement–loyalty connection in an online retail context. They reported that brand-like signage, interest, and pleasure were critical to maintaining customer loyalty and further suggested that these elements be provided to customers by not only enabling the customers to purchase from the brand but also engage with the brand. Additionally, in their study on information search channel selection for consumers, Khatwani and Srivastava (2018) emphasized the importance of service providers optimizing the various available digital channels on the basis of relevant insights into consumer behavior and preferences, which can be further translated into marketing strategies. A highly dynamic market poses great challenges to service operations; however, service providers can increase their competitiveness by understanding the psychological benefits perceived by their customers. This entails serious thinking on part of service operators.

Third, developing customers' consensus on a service and increasing their sense of honor, which demonstrates their knowledge or social status, when they adopt the service are also essential for increasing customers' willingness to adopt IOBSs. The service consensus established through customer involvement generates a sense of brand recognition that reduces the negative influences of perceived risk (Wei & Ho, 2019), provides an intangible connection between the service operator and customer, and further creates a cohesive social environment. Shang, Chen, and Liao (2006) stated that customers join communities to learn from other customers' experiences or acquire information, and involvement has been considered a main reason why customers seek service information. Involvement relates to uncertainty and plays a role in how customers perceive risk and seek information. Involvement thus provides a means of formulating more precise customer communication strategies.

Such an argument corresponds to the findings of many recent studies, which reported that service adoption and diffusion require the application of all types of social networking activities—such as customer walkthroughs, prototypes, and pilot implementations—to encourage customers to participate and enhance the connection with customers (Kim, 2019; Lee, Trimi, Byun, & Kang, 2011). In summary, greater customer involvement results in lower risk that an IOBS will be incongruent with customer needs, reducing the associated perceived risk.

CONCLUSION

Our study is the first to examine the roles of customer involvement in the perceived risk–value model used to predict customer's intention to use IOBSs. The results clearly indicate that understanding a customer's involvement is worthwhile in terms of predicting that customer's future intention to use an IOBS. The same finding has been made by numerous studies (e.g., Sanchez-Franco, 2009; Xue, 2008); moreover, the current study contributes to the understanding of customer involvement in IOBS adoption from the facet level rather than the construct level. Because customer involvement has a moderating effect on the perceived risk–value model, service operators should utilize various qualitative or quantitative methods to identify customers' values, experiences, and needs with respect to their internalization of IOBSs and strengthen the connections between IOBSs and customers' life and work (Püschel et al., 2010; Veríssimo, 2016). Fabisiak (2018) further proposed that user preferences from log data provide more direct insights into their wants and needs, and this understanding is conducive to information technology services that are dynamic and usually vary during the design.

Additionally, service operators should design customer relationship activities to not only maintain communication with customers (Khatwani & Srivastava, 2018; Parihar et al., 2018) but also develop customers' recognition on a service and enhance the value they attach to the service and even the brand (Shang et al., 2006; Shahri, Hosseini, Phalp, Taylor, & Ali, 2019; Wei & Ho, 2019); this can improve their loyalty and thus achieve continual service diffusion. From this perspective, our results have clear implications regarding which facets of customer involvement service operators should address in their marketing systems to maximize the adoption intention of customers. Our findings indicate that to curb continuous service diffusion, service operators should not only increase customers' perceived value by enhancing the positive utility of IOBSs, nor should they ignore the direct and indirect impacts of different facets of perceived risk. Understanding customer involvement is an effective approach with which service operators can reduce unexpected effects of perceived risk and should be a crucial element of marketing for an IOBS.

This study has some limitations. First, although the amount of data employed in the present study meets the convergence requirement for multivariate statistical analysis, the data were mainly collected from a single city. The sample profile means that the results are not fully representative of the Chinese population of potential IOBS users. Thus, while our findings may be somewhat generalizable across IOBS contexts, they are not necessarily generalizable to different countries or cultures. Second, the research was conducted in the context of IOBSs, and its applicability to other situations remains to be further investigated. This study encourages future studies to adopt our proposed alternative customer involvement models to supplement the negligible evidence on how customer involvement and the perceived value–perceived risk model interact in the current research. Third, we limited our analyses to the key objective of identifying the customer involvement facets that are most valuable to managers in predicting IOBS adoption intention. We discussed the facets separately and considered only those that are simple to comprehend and observe. Additionally, we examined only the interaction effects at the construct level of perceived risk and did not explore possible interactions between the different perceived risk facets. Future research exploring and examining possible facet-level moderating effects on the perceived risk–value model may provide further insights for marketing theory.

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Mei-Lan Li is currently a Lecturer at the Institute of Economics and Management, Sanming University. She obtained Ph.D. degree from Chung Hua University. Her research expertise is mainly on services marketing. She keeps an academic track record with a recent focus on the Fintech and Sharing Economy fields.

Shu-Ping Lin is a Professor and Head of the Department of Banking and Finance, CTBC Business School (Taiwan). She was professor at Chung Hua University from 2010-2017. Her received a PhD in Statistics from the Institute of Statistics, National Tsing Hua University. Her research expertise includes research methodology, Artificial Intelligence, service quality management, data science and finance technology management.

Ya-Hui Chan has been invited as a Research Fellow at CTBC business school from 2018. She was a director of big data analytics and service design at Fusion$360.com from 2017-2018; was hired as an associate professor at Asia University from 2016-2017, and a manager at the Advanced Research Institute and Data Analytics Technology and Applications Institute at III from 2012-2016. Her research interests include statistical analysis, consumer behavior analysis, and service design and innovation.

Chia-Huei Wu (PhD) is currently an Assistant Professor at Institute of Service Industries and Management, Minghsin University of Science and Technology in Taiwan. She received Ph.D. degree in Chung Hua University. Dr. Wu has well over 30 published peer-reviewed journal articles. Her recent research interests in Service Management, Marketing Management, Consumer Behavior and E-commerce. She is serving on the editorial boards of some journals.