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Social influence on innovation resistance in internet banking services

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A B S T R A C T

The primary goal of this study was to examine the moderating effect of experiences on the relationship between social influence and innovation resistance. Multi-group structural equation modeling was performed to test the model, which used survey data on Japanese consumers' use of internet banking services. The results revealed that social influence directly reduced the innovation resistance of non-experienced consumers while directly enhancing the innovation resistance of experienced consumers. Moreover, the mediating effect of barriers was found to be different for experienced and non-experienced consumers. This paper contributes to a better understanding of innovation resistance and diffusion processes by clarifying the effect of social influence on innovation resistance, based on social learning and influence theories.

1. Introduction

The high failure rates for new products, averaging around 40% across industries (Castellion and Markham, 2013), suggest that consumers often resist change when confronted with innovation (Ram, 1987). Heidenreich and Kraemer (2016) argued that consumer innovation resistance is a significant reason for new product failure. Therefore, recent empirical studies have begun to focus on the phenomenon of innovation resistance (e.g., Mani and Chouk, 2017; Patsiotis et al., 2013, Talke and Heidenreich, 2014).

Prior research has shown that innovation resistance results primarily from functional and psychological barriers (Talke and Heidenreich, 2014). Functional barriers appear when perceived functional attributes of an innovation do not fulfil consumers' ideal expectations; psychological barriers emerge when perceived attributes of an innovation bring about psychological conflicts or problems for consumers (Heidenreich and Handrich, 2015). The perceived barriers and resistance may be influenced by their peer group, which provides information and sets normative standards of conduct (Mangleburg et al., 2004). Although previous research on the technology acceptance model (TAM) found that social and interpersonal influences have positive effects on consumers' intentions to use new products, services, or technologies (Lian and Yen, 2014; Messing and Westwood, 2014; Slade et al., 2007; Thomas and Vinuales, 2017), little is known about the relationships between social influence, consumers' perceived barriers and resistance to change.

To address this research gap, this study investigated the direct and indirect effects of social influence on innovation resistance mediated by several barriers, including complexity, performance risk, and existing usage patterns. Importantly, innovation resistance can arise even after consumers experience or adopt new services and products. A previous study reported that some customers generally discontinue online shopping on certain websites within a short period of time (Kim and Gupta, 2012). Therefore, innovation resistance may also arise after consumers have experienced or adopted new services and products. We also need to recognize the possibility that the strength of social influence on perceived barriers and resistance differs between experienced and inexperienced consumers. For example, Karahanna et al. (1999) argued that pre-adoption behavior should be distinguished from post-adoption behavior when investigating the technology adoption process. This is because pre-adoption beliefs are mainly established through indirect experiences or perceptions, whereas post-adoption beliefs result from direct experiences or the actual use of products. Accordingly, several studies on TAM found that the effect of social influence on the utilization of new technology is different for inexperienced and experienced users (Thompson et al., 1994; Venkatesh et al., 2003).

Therefore, it is essential to examine the role of social influence on innovation resistance both before and after new technologies are adopted. However, to date, there has been minimal research on the moderating effects of experience on the relationship between social influence and innovation resistance.

Based on these propositions, we tested the moderating effect of experience on relationships between social influence, perceived barriers and innovation resistance, drawing on interpersonal influence theory (Deutsch and Gerard, 1955; Yi et al., 2013) and social learning theory (Bandura, 1977). This paper contributes to the existing literature by highlighting the antecedents of innovation resistance in terms of experiential, social, and psychological processes. Internet banking services were the focus of this investigation because such services represent a widely used innovation in the financial industry that has been investigated by TAM researchers since 1999 (Hanafizadeh et al., 2014). Internet banking, as type of financial service, involves security issues and a degree of technical complexity that may constitute barriers promoting innovation resistance.

The remainder of this article is presented as follows. The next section reviews the literature on innovation resistance, barriers to adoption, social influence, experience, and social learning. This is followed by an outline of our conceptual model and our hypotheses. Subsequently, our methodology and results are presented. Finally, the theoretical and practical implications of the findings are discussed.

2. Conceptual background and hypotheses

2.1. Innovation resistance and barriers

Innovation, which always involves change and a threat to the status quo, tends to provoke resistance, which reduces willingness to adopt new products (Heidenreich and Handrich, 2015). Ram (1987) defined innovation resistance as the resistance offered by consumers to the changes imposed by innovations. The innovation diffusion process consists of five stages: (1) knowledge, (2) persuasion, (3) decisions, (4) implementation, and (5) confirmation (Rogers, 2003), and it has been assumed that innovation resistance results from negative evaluations of services and products that emerge in the persuasion stage or afterwards (Talke and Heidenreich, 2014).

There are two types of innovation resistance: ‘active innovation resistance’ and ‘passive innovation resistance’. The former involves the formation of a negative attitude based on the functional and psychological barriers that are identified during the deliberate evaluation of a new product, whereas the latter is regarded as a tendency to resist innovations due to personality-specific inclinations to resist change (Heidenreich and

Handrich, 2015; Patsiotis et al., 2013).

Innovation resistance, especially active resistance, results primarily from functional and psychological barriers (Ram and Sheth, 1989; Talke and Heidenreich, 2014). Functional barriers arise when consumers consider product attributes as inappropriate or insufficient for their personal expectations, whereas psychological barriers arise when the innovation conflicts with consumers' social norms, values, or usage patterns (Talke and Heidenreich, 2014). Both the functional and psychological dimensions of barriers are considered important contributors to innovation resistance. This study treats complexity barriers and performance risk barriers as functional barriers, and existing usage patterns as psychological barriers. Complexity barriers emerge when a perception of innovation is associated with unease regarding use and/or difficulty in comprehension (Talke and Heidenreich, 2014), whereas performance risk barriers refer to the possibility that the product will not work according to expectations and/or will not supply ideal benefits (Grewal et al., 1994). Existing usage patterns are described as habitually consistent behavior formed after a service/product has been adopted over a long period of time (Kleijnen et al., 2009). As the term ‘usage barriers’ has been used to imply both barriers of complexity (Laukkanen, 2016) and existing usage patterns (Heidenreich and Kraemer, 2016; Ram and Sheth, 1989), we avoided using this term to pinpoint the idea of “unease regarding use”. Following Heidenreich and Handrich (2015), we operationally define existing usage patterns as satisfaction with existing services.

Our decision to focus on these barriers in this study was based on the following considerations. First, the causal model underpinning TAM consists of the beliefs, attitudes, behavioral intentions, and actual behaviors of individuals in the context of accepting technology (Davis et al., 1989). It is based on the theory of reasoned action (TRA) (Ajzen and Fishbein, 1980), which holds that an individual's behavioral intention to perform a particular behavior is informed by that person's attitude (Lee, 2012). Davis et al. (1989) developed measures of perceived usefulness and perceived ease of use based on the assumption that attitudes and behavioral intentions underpin these phenomena. It can be said that lower degrees of perceived usefulness and lower perceived ease of use may imply enhanced performance risk barriers and complexity barriers.

Beliefs about perceived usefulness and perceived ease of use have been treated as variables of interest in attempts to explain acceptance of perceived newness (e.g., Davis, 1989; Roy et al., 2018; Wells et al., 2010). Previous studies on the acceptance of Internet banking services have also indicated that perceived risk and ease of use affected intentions to use these services (Chaouali et al., 2016; Kuisma et al., 2007; Laukkanen, 2016; Lee et al., 2012; Patsiotis et al., 2013). Studies based on the TAM imply that innovation resistance occurs when individuals fail to perceive the usefulness and ease of use of new products and services, which suggests an enhanced degree of complexity and performance risk barriers.

As mentioned above, this study conceptualized an existing usage pattern as an individual's satisfaction with existing services. Indeed, many consumers follow routines and habitual behavior patterns arising from frequently using a product or a service over a long period of time, and this may lead to innovation resistance (Hurmerinta and Sandberg, 2015; Laukkanen, 2016; Lee, 2012). For example, Kuisma et al. (2007) suggest that the habit of using automatic teller machines (ATMs) can inhibit use of the Internet to perform banking-related tasks.

2.2. Social influence

Social or interpersonal influence is a significant determinant of consumer attitudes or behaviors (Bearden et al., 1989). Social influence refers to the extent to which members of a social network influence one another's attitudes or behaviors (Rice et al., 1990; Venkatesh and Brown, 2001). Cialdini and Goldstein (2004) explained social influence in the context of the importance of forming accurate perceptions of reality and reacting accordingly and of developing social relationships and maintaining a favorable self-concept. Slade et al. (2007) found that individuals tend to consult their social network when adopting new technologies and note that they are influenced by the perceived social pressure emanating from important others. Chaouali et al. (2016) also reported that social influence had positive impacts on the intention to adopt Internet banking on the basis of trust. Further, importantly, Kleijnen et al. (2009) stated that consumer decision processes are significantly affected by peer observation, and that so-called socially-unaccepted innovation users may be forced to isolate themselves from their social group when there is insufficient social support.

According to interpersonal influence theory, social influence can be classified into informational and normative (Deutsch and Gerard, 1955; Yi et al., 2013). Normative social influence refers to influence that promotes conformity with the positive expectations of another, whereas informational social influence is defined as influence that promotes acceptance of information provided by another person as evidence about reality (Deutsch and Gerard, 1955). According to Mangleburg et al. (2004), reference groups exert influence on consumer behaviors by establishing normative standards of conduct (i.e., normative influence), by improving an individual's self-image (i.e., normative influence), and by providing information in ambiguous situations (i.e., informational influence).

Previous empirical studies have reported that social or interpersonal influence affect consumer attitudes and behavioral intentions (Thomas and Vinuales, 2017), citizenship behaviors (Yi et al., 2013), decisions about the social media on which to rely (Messing and Westwood, 2014), online shopping intentions (Lian and Yen, 2014), usage of brands (Escalas and Bettman, 2005), and intentions to use mobile payment options (Slade et al., 2007).

Informational social influence is closely associated with Bandura's (1977) social learning theory, according to which self-efficacy plays an important role in changing fearful and avoidant behavior. Expectations of personal efficacy are derived from four major sources of information: performance accomplishments, vicarious experiences, attempts at verbal persuasion, and emotional arousal (physiological states) (Bandura, 1977). Of these four sources, vicarious experiences and verbal persuasion are most relevant to social or personal influence. Specifically, consumers' resistance to innovative products or services may decrease when they observe others' adoption of these products or services in the absence of unfavorable consequence or when others encourage them to adopt such products or services. Im et al. (2007) found that consumer innovativeness influences adoption behavior through the social learning process. Based on social learning theory, it is predicted that social influence reduces innovation resistance through lowering complexity risk, performance risk, and existing usage patterns.

On the other hand, normative social influence or conformity pressure involve pressure to comply with the positive expectations of others (Bearden and Rose, 1990; Mangleburg et al., 2004). According to Mangleburg et al. (2004), normative social influence includes 'utilitarian influence', which arises when others can observe the behavior and have the ability to mediate rewards and punishments, and 'value-expressive influence', which occurs when members of a social group affect an individual's self-concept.

It should be noted that informational and normative social influences have different effects on responses to new products or services. For example, Li (2013) reported that informational social influence affects cognitive responses with regard to such issues as perceived usefulness and ease of use, whereas normative social influence impacts affective or emotional responses to a given situation.

Based on this argument, we predict that normative social influence directly reduces innovation resistance, whereas informational social influence indirectly reduces innovation resistance through the mediation of perceived usage, risk, and existing usage patterns.

2.3. Experience and social learning

It is important to note that innovation resistance can arise even after new services have been experienced or adopted. For example, Datta et al. (2015) note that recipients of free trials are more likely to rely on their usage behavior when deciding whether to retain the service or product in question; thus, it is crucial that firms attempt to retain customers who have been recruited via an offer of a free trial.

Nevertheless, trialability, or the degree to which an innovation may be experimented with before adoption, is one of the factors that influence adoption of products or services (Rogers, 2003; Moore and Benbasat, 1991). Meuter et al. (2005) suggest that, because trial use leads to repeated use and commitment, a key barrier to the adoption of new technologies is the difficulty of getting customers to actually try the technologies for the first time. Patsiotis et al. (2013) also suggest that the lack of trial opportunities may inhibit the adoption of Internet banking.

According to cognitive dissonance theory, the beliefs formed after using a product or service may differ from those in force before use (Karahanna et al., 1999). Karahanna et al. (1999) stress the importance of distinguishing pre-adoption from post-adoption behavior when investigating the technology adoption process because pre-adoption beliefs are formed mainly by indirect experience, whereas post-adoption beliefs are developed on the basis of direct experience.

In a similar vein, Venkatesh et al. (2003) suggest that experience plays an important moderating role in the TAM and report that the effect of social influence on behavioral intentions about using new technology is stronger among those with limited experience of the technology in question. Thompson et al. (1994) also reported that the influence of social factors on the utilization of new technology is greater for inexperienced than for experienced users.

However, based on social learning theory (Bandura, 1977), we would expect that experienced consumers, who have had direct experience with new services, would be better able to understand information provided by others than would non-experienced consumers, who learn about the services only vicariously or who are the targets of verbal persuasion. In other words, it may be easier for experienced than non-experienced consumers to perceive the usefulness and ease of use of new services. Based on this argument, the effect of social influence on innovation resistance may differ among experienced and non-experience consumers. We propose the following hypotheses regarding the relationship between social influence and innovation resistance, taking into consideration the moderating effect of experience.

2.4. Hypotheses

Fig. 1 shows the conceptual model developed based on the foregoing argument. With regard to normative social influences, experienced consumers will be less affected by conformity pressure from others compared with non-experienced consumers because experienced consumers have already used the service. In contrast, non-experienced consumers may feel more conformity pressure from others who have used the new services. Following the results of prior studies (Thompson et al., 1994; Venkatesh et al., 2003), we predict that social influence is associated with a stronger direct reduction in innovation resistance among non-experienced than among experienced consumers. Therefore, we propose the following hypothesis:

H1.. The negative effect of social influence on innovation resistance is less among experienced consumers than it is among non-experienced consumers.

According to social learning theory (Bandura, 1977), personal efficacy is determined by performance accomplishments, vicarious experiences, verbal persuasion, and emotional arousal. As experienced consumers have direct experiences with accomplishments, they are more able to appreciate the meaning of suggestions or advice regarding the ease of use and usefulness of new services than are non-experienced consumers, who must learn about the services indirectly. In other words, experienced consumers are able to evaluate the new service better than non-experienced consumers because the former can combine their own direct experience with the indirect experience garnered from others' accounts and suggestions. Based on this argument, we predict that, by lowering barriers related to perceived usefulness and ease of use, social influence is associated with a stronger reduction in innovation resistance among experienced consumers than among non-experienced consumers. Thus, we propose the following hypotheses:

H2.. The negative effect of social influence on innovation resistance, as partially mediated by complexity barriers, is stronger among experienced consumers than among non-experienced consumers.

H3.. The negative effect of social influence on innovation resistance, as partially mediated through performance risk barriers, is stronger among experienced consumers than among non-experienced consumers.

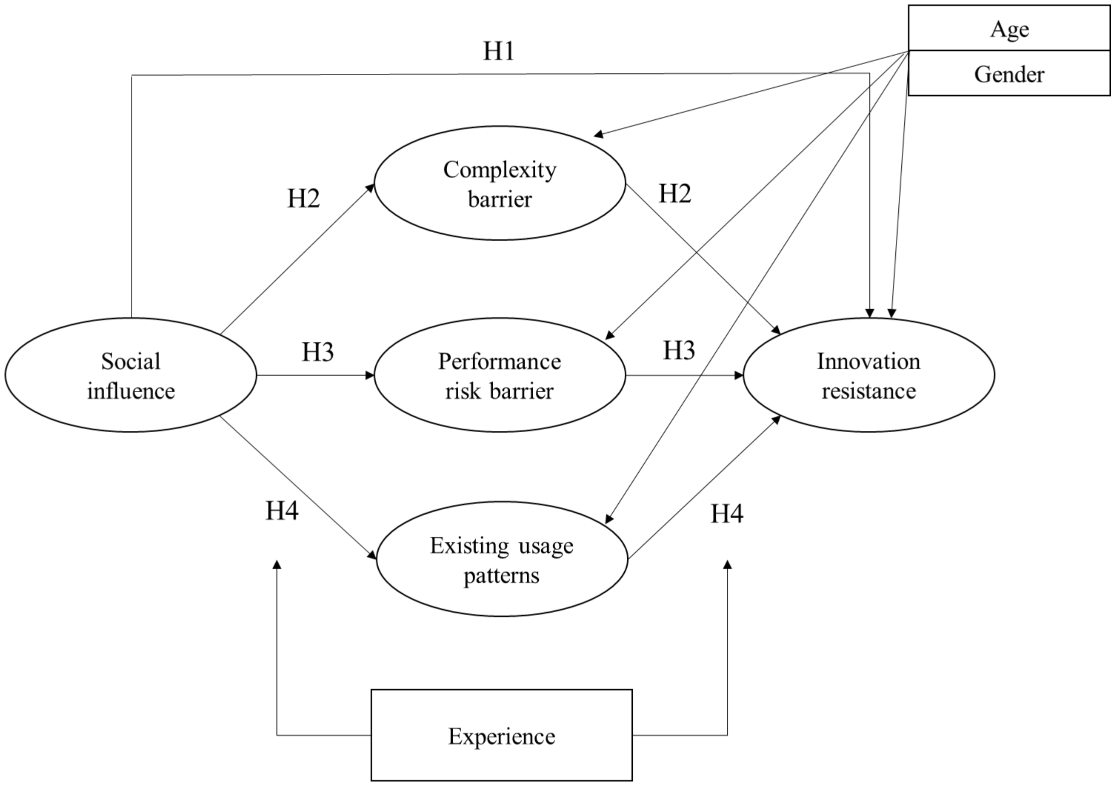


Fig. 1. Conceptual model.

We predict that existing usage patterns, or satisfaction with existing services, may be reduced by social influence. As experienced consumers have much more information on new services through direct experience, it is easier for them to evaluate the new services by comparing them with existing ones. In contrast, it is difficult for non-experienced consumers to assess the relative advantages of Internet and conventional bank services. Therefore, we propose the following hypothesis:

H4.. The negative effect of social influence on innovation resistance, as partially mediated by existing usage patterns, is stronger among experienced consumers than among non-experienced consumers.

Based on the hypotheses presented above, we propose the conceptual framework shown in Fig. 1.

3. Method

3.1. Data collection and sample

To test these hypotheses, data were collected from Japanese consumers with experience using Internet banking services as well as from consumers who do not have such experience. The decision to focus on Internet banking services is partially motivated by our goal of testing the moderating effect of use experience on the relationship between social influence and innovation resistance. As the coverage ratio of Internet banking services is about 60% in Japan (MyVoice Communications, 2017), these services are appropriate for examining differences in consumers' attitudes toward service innovation. Indeed, Internet banking services have often been investigated in research regarding the adoption of new services (e.g., Martins et al., 2014; Xue et al., 2011).

The online survey research was performed by a marketing research company in Japan, in October 2017. Potential respondents were recruited by the company from their professional research pool, consisting of individuals in various occupations; all respondents were aged between 20 and 69 years. Online surveys administrated by marketing research companies have been used in prior studies on technology acceptance (e.g., Parry et al., 2012). One advantage of this procedure is its ability to collect data from individuals in a broad range of occupational roles (Holland et al., 2013). Among the 626 respondents who generated usable responses, 313 had experience using Internet banking services, and 313 had not had such experience. Respondents consisted of 312 males and 314 females. Additionally, among all respondents, 86 were in their 20 s, 95 were in their 30 s, and the rest were over 40.

The sample includes 312 males (49.8%) and 314 females (50.2%), and 15.5% aged 20–29 years, 19.3% aged 30–39 years, 23.3% aged 40–49 years, 19.2% aged 50–59 years, and 22.7% aged 60–69 years. According to the national census of Japan (Statistics Bureau of Japan, 2017), the Japanese population consists of 48.7% males and 51.3% females. The age distribution is as follows: 15.7% aged 20–29 years, 18.8% aged 30–39 years, 23.7% aged 40–49 years, 19.7% aged 50–59 years, and 22.2% aged 60–69 years. Therefore, in terms of gender and age, the research sample is more or less identical to the national population. More detailed information on sample characteristics is shown in Table 1. According to chi-square testing, no statistically significant differences were found between experienced and non-experienced consumers with regard to gender and age, whereas experienced consumers report more income than do non-experienced consumers ($\chi^2 = 13.38$, $p<0.05$). The proportion of business employees is higher and that of housewives/househusbands is lower among experienced consumers than among non-experienced consumers ($\chi^2 = 15.13$, $p<0.05$).

3.2. Measures

As this study uses measures adapted from previously published studies, to mitigate discrepancies between the original and the translated questionnaires, back-translation was performed following the procedure recommended by Douglas and Craig (2006). First, the original English versions of the scales were translated into Japanese by one of the authors. Then, a bilingual language professional translated them back into English. The translated Japanese items were revised if any discrepancies were found. After completing the back-translation, the wordings are revised to fit the context of Internet banking services without changing the meaning of the originals. The revised items are checked by a bilingual language professional.

Social influence was measured with the three items adopted from Lian and Yen (2014). Each item was rated on a five-point scale from (1) strongly disagree to (5) strongly agree. The score for each item was used as an observable variable (average variance extracted (AVE) = 0.67, CR = 0.80).

Complexity barriers were measured with the four items adopted from Laukkanen (2016). Each item was rated on a five-point scale from (1) strongly disagree to (5) strongly agree. The score for each item was used as an observable variable (AVE = 0.76, CR = 0.90).

Performance risk barriers were measured with the three items adopted from Heidenreich and Kramer (2016). Each item was rated on a five-point scale from (1) strongly disagree to (5) strongly agree. The score for each item was used as an observable variable (AVE = 0.73, CR = 0.86).

Existing usage patterns were measured with the three items derived from Heidenreich and Handrich (2015). Each item was rated on a five-point scale from (1) strongly disagree to (5) strongly agree. The score for each item was used as an observable variable (AVE = 0.77, CR = 0.88).

Innovation resistance was measured with the six items adopted from Cho and Chang (2008). Each item is rated on a five-point scale ranging from (1) strongly disagree to (5) strongly agree. The score for each item was used as an observable variable (AVE = 0.55, CR = 0.80).

Experience was measured by asking, “Do you have experience using Internet banking?” The multigroup structural equation modeling was conducted using the dichotomous variable (experience = 1, non-experience = 0).

Control variables are included in the model: dichotomous dummy variables for gender (1= male, 2= female) and age (1= 20 s, 2= 30 s, 3= 40 s, 4= 50 s, and 5= 60 s). Gender and age were analyzed as control variables because they may influence consumer acceptance of internet banking (Martins et al., 2014).

Table 1

Characteristics of respondents (percent).

Item	Description	All	Experienced consumer	Non-experienced consumer
Gender	Female	50.2	50.2	50.2
	Male	49.8	49.8	49.8
Age	20–29	15.5	15.7	15.3
	30–39	19.3	19.2	19.5
	40–49	23.3	23.3	23.3
	50–59	19.2	19.2	19.2
	60–69	22.7	22.7	22.7
Occupation	Business employees	37.1	41.2	32.9
	Public servant	5.1	6.7	3.5
	Self-employed	7.5	6.7	8.3
	Part-time	16.0	15.0	16.9
	Unemployed	7.2	7.7	6.7
	Student	3.8	1.9	5.8
	Housewife/husband	20.4	17.9	23.0
	Other	2.9	2.9	2.9
Annual household income (Thousand yen)	Less than 1,999	8.0	39.3	50.4
	2,000–3,999	22.4	24.3	20.8
	4,000–5,999	25.6	18.0	9.8
	6,000–7,999	14.4	7.7	5.7
	More than 8,000	19.0	6.3	3.4
	unknown	10.5	4.4	9.8

3.3. Validation in measures

To assess the convergent and discriminant validity of the model constructs, we conducted a confirmatory factor analysis (CFA) with five latent learning constructs (social influence, complexity barriers, performance risk barriers, existing usage patterns, and innovation resistance) and a total of 19 items. The results show that all items are significant for the respective constructs ($p<0.001$), and the goodness-of-fit statistics for the model are as follows: χ^2 =514.07 (df = 142, $p<0.001$), comparative fit index (CFI)

=0.955, Tucker–Lewis index (TLI) =0.946, and root mean square error of approximation (RMSEA) = 0.065. All items significantly loaded on the assigned constructs, and the fit indices of the model are considered acceptable as per the cutoff value criteria in previous research (CFI & TLI < 0.90; RMSEA < 0.07) (Hu and Bentler, 1999; Lane et al., 2006). Additionally, the AVE and composite reliability (CR) exceeded 0.50 and 0.70, respectively, for all constructs, suggesting adequate convergent validity and internal consistency (Gefen et al., 2000). Next, the discriminant validity of the model is evaluated with a comparison of the AVE of each construct with the squared correlations between that construct and other constructs (Fornell and Larcker, 1981). Table 3 shows that the square root of AVE for each construct is larger than the correlation between any pair of constructs in the model. Thus, the discriminant validity of the instrument is established.

Because the data are self-reported and obtained from a single source, there is a possibility that the results suffer from common method bias. To address this issue, several diagnostic analyses are conducted. First, we apply Harman's one-factor method test. As shown in Table 2, the estimation of a single-factor model generates the following fit statistics: χ^2 =4320.7 (df = 152, p<0.001), CFI =0.498, TLI =0.435, and RMSEA =0.209. Table 2 also shows that the five-factor model fits the data much better than the single-factor, two-factor, three-factor, or four-factor models. These results indicate that the influence of common method bias has been minimized in this study (Podsakoff et al., 2003). Furthermore, we apply the partial correlation procedure proposed by Lindell and Whitney (2001). One item ('Little interest or pleasure in doing things') on the Depression Scale (Kroenke et al., 2009) is adopted as the theoretically unrelated marker variable. The effect of this variable is then partialled out from the relationships between social influence, complexity barriers, performance risk barriers, existing usage patterns, and innovation resistance. The original correlations matrix among variables is almost identical to the partial correlation matrix, suggesting that common method bias does not contaminate the results.

3.4. Measurement invariance

As our data consist of experienced and non-experienced consumers, measurement invariance must be assessed using multigroup confirmatory factor analysis (Steenkamp and Baumgartner, 1998). First, we focused on the configural invariance, assessing whether the same factor structures exist across different groups. The multigroup analysis of the baseline model in which no constraints were imposed on the parameters had acceptable fit indices ($\chi 2$ = 678.69, df = 284, p<0.001, CFI = 0.944, TLI = 0.932, and RMSEA = 0.047), indicating that the model exhibited configural invariance. Next, we tested the metric variance model, which constrained all the factor loadings to be equal between experienced and non-experienced samples. The results show that CFI (0.943) declined insubstantially (0.001). Considering the cut-off criteria (Cheung and Rensvold, 2002), full metric invariance was supported.

Table 2

Confirmatory factor analysis (CFA) results for measurement models.

Models	$\chi 2$	*df*	CFI	TLI	RMSEA
5-factor model	514.07	142	0.950	0.946	0.065
4-factor model	1699.34	146	0.813	0.781	0.130
3-factor model	3032.16	149	0.653	0.601	0.176
2-factor model	3725.31	151	0.569	0.512	0.195
1-factor model	4320.70	152	0.498	0.435	0.209

Note: N = 626. 5-factor model: Each variable was loaded on a single factor; 4-factor model: Usage barriers and performance risk barriers are loaded on one factor; 3-factor model: Usage barriers, performance risk barriers and tradition barriers are loaded on one factor; 2-factor model:Usage barriers, performance risk barriers, tradition barriers and social influence are loaded on one factor; 1-factor model: All variables are loaded on a single factor.

Table 3

Descriptive statistics and correlations.

	Mean	S.D.	CR	1	2	3	4	5	6	
1. Gender	1.50	0.50	-	-						
2. Age	46.07	13.68	-	-0.01	-					
3. Social influence	3.45	0.91	0.80	0.14 ***	-0.01	**.82**				
4. Complexity barriers	3.46	1.02	0.90	-0.01	-0.01	-0.45 ***	**.87**			
5. Performance risk barriers	2.79	0.94	0.86	-0.13 **	0.01	-0.27 ***	0.34 ***	**.85**		
6. Existing usage patterns	2.93	0.92	0.88	-0.11 **	0.06	-0.13 **	0.10 *	0.38 ***	**.88**	
7. Innovation resistance	3.15	0.84	0.80	-0.11 **	-0.02	-0.39 ***	0.53 ***	0.63 ***	0.40 ***	**.74**

Note: * $p <. 05$, ** $p < .01$, ** $p < .001$. The diagonal line shows the square root of AVE for each construct.

4. Results

Table 3 provides the descriptive statistics and the correlations among the variables. We perform several analyses to test the proposed conceptual model. First, to determine how experience moderated the causal relationships in the model, a multi-group structural equation modeling is performed by comparing the separate estimates between two groups (experienced and non-experienced consumers), and the critical ratios for differences are calculated to test the significance of differences (Table 4). A summary of the results is shown in Fig. 2, where the effects of gender and age are controlled. Next, to test the indirect effects, the bootstrapping estimates using 2000 random samples are calculated, and the results are interpreted using the 95% confidence interval (CI). To establish significance, the CI must exclude zero. Additionally, Sobel's (1982) tests are performed to determine the indirect effects. The existence of an indirect effect can be observed when the CI excludes zero in the bootstrapping and the Sobel test is significant.

Table 4

Structural model estimates (N = 626).

Structural path			Experienced consumer	Non-experienced consumer	Difference between the groups
Social influence	=>	Complexity barriers	-0.38 ***	-0.33 ***	0.20
Social influence	=>	Performance risk barriers	-0.23 ***	-0.11	1.14
Social influence	=>	Existing usage patterns	-0.11	-0.01	1.08
Social influence	=>	Innovation resistance	0.12 *	-0.15 **	-3.43 ***
Complexity barriers	=>	Innovation resistance	0.44 ***	0.13 *	-3.99 ***
Performance risk barriers	=>	Innovation resistance	0.55 ***	0.37 ***	-2.27 *
Existing usage patterns	=>	Innovation resistance	0.27 ***	0.26 ***	-0.25
Control variables					
Age	=>	Complexity barriers	-0.04	0.01	0.55
Age	=>	Performance risk barriers	0.07	-0.07	-1.72
Age	=>	Existing usage patterns	0.14 *	-0.02	-1.91
Age	=>	Innovation resistance	0.11 *	-0.20 ***	-4.61 ***
Gender	=>	Complexity barriers	-0.02	0.10	1.44
Gender	=>	Performance risk barriers	-0.13 *	-0.10	0.29
Gender	=>	Existing usage patterns	-0.10	-0.12 *	-0.38
Gender	=>	Innovation resistance	0.02	-0.11 *	-1.90

Note: * $p < .05$; ** $p < .01$; *** $p < .001$

CFI = 0.924; TLI= 0.909; RMSEA = 0.049

H1 states that the negative effect of social influence on innovation resistance is less among experienced consumers than among non-experienced consumers. As shown in Table 4 and Fig. 2, the results of the multi-group structural equation modeling indicate that social influence has a negative direct effect on innovation resistance among non-experienced consumers (-0.15, p<0.01), whereas it has a positive direct effect on innovation resistance among experienced consumers (0.12, p<0.05). The difference in the estimates is statistically significant (z=-3.43, p<0.001), and the results are consistent with H1; however, the positive relationship between social influence and innovation resistance among experienced consumers is unexpected. Thus, H1 is partially supported.

H2 states that the negative effect of social influence on innovation resistance, as partially mediated by complexity barriers, is stronger for experienced than for non-experienced consumers. The bootstrapping results indicate that the CIs for the indirect effect (social influence → complexity barriers → innovation resistance) exclude zero among experienced (indirect effect = −0.17, 95% CI [-0.24, −0.11]) and non-experienced (indirect effect = −0.04, 95% CI [-0.09, −0.01]) consumers. The results of Sobel tests are also significant for both subsamples (-4.71, $p<0.001$ for experienced consumers; −2.05, $p<0.05$ for non-experienced consumers). These results reflect a negative indirect effect of social influence on innovation resistance that is partially mediated through complexity barriers in both subsamples. Meanwhile, Table 4 shows that the effect of complexity barriers on innovation resistance is stronger among experienced (0.44, $p<0.001$) than among non-experienced (0.13, $p<0.05$) consumers. The difference in these estimates is statistically significant ($z=-3.43$, $p<0.001$), but there is not a significant difference between experienced and non-experienced consumers with regard to the effect of social influence on complexity barriers ($z=0.20$, ns). Therefore, the results partially support H2.

H3 states that the negative effect of social influence on innovation resistance, as partially mediated through performance risk barriers, is stronger among experienced than among non-experienced consumers. The bootstrapping results indicate that the CIs for the indirect effect (social influence → performance risk barriers → innovation resistance) exclude zero among both experienced (indirect effect = −0.12, 95% CI [-0.21, −0.05]) and non-experienced (indirect effect = −0.04, 95% CI [-0.09, −0.01]) consumers. However, the Sobel test results are significant for experienced consumers (-3.24, $p<0.01$) but not for non-experienced consumers (-1.78, ns). Table 4 also shows that the effect of performance risk barriers on innovation resistance is stronger among experienced (0.55, $p<0.001$) than among non-experienced (0.37, $p<0.05$) consumers and that the difference in the estimates is statistically significant ($z=-3.99$, $p<0.001$). These results suggest that the negative indirect effect of social influence on innovation resistance, as partially mediated through performance risk barriers, is stronger for experienced than for non-experienced consumers, which supports H3.

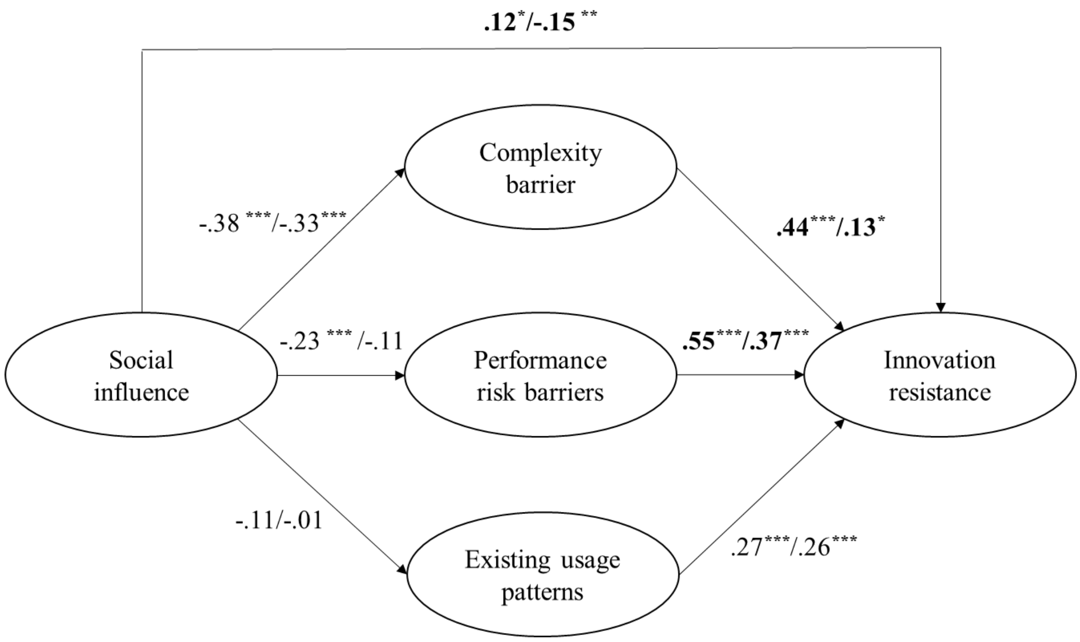
H4 states that the negative effect of social influence on innovation resistance, as partially mediated through existing usage patterns, is stronger for experienced than for non-experienced consumers. The bootstrapping results indicate that the CIs for the indirect effect (social influence → existing usage patterns → innovation resistance) include zero for both experienced (indirect effect = −0.03, 95% CI [-0.07, 0.01]) and for non-experienced (indirect effect = −0.01, 95% CI [-0.04, 0.03]) consumers. The Sobel test results are also not significant for experienced (-1.60, ns) and non-experienced (-0.13, ns) consumers. Table 4 shows that there are no significant differences in the estimates for experienced and non-experienced consumers with regard to the hypothesized relationship (social influence → existing usage patterns ($z=1.08$, ns); existing usage patterns → innovation resistance ($z=-0.25$, ns)). Therefore, H4 is not supported.

Table 5

Results of indirect effects based on bootstrap estimates and Sobel test.

Indirect effects	Estimate	Bias-corrected 95% CI		Sobel test
		Lower	Upper	
Experienced consumer				
SI => CB => RI	-0.17	-0.24	-0.11	-4.71 ***
SI => PRB => RI	-0.12	-0.21	-0.05	-3.24 **
SI => EUB => RI	-0.03	-0.07	0.01	-1.60
Non-experienced consumer				
SI => CB => RI	-0.04	-0.09	-0.01	-2.05 *
SI => PRB => RI	-0.04	-0.09	-0.01	-1.78
SI => EUB => RI	-0.01	-0.04	0.03	-0.13

Note. N = 626. Standardized estimates are reported. Bootstrap sample size = 2000. SI = social influence; CB = complexity barriers; PRB = performance risk barriers; EUB = existing usage patterns; RI = innovation resistance. *p < .05; **p < .01; ***p < .001.



Note: n = 626. Standardized coefficients are described (experienced/non-experienced). *p <.05; **p < .01; *** p < .001. Bold figures indicate significant difference between experienced and non-experienced consumer groups. The effects of age and gender were controlled but not shown.

Fig. 2. Multi-group structural equation modeling results.

5. Discussion

Despite its importance, there has been scant research on the effect of social influence on innovation resistance. Moreover, although the effect of social influence on innovation resistance may be moderated by experience, there has also been little research on this area. This study shows that social influence has direct and indirect effects on innovation resistance, that these effects are partially mediated through usage and performance risk barriers, and that experience moderates these relationships. The main contribution of this study to the literature involves its identification of the different effects by which social influence affects the innovation resistance of experienced and non-experienced consumers.

5.1. Theoretical implications

The findings of the present research extend the existing literature in four important ways. First, the results indicate that social influence directly reduces the innovation resistance of non-experienced consumers but that it directly enhances the innovation resistance of experienced consumers. This partially corresponds to the findings of previous studies (Thompson et al., 1994; Venkatesh et al., 2003), which report that the influence of social factors on the utilization of new technology is stronger for non-experienced users than for experienced users. These results can be interpreted in terms of normative social influence (Deutsch and Gerard, 1955; Li, 2013; Yi et al., 2013), which suggests that non-experienced consumers have less resistance to innovation (Internet banking services) because they may feel more conformity pressure from others than do experienced consumers, who have already used the new services. However, our finding that social influence enhances the innovation resistance of experienced consumers is unexpected. It is possible that experienced consumers may resent individuals who attempt to persuade them to continue to use new services. This corresponds to the findings of Algesheimer et al. (2005), who report that the effect of normative community pressure is stronger for knowledgeable consumers than for novice consumers and that normative community pressure enhances the resistance of individuals to pressure from their community.

Second, our results show that social influence reduces innovation resistance through usage and performance risk barriers more strongly for experienced than for non-experienced consumers. These results should be interpreted in the context of social learning theory (Bandura, 1977), which is closely related to theories of adoption behavior (Im et al., 2007). As Kanahanna et al. (1999) state, pre-adoption beliefs are formed based on indirect experience, whereas post-adoption beliefs are developed based on actual experience. Experienced consumers may be better able than non-experienced consumers to appreciate suggestions about the usefulness and usability of Internet banking services because the former have had direct experience using new services. In other words, experienced consumers may have more self-efficacy with regard to using Internet banking services insofar as they integrate the lessons learned from performance accomplishments with the vicarious experience of others.

Third, the aforementioned results indicate that social influence can either reduce or increase the innovation resistance of experienced consumers. This is consistent with the findings of Sridhar and Srinivasan (2012), who report that the effect of social influence on online word-of-mouth reviews depends on the product experience of consumers. As described above, the different effects can be explained by social influence theory (Deutsch and Gerard, 1955; Li, 2013; Yi et al., 2013) and social learning theory (Bandura, 1977). Informational social influence may reduce innovation resistance to new services by reducing cognitive responses (usage and performance barriers) more strongly when consumers have direct experience that can help them understand comments from others. Meanwhile, normative social influence may directly increase the innovation resistance resulting from normative pressures from others, leading to negative affective responses among experienced consumers with self-efficacy regarding making decisions about the use of services. One of the main contributions of this study is its identification of the moderating effect of experience on the relationship between social influence and innovation resistance in terms of social learning theory and social influence theory.

Finally, our results do not reflect an indirect effect of social influence on innovation resistance as mediated through existing usage patterns among either experienced or non-experienced consumers. Table 4 and Fig. 2 show that suggestions and comments regarding Internet banking services do not reduce satisfaction with existing banking services, regardless of respondents' experience with new services. This may relate to the fact that many consumers use both conventional and Internet banking services simultaneously, which means that Internet banking services are complements to, not substitutes for, conventional ones. Thus, Internet banking services do not lower satisfaction with conventional arrangements, and information on Internet banking services may not be related to evaluations of conventional banking services. However, examinations of new services that do replace existing services may reveal that social influence affects the strength of existing usage patterns.

5.2. Practical implications

The results of this study have practical implications regarding the efforts of service firms to reduce customer innovation resistance to new services. First, marketers should be aware that the informational aspects of social or interpersonal influence have stronger effects on the innovation resistance to new services among consumers with experience using such services. This may be because experienced consumers are able to understand suggestions from others based on their direct experience. Marketers should develop promotional programs in which existing customers share their experiences with the usefulness or ease of use of the services with other users and non-users in their circle of acquaintances, friends, and peers to retain existing customers and acquire new ones (Kawakami et al., 2012). For example, it may be effective to develop online customer communities by providing several platforms where users can exchange information on how to use services and products such as 'Lego user communities' (Antorini et al., 2012). (Table 5).

Second, our findings indicate that the direct effect of social influence on innovation resistance is negative among non-experienced consumers but positive among experienced consumers. These results suggest that normative conformity pressure is effective in reducing the innovation resistance of non-experienced consumers but is detrimental for experienced consumers. It is important for financial organizations to take different approaches in relation to experienced and non-experienced customers. In targeting non-experienced consumers, it may be important to create more exposure to advertising, including customer stories. If such users are aware of how others in their surroundings are reacting to the new services, their resistance is expected to be reduced as a result of vicarious learning. On the other hand, affiliate programs could be an effective approach to lessen the resistance of experienced consumers if such programs provide more opportunities for users to obtain information on complexity/usability and performance risks.

Finally, our study indicates that complexity barriers mediate the relationship between social influence and innovation resistance among both experienced and non-experienced consumers, suggesting that information about the ease of use of Internet banking services is important for reducing innovation resistance. Laukkanen et al. (2009) found that consumers who report functional resistance to Internet banking are dissatisfied with the information and guidance offered by the bank and proposed the development of communication strategies to reduce such resistance. Thus, marketers should provide appropriate information and guidance with regard to how to use Internet banking services so that existing customers can convey the information to acquaintances.

5.3. Limitations and future research

The limitations of the present research should be acknowledged. First, as the empirical analysis focuses on Internet banking services, it is possible that some of our findings are not generalizable to other service or product categories. Future research should test the conceptual model proposed here in other contexts.

Second, the present research includes complexity barriers, performance risk barriers, and existing usage patterns as mediators between social influence and innovation resistance. However, it is possible that other barriers, such as those involving image and values, also mediate this relationship.

Third, this study also addresses social influence; informational and normative social influence are not considered. To identify the effects of both types of social influence on innovation resistance, a revised conceptual model should be applied to distinguish information from normative social influence in future research.

Fourth, although the common sources of method bias are considered, these findings are based on cross-sectional data obtained from a single source. Thus, it would be desirable to conduct a longitudinal sur vey to replicate the conceptual model to establish causal relationships among variables.

Fifth, we used a dichotomous variable to measure ‘experience’. Since experience can be something of a spectrum, future research should measure experience as a continuous variable and examine its effect on relationships between social influence, barriers, and innovation resistance.

Sixth, experienced consumers reported more income than non-experienced consumers. Thus, it would be desirable to incorporate income levels into the research model in future studies.

Finally, the results of this study are based on data collected from Japanese consumers. The applicability of these findings to countries with cultures that differ from that of Japan should be explored. A multicultural comparison of the effect of social influence on innovation resistance would be an interesting topic for future research.

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