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Influencing factors of the extent, timing, and pattern of online insurance adoption

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ABSTRACT

This study investigates the influence of consumer traits, product attributes, marketing activities, and word of mouth (WOM) on three aspects of online insurance adoption: the number of products adopted, adoption timing, and adoption pattern. We empirically examine the relationships between these variables using data from 509 consumers collected through an online survey. The results from three statistical analyses suggest that consumers with low social needs, are price-conscious, and perceive fewer risks when buying on the Internet tend to purchase more online insurance products. Furthermore, products advertised on television and the Internet or perceived as having high premium variability are likely to have shorter adoption timing than other products. Moreover, the adoption of an insurance product appears contingent upon the type of insurance previously adopted and the attribute discrepancy between products. Finally, we discuss the managerial implications of our findings to increase the effectiveness of marketing efforts.

Keywords: Online insurance, consumer heterogeneity, adoption timing, adoption pattern, ordered-logit model.

1. INTRODUCTION

Despite the rapid adoption of online channels in various industries over a decade ago, many insurance industry agents were reluctant to follow this trend [1, 2]. However, recent market development has shown that the online insurance market in various countries has grown significantly and consistently. For example, anecdotal evidence suggests that the average annual growth rate of online insurance revenues in European countries was around 22% from 2000 to 2015, exceeding the overall insurance market, which is approximately 5% per year [3]. Similarly, Chinese insurance companies registered an approximately 37% annual growth rate in 2018, shaping a CNY 32.64 billion online insurance market in the country [4]. This trend is projected to persist in the foreseeable future due to an increase in the number of consumers purchasing

insurance products through online channels and the entry of pure online insurance companies into the market. As a result, while incumbent firms now have the opportunity to meet growing demand, they are simultaneously facing fierce competition [5]. Thus, insurance companies must better understand their target customers' adoption behavior of online insurance products.

Previous studies suggest that consumers' decisions to adopt online insurance are influenced by several factors, such as consumer traits and perceptions [2,6], marketing communication [7], insurance technology implementation [8], corporate trust or credibility [9, 10], and the system and informational quality provided by a firm [11]. However, we note some limitations in the extant literature concerning the recent trend in the online insurance market, in which consumers' adoption of multiple insurance products has become commonplace. First, although consumers appear to be heterogeneous in how they adopt online insurance products, it is currently unclear why some consumers adopt more products than others. We argue that addressing this issue will have valuable implications for marketers to promote their offerings better. More specifically, if marketers know which consumers are likely to adopt multiple products, marketing to this segment should improve efficiency. Second, to the best of our knowledge, no study has investigated the timing of the adoption of different online insurances and their influencing factors. Therefore, we have little understanding of which products will likely be adopted early by consumers and why. This knowledge would help marketers decide which products to sell to prospective customers. Third, it is unclear how a consumer decides which product to buy, given that he/she has purchased some insurance products online. Meanwhile, marketers in the industry are struggling to improve the efficiency of cross-selling activities. Thus, identifying factors that influence the adoption pattern of online insurance would be critical for enhancing consumer responses to such efforts.

This study aims to fill the gap in the literature. We specifically address the following questions: (1) how differences in the number of online insurance products adopted by consumers can be explained by their personality traits, including social need, price consciousness, perceived risk, and self-efficacy; (2) how the adoption timing of various online insurance products is affected by firms' marketing activities, WOM, and product attributes; and (3) how consumers' decisions to buy an additional insurance product are influenced by previously adopted products along with their attributes. We focus on six attributes: premium, complexity, premium variability, the policy period, claim likelihood, and insurance amount.

This study contributes to the literature in three ways. First, it clarifies how consumers differ in the number of online insurance products they adopt and how this can be attributed to their traits. This finding deepens our understanding of market consumer behavior and enables marketers to identify valuable customer segments. Second, it delineates the role of marketing and product attributes in governing the adoption timing of different insurance products, thereby providing insight into how marketers can use marketing tools to shorten their products' selling duration. Third, this

study helps us better understand the adoption pattern of multiple insurance products and how product attributes and current product ownership influence it. We argue that this finding can assist marketers in deciding which product to cross-sell to a customer with a given purchasing history.

2. LITERATURE REVIEW

2.1 Antecedents of online insurance adoption

Extant literature has shown that consumers' decisions to adopt online insurance are influenced by consumer perception, trust, and attitudes. Most studies adopted Ajzen's [12] theory of planned behavior (TPB) or Davis' [13] technology acceptance model (TAM) to delineate the effect of these antecedents. In either framework, consumers' intention to engage in that behavior is assumed to precede the adoption of online insurance. Several influencing factors of online insurance adoption are examined under this underlying mechanism regarding whether and how they induce behavioral intention. According to Lim et al. (2009), consumers' intention to adopt online insurance is positively influenced by their trust in the insurance product, service, and provider company [9]. These authors also demonstrate how an excellent web system and information quality can enhance these trust elements. Khare et al. [14] corroborated these findings by empirically showing that the reliability and security of an online insurance's technological attributes, such as informational and transactional systems, increase usage intention. However, these authors found an insignificant relationship between behavioral attention and service attributes. Based on TAM, Maheswari and Chandrasekaran [11] discovered that perceived benefits and technological attributes play a critical role in leading consumers to adopt online insurance.

A recent study by Yu and Chen [15] confirmed the importance of trust and further indicates that consumer perception of product uncertainty and online experience can affect consumer purchase intention. Using online travel insurance data, the authors discovered that consumers who perceive less product uncertainty and have more online usage experience exhibit a stronger intention to purchase the product. Luo et al. [16] scrutinized the role of trust in inducing purchase intention by decomposing the construct's effect into that stemming from the perceived insurer's ability and integrity. The two dimensions of trust have been shown to affect purchase intention significantly and appear to be determined by company reputation, system quality, cooperation, financial risk, and benefit. Drawing on TPB, Ettis and Haddad [17] found that the perceived hedonic and utilitarian benefits of an online insurance product positively influence consumer attitude and, as a result, enhance behavioral intention to use it. Toukabri and Ettis [6] developed and empirically tested a framework based on TPB and TAM; they confirmed that perceived ease of use, subjective norms, perceived behavioral control, and attitude toward online insurance adoption all had significant and positive effects.

While extant studies have contributed to a conceptual understanding of why consumers adopt online insurance, their focus has been limited to behavioral intention. Moreover, as the life cycle of online insurance enters the growth stage [3], many consumers purchase multiple insurance products through online channels. Thus, the literature has yet to delineate why some consumers adopt more products than others. In this regard, this study builds on previous research by identifying factors that may explain the heterogeneity in the number of insurance products adopted by consumers.

2.2 Adoption timing

The scientific literature is replete with studies on the timing of innovation adoption. Typically, adoption timing is conceptualized as the time elapsed between the introduction of a product and its adoption by a consumer. In his seminal work, Rogers [18] posits that innovation adoption timing is influenced by the social system, communication, and the innovation's characteristics, including relative advantage, compatibility, complexity, trialability, and observability. He further contends that adoption timing varies depending on an individual's perceived risks, social status, financial liquidity, and social orientation. The difference in these characteristics leads to the classification of consumers as innovators, early adopters, early majority, late majority, and laggards. Bemmaor [19] observes the role of individual traits in governing adoption timing, modeling consumers as either independent or imitative adopters. Similarly, Shabanpour et al. [20] confirm the positive effect of socio-demographic factors, technology awareness, and innovation perceptions on consumers' decisions to buy a new product.

Another research stream has attempted to elucidate the role of interpersonal communication in accelerating innovation adoption. For example, Bilgicer et al. [21] demonstrate that social contagion plays a crucial role in the timing of new sales channels, although its effect appears to be less prominent for long-tenured customers. Furthermore, Bemmaor [19] suggests that WOM can motivate imitating behavior and accelerate the diffusion of a new product. Vilpponen et al. [22] highlight that the extent of such social communication effects is contingent upon the social network structure; specifically, the effects are more salient in highly centralized networks. Previous studies have also shown that a new product's adoption timing is contingent upon consumer evaluation or preference for its attributes [23-25]. For example, Sachdeva et al. [25] show that the continuation time of a new product in the market positively affects its diffusion, while its price appears to have a negative effect. Noppers et al. [24] find that certain symbolic attributes of a new product can accelerate consumer adoption. More importantly, studies report that marketing efforts can expedite a new product's adoption timing [25-27]. Prins and Verhoef [26] demonstrate that advertising and direct mail activities reduce the time required for new service adoption. Interestingly, they also report that advertisements launched by competitors could have the same effect. Foubert and Gijsbrechts [27] provide evidence that free trials increase consumer affinity for a new product, resulting in early consumer adoption.

In essence, individual characteristics, product attributes, social communication, and marketing activities can affect the adoption timing of a new product or service. However, to the best of our knowledge, no study has investigated the effect of these factors on the adoption timing of online insurance products. We address this issue by focusing on the effects of mass, direct marketing, WOM, and product characteristics. In contrast to previous studies, we conceptualize adoption timing as the order in which consumers purchase one or multiple insurance products.

2.3 Adoption pattern

Cross-selling literature can provide a conceptual understanding of the adoption pattern of multiple products or services. Focusing on financial services, Kamakura et al. [28] show that given current product ownership, a customer's decision on which service to purchase next is influenced primarily by the customer's financial maturity and the attributes (termed as "difficulty") of the services being considered. The basic premise is that the probability of adopting a more complex financial service increases as a customer progresses along the maturity continuum. Furthermore, the likelihood of purchasing an additional service is positively influenced by the similarity between the service and those previously purchased. Subsequent studies have confirmed that a service's adoption depends on currently owned services [e.g., 29-31]. Knott et al. [29] suggest that in addition to product similarity, a customer's monetary value and demographic information can be used to predict which product they will purchase next. This might be because customers with similar monetary values or demographics require the same product. According to Li et al. [32], demographic variables such as sex, age, and education are instrumental in predicting customers' purchase of additional financial services. We examine how consumer ownership of online insurance products and their attributes affect the likelihood of a product being purchased by consumers.

3. ANALYTICAL FRAMEWORK AND HYPOTHESES

3.1 Conceptual Model

The conceptual model of this study is depicted in Figure 1. Three dependent variables related to the adoption of online insurance are central to the model: the number of adopted products, adoption timing, and adoption pattern. Herein, we attempt to explain the variability of these variables among consumers and products by using several sets of independent variables. We analyze how four individual traits influence the number of products consumers adopt: social need, price consciousness, perceived risk, and self-efficacy. We also controlled for the effect of three consumer demographic variables in the analysis (i.e., sex, age, and marital status). Adoption timing refers to the order in which an online insurance product is adopted by a consumer (i.e., first, second, and so on). Herein, we consider the adoption timing of six insurance products: life, health, cancer, car, property, and pension insurance. The variability of adoption timing across these products is explained by using variables such as marketing activities (advertising, direct marketing, social media marketing), WOM, and product attributes.

We consider an insurance category's premium, complexity, premium variability, the policy period, claim likelihood, and insurance amount perceived by consumers for product attributes. Lastly, by adoption pattern, we specifically refer to consumers' purchasing behavior of a specific insurance product if they have previously adopted some other products. We examine how previously adopted products and their attributes can explain these patterns.

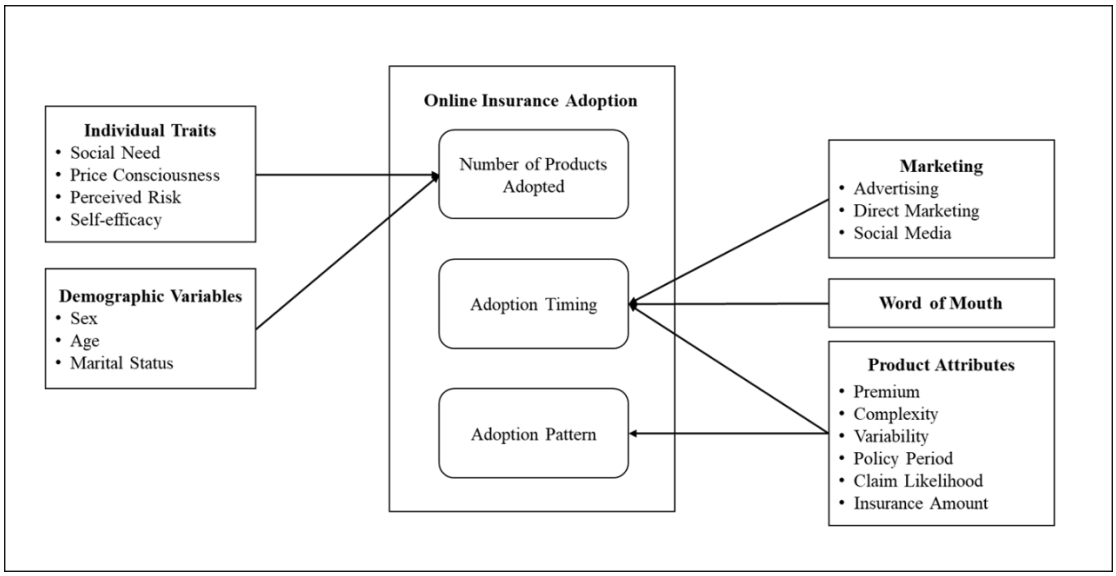

Figure 1. Conceptual model

3.2 Hypothesis development

3.2.1 Social need

Social need refers to the basic human need for love, acceptance, and belonging [33]. It motivates people to connect with others and recognizes them as members of a group or society [34]. Thus, individuals with a strong social need are eager to develop and maintain their interactions with others. The literature indicates that this construct is positively associated with extraversion traits [35,36], implying that individuals with high social needs have a high degree of sociability, activity, assertiveness, and positive emotionality. Similarly, extroverts have been shown to have sociable, outgoing, interactive, assertive, talkative, outspoken, open, and energetic personalities [37, 38]. According to some researchers, extraversion positively affects the intensity and quality of social interactions because it allows individuals to adapt themselves when interacting with people they are unfamiliar with [39, 40]. Furthermore, extroverts are highly motivated to seek excitement and pleasure from interacting with others as they have a great interest in self-disclosure and conspicuous self-presentation [41,42].

Based on these findings, we anticipate that consumers with a high social need are more likely to purchase insurance products through traditional channels than those with a low social need. This is because purchasing insurance products from traditional channels necessitates intense interactions between consumers and salespersons. Consumers with a high social need may find such interactions pleasing or exciting because they allow them to communicate with others and engage in self-disclosure

behavior [36]. In contrast, consumers with low social needs are expected to prefer online channels as they can purchase an insurance product without interacting with an unfamiliar salesperson. Hence, we predict the following relationship.

Hypothesis 1: Social needs negatively influence the number of online insurance products adopted by consumers.

3.2.2 Price consciousness

Price consciousness can be defined as the degree to which consumers are concerned with paying low prices [e.g., 43]. It describes consumers' aversion to buying high-priced products. A previous study indicates that this construct is positively associated with perceived product uncertainty and price unfairness while negatively associated with perceived price-quality correlation [44]. Price-conscious consumers generally have lower reservation prices, the maximum price they are willing to pay for a product [45]. These consumers also have low search costs, making them less reluctant to spend time researching the best alternatives based on various sources [43, 46]. Moreover, it is evident that price consciousness negatively affects consumer loyalty to a brand or store [47]. Thus, price-conscious consumers are more likely to switch brands if they find a lower-cost alternative.

The primary selling point of online insurers is the financial benefit that consumers receive when purchasing an insurance product at a low price [48]. This is due to the absence of expenses allocated by online insurers to salesforce and physical store operations, which result in lower costs for the provision of online insurance products than traditional ones. Thus, because online insurance products are typically priced lower than their offline counterparts, price-conscious consumers are expected to prefer the former over the latter. As a result, these consumers are more likely than price-conscious consumers to buy insurance products online. Moreover, as the cost advantages of online insurance firms appear to be a common phenomenon for various types of insurance products, it is anticipated that price-conscious consumers will purchase a larger variety of insurance products through online channels than price-unconscious consumers. Hence, we anticipate the following effect:

Hypothesis 2: Price consciousness positively influences the number of online insurance products adopted by consumers.

3.2.3 Perceived risk

Perceived risk refers to the potential losses consumers perceive when buying a product through an online channel. The risks associated with online shopping stem primarily from a high degree of uncertainty associated with product performance, service delivery quality, privacy protection, and technical difficulties encountered during the buying process [49]. Consumers' perception of risks in the online insurance context may include the possibility of failure when searching for an appropriate insurer, developing an insurance policy, and filing a claim on their insurance. Previous studies have shown that perceived risk renders consumers more reluctant to buy a product from

an online channel or firm [46, 50]. In fact, evidence suggests that online shoppers are less likely to be risk-averse than those who frequently shop through traditional channels [51]. These findings suggest that consumers with a higher degree of perceived risk are less likely to adopt online insurance products than those with a lower degree of perceived risk. Hence, we anticipate that the former will adopt more online insurance products than the latter.

Hypothesis 3: Perceived risk negatively influences the number of insurance products adopted by consumers.

3.2.4 Self-efficacy

Self-efficacy refers to people's judgments or perceptions of their ability to organize and execute the courses of action required to attain a performance [52]. This perception can be developed in several ways, such as personal experiences, vicarious experiences, and persuasion by others. The extent of self-efficacy has been shown to determine how an individual approaches goals, tasks, and challenges [53]. Typically, individuals with high self-efficacy view complex tasks as challenges to overcome rather than threats to avoid. As a result, they have a high ability to utilize cognitive resources to deliberately resolve problems and sustain their efforts to achieve predetermined goals. Furthermore, such individuals tend to attribute failures that occur while performing a task to external, controllable causes rather than indigenous ones. In the context of new technology adoption, it is evident that self-efficacy positively influences an individual's intention to adopt and use new technology [54, 55]. For example, an early study by Compeau and Higgins [56] showed that self-efficacy is critical in encouraging people to use computers. In this regard, we argue that self-efficacy positively affects consumer decisions to adopt online insurance products. As purchasing online insurance products entails several challenging tasks (e.g., developing an insurance policy and settling a claim through the Internet), some consumers may consider it difficult to accomplish. However, these obstacles would be less influential for consumers with high self-efficacy, as they have the confidence to overcome such challenges. Thus, we anticipate that consumers with high self-efficacy will adopt more online insurance products than those with low self-efficacy.

Hypothesis 4: Self-efficacy positively influences the number of online insurance products adopted by consumers.

4. DATA DESCRIPTION

4.1 Sample and data collection

We collected data through an online survey administered by a marketing research company in Japan. The sample comprised 509 participants, of whom 335 were male (65.82%). Table 1 presents the participants' demographic information, including age and marital status. We asked respondents about their adoption of the six previously

described online insurance products. Furthermore, we asked those who had adopted at least two products about the order in which they had adopted them. As we do not have information on firms' marketing activities, we asked the respondents to rate how often they encounter the online insurance products' advertisements in various media, their information on social media, and WOM on a five-point scale (1 = not often, 5 = very often). Regarding product attributes, we asked respondents how they perceived the five attributes on a five-point scale (1 = strongly disagree, 5 = strongly agree). For example, one statement reads, "I think the insurance product's premium is high." Lastly, we asked them to rate several questions about their previously discussed personality traits on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree; see the Appendix). Social need was measured using seven items adapted from Alan and Kabadayı [57]. We modified the scale used by Dahana et al. [46] to measure price consciousness. The items used to measure perceived risk were taken from a study conducted by [49]. Finally, self-efficacy was measured using ten items adapted from San-Martín et al. [58].

Table 1. Sample descriptive statistic

	Sample Size	Percentage
Gender		
Men	335	65.82%
Women	174	34.18%
Age (years old)		
20-30	76	14.93%
31-40	77	15.13%
41-50	128	25.15%
51-60	114	22.40%
61-70	114	22.40%
Marital status		
Married	174	34.18%

4.2 Measurement model assessment

We assessed our constructs' reliability and validity (i.e., social need, price consciousness, perceived risk, and self-efficacy) by conducting an exploratory factor analysis to check whether the items converge to the intended constructs. The measurement model was evaluated based on the reliability of individual items, internal consistency between items, and the model's convergent and discriminant validity. We confirmed that all items correlated with the intended constructs by retaining the items with a factor loading greater than .50 (see Table 2). First, the measures' reliability was evaluated by computing Cronbach's alpha; we confirmed that the values were greater than .70, implying good internal consistency [59]. Next, we examine the measures' convergent validity using composite reliability and variance-extracted measures. As can be seen from Table 2, composite reliabilities were greater than .70, and all variance-

extracted measures were greater than .63, indicating convergent validity [60]. Finally, we tested discriminant validity by comparing the error-adjusted inter-construct correlations with their respective variance-extracted measures [61]. The results shown in Table 3 suggest that all correlations were less than the respective constructs' variance-extracted measures, indicating discriminant validity.

Table 2. Factor analysis results, Cronbach's alpha, composite reliability, and AVE

Item	Factor Loadings	Cronbach α	Composite Reliability	AVE
Social Need		0.82	0.82	0.68
SN1	0.83			
SN4	0.75			
SN6	0.82			
SN7	0.52			
Price Consciousness		0.76	0.76	0.65
PC3	0.50			
PC5	0.67			
PC6	0.74			
PC7	0.75			
Perceived Risks		0.83	0.83	0.63
PR1	0.52			
PR2	0.63			
PR3	0.54			
PR4	0.55			
PR5	0.66			
PR6	0.62			
PR7	0.65			
PR8	0.60			
PR9	0.62			
Self-Efficacy		0.83	0.83	0.66
SE1	0.62			
SE2	0.59			
SE3	0.66			
SE4	0.85			
SE5	0.63			
SE10	0.67			

Table 3. Discriminant validity of personal traits measurement

	(1)	(2)	(3)	(4)
(1) Social Needs	**0.68**	0.00	0.00	0.02
(2) Price Consciousness	0.00	**0.65**	0.02	0.35
(3) Perceived Risks	0.00	0.02	**0.63**	0.02
(4) Self-Efficacy	0.02	0.35	0.02	**0.66**

Notes: The diagonal elements are the average variance extracted, and the non-diagonal elements are between-construct correlations.

5. NUMBER OF ADOPTED PRODUCTS ANALYSIS

5.1 Outline

Our first analysis is intended to address how their individual traits can explain the variation in the number of online insurance products adopted by consumers. We analyzed the data to determine the number of products adopted by each consumer. Figure 2 depicts the distribution of this quantity among consumers. The majority of respondents adopted only one product (265 people), and the number of consumers decreased as the number of adopted products increased. Only 13 respondents adopted all six online insurance products. The figure indicates that while purchasing insurance products through online channels has become common, many adopters have only purchased one product. The following section describes a stochastic model that links the number of products adopted by consumers with their individual traits.

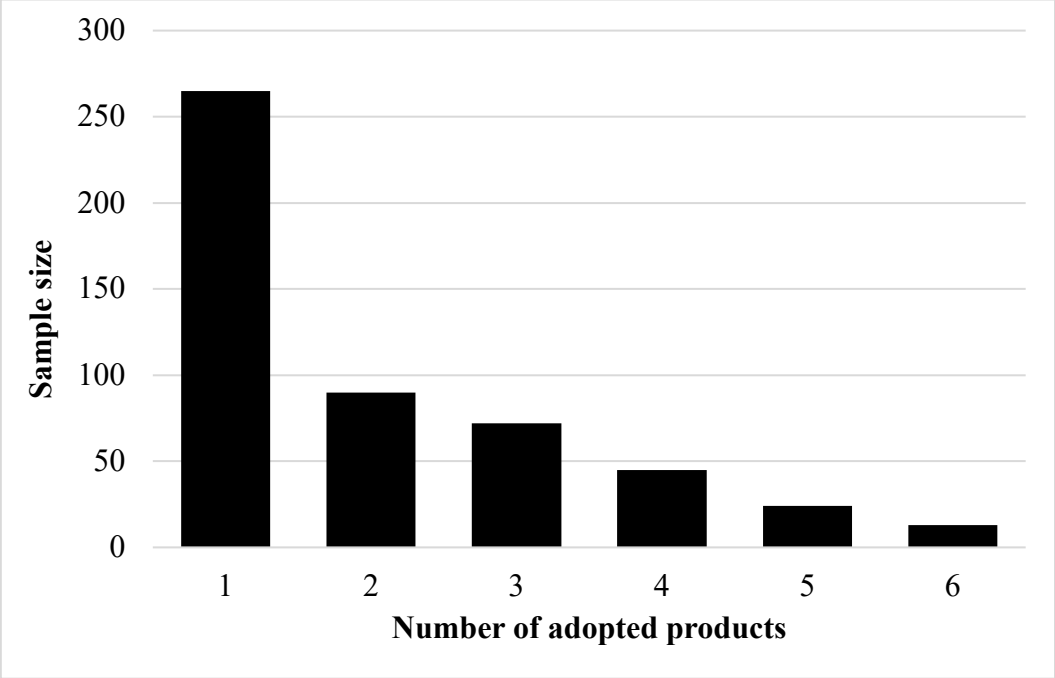

Figure 2. Distribution of the number of adopted products

5.2 Method

Let y_i $(y_i = 1,2,\cdots,6)$ be the number of online insurance products purchased by consumer i $(i = 1,2,\cdots,n)$. As y_i is a count variable, we employ a Poisson regression model to explain the variable's variation among consumers as follows:

$$f(y_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} \tag{1}$$

where $f(\cdot)$ is the probability density function of the Poisson distribution and λ_i denotes the distribution parameter. The link between y_i and the independent variables can be represented by the reparameterization of λ_i as follows:

$$\log(\lambda_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik}. \quad (2)$$

Here, $x_i = (1, x_{i1}, x_{i2}, \cdots, x_{ik})'$ is a vector of constant and independent variables, including the customer's individual traits (i.e., social need, price consciousness, perceived risk, and self-efficacy) and demographic variables (i.e., sex, age, and marital status). The effect of these variables is captured by the parameters $\beta = (\beta_0, \beta_1, \cdots, \beta_k)'$. We estimate the model using the maximum likelihood method, where the log-likelihood function is given by

$$\log L = -\sum_{i=1}^{n} \exp(x_i'\beta) + \sum_{i=1}^{n} y_i x_i'\beta - \sum_{i=1}^{n} \log(y_i!). \quad (3)$$

We confirmed the validity of this model specification by conducting a regression-based overdispersion test [62].

5.3 Results

Table 4. Estimation results of the Poisson regression analysis

	Estimate	z-value	p-value
(Intercept)	**0.57**	**2.47**	**0.01**
Social need	**−0.19**	**−5.03**	**0.00**
Price consciousness	**0.14**	**3.25**	**0.00**
Perceived risk	**−0.12**	**−3.15**	**0.00**
Self-efficacy	−0.02	−0.34	0.73
Sex (women)	**−0.21**	**−2.37**	**0.02**
Age	0.00	−0.93	0.35
Marital status (married)	**0.19**	**2.05**	**0.04**

Note: Bold indicates significant estimates at 95%.

The Poisson regression analysis results are shown in Table 4. The coefficient of social need is negative and significant ($\beta = -.19, p < .01$), implying that consumers with a higher social need adopt fewer products than those with a lower social need. Thus, hypothesis 1 is supported. The result for price consciousness shows that this trait positively affects the number of online insurance products adopted by consumers ($\beta = .14, p < .01$), providing support for hypothesis 2. The result for perceived risk was also significant but with a negative sign ($\beta = -.12, p < .01$), suggesting that this variable has a negative effect on the number of online insurance products adopted by consumers. Thus, we have support for hypothesis 3. In contrast, the effect of self-efficacy appears to be non-significant, indicating that this trait level is unlikely to influence the adoption of online insurance products. As a result of this finding, hypothesis 4 is rejected. Additionally, we observed significant results for some demographic variables. The coefficient of sex (women) is negative ($\beta = -.21, p < .05$), indicating that male customers tend to adopt more products than their female

counterparts. Similarly, the effect of marital status is positive and significant ($\beta = .19, p < .05$), suggesting that married consumers are more likely than single consumers to adopt more products. Lastly, the adoption of online insurance does not appear to be affected by a consumer's age ($\beta = 0.00, p = .35$).

6. ADOPTION TIMING ANALYSIS

6.1 Outline

The subsequent analysis examines how marketing communication activities, WOM, and product attributes influence online insurance product adoption timing. Figure 3 illustrates the data-driven timing of online insurance product adoption. As shown in the figure, car and life insurance tend to be adopted earlier than other products. Among those who purchased the products, a sizable proportion selected either car insurance (71.88%) or life insurance (65.10%) as their first online purchase. Furthermore, as a second product, consumers prefer to purchase health insurance (46.82%) or property insurance (24.73%). Moreover, it appears that it takes time for consumers to adopt cancer insurance and pension insurance, as the majority of those who purchased these products (i.e., cancer insurance 66.05%, pension insurance 62.50%) did so after adopting two other different products.

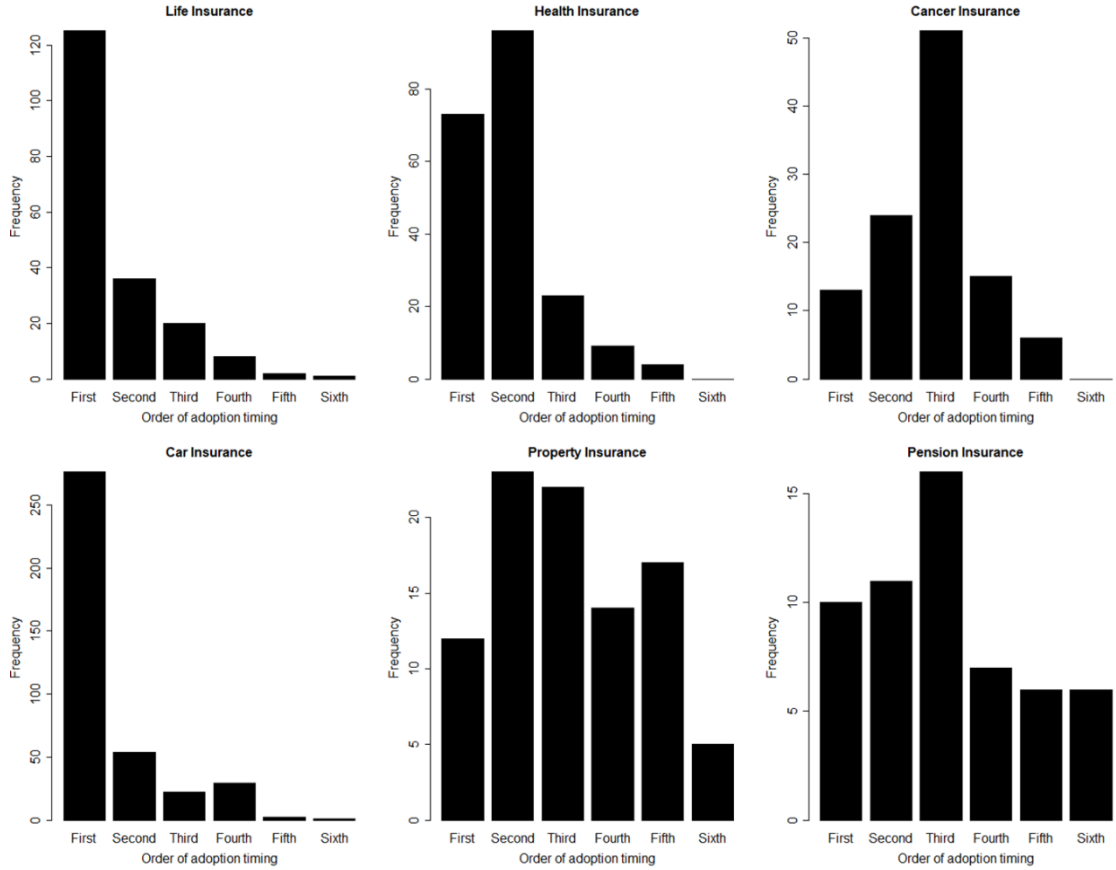

Figure 3. Adoption timing of each insurance product

6.2 Method

We use an ordered logit model to examine how a set of variables can explain the adoption timing of various online insurance products. Let Y_{ij} denote the observed adoption order of product j by consumer i, $(Y_{ij} = 1,2,\cdots,6)$. For example, if product j is the first product adopted by consumer i, then $Y_{ij} = 1$. Denoting a vector of independent variables by $x_{ij} = (1, x_{ij1}, \cdots, x_{ijk})'$, we define a latent variable y_{ij}^* as follows:

$$y_{ij}^* = \gamma_0 + \gamma_1 x_{i1} + \gamma_2 x_{i2} + \cdots + \gamma_k x_{ik} + \varepsilon_{ij}, \tag{4}$$

where $\gamma = (\gamma_0, \gamma_1, \cdots, \gamma_k)'$ is a vector of coefficient parameters, and ε_{ij} is a random error following an extreme value distribution. The link between the observed order and latent variables is given as follows:

$$\begin{gathered} Y_{ij} = 1 \;\Rightarrow\; y_{ij}^* \le \alpha_1, \\ Y_{ij} = m \;(m \in \{2,3,4,5\}) \;\Rightarrow\; \alpha_{m-1} < y_i^* \le \alpha_m \\ Y_i = 6 \;\Rightarrow\; y_i^* > \alpha_5 \end{gathered} \tag{5}$$

Here, $\alpha_1, \alpha_2, \cdots, \alpha_5$ are the cut-off point parameters to be estimated from data. Let δ_{ijm} be a dummy variable such that $\delta_{ijm} = 1$ if $Y_{ij} = m$, and $\delta_{ijm} = 0$ otherwise. The likelihood function is then given by:

$$\begin{aligned} L &= \prod_{i=1}^{n}\prod_{j=1}^{J}\prod_{m=1}^{6} P\left(Y_{ij} = m\right)^{\delta_{ijm}} \\ &= \prod_{i=1}^{n}\prod_{j=1}^{J}\prod_{m=1}^{6} \left(F\left(\alpha_m - x_{ij}'\gamma\right) - F\left(\alpha_{m-1} - x_{ij}'\gamma\right)\right)^{\delta_{ijm}}, \end{aligned} \tag{6}$$

where,

$$F\left(\alpha_m - x_{ij}^{'}\gamma\right) = \frac{\exp\left(\alpha_m - x_{ij}^{'}\gamma\right)}{1 + \exp\left(\alpha_m - x_{ij}^{'}\gamma\right)}. \tag{7}$$

We use the maximum likelihood method to estimate the model.

6.3 Results

The results of the ordered logit model are shown in Table 5. The coefficient of TV advertisements is negative and significant ($\gamma = -.15, p < .05$), suggesting that this marketing tool can accelerate the adoption of online insurance products. However, advertisement effects through vehicles such as newspapers, radio, and magazines appear to be non-significant (p-values ranging from .39 to .82). For Internet advertisements, we found that the result is significant with a negative sign ($\gamma = -.11, p < .05$); thus, if an online insurance product is heavily advertised on the Internet media, consumers will adopt it sooner. Furthermore, direct marketing activities do not seem to accelerate adoption timing, as the results for the flier ($\gamma = .01, p = .78$) and direct mail ($\gamma = -.07, p = .20$) are not significant. Similarly, we did not find a significant effect of social media marketing ($\gamma = -.01, p = .92$), as shown by the coefficient estimate of the variable. The results for the effect of WOM reveal that while online WOM can accelerate the adoption of an online insurance product ($\gamma = -.12, p < .05$), this is not the case for traditional WOM ($\gamma = -.07, p = .16$). Lastly, when we looked at the effect of product characteristics, we found that perceived premium variability was the only variable with a significant effect ($\gamma = -.18, p < .01$). The results suggest that the adoption timing of online insurance products is faster for those perceived as having a more heterogeneous pricing structure.

Table 5. Estimation results of the ordered logit regression

	Estimate	*t*-value	*p*-value
Advertising:			
Television	**−0.15**	**−2.79**	**0.01**
Newspaper	0.01	0.22	0.82
Radio	−0.04	−0.85	0.39
Magazine	−0.02	−0.35	0.73
Internet	**−0.11**	**−2.40**	**0.02**
Direct marketing:			
Flier	0.01	0.28	0.78
Direct mail	−0.07	−1.27	0.20
Social media	−0.01	−0.11	0.92
Word of mouth:			
Internet	**−0.12**	**−2.05**	**0.04**
Family/friends	−0.07	−1.42	0.16
Product characteristics:			
Premium	0.00	−0.10	0.92
Complexity	0.00	0.02	0.99
Variability	**−0.18**	**−4.12**	**0.00**
Policy Period	−0.07	−1.51	0.13
Claim Likelihood	0.04	0.85	0.40
Insurance Amount	0.02	0.38	0.70

Note: Bold indicates significant estimates at 95%.

7. ADOPTION PATTERN ANALYSIS

7.1 Outline

Our final analysis delineates consumer decisions regarding the next product to buy, given the adoption of a certain insurance product. As outlined earlier, our objective is to examine how adoption patterns are contingent upon the previously purchased product and product attributes. Table 6 provides model-free evidence of the adoption patterns observed in our data for various insurance products. For example, among those who purchased a life insurance product, seventy-eight consumers (57.78%) purchased a health insurance product, 16 consumers (11.85%) purchased a cancer insurance product, and so on. Those who purchased a health insurance product were more likely to make additional purchases of cancer and car insurance products. In addition, car insurance adopters appear to select property insurance as the next product to buy online.

However, the adoption patterns reported in Table 6 should be interpreted with caution because it is unclear whether the patterns are statistically significant and they ignore product characteristics. The next section discusses the model used to address this issue.

Table 6. Subsequent product purchased based on the previously purchased product

		Next Product Purchased					
		Life Insurance	Health Insurance	Cancer Insurance	Car Insurance	Property Insurance	Pension Insurance
Previously Purchased Product	Life Insurance	—	78	16	27	4	10
	Health Insurance	24	—	63	33	12	9
	Cancer Insurance	6	8	—	32	11	2
	Car Insurance	26	33	10	—	48	16
	Property Insurance	9	9	2	10	—	9
	Pension Insurance	2	4	5	6	6	—

7.2 Method

We employed a multinomial logit model to examine how the product a consumer previously purchased and the perceived characteristics of the products effect the adoption of an insurance product. Let y^*_{irs} denote the utility obtained by consumer i from purchasing product s after purchasing product r $(r, s = 1,2,\cdots,J)$. Further, we denote the m-th perceived attribute of products r and product s by x_{irm} and x_{ism}. We model adoption utility as follows:

$$y^*_{irs} = \theta_s + \theta_1 x^*_{is1} + \theta_2 x^*_{is2} + \cdots + \theta_k x^*_{isk} + \varepsilon_{irs}. \tag{8}$$

where $x^*_{ism} = x_{ism} - x_{irm}$. Parameter θ_s represents the intrinsic utility of purchasing product s and $\theta_1, \cdots, \theta_k$ are the coefficients capturing the effect of product attributes on purchasing behavior. The term ε_{irs} is a random error following an extreme-value distribution. Denoting the deterministic part of Equation (8) by v_{irs}, the probability that consumer i purchases product s after adopting product r is given by

$$P_i(s|r) = \frac{\exp(v_{irs})}{\sum_{j \neq r} \exp(v_{irj})}. \tag{9}$$

Defining $\delta_{irs} = 1$ if consumer i purchased product s after adopting product r and $\delta_{irs} = 0$ if otherwise, the likelihood function is given as follows:

$$L = \prod_{i=1}^{n}\prod_{s=1}^{J} P_i(s|r)^{\delta_{irs}} = \prod_{i=1}^{n}\prod_{s=1}^{J}\left(\frac{\exp(v_{is})}{\sum_{j\neq r}\exp(v_{ij})}\right)^{\delta_{irs}} \quad (10)$$

The maximum likelihood method is used to estimate the parameters.

7.3 Results

We report the estimation results of the multinomial logit model in Table 7. As can be seen, consumer decisions to buy insurance online likely depend on previously purchased products for some products. For example, consumers have a low likelihood of purchasing property insurance after purchasing a life insurance product ($\theta = -1.51, p < .10$). On the other hand, those who have purchased health insurance online have a high likelihood of adopting cancer insurance ($\theta = .74, p < .05$) and a low likelihood of adopting property insurance ($\theta = -.83, p < .05$) and pension insurance ($\theta = -.76, p < .05$). For pension insurance, we found that the results are all non-significant (p-values ranging from .34 to .93), suggesting that the adoption patterns do not depend on whether consumers have previously adopted a pension insurance product. We also found that the adoption patterns are, to some extent, explained by the characteristics of the products. For example, consumers tend to buy products they perceive as having less expensive premiums than the ones they previously adopted: life insurance ($\theta = -.20, p < .10$), health insurance ($\theta = -.21, p < .05$), and property insurance ($\theta = -.39, p < .05$). Furthermore, consumers who have adopted car insurance are likely to adopt a product with a higher claim likelihood (θ=.24,p<.05), while those who have adopted pension insurance have a higher probability of purchasing a product that is perceived to be more complex ($\theta = .47, p < .10$). Lastly, the adoption pattern does not appear to be affected by perceived product characteristics after consumers purchase cancer insurance, as none of the product-related estimates were significant (p-values ranging from .10 to .92).

Table 7. Estimation results of the multinomial logit regression

	Previously Purchased Product											
	Life insurance		Health insurance		Cancer insurance		Car insurance		Property insurance		Pension insurance	
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept												
Life insurance	—	—	0	Fixed	0.71	0.58	−0.13	0.87	0.55	0.69	−0.35	0.83
Health insurance	0	Fixed	—	—	0	Fixed	0	Fixed	0	Fixed	0	Fixed
Cancer insurance	−0.57	0.45	**0.74**	**0.04**	—	—	0.54	0.46	**−2.29**	**0.02**	0.15	0.93
Car insurance	−0.29	0.72	−0.61	0.26	**2.12**	**0.05**	—	—	0.39	0.80	2.14	0.34
Property insurance	**−1.51**	**0.05**	**−0.83**	**0.04**	0.66	0.67	**2.75**	**0.00**	—	—	1.72	0.47
Pension insurance	−1.06	0.29	**−0.76**	**0.03**	0.80	0.61	−0.65	0.46	2.37	0.15	—	—
Perceived product characteristics												
Premium	**−0.20**	**0.08**	**−0.21**	**0.04**	−0.27	0.10	−0.06	0.58	**−0.39**	**0.04**	0.19	0.46
Complexity	0.08	0.47	0.05	0.63	0.17	0.33	0.04	0.68	0.14	0.49	**0.47**	**0.07**
Variability	0.08	0.53	0.12	0.27	0.03	0.87	0.17	0.11	−0.21	0.31	0.18	0.54
Policy Period	0.08	0.50	−0.10	0.39	0.02	0.92	0.14	0.18	−0.17	0.40	0.01	0.97
Claim Likelihood	0.07	0.48	0.09	0.38	−0.16	0.37	**0.24**	**0.02**	−0.03	0.87	−0.06	0.79
Insurance Amount	−0.02	0.87	−0.10	0.33	0.08	0.65	−0.09	0.40	0.26	0.15	0.01	0.97

Notes: Bold indicates significant estimates at 90%. The intercepts of the basis alternatives were fixed at zero for identification purposes.

8. DISCUSSION AND IMPLICATIONS

8.1 Summary of key findings

This study addresses three critical issues regarding online insurance adoption. The first issue is the extent to which consumers adopt online insurance products due to their characteristics. We focused on how their psychological traits and demographic factors can explain the number of products adopted by consumers. The influence of four individual traits, including social need, price consciousness, perceived risk, and self-efficacy, were empirically examined using survey data. The results reveal that consumers with a lower degree of social need, are more price-conscious, and perceive fewer risks when transacting on the Internet tend to adopt a larger variety of insurance products than other consumers. These results corroborated our predictions. We anticipated that social need would have a negative effect on the number of insurance products adopted by consumers, as those with a high social need have a strong preference for purchasing insurance products through an agent, which allows them to interact with other people [36]. Similarly, price consciousness was predicted to have a positive effect as price-conscious consumers would find online insurance, which is typically low-priced [48], more attractive than offline insurance. Furthermore, consumers with high perceived risks are anticipated to buy fewer online insurance products due to high psychological barriers that prevent them from making online transactions [49]. Regarding the effect of demographic variables, the results suggest that female and married consumers adopt more products than their married and single counterparts.

We subsequently addressed how firms' marketing activities, WOM, and product attributes influence the adoption timing of various online insurance products. The results reveal that consumers' exposure to product advertisements aired on television and the Internet can accelerate product adoption. However, advertisements in other traditional media, such as newspapers, radio, and magazines, do not accelerate online insurance product adoption. These findings are critical for insurance companies looking to improve the impact of marketing communication activities by allocating marketing budgets more efficiently across media. Another important finding is that favorable messages regarding a product conveyed via Internet WOM can assist insurers in shortening the sales cycle of their products. Although this type of information is difficult to control directly, insurance companies may need to increase customer satisfaction to encourage them to spread positive WOM [63]. Finally, regarding the effect of product characteristics, we find that the adoption timing of an insurance product is negatively associated with perceived premium variability. Thus, an insurance category perceived as containing products with heterogeneous premiums is more likely to be adopted early by consumers. This implies that insurers can anticipate the time consumers take to purchase their products if they know how consumers perceive the variability of the products' premiums.

The last issue we address is what product consumers will adopt after adopting a specific insurance product. The results indicate that the adoption of insurance products

governs the next product purchased by a consumer. For example, consumers who have adopted health insurance are more likely to adopt cancer insurance but are less likely to adopt property and pension insurance. The patterns appear to be dependent on the characteristics of previously and subsequently adopted products. In many cases, consumers are inclined to purchase insurance that is thought to have a lower premium than the previously adopted one, such as life, health, and property insurance. However, those who have adopted pension insurance tend to adopt products perceived as being more complex. Thus, the effect of product characteristics on adoption patterns appears to be contingent upon the product previously adopted.

8.2 Managerial implications

We believe that this study's findings will help marketers in the online insurance industry improve the impact of their marketing efforts. The results from the first analysis should be useful in creating an effective targeting strategy intended to increase the number of online insurance products adopted by consumers. The insights from this study advocate focusing on consumers who have low social needs, are price-conscious and perceive fewer risks when cross-selling an insurance product, as these consumers have a strong tendency to buy various insurance products online. Although data on consumer psychographics is still scarce for many companies, advances in information and telecommunication technology should enable collecting such information from customers. In fact, some e-commerce companies periodically conduct surveys of their customers to update their understanding of consumers' needs and lifestyles.

Another critical implication of this study's findings is that insurance companies can optimize the allocation of advertising budgets across different media. Our results suggest that each communication medium induces different responses from consumers. While television and Internet advertisements appear to be effective in shortening the adoption timeline in our case, newspaper, radio, and magazine advertisements do not. We conjecture that this is because consumers who buy insurance online do not use traditional media in everyday life, thus preventing exposure to any online insurance advertisement displayed on the media's vehicles. It is also important to note that the adoption timing of online insurance is shorter for a category perceived as highly variable in terms of premium. The results indicate that e-marketers can accelerate the sales of their insurance products by appealing to the price attractiveness of their products to target consumers. Moreover, the analysis of the adoption pattern provides valuable insights for improving cross-selling efficiency. Specifically, marketers can use the information on current adoption to decide which product to cross-sell to a particular consumer. For example, knowing that a consumer has purchased a health insurance product, a marketer can recommend a cancer insurance product to the consumer as our data support such an adoption pattern. Similarly, it would be effective to cross-sell insurance that is perceived as having a lower premium than the one already adopted by consumers; this is particularly true for those who have adopted life, health, and property insurance.

9. LIMITATIONS AND FUTURE RESEARCH DIRECTION

Despite its contribution to the literature, this study has several limitations. First, this study used a sample from only one country (Japan). Thus, examination using samples from different countries is needed to improve the external validity of our findings. Second, we only investigated the adoption of six commonly transacted online insurance products in Japan: life insurance, health insurance, cancer insurance, car insurance, property insurance, and pension insurance. Therefore, the adoption of other insurance products remains unexplored. Future research can explore the adoption timing and patterns of these insurance products to address this limitation. Third, we did not investigate the role of consumer satisfaction in inducing additional purchases of insurance products. This is a critical issue, as previous studies have shown that consumers' decision to purchase an additional product from the same seller is affected by how satisfied they are with the previously purchased product [e.g., 64]. Lastly, we did not investigate how consumer adoption of online insurance alters the profitability of an insurance company. This issue has critical managerial implications, given the significant investment made by insurance companies to establish the online market. Future research can address this issue using a company's actual financial data, which is currently difficult for researchers to obtain.

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Appendix

Table A. List of items used in this study

Item ID	Item
	Social Need
SN1	I am mostly outgoing and enjoy direct conversation with other people.
SN2*	I enjoy online interactions more than face-to-face interactions.
SN3*	I like distance and avoid face-to-face interactions.
SN4	I am outgoing and enjoy being constantly surrounded by others.
SN5*	I like to deal with many things by myself.
SN6	I am talkative and often seek external interactions.
SN7*	I am reserved and enjoy being alone most of the time.
	Price Consciousness
PC1*	I am not willing to make an extra effort to find a lower price.
PC2*	The money saved by finding lower prices is typically not worth the time and effort.
PC3	The time it takes to find low prices is usually worth the effort.
PC4	I prefer dealing directly with the staff as they provide price information in detail.
PC5	I will buy products and services online to take advantage of the low prices.
PC6	Internet shopping provides a reasonable price for quality value.
PC7	Compared to traditional companies, online stores charge me reasonably for similar products/services.
	Perceived Risk
PR1	I do not trust online companies.
PR2	I am reluctant to provide my credit card number to online companies.
PR3	Online transactions are likely to be subject to hacking issues.
PR4	I think many online companies are likely to violate my privacy.
PR5	I would be concerned that I really would not get benefits.
PR6	I think the security of online transactions is inadequate.
PR7	It is challenging to evaluate the characteristics of online products accurately.
PR8	I think mistakes are likely to be made during transactions online.
PR9	I would be concerned that a product would not perform as advertised on the website.
PR10	Online insurance might not perform well and will create problems with my insurance policy.
	Self-efficacy
SE1	I feel capable of using the Internet for purchasing products and services.
SE2	I feel comfortable searching for information about a product and services on the Internet.
SE3	I am very adept at searching for products and services on the Internet.
SE4	I find it very easy to get acquainted with several online purchasing platforms.
SE5	I know how to solve most of the problems that arise during online purchases.
SE6	I consider myself an expert online buyer.
SE7*	I am very unsure of my abilities to use the online system.
SE8*	I often have difficulties when trying to purchase online.
SE9*	I seem to have difficulties with most of the online applications I have tried to use.
SE10	I am able to do transactions through the Internet by myself.

Note: * represents reversed items.