The Factors of Behavioral Intention Affecting User Loyalty on Knowledge Payment Platforms in China

Luo Beibei[1], Patima Rungruang[2] and Ampol Navavongsathian[3]

Southeast Bangkok University, Bangkok, Thailand

Corresponding Author, E-mail: [1]spiritlb@hotmail.com

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Abstract

Background: In the increasingly competitive and segmented market of knowledge payment platforms in China, it is essential to grasp the aspects that effect behavioral intention and user loyalty in order to ensure the long-term viability of the platform. Aims: The current research aims to examine the variables that influence behavioral intention and user loyalty on knowledge payment platforms in China. Methodology: To achieve this, a complete theoretical model is developed, drawing upon the Unified Theory of Acceptance and Use of Technology (UTAUT), perceived risk theory, and user loyalty theory. The proposed model incorporates social influence, performance expectancy, effort expectancy, and perceived risk as independent variables. It evaluates the direct and indirect effects of these factors on behavioral intention and user loyalty. Results: In this research, a sample of 462 valid respondents obtained from an online survey was analyzed using Structural Equation Model (SEM). The results of the data analysis confirmed that social influence, performance expectancy, and effort expectancy had a favorable impact on behavioral intention and user loyalty. In contrast, there was a significant inhibitory effect on perceived risk. Behavioral intentions, on the other hand, mediated the effects of social influence, performance expectations, effort expectations, and perceived risk on user loyalty.

Conclusion: The findings indicate strong empirical support for platform administrators and marketers to implement strategies that enhance user experience, reduce perceived risks, and leverage social influence. Effectively executing these strategies is essential for building customer loyalty and achieving sustained success in the knowledge payment industry. This research provides valuable insights

into the relationships among these factors within the context of knowledge payment platforms in China, setting the stage for future research.

Keywords: Knowledge Payment Platforms; Behavioral Intention; User Loyalty; Structural Equation Model; UTAUT Model

Introduction

Against the backdrop of the sustained growth of the world economy, both digitization and informatization have gained rapid development, and knowledge payment, as an emerging business model (Zhang et al., 2020), is gradually becoming one of the main ways of knowledge dissemination and acquisition (Yu et al., 2021). Especially affected by the epidemic, the onlineization of education has accelerated. According to the 54th Statistical Report on Internet Development in China released by China Internet Network Information Center (CNNIC), as of June 2024, there were nearly 1.1 billion Internet users in China (1,099.67 million people), an increase of 7.42 million people compared with December 2023, and the Internet penetration rate reached 78.0% (CNNIC, 2024), and the number of Internet users in China reached 1.1 billion (1,099.67 million people), an increase of 7.42 million people compared with December 2023, and the Internet penetration rate reached 78.0%. From the perspective of business model and technological change, the exploration around “traffic realization” has become more active and more diversified. The knowledge payment industry has seen disruptive changes and explosive growth. As the COVID-19 epidemic continues to improve, the “home dividend” of knowledge payment may gradually fade, but the habit of paying for knowledge and online learning has been formed since the epidemic.

This study delves into the key factors that influence the behavioral intentions and loyalty of paid knowledge users. Understanding these factors is critical to understanding the motivations and attitudes behind user behavior. Perceived risk factors are added to the fused UTAUT model to create a more comprehensive and accurate model of user loyalty. By constructing this comprehensive model, the process of forming user loyalty to knowledge payment platforms will be better understood and the driving factors behind user behavior will be further explored. This will provide more guiding suggestions for practicing knowledge payment platforms and provide theoretical support for the development of the platforms.

Research objectives

1. Investigate the factors influencing user loyalty on knowledge payment platforms.
2. Examine and clarify the relationships among the influencing factors.
3. Explore the mediating role of behavioral intention in the model.

Literature review

1. Knowledge payment platforms

The concept of knowledge markets first emerged in the work of Davenport and Prusak (1998), who argued that knowledge is subject to market forces and operates as if there were buyers and sellers in a market. Knowledge markets exist in organizations in the same way that physical goods do. In a knowledge market, knowledge can be traded (shared) because all participants believe that utility can be gained from it. Dignum and Dignum (2003) stated that knowledge markets are designed to protect knowledge, reward knowledge holders, and enable those who need knowledge to have access to timely and adequate knowledge by supporting people to trade knowledge. Desouza et al. (2005) defined knowledge markets as environments where buyers and sellers can trade expertise within defined pricing and trading rules. Natalicchio et al. (2014) introduced the concept of general knowledge markets, which they stated are virtual markets that facilitate the display, search and trading of knowledge assets with potential economic value among individuals or organizations. iiMedia Research (2022) defines China's knowledge payment industry as knowledge payment is a means of accessing high-quality information services, where providers transform their personal knowledge or skills into knowledge commodities, and consumers trade knowledge by paying for it. Early knowledge payment is embodied in the form of education, consulting, publishing, etc. With the development of the mobile Internet, knowledge payment gradually developed from terminal systematization to mobile fragmentation, and knowledge payment became a mode of communication in which individuals share knowledge and information through online transactions to gain revenue.

2. Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003). It integrates eight significant models: Task-Technology Fit (TTF), Innovation Diffusion Theory (IDT), Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Motivational Model (MM), Combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), and Social Cognitive Theory (SCT). UTAUT distills four core variables that influence Behavioral Intention and Use Behavior: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. UTAUT improves the explanation of Behavioral Intention (BI) to 70% (Venkatesh et al., 2003). UTAUT has since been widely applied and is considered an effective tool for measuring user behavior in various research contexts. Han (2017) conducted a statistical analysis of 161 papers applying the UTAUT model in China from 2007 to 2016. He found that Facilitating Conditions had a relatively weak impact on adoption behavior. Given the current widespread adoption of 4G technology and the development of 5G, which have significantly improved convenience, Facilitating Conditions are not considered as a factor in this research's model.

Al-Okaily et al. (2024) explored the factors of using a mobile payment system in the public sector in Amman city, Jordan, and the results of The research showed that the determinants of using this mobile payment system are price value, social influence, performance expectancy, awareness and trust, which explained 60.2% of the variance. NAVAVONGSATHIAN et al. (2020) in studying the causal factors affecting the acceptance of mobile banking services by Thai customers showed that service quality, perceived usefulness, perceived ease of use, security of use, and social factors influence the acceptance of mobile banking services by Thai customers. Raza et al. (2021) concluded that performance expectancy, effort expectancy, social influence, and social isolation during the COVID-19 pandemic were related to the learning management system's Behavioral Intentions during the COVID-19 pandemic, and that the new crown of fear only moderated the link between performance expectancy and social influence and behavioral intentions of the learning management system. Vinerean et al. (2022) validated the eight hypotheses of the m-commerce research model based on the theoretical framework of the UTAUT2 , and stated that performance expectancy, hedonic motivation, and social influence constituted the important drivers of consumers' behavioral intentions.

3. Perceived Risk

Perceived risk originated in the marketing and consumer behavior research fields of the 1960s. Bauer (1960) first introduced the concept, emphasizing that purchasing behavior inherently involves risk, as consumers face uncertainty and potential adverse consequences when making purchase decisions. With the rise of the internet and e-commerce, research on perceived risk has found new avenues for development. Gefen et al. (2003) identified that consumers' perceived risks in online transactions predominantly revolve around privacy and financial concerns, emphasizing that perceived risk is a key factor influencing online purchase intentions. Similarly, Pavlou (2003) highlighted the critical role of perceived risk in shaping consumer trust and purchase intentions in e-commerce acceptance models, further expanding the application of this concept.

Lingming et al. (2021) used an integrated technology acceptance model (Unified Theory Acceptance and Use of Technology (UTAUT)) as a framework for a study on fresh food e-commerce platforms and found that performance expectancy, social influence had a significant positive impact on consumer platforms, while perceived risk had a negative impact. Esmaeili et al. (2021) investigated the factors affecting mobile banking customer loyalty through Structural Equation Model (SEM) testing and LISREL 8.8 software, and the results of The research showed that perceived risk has a negative impact on loyalty. Khasbulloh and Suparna (2022) used an analytical tool called PLS (Partial Least Squares) to explain the impact of perceived risk and perceived value on customer loyalty through customer satisfaction as a mediating variable. The results showed that perceived risk has a significant negative effect on customer satisfaction and customer loyalty. Harianto and Ellyawati (2023) in their study analyzing the effect of perceived usefulness, trust and risk on TikTok store loyalty showed that risk has a significant effect on customer satisfaction and loyalty.

4. User Loyalty

The concept was first introduced by Copeland (1923), who examined consumer purchasing habits and introduced the idea of "brand loyalty." In recent years, the research of user loyalty has increasingly incorporated digital and big data analysis. Reichheld and Teal (1996) defined loyalty as a customer's willingness to make repeat purchases and positive word-of-mouth about a specific brand or product. Janahi and Al Mubarak (2017) argued that loyalty reduces operating expenses, improves revenues and profitability as well as reduces marketing expenses.

Khan et al. (2021) found a significant effect on customer loyalty when exploring the impact of social media's influence on purchase intention and customer loyalty with the mediating effect of beliefs in Generation Y found that purchase intention has a significant impact on customer loyalty. Panda et al. (2020) in using the Theory of Planned Behavior (TPB) framework to understand how increased levels of sustainability awareness affect other factors showed that purchase intention has a positive impact on customer loyalty for green brands as well as green brands' customer loyalty has a positive impact on brand communication. Le (2021) The results of a study on the factors influencing the propensity to use fintech services as a new normal behavior after the COVID-19 embargo using the TRA model to construct the fintech services showed that the intention to adopt fintech has a considerable positive impact on the loyalty to use fintech. Alkhwaldi et al. (2022) From a developing country's Perspective COVID-19 The post COVID-19 study on intention and e-loyalty shows that users' intention to use fintech has a direct positive impact on their e-loyalty.

Research Hypotheses

According on the preceding research, the hypotheses of this study are summarized as follows:

H1: Social influence has a positive effect on behavioral intention of knowledge payment platforms.

H2: Social influence has a positive effect on user loyalty of knowledge payment platforms.

H3: Performance expectancy have a positive effect on behavioral intention of knowledge payment platforms.

H4: Performance expectancy has a positive effect on user loyalty of knowledge payment platforms.

H5: Effort expectancy has a positive effect on behavioral intention of knowledge payment platforms.

H6: Effort expectancy has a positive effect on user loyalty of knowledge payment platforms.

H7: Perceived risk has a negative effect on the behavioral intention of knowledge payment platforms.

H8: Perceived risk has a negative effect on user loyalty of knowledge payment platforms.

H9: Behavioral intention has a positive effect on user loyalty of knowledge payment platforms.

H10: Behavioral intention has a mediating role in the effect of social influence on user loyalty of knowledge payment platforms.

H11: Behavioral intention has a mediating role in the effect of performance expectancy on user loyalty of knowledge payment platforms.

H12: Behavioral intention has a mediating role in the effect of effort expectancy on user loyalty of knowledge payment platforms.

H13: Behavioral intention has a mediating role in the effect of perceived risk on user loyalty of knowledge payment platforms.

Research Methodology

In this research, relevant research was conducted through a combination of qualitative and quantitative methods, and data were collected using questionnaires. The qualitative research is mainly conducted through the literature analysis method, combing through relevant studies and discussing the first draft of the scale with academics and industry experts. The quantitative study measures and analyzes the four potential variables of social influence, performance expectancy, effort expectancy, and perceived risk, the mediator variable of behavioral willingness, and the dependent variable of user loyalty of knowledge payment platforms through the questionnaire survey method, and empirically examines the model's appropriateness as well as the reasonableness of the theoretical assumptions by adopting the Structural Equation Model (SEM) empirical method.

1. Population and Sample

The research focuses on individual users who utilize knowledge payment platforms, as these users represent the ultimate audience of the platforms. According to a report by iiMedia Research (2023), by 2023, the number of knowledge payment users in China has exceeded 400 million, accounting for approximately 30%-40% of the total number of internet users in the country.

Kline (2016) proposed that when using maximum likelihood estimation, the ratio of sample size to the number of estimated parameters should ideally be 20:1, with 10:1 being the minimum requirement. The sample size is considered to be 20 times ~~of~~ the observed variables in this research. It involves a sampling survey of individual users of knowledge payment platforms. The questionnaire of this study has 6 latent variables and 25 observed variables, the sample consists of 500 individual users from these platforms.

A certain number of samples will be selected by a simple random sampling method in this research. The questionnaire was mainly targeted at individual users of China's knowledge payment platforms, and the questionnaire was created according to the “wenjuanxing” software, and the link to the questionnaire was sent to the respondents. Using five-point Likert scale to measure respondents' attitudes and perceptions of each variable, as well as their level of loyalty to the platform.

2. Pilot Study

The content validity of the questionnaire's scales is usually assessed through expert review and theoretical analysis, and was determined through a review by three experts in the field prior to the pilot study to ensure that the content of the scales comprehensively and accurately reflected the target constructs.

According to the results of the reliability and validity analysis of the 113 pilot study data, Cronbach's alpha coefficients of social marketing, performance expectancy, effort expectancy, perceived risk, behavioral intention, and user loyalty are higher than 0.7, respectively, which comprehensively indicates that the data reliability is of high quality, indicating that the questionnaire has a high degree of internal consistency and stability. The KMO test value is 0.866, which is greater than 0.8, indicating that the questionnaire is well suited for factor analysis; Bartlett's spherical test results show that the approximate chi-square value is 2508.889, and the significance level p-value is 0.000, which is less than 0.01, which passes the test, indicating that the scale is suitable for factor analysis, and it has good structural validity.

Research Results

The research cleaned the 500 official questionnaires collected by Questionnaire Star from the inapplicable samples, after eliminated of 38 invalid values, the sample validity rate of the recovered questionnaires was 92.4%.

In this research, Harman's one-way factorial test was used to test for possible common method bias effects. A total of six common factors were extracted based on the factors and the cumulative variance contribution was 66.326% greater than 60%, the level of explanation of the extraction was good and the amount of variation explained by the first factor was 36.397%, which is less than the critical criterion of 40%, the results indicate that the questionnaire data collection used in this research does not suffer from a serious common method bias.

With kurtosis absolute values below 10 and skewness absolute values below 3, the sample can be considered approximately normal and suitable for SEM analysis.

The Cronbach alpha coefficients for the variables of the formal questionnaire ranged from 0.818-0.857 (>0.7); the KMO value was 0.927>0.8, and Bartlett's test of sphericity approximated a chi-square of 5359.743, with a Sig=.000<0.05, which indicates that the data are highly reliable and valid.

The values of x2=361.635, df=260, x2/df=1.391, p-value=.050, and GFI=0.941, AGFI=0.926, NFI=0.934, IFI=0.980, TLI=0.977, and CFI=0.980 are all greater than 0.9, and RMSEA=0.029<0.08, In conclusion These index values according to the standard test of consistency between the model and empirical data, the level of consistency is good.

All AVE values are between 0.529 to 0.569 greater than 0.5, and all CR values are between 0.818 to 0.858 exceed 0.7, indicating that the data analyzed has good convergent validity. On other hand, all factors' AVE square root values are greater than the maximum absolute value of the inter-factor correlations, indicating good discriminant validity.

Regarding the variables social influence, performance expectancy, effort expectancy, perceived risk, and behavioral intention, these are the direct or indirect influences on behavioral intention and user loyalty of knowledge payment platforms in China of influencing factors. When adding the coefficients to the model, values adjusted to standard form (normalized) are used, as shown in Figure 1.

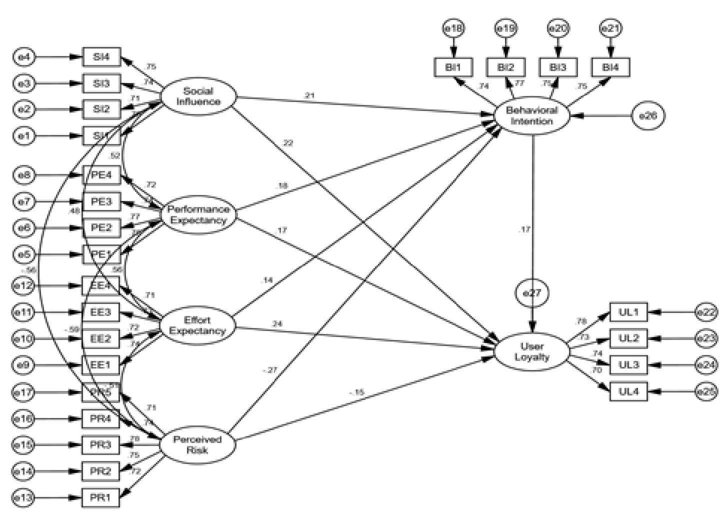

Figure 1 Structural Equation Model (Source: Constructed by the researcher)

Table 1 The results of variable path coefficient

Hypothesis	Observation Variable	Effect Variable	Estimate	S.E.	C.R. (t value)	P	R^2
H1	Social Influence	Behavioral Intention	0.211	0.064	3.297	***	0.423
H3	Performance Expectancy		0.167	0.064	2.601	0.009	
H5	Effort Expectancy		0.15	0.069	2.182	0.029	
H7	Perceived Risk		–0.301	0.077	–3.908	***	
H2	Social Influence	User Loyalty	0.223	0.063	3.57	***	0.562
H4	Performance Expectancy		0.163	0.062	2.641	0.008	
H6	Effort Expectancy		0.265	0.067	3.952	***	
H8	Perceived Risk		–0.17	0.075	–2.283	0.022	
H9	Behavioral Intention		0.178	0.062	2.874	0.004	

Note: *** p<0.001

Table 1 shows the results of testing the path coefficient of social influence, performance expectancy, effort expectancy, perceived risk, behavioral intentions, and user loyalty and checking the consistency of the model with an empirical data. P–value<0.05, the hypotheses h1–h9 are all supported due to significant path coefficient.

Table 2 Influence coefficient

Cause Variable	Effect Variable					
	Y = Behavioral Intention			Z = User Loyalty		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
X1 = Social Influence	0.211	0	0.211	0.223	0.038	0.261
X2 = Performance Expectancy	0.167	0	0.167	0.163	0.03	0.193
X3 = Effort Expectancy	0.15	0	0.15	0.265	0.027	0.292
X4 = Perceived Risk	–0.301	0	–0.301	–0.17	–0.054	–0.224
Y = Behavioral Intention	0	0	0	0.178	0	0.178
Prediction coefficient(R^2)	R^2 = 0.423			R^2 = 0.562		

Table 2 shows in detail the effects of the independent variables on social influence, performance expectancy, effort expectancy and perceived risk on the dependent variables behavioral intention and user loyalty. The data in the table reveals the direct effect of each independent variable on behavioral intention (direct effect) as well as the indirect effect on user loyalty through behavioral intention (indirect effect), which leads to the total effect. In addition, the table provides the R2 values of the predictive coefficients of behavioral intention on user loyalty, which are 0.423 and 0.562, respectively, indicating that the model explains user loyalty with high strength. Overall, the table provides an empirical basis for understanding user behavior on knowledge payment platforms and reveals how different factors work together through direct and indirect paths to influence user behavioral intention and loyalty.

Table 3 Estimates of different effects in Structural Equation Model

Effects	Parameter	Estimate	95%CI Lower	95%CI Upper	p	Support
Direct Effects	Social Influence⟶User Loyalty	0.223	0.097	0.384	0.001	Yes
	Performance Expectancy⟶User Loyalty	0.163	0.037	0.304	0.009	Yes
	Effort Expectancy⟶User Loyalty	0.265	0.124	0.438	0.001	Yes
	Perceived Risk⟶User Loyalty	–0.17	–0.334	–0.03	0.015	Yes
Indirect Effects	Social Influence⟶Behavioral Intention⟶User Loyalty	0.038	0.011	0.091	0.002	Yes
	Performance Expectancy⟶Behavioral Intention⟶User Loyalty	0.03	0.006	0.081	0.01	Yes
	Effort Expectancy⟶Behavioral Intention⟶User Loyalty	0.027	0.002	0.079	0.032	Yes
	Perceived Risk⟶Behavioral Intention⟶User Loyalty	–0.054	–0.127	–0.016	0.002	Yes
Total Effects	Social Influence⟶User Loyalty	0.261	0.131	0.42	0	Yes
	Performance Expectancy⟶User Loyalty	0.193	0.065	0.336	0.002	Yes
	Effort Expectancy⟶User Loyalty	0.292	0.145	0.476	0.001	Yes
	H11: Perceived Risk⟶User Loyalty	–0.224	–0.382	–0.083	0.002	Yes

Following Table 3 provides the estimates of the different effects in Structural Equation Model (SEM), including direct, indirect, and total effects, along with their confidence intervals and p–values. The total effect is the sum of the direct effect and all possible indirect effects, which indicates the overall effect of the independent variable on the dependent variable. In this table, the total effects of social influence, perceived risk, performance expectancy, and effort expectancy are all significant, indicating that these factors have a significant impact on user loyalty. All effects are established, with all four mediating effects being valid and each representing partial mediation, H10-H13 all supported.

Discussion

The results of the research found that social influence, performance expectancy, effort expectancy, perceived risk, and behavioral intention directly or indirectly affect user loyalty on Chinese knowledge payment platforms. This is consistent with the findings of UTAUT model (Venkatesh et al., 2003). The positive effect size of the UTAUT model of the influence of performance expectancy, effort expectancy, and social influence on the influence of users' behavioral intentions has also been verified.

Social influence has a significant positive impact on both behavioral intention and user loyalty, aligning with findings from several empirical studies (Lu et al., 2023; Raza et al., 2021; Viswanathan et al., 2020; Alexander & Hidayat, 2022; Venkatesh et al., 2003). This suggests that users are significantly influenced by opinion leaders and peers within their social networks when considering using a knowledge payment platform. Positive social influence enhances users' trust in the platform, thereby promoting behavioral intention and loyalty.

Performance expectancy and effort expectancy also positively influence behavioral intention and user loyalty, consistent with other research findings (Nikolopoulou et al., 2021; Md Yunus et al., 2021; Park & Kim, 2020; Bajunaied et al., 2023; Gunawan, 2024; Venkatesh et al., 2003). Users have clear expectations regarding platform performance and ease of use, and when these expectations are met, their satisfaction and loyalty increase. This underscores the importance of continually optimizing service quality and user experience to meet user needs.

Perceived risk negatively impacts behavioral intention and user loyalty, in line with previous research (Lingming et al., 2021; Widyanto et al., 2022; Esmaeili et al., 2021). Users' concerns about potential losses or inconveniences may deter them from accepting and using knowledge payment platforms. Therefore, reducing perceived risk through increased transparency and security is crucial for enhancing user loyalty.

Most importantly, behavioral intention serves as a mediator between all influencing factors and user loyalty. Whether the factors are positive or negative, they influence user loyalty through their impact on behavioral intention. This indicates that to improve user loyalty, knowledge payment platforms must first stimulate positive behavioral intentions among users.

Conclusion

The theoretical model was tested using 462 sample data, and it was found that the theoretical path structural model fit well with the sample data, and all 13 hypotheses passed the path coefficient significance test, the theoretical hypotheses can be accepted, indicating that the behavioral intention and user loyalty influencing factors constructed in this research are relatively ideal. Through empirical analysis, this study obtains the following conclusions:

1. Basic Characteristics of Chinese Knowledge Payment Platform Users

A sample survey of Chinese knowledge payment platform users (462 samples) in the form of questionnaires distributed online by wenjuanxing software found that Chinese knowledge payment platform users are characterized by youthfulness and high education level, with a higher proportion in regions with better economic development such as eastern and southern China, and mostly middle- and low-income school students, corporate employees and freelancers, and also found that users have higher willingness to use video-based knowledge payment platforms; most users have some experience in using knowledge payment platforms and use them more frequently every week, and have better usage habits; they have a certain level of consumption, but their consumption level is not high.

2. Analysis of influencing factors of behavioral intention and user loyalty of knowledge payment platforms in China

Based on the empirical analysis, this study finds the significant influence of social influence, performance expectancy, effort expectancy, perceived risk, and behavioral intention on user loyalty, which provides an empirical basis for understanding user behavior on knowledge payment platforms.

Based on empirical analysis, this study finds significant effects of social influence, performance expectancy, effort expectancy, perceived risk, and behavioral intention on user loyalty, which provides an empirical basis for understanding user behavior on knowledge payment platforms. The order of effect size of potential factors that have a direct influence on behavioral intention is: perceived risk (β=-0.269), social influence (β=0.212), performance expectancy (β=0.178), and effort expectancy (β=0.139). The order of the effect size of the potential factors that have a direct influence on user loyalty is: effort expectancy (β=0.24), social influence (β=0.218), performance expectancy (β=0.17), and perceived risk (β=-0.147).

Suggestions

1. Theoretical Suggestions

Although the UTAUT model doesn't explicitly include the variables perceived risk and user loyalty, this research found that perceived risk has a significant negative impact on behavioral intention and user loyalty. Users who perceive a higher risk of security, privacy, or financial loss when using knowledge payment platforms will experience a significant decrease in their intention to use and their user loyalty will be negatively impacted. This finding suggests that perceived risk and user loyalty can be used as extension variables of the UTAUT model in future studies to explain user loyalty more comprehensively.

In addition, this research confirms the mediating role of behavioral intention in the relationships between social influence, performance expectancy, effort expectancy, and perceived risk on user loyalty. This suggests that users' behavioral intention not only directly influences their loyalty, but also indirectly enhances or diminishes it by moderating the influences of social influence, performance expectancy, effort expectancy, and perceived risk. This finding expands the application scenarios of the UTAUT model in discribing complex user loyalty decision-making processes and provides new insights into the management practices of knowledge payment platforms.

2. Practical Suggestions

To enhance social influence, knowledge payment platforms should focus on actively building and strengthening user communities, fostering trust and reliance among users through increased interaction and sharing. This can be achieved by implementing features such as user evaluation systems, social sharing options, and expert recommendations, all of which enhance user engagement and communication. These strategies can positively impact users' behavioral intentions and loyalty by leveraging social influence.

To improve the quality of platform content and functionality, it is crucial to emphasize content quality and diversity, ensuring that the knowledge and information provided are both highly specialized and practical. Optimizing the functional design of the platform to meet users' expectations of high performance is also vital. Such measures not only increase initial user adoption but also encourage continued use and foster loyalty.

For a more user-friendly experience, platforms should prioritize user-centered design by simplifying operational processes and interface layouts. This approach reduces users' learning curve and minimizes the difficulty of use.

To mitigate users' perceived risks, platforms should invest more resources in enhancing security, particularly in areas like data privacy protection and payment security. Strengthening security measures, maintaining transparency in platform policies, and establishing trust mechanisms can effectively reduce perceived risks, thereby boosting user trust and loyalty.

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