The Influence of Perceived Trust, Perceived Value, Perceived Usefulness, and Perceived Risk on College Students' Initial Willingness to Pay for Online Knowledge

Long Kou*
Xuemei Sun**

Abstract

The market size of online knowledge payment continues to expand, yet the proportion of users who persistently engage in knowledge payment is continuously decreasing, which significantly hinders the development of online knowledge payment platforms. This study examines the factors influencing users' initial willingness to pay for online knowledge based on the theory of perceived value and the technology acceptance model by integrating the payment contexts, and influential factors related to online knowledge payment intention. This study employed convenience sampling to select 412 students from Guangzhou, Guangdong Province, China, as participants. PLS-SEM analysis reveals that perceived usefulness, perceived value, and perceived trust positively influence initial willingness to pay for online knowledge, while perceived risk has a negative impact. Perceived trust and perceived value act as complementary mediators in the relationship between perceived risk, perceived usefulness, and initial payment intention. The findings contribute to understanding users' initial knowledge payment decisions and offer practical implications for knowledge payment platform users, producers, and service providers. These insights can help improve user experience, satisfaction, and promote sustainable development through effective marketing strategies and service models.

Keywords: Perceived Trust; Perceived Value; Perceived Risk; Perceived Usefulness; Initial Payment Intention

Received: July 25, 2023 | **Revised:** October 16, 2023 | **Accepted:** November 8, 2023

---

* Master, International College, National Institute of Development Administration, Thailand. Research intern, Guang Zhou Hua Shang College, China. Email: long.kou1988@gmail.com
** Lecturer, Ph.D. International College, National Institute of Development Administration, Thailand. Email: xuemei.sun@nida.ac.th
Funding Project: Guangzhou Huashang College 2022 Youth Academic Resecar Project (2022HSXS053)

Introduction

In recent years, the rapid development of the Internet and information science and technology has had a significant impact on various aspects of the economy and society. People's work, study, life, and entertainment have undergone substantial changes compared to the past. Taking the United States as an example, data released by the Internet Association indicates that in 2018, the Internet and related industries contributed $2.1 trillion to the U.S. GDP, accounting for 10.1% of the country's GDP. This contribution is more than double the economic impact of the Internet in 2014 (Hooton, 2019). In China, the scale of the digital economy reached 39.2 trillion yuan in 2020, accounting for 38.6% of the GDP and maintaining a high growth rate of 9.7% (China Government Online, 2021). Especially after the concept of the "sharing economy" was introduced, the impact of the Internet and information technology on the economy and society has become even more significant, giving rise to a series of new business models and economic forms. Simply put, the sharing economy is a business model that utilizes online platforms to facilitate the sharing and utilization of idle resources. This business model greatly enhances resource utilization and efficiency, thereby offering significant economic and social value (Zheng, 2016). Among them, knowledge payment platforms belong to the application of the sharing economy in the field of knowledge and skills. A knowledge payment platform is a platform that offers users functions related to knowledge consumption. By establishing the infrastructure for knowledge transactions, the platform helps users access high-quality and personalized knowledge services, thereby meeting users' personalized needs for knowledge and their desire to gain value (Zhang, 2019).

In China, knowledge payment has become one of the rapidly growing industries in recent years. Since 2016, various knowledge payment platforms have emerged in China, including "Dedao App" "Zhihu Live" "Ximalaya FM" and "Fandeng Book Club" and gradually industrialized (Shen, 2018). As a result, China has entered a new era of paid knowledge, leading to the belief that 2016 marked the "First Year of Knowledge Payment" (Huang & Tang, 2019). Consequently, the number of Chinese knowledge payment users has experienced rapid growth. The industry itself has reached a size of CNY 67.5 billion in 2021, which is approximately 42 times larger in comparison to 2015. Projections estimate that it will surpass CNY 180 billion by 2023 (iResearch Consulting Group, 2022). However, the fast development of the knowledge payment industry also confronts challenges, particularly related to user experience, contributing to a gradual increase in the user churn rate (Cai et al., 2019). Existing research indicates that user consumption habits have transitioned from impulsive to rational consumption, resulting in new operational situations for many knowledge payment platforms, namely, low user willingness to pay and inconsistent content quality (He, 2021; Xu, 2018). Simultaneously, the commercial value realization of the knowledge payment industry encounters obstacles. Among these challenges is the insufficient number of paid users due to their limited inclination to invest in knowledge products, and at times, actively resisting knowledge payment (Lu et al., 2021). These issues have influenced the industry's development, making it challenging for the knowledge payment sector to fully unlock its commercial potential. It addresses the users' need to obtain valuable information from a vast amount of content. However, users' payment behavior directly affects the profitability of knowledge payment platforms. Despite the considerable research on user payment intentions, existing perspectives and theoretical models are relatively limited, with less focus on segmenting the usage intentions of knowledge payment users. In particular, there is a lack of in-depth research on initial payment intentions. Lu and Zhang (2021) found that there are differences in the influencing factors and mechanisms between users' initial payment intentions and their sustained payment intentions in the knowledge payment context. It can be said that users' initial payment represents the process of transitioning from non-payment to payment, and it plays a crucial role in expanding the market share of a product. Initial payment users lack relevant transaction experience and have limited firsthand experience with paid knowledge products. Compared to repeat payment users, initial payment users experience a higher level of uncertainty (Yin et al., 2019). Therefore, identifying the essential factors that influence users' initial willingness to pay for online knowledge is crucial for understanding their subsequent repeat payment behavior. In order to explore the influencing factors of users' initial knowledge payment intentions, this study adopts the perspective of perceived value theory and incorporates various contextual variables based on the technology acceptance model. The aim is to construct a theory model of influential factors for initial online knowledge payment that possesses a certain universality. This research enriches the relevant studies in the field of technology acceptance models and knowledge payment while providing recommendations for the development of online knowledge payment platforms based on the research findings. This study aims to discover the influencing factors of online knowledge payment, focusing on the initial willingness to pay for online knowledge. It adopts the perceived value theory and technology acceptance model to study the influencing factors of the initial online knowledge payment. The research framework is divided into five parts: the first part is an introduction, the second part is a research review, the third part details the research methods, the fourth part outlines the research conclusions, and the fifth part presents the results and discussions.

Literature Review

The concept of Initial Willingness to Pay (IWTP) was proposed when researching user's willingness to pay. In this research field, most scholars do not differentiate willingness to pay into different stages, such as initial payment and repeated payment. Initial willingness to pay is the prerequisite for continuous willingness to pay. Therefore, there are differences in the levels of willingness to pay for the first time and multiple times. Pavlou and Fygenson (2006) used the theory of planned behavior to study the initial willingness to pay, and regarded it as one of the important indicators to measure the adoption of e-commerce by consumers. The authors believe that the initial willingness to pay refers to whether consumers are willing to pay for products or services when they first use the e-commerce platform. Similarly, Yin et al. (2019) considered the initial willingness to pay as the purchasing willingness for knowledge-payment products from users with no payment experience, and found differences between initial willingness to pay and repeated willingness to pay in their research. Yu (2022) extracted the influencing factors of the initial willingness to pay for online knowledge by interviewing users who had their first online knowledge payment experience within 30 days. The research found that the influencing factors of the initial willingness to pay and the continuous willingness to pay for online knowledge are different.

In summary, it is crucial to research users' initial willingness to pay for online knowledge, as it is the first step for users to pay for knowledge on an online knowledge-payment platform. Understanding the factors that influence users' initial willingness to pay can help platforms improve users' initial satisfaction, thereby enhancing their willingness to continuously use the platform for knowledge payment. Additionally, attracting more users to make their initial online knowledge payments is key to the growth and development of online knowledge-payment platforms.

Hypotheses Development and Conceptual Model

This study integrates the theories of perceived value and the Technology Acceptance Model (TAM) to analyze users' willingness to pay for online knowledge platforms effectively. The perceived value theory evaluates factors influencing payment decisions, while the technology acceptance model explores users' acceptance of technical aspects. Building on previous research, the study proposes a new research model and hypotheses by incorporating trust theory with these foundational frameworks. In general, the Technology Acceptance Model and its evolved versions all aim to explain and predict user behavior in adopting information technology. However, these models differ in terms of theoretical construction and choice of factors, though they all include key elements such as perceived usefulness, perceived ease of use, subjective norms, self-efficacy, and social influence. The choice of which model to use in research depends on the specific circumstances and objectives of the study. Therefore, this research chooses to integrate factors from the Technology Acceptance Model such as perceived usefulness, perceived ease of use, subjective norms, and work relevance, based on the practical nature of the study.

Perceived trust (PT) is crucial in e-commerce and plays a significant role in online shopping (Gefen et al., 2003). Perceived trust is the trust that arises when one party, based on their own experiences and observations, considers the other party to be reliable and worthy of trust (Sun et al., 2016). In knowledge payment transactions, where communication and legal protection may be limited, users' perceived trust becomes even more important. Previous studies have shown that higher levels of trust in online shopping lead to increased purchase behavior (Harrison et al., 2002; Pavlou & Fygenson, 2006). Therefore, it is reasonable to hypothesize that higher perceived trust in online knowledge payment platforms, knowledge creators, and knowledge products positively influences initial payment intentions.

H1: Perceived trust positively influences initial payment intentions.

Perceived value (PV) represents consumers' overall evaluation of a product or service, encompassing factors like quality, price, and benefits. Previous research has consistently shown that perceived value significantly impacts payment intentions. Studies have found that higher perceived value leads to stronger initial payment intentions (Yang et al., 2017; Zhao et al., 2018). When users perceive a technology or product to have high utility value, they are more willing to pay for it. Given the importance of perceived value in shaping payment intentions, the following hypothesis is proposed:

H2: Perceived value positively influences initial payment intentions.

Perceived risk (PR) in this study refers to users' subjective assessment of potential losses when using an online knowledge payment platform to fulfill their information needs. Perceived risk is commonly regarded as a negative cost associated with user behavior (Ming et al., 2014). Research by Crespo et al. (2009) revealed that for individuals without prior online shopping experience, perceived risk negatively affects their willingness to engage in future online transactions and their attitudes toward the system. In the online environment, due to the presence of risks such as privacy breaches, perceived trust plays an important role (Zhou et al., 2011). Building a reliable and secure online knowledge payment platform and strengthening user trust can help alleviate uncertainty and perceived risk, thereby enhancing perceived trust in the platform. However, previous studies present different perspectives on the relationship between trust and perceived risk, suggesting that trust can result from, precede, coexist with, or complement perceived risk (Xia et al., 2010). In the field of knowledge payment, the presence and similarity of similar knowledge payment platforms may weaken users' trust in the platforms. Therefore, a knowledge payment platform built on a foundation of trust needs to address users' perceived risk issues in order to enhance trust and encourage user engagement and willingness to pay. Overall, perceived risk, perceived trust, and payment intentions are closely related. Consequently, the following hypotheses are proposed:

H3a: Perceived risk negatively influences initial payment intentions.

H3b: Perceived risk negatively influences perceived trust.

Perceived usefulness (PU) stems from the Technology Acceptance Model (TAM) and refers to the subjective assessment of how the use of information technology impacts work performance (Davis, 1989). In this study, perceived usefulness represents users' belief in the extent to which an online knowledge payment platform enhances their work performance and efficiency. Research by Zheng et al. (2012) revealed that users' perceived usefulness of mobile shopping affects perceived value, jointly influencing adoption intentions. Similarly, Fang et al. (2018) demonstrated that users' perceived value significantly influences their willingness to pay in virtual communities, mediating the effects of perceived gains and losses. Perceived usefulness is a component of perceived value, where individuals perceive a technology or product as economically, socially, or psychologically valuable when they believe it improves work efficiency. Consequently, when users perceive high usefulness in knowledge products, they also perceive them as informative, entertaining, and socially valuable. This perception of greater value in knowledge products leads to a higher willingness to pay. Therefore, the following hypotheses are proposed:

H4a: Perceived usefulness positively influences perceived value.

H4b: Perceived usefulness positively influences initial payment intentions.

Perceived content quality (PCQ) can be defined differently. Tan et al. (2023) demonstrated that improving the content quality of questions and answers in social Q&A communities enhances users' perceived value of the community. Therefore, perceived content quality refers to users' subjective evaluation of the questions and answers provided in social Q&A communities. On the other hand, Zhang and Zhu (2019) defined perceived content quality as users' quality evaluation of specific articles or posts in online knowledge communities. Their research found that higher user evaluations of such content corresponded to a perception of higher overall value in the community. High-quality content attracts more users to engage in discussions and interactions, thereby enhancing the overall value of the community. Perceived content quality and perceived value are closely related. Therefore, the following hypothesis is proposed:

H5: Perceived content quality positively influences perceived value.

Perceived service quality (PSQ) is the subjective evaluation of the services provided by service providers by customers, as stated by Professor Christian Grönroos, an expert in service marketing (Grönroos, 1984). Cronin and Taylor (1992) defined perceived service quality as the overall evaluation made by consumers regarding service providers' performance in dimensions such as tangibles, reliability, responsiveness, assurance, and empathy. In the context of knowledge payment, perceived service quality refers to users' satisfaction with the content, delivery methods, and channels offered by online knowledge payment platforms. It is worth noting that users' perceived value of online knowledge payment platforms includes their perceptions of service benefits and value. Therefore, perceived service quality and perceived value are interrelated, as high-quality services can enhance users' positive perceptions and evaluations of the platform, thereby increasing their perceived value. Thus, the following hypothesis is proposed:

H6: Perceived service quality positively influences perceived value.

Perceived cost (PC) encompasses the costs perceived by users when purchasing a product or service (Fang et al., 2018). Scholars have categorized perceived cost into various dimensions. Murphy and Enis (1986) identified price effort and risk as components of perceived cost. Additionally, perceived cost can be classified into four categories: monetary price effort, non-monetary price effort, monetary risk, and non-monetary risk, based on the perceptions of organizations and end consumers. Sun et al. (2014) suggested that perceived cost includes opportunity cost and actual cost, indicating that it results from multiple factors. Empirical studies have confirmed the significant influence of perceived cost on the satisfaction and knowledge-sharing behavior of knowledge contributors in virtual communities.

In the context of online knowledge payment platforms, users incur costs such as time, money, and effort when acquiring knowledge. However, they also perceive the benefits of knowledge, such as personal skill improvement. When the perceived benefits outweigh the perceived costs, users perceive higher value. Consequently, when the perceived value reaches a certain level, it stimulates users' strong willingness to pay. Zeithaml (1988) demonstrated that reducing user costs can enhance their perceived value. Sullivan and Kim (2018) also found that as perceived price costs increase, the perceived value decreases accordingly. Therefore, the following hypothesis is proposed:

H7: Perceived cost negatively influences perceived value.

Perceived Ease of Use (PEU) and Perceived Usefulness (PU) are essential factors in the Technology Acceptance Model (TAM). According to the model, these factors influence users' attitudes towards system usage, subsequently affecting their behavioral intentions and purchase preferences. Perceived Ease of Use refers to the belief that using a system requires minimal effort. Users generally prefer applications that are perceived as easier to use under similar conditions. Perceived Ease of Use also impacts Perceived Usefulness because users are more inclined to use systems that they perceive as easy to use (Davis, 1989). In the context of knowledge payment platforms, users may prioritize ease of use over the actual functionality of the product. The Technology Acceptance Model, employed in this study, has received substantial support, and the influence of Perceived Ease of Use on Perceived Usefulness has been extensively validated. Therefore, the following hypothesis is proposed:

H8: Perceived Ease of Use positively influences Perceived Usefulness.

Job Relevance (JR) is a concept found in TAM2 and TAM3 models, both of which indicate that users are more likely to perceive an information technology system as useful when they perceive it as compatible with their job requirements and values (Venkatesh & Bala, 2008). Thus, in the context of using an information technology system, job relevance positively influences users' perception of the system's usefulness, and this finding has received substantial support (Venkatesh & Davis, 2000). Knowledge payment, as a typical information system, is directly linked to work or learning objectives. Initially, users may struggle to accurately assess the quality of the knowledge obtained through payment. However, with time, users gradually evaluate the extent to which this "instant" knowledge contributes to their work (Peng, 2018). Therefore, the hypothesis is proposed as follows:

H9: Job relevance positively affects perceived usefulness.

Subjective Norm (SN) originates from the Theory of Reasoned Action and refers to an individual's perception of social attitudes or pressures regarding a specific behavior (Bandura, 1986). In the context of knowledge payment applications, Peng (2018) suggests that subjective norm factors should positively influence payment behavior, indicating a broad acceptance of knowledge payment applications in society. As societal acceptance of paying for knowledge grows, individuals will perceive the usefulness of knowledge payment applications more strongly. Moreover, subjective norm can enhance users' self-image, further reinforcing their perception of usefulness. Therefore, the hypothesis is proposed as follows:

H10: Subjective norm positively affects perceived usefulness.

Research Methodology

Research Samples

The iResearch Consulting Group (2022) survey report on China's knowledge payment industry indicates that the majority of users who pay for knowledge fall within the age range of 25 to 30 years old. However, the primary consumer group is gradually transitioning to individuals aged 35 and above. Although young individuals under 25 have a demand for practical knowledge acquisition, the percentage of them who actually make payments is comparatively low. Nevertheless, these younger users exhibit stronger copyright awareness and a higher tolerance for online payments (Li & Shen, 2022). This observation highlights the significant growth potential for knowledge payment platforms, with the younger demographic (under 25) being more inclined to serve as the initial user base. Since college students happen to fall within this age category, it holds certain practical significance to focus on them as the primary subjects of research.

The study focused on undergraduate students in Chinese regular higher education institutions. By sampling survey methods, a survey should have been conducted by selecting higher education institutions from different regions across China. However, this study employed a representative approach by selecting Guangdong Province as a typical unit of Chinese regular higher education institutions and then conducting the survey within Guangdong Province, selecting representative higher education institutions. Guangdong Province is a major province for higher education in China, ranking second in terms of the number of regular universities and the number of undergraduate students in 2021 (Chen, 2023). According to statistics from the National Association of Private Education in China, Guangdong Province has a total of 150 higher education institutions, including 50 private universities. The majority of private universities are located in the Pearl River Delta region, mainly referring to the central and southern parts of Guangdong Province, including cities such as Guangzhou, Foshan, Zhaoqing, and Shenzhen. They account for 92% of the total, with private undergraduate institutions accounting for 95.65% of this proportion (Li, 2019). Therefore, private universities in Guangdong Province have a certain level of representativeness among Chinese universities. Furthermore, the researcher is currently affiliated with one of the universities, taking into consideration the accessibility of other university staff, and has selected six representative private undergraduate institutions in Guangdong Province after comprehensive consideration. In relation to the number of research samples, Hair Jr et al. (2021) suggest that a minimum of 200 case samples are necessary for PLS-SEM analysis using complex research models. Xiao (2020) recommends that the number of research samples for PLS-SEM should be greater than the total number of scale items, ideally ten times more. Therefore, in the model of this study, the number of scale items is 37, so the minimum effective sample size should not be less than 370. As of March 2023, the total number of students in the six universities studied, based on publicly available data from admissions websites, is 140,727. The study estimates a population size of 140,000, with error range, confidence level, and population proportion set at 5%, 95%, and 50% respectively. Thus, 384 samples are needed, with at least 64 valid questionnaires per school. Considering the need to exclude some invalid questionnaires, this study stipulates a minimum sample size of 400. This sample size also meets the requirements for a reasonable sample size needed for a structural equation model (Zhang et al., 2020).

Table 1: Demographic Characteristics of the Respondents

Demographic Factors	Descriptive Statistics
Gender	Male:213（51.7 %）
	Female:199（48.3 %）
Hometown	Rural:243（59.0 %）
	Urban:169（41.0 %）
School	Guangzhou Huashang College:82（19.9 %）
	Guangzhou Huali College:63（15.3 %）
	Guangzhou College of Applied Science and Technology: 56（13.6 %）
	Guangdong Baiyun University:63（15.3 %）
	Guangzhou Institute of Science and Technology:75（18.2 %）
	Nanfang College Guangzhou:73（17.7 %）
Grade	Freshman:33（8.0 %）
	Sophomore:101（24.5 %）
	Junior:142（34.5 %）
	Senior:136（33.0 %）
Academic disciplines	Arts and Humanities:267（64.8 %）
	Science and Technology:145（35.2 %）
Monthly living expenses	5001 RMB and above:22（5.3 %）
	4001-5000 RMB:21（5.1 %）
	3001-4000 RMB:22（5.3 %）
	2001-3000 RMB:143（34.7 %）
	1001-2000 RMB:136（33.0 %）
	1000 RMB and below:68（16.5 %）

A convenience sampling method was used in this study to collect survey data through online questionnaires. To ensure questionnaire reliability, a pilot test was conducted before formal distribution. The survey questionnaire was posted on social media platforms, and data collection spanned two weeks (April 17th to April 28th, 2023), resulting in 554 questionnaire responses. However, a small portion of respondents provided short completion times and exhibited consistent answers to certain scale items. These data were excluded, removing 142 questionnaires. The final sample included 412 valid questionnaires. Descriptive statistical analysis of the maximum, minimum, mean, standard deviation, skewness, and kurtosis of 11 latent variables reveals that the range of the standard deviation is between 0.76876 and 0.92409, indicating a significant difference in the dispersion of data across categories. The minimum and maximum means are 1.8503 and 3.9436 respectively, reflecting a discrepancy in the overall level of data between different categories. The skewness data ranges from -0.763 to 1.493, with most skewness values close to or below 0, indicating that most data is approximately symmetrical or slightly left-skewed. However, the skewness of the PR variable is 1.493, suggesting the presence of outliers on the high end of the PR category's data. Kurtosis ranges from -0.736 to 3.043, with the PR category exhibiting the highest kurtosis of 3.043. This suggests that the distribution of sample data is approximately normal. Table 1 displays the respondents' demographic characteristics.

Measures

The scale used in the questionnaire is derived from mature scales that have been empirically tested in previous studies. Some of the items are sourced from English literature.

To ensure the accuracy of the translated items, the "back-translation" method was employed to ensure the effectiveness of the translated text (Behr, 2017). The scale utilizes a five-point Likert scale, where "1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree".

The measurement of perceived content quality is based on the scale developed by Ho Cheong and Park (2005), consisting of 3 items. Perceived service quality is measured using the scale by Kwong and Park (2008) comprising 3 items. Perceived cost and perceived value are measured using the scale by Fang et al. (2018), each consisting of 3 items. Perceived ease of use and perceived usefulness utilize the scale developed by Davis (1989), with 4 items each. Job relevance is measured using the scale by Venkatesh and Davis (2000), consisting of 3 items. Subjective norm adopts the scale developed by Du and Xu (2018), comprising 3 items. Perceived trust and perceived risk are derived from the scale by Fang et al. (2018), with 4 items and 3 items, respectively. Initial payment intention is measured using the scale by Lu and Zhang (2021), consisting of 4 items.

Statistical Analyses

Common data analysis methods include descriptive statistics, regression analysis, analysis of variance (ANOVA), and structural equation modeling (SEM). SEM can be further divided into covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). Compared to CB-SEM, PLS-SEM has lower requirements on sample size and data distribution (Ringle et al., 2012). It can analyze highly complex models and generate latent variable scores for subsequent analysis (Hair et al., 2019). Due to the complexity of the model in this study, which includes two mediating variables, PLS-SEM was employed to analyze the data. The data were processed using SmartPLS 3.0 (Ringle et al., 2015).

Research Findings

Measurement Model

To ensure the stability and accuracy of the research results, reliability and validity tests need to be conducted. Table 2 describes Cronbach's Alpha coefficient, average variance extracted (AVE), composite reliability (CR) values, square root of AVE, variable correlations, and Heterotrait-Monotrait (HTMT) ratio values for each latent variable. It can be observed that all latent variables have Cronbach's Alpha coefficients greater than 0.70, indicating high reliability of the scales (Nunnally, 1978). Moreover, the AVE values are all greater than 0.50, indicating good convergent validity of the scales (Bagozzi & Yi, 1988). Additionally, the CR values for each latent variable are all greater than 0.70, indicating good composite reliability of the scales (Chin, 1998). Finally, the bolded values on the diagonal represent the square root of AVE. It can be seen that the square root of AVE for each latent variable is greater than the correlation coefficients with other latent variables, indicating good discriminant validity (Fornell & Larcker, 1981). Furthermore, in this study, the HTMT ratio is used as an indicator to assess discriminant validity, which improves the accuracy and reliability of the model. The values in parentheses represent the HTMT ratio, and it can be observed that the HTMT values between latent variables are all less than 0.85, indicating good discriminant validity of the scales (Henseler et al., 2016). Table 3 presents the outer loadings and cross-loadings of each latent variable. It can be observed that the outer loadings of all measurement items are greater than 0.70, indicating good convergent validity of the scales. Each measurement item has a higher loading on its corresponding latent variable compared to other latent variables, indicating good discriminant validity of the scales. Through bootstrapping with 5000 resamples, the T-values for the paths between latent variables and observed variables are all greater than 1.96, indicating the significance and effectiveness of the paths.

Creative Business and Sustainability Journal (CBSJ)
Vol.46 No.1 January – June 2024, pp.1-24

Table 2: Reliability and Validity Tests

Cronbach's Alpha、CR and AVE				Correlation of Constructs and Heterotrait-Monotrait (HTMT) Ratio										
Constructs	**CA**	**CR**	**AVE**	**IWTP**	**JR**	**PC**	**PCQ**	**PEU**	**PR**	**PSQ**	**PT**	**PU**	**PV**	**SN**
IWTP	0.849	0.898	0.689	**0.830**										
JR	0.833	0.900	0.749	0.352 (0.419)	**0.866**									
PC	0.829	0.898	0.746	-0.441 (0.526)	-0.219 (0.265)	**0.864**								
PCQ	0.836	0.900	0.751	0.284 (0.330)	0.328 (0.393)	-0.221 (0.257)	**0.866**							
PEU	0.851	0.899	0.691	0.346 (0.405)	0.223 (0.265)	-0.274 (0.325)	0.214 (0.245)	**0.832**						
PR	0.853	0.911	0.773	-0.617 (0.723)	-0.339 (0.402)	0.376 (0.447)	-0.206 (0.233)	-0.275 (0.325)	**0.879**					
PSQ	0.807	0.886	0.722	0.467 (0.566)	0.266 (0.325)	-0.406 (0.496)	0.220 (0.264)	0.272 (0.332)	-0.442 (0.532)	**0.850**				
PT	0.843	0.895	0.681	0.580 (0.684)	0.368 (0.439)	-0.350 (0.420)	0.347 (0.405)	0.275 (0.322)	-0.505 (0.592)	0.306 (0.370)	**0.825**			
PU	0.868	0.911	0.718	0.481 (0.559)	0.485 (0.569)	-0.323 (0.381)	0.402 (0.469)	0.407 (0.470)	-0.413 (0.477)	0.272 (0.326)	0.437 (0.510)	**0.848**		
PV	0.808	0.886	0.722	0.598 (0.721)	0.304 (0.370)	-0.516 (0.623)	0.356 (0.419)	0.327 (0.395)	-0.604 (0.727)	0.531 (0.652)	0.422 (0.510)	0.398 (0.479)	**0.850**	
SN	0.841	0.904	0.759	0.371 (0.438)	0.395 (0.469)	-0.296 (0.354)	0.371 (0.447)	0.309 (0.360)	-0.293 (0.345)	0.271 (0.326)	0.397 (0.469)	0.493 (0.577)	0.307 (0.371)	**0.871**

Notes: The bold and italicized values represent the square root of AVE; values in parentheses indicate the HTMT ratio; IWTP = Initial Willingness to Pay; JR = Job Relevance; PC = Perceived Cost; PCQ = Perceived Content Quality; PEU = Perceived Ease of Use; PR = Perceived Risk; PSQ = Perceived Service Quality; PT = Perceived Trust; PU = Perceived Usefulness; PV = Perceived Value; SN = Subjective Norm.

Creative Business and Sustainability Journal (CBSJ)
Vol.46 No.1 January – June 2024, pp.1-24

Table3: Factor Loadings and Cross Loadings for the Indicators

Indicators	IWTP	JR	PC	PCQ	PEU	PR	PSQ	PT	PU	PV	SN
IWTP1	**0.857 (67.053)**	0.335	-0.378	0.213	0.274	-0.546	0.390	0.475	0.419	0.497	0.301
IWTP2	**0.810 (43.539)**	0.305	-0.371	0.225	0.290	-0.508	0.372	0.479	0.425	0.492	0.321
IWTP3	**0.837 (51.760)**	0.275	-0.353	0.242	0.303	-0.532	0.403	0.532	0.390	0.491	0.302
IWTP4	**0.814 (41.990)**	0.251	-0.360	0.265	0.281	-0.459	0.387	0.437	0.361	0.507	0.309
JR1	0.293	**0.892 (65.019)**	-0.201	0.275	0.199	-0.310	0.246	0.347	0.450	0.293	0.381
JR2	0.339	**0.852 (49.223)**	-0.198	0.307	0.206	-0.321	0.234	0.319	0.390	0.273	0.323
JR3	0.285	**0.852 (50.904)**	-0.172	0.273	0.174	-0.251	0.210	0.288	0.415	0.224	0.319
PC1	-0.399	-0.197	**0.917 (114.683)**	-0.198	-0.241	0.326	-0.372	-0.308	-0.274	-0.467	-0.235
PC2	-0.345	-0.121	**0.841 (46.525)**	-0.181	-0.192	0.263	-0.301	-0.263	-0.250	-0.437	-0.231
PC3	-0.397	-0.251	**0.831 (77.684)**	-0.193	-0.277	0.387	-0.377	-0.338	-0.314	-0.432	-0.303
PCQ1	0.245	0.288	-0.195	**0.908 (77.684)**	0.242	-0.177	0.188	0.322	0.359	0.324	0.338
PCQ2	0.291	0.298	-0.230	**0.877 (55.243)**	0.173	-0.223	0.221	0.327	0.374	0.349	0.298
PCQ3	0.185	0.263	-0.132	**0.812 (34.464)**	0.130	-0.117	0.153	0.237	0.303	0.232	0.340

Creative Business and Sustainability Journal (CBSJ)
Vol.46 No.1 January – June 2024, pp.1-24

Table3: Factor Loadings and Cross Loadings for the Indicators (Cont.)

Indicators	IWTP	JR	PC	PCQ	PEU	PR	PSQ	PT	PU	PV	SN
PEU1	0.314	0.212	-0.215	0.211	**0.838 (46.109)**	-0.236	0.223	0.251	0.387	0.302	0.295
PEU2	0.266	0.163	-0.265	0.143	**0.861 (46.196)**	-0.213	0.224	0.214	0.315	0.239	0.240
PEU3	0.302	0.170	-0.253	0.185	**0.874 (55.824)**	-0.216	0.222	0.244	0.359	0.269	0.260
PEU4	0.262	0.195	-0.172	0.166	**0.748 (20.802)**	-0.256	0.241	0.197	0.277	0.277	0.222
PR1	-0.548	-0.308	0.347	-0.240	-0.253	**0.881 (52.893)**	-0.398	-0.462	-0.350	-0.566	-0.291
PR2	-0.536	-0.274	0.296	-0.131	-0.250	**0.884 (46.361)**	-0.397	-0.384	-0.344	-0.516	-0.233
PR3	-0.544	-0.311	0.346	-0.167	-0.224	**0.872 (50.676)**	-0.371	-0.479	-0.392	-0.509	-0.247
PSQ1	0.389	0.226	-0.331	0.161	0.212	-0.381	**0.834 (43.967)**	0.245	0.229	0.467	0.209
PSQ2	0.366	0.208	-0.348	0.173	0.215	-0.374	**0.868 (57.802)**	0.245	0.183	0.457	0.243
PSQ3	0.440	0.246	-0.356	0.229	0.268	-0.370	**0.847 (48.085)**	0.291	0.285	0.429	0.238
PT1	0.459	0.323	-0.312	0.302	0.227	-0.395	0.224	**0.810 (41.295)**	0.357	0.341	0.312
PT2	0.470	0.256	-0.270	0.262	0.212	-0.423	0.219	**0.818 (40.450)**	0.372	0.313	0.319
PT3	0.513	0.311	-0.315	0.323	0.239	-0.437	0.311	**0.856 (55.268)**	0.357	0.387	0.362
PT4	0.471	0.326	-0.258	0.254	0.229	-0.409	0.251	**0.815 (36.632)**	0.357	0.349	0.314

Table3: Factor Loadings and Cross Loadings for the Indicators (Cont.)

Indicators	IWTP	JR	PC	PCQ	PEU	PR	PSQ	PT	PU	PV	SN
PU1	0.366	0.377	-0.267	0.389	0.352	-0.301	0.213	0.333	**0.772 (31.286)**	0.311	0.433
PU2	0.407	0.427	-0.284	0.354	0.323	-0.321	0.257	0.375	**0.876 (67.669)**	0.336	0.429
PU3	0.447	0.426	-0.298	0.327	0.325	-0.409	0.257	0.429	**0.893 (76.555)**	0.381	0.424
PU4	0.408	0.410	-0.243	0.298	0.383	-0.363	0.192	0.339	**0.844 (44.528)**	0.318	0.386
PV1	0.522	0.283	-0.471	0.356	0.281	-0.522	0.511	0.364	0.327	**0.882 (80.153)**	0.296
PV2	0.534	0.256	-0.500	0.300	0.281	-0.521	0.462	0.375	0.328	**0.867 (69.503)**	0.217
PV3	0.465	0.235	-0.328	0.242	0.274	-0.497	0.371	0.335	0.369	**0.799 (37.843)**	0.273
SN1	0.294	0.295	-0.210	0.312	0.233	-0.240	0.174	0.318	0.397	0.202	**0.852 (57.907)**
SN2	0.360	0.373	-0.302	0.320	0.241	-0.274	0.280	0.367	0.443	0.327	**0.874 (54.183)**
SN3	0.313	0.361	-0.258	0.336	0.329	-0.252	0.248	0.349	0.447	0.267	**0.887 (73.599)**

Notes: The bold values represent the external loadings; values in parentheses are the T-values for the internal paths; IWTP = Initial Willingness to Pay; JR = Job Relevance; PC = Perceived Cost; PCQ = Perceived Content Quality; PEU = Perceived Ease of Use; PR = Perceived Risk; PSQ = Perceived Service Quality; PT = Perceived Trust; PU = Perceived Usefulness; PV = Perceived Value; SN = Subjective Norm.

Multicollinearity and Common Method Bias Assessment

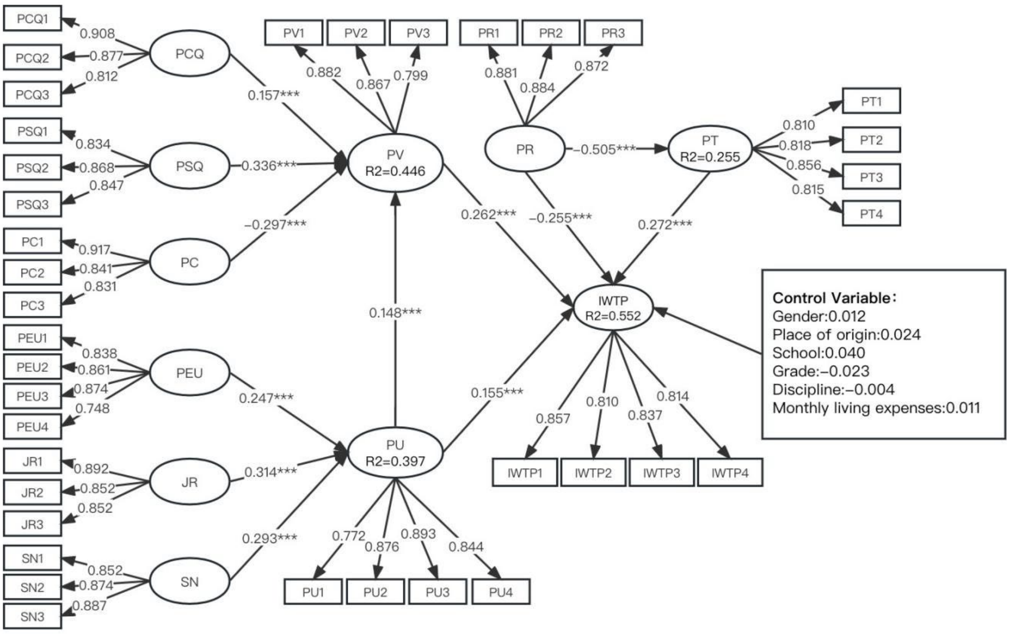
Variance Inflation Factor (VIF) was used as a statistical measure to detect multicollinearity. VIF values exceeding 5 indicate multicollinearity (Hair et al., 2011). In this study, VIF values for the latent variables ranged from 1.000 to 1.846, within an acceptable range, indicating no serious multicollinearity concerns. Therefore, it can be concluded that multicollinearity is not a serious concern. Furthermore, as the data in this study were collected through a questionnaire survey, there is a potential issue of common method bias (CMB) arising from all items being filled out by the same person (Doty & Glick, 1998). To address this concern, this study followed the recommendation of Lindell and Whitney (2001) and employed a marker variable technique to test for CMB. First, an unrelated variable, Perceived Threat of Covid-19 (Sun & Ma, 2022), was introduced as a marker variable in the formal questionnaire. Then, the correlation between the marker variable and the variables in the structural model was calculated. If the marker variable shows a significant correlation with other variables above 0.30, it indicates the presence of CMB (Lindell & Whitney, 2001). Finally, the presence of CMB was further examined by comparing whether the inclusion of variables significantly changed the R-squared values of the variables (Tehseen et al., 2017). The results showed that the path coefficients between the marker variable and the latent variables were all below 0.30 and non-significant, indicating a minimal impact of common method bias on the scales. The addition of the marker variable did not significantly increase the R-squared values, suggesting that the marker variable had a negligible effect on the model results. Therefore, it can be concluded that the scales in this study were not significantly affected by common method bias.

Structural Model

The model fit analysis in PLS-SEM refers to the degree of fit between the model and the actual data (Dijkstra & Henseler, 2015). In SmartPLS, indicators used to evaluate model fit include the Standardized Root Mean Square Residual (SRMR), squared Euclidean distance (d_ULS), geodesic distance (d_G), chi-square value, Normed Fit Index (NFI), and Root Mean Square Theta (RMS-theta) (Henseler et al., 2016). These indicators help assess whether the PLS-SEM model adequately explains the data, thereby enhancing the credibility and accuracy of the research findings. Previous studies have suggested that an SRMR value below 0.08 or 0.10 indicates a good model fit (Xiao, 2020). Bentler and Bonett (1980) suggested that NFI values should range between 0 and 1, with values closer to 1 indicating a better fit of the model. The d_ULS and d_G values should be lower than the 95% confidence interval (Xiao, 2020). An RMS-theta value below 0.12 suggests a good model fit (Hair et al., 2017). In this study, the SRMR = 0.04, d_ULS = 1.538, d_G = 0.68, chi-square value = 1696.869, NFI = 0.81, and RMS-theta = 0.109. Overall, the model in this study demonstrated a good fit to the data.

Path Analysis Results

The hypothesis testing results are presented in Figure 1. It can be observed that perceived trust (β=0.272, $p<0.000$; $f2$=0.110) and perceived value (β=0.262, $p<0.000$; $f2$=0.088) are positively associated with initial willingness to pay. Therefore, H1 and H2 are supported. Furthermore, perceived risk (β=-0.255, $p<0.000$; $f2$=0.079) is negatively related to initial willingness to pay, and perceived risk (β=-0.505, $p<0.000$; $f2$=0.342) is also negatively related to perceived trust. Thus, H3a and H3b are supported. Next, perceived usefulness (β=0.148, $p<0.001$; $f2$=0.030) is positively associated with perceived value, and perceived usefulness (β=0.155, $p<0.001$; $f2$=0.039) is positively associated with initial willingness to pay. Therefore, H4a and H4b are supported. Moreover, perceived content quality (β=0.157, $p<0.000$; $f2$=0.036) and perceived service quality (β=0.336, $p<0.000$; $f2$=0.165) are positively related to perceived value, while perceived cost (β=-0.297, $p<0.000$; $f2$=0.125) is negatively related to perceived value. Hence, H5, H6, and H7 are supported. Finally, perceived ease of use (β=0.247, p<0.000; $f2$=0.090), job relevance (β=0.314, p<0.000; $f2$=0.136), and subjective norms (β=0.293, p<0.000; $f2$=0.113) are positively associated with perceived usefulness. Therefore, H8, H9, and H10 are supported. All hypotheses in this study have been supported. Additionally, the influence of control variables on initial willingness to pay was found to be statistically non-significant in this study. Figure 1 displays the results of the PLS analysis, presenting the path coefficients and significance levels. The results indicate that the R-squared values for initial willingness to pay, perceived value, perceived usefulness, and perceived trust



in the model are 55.20%, 44.60%, 39.70%, and 25.50% respectively.

Notes: *** indicates P ＜0.001; IWTP = Initial Willingness to Pay; JR = Job Relevance; PC = Perceived Cost; PCQ = Perceived Content Quality; PEU = Perceived Ease of Use; PR = Perceived Risk; PSQ = Perceived Service Quality; PT = Perceived Trust; PU = Perceived Usefulness; PV = Perceived Value; SN = Subjective Norm.

Figure 1: Structural Model Results

The results of the mediation analysis

The model constructed in the study includes two assumptions: first, perceived trust mediates the relationship between perceived risk and initial willingness to pay; second, perceived value mediates the relationship between perceived usefulness and initial willingness to pay. The study utilized the Bootstrap method for mediation analysis. As shown in Table 4, the direct effects of perceived usefulness and perceived risk on initial willingness to pay are significant, with effect values of 0.155 and -0.256, respectively. When incorporating the mediating variables, the path coefficients of all mediating variables are significant. The indirect effect of perceived risk on initial willingness to pay through perceived trust is -0.137, and the total effect is -0.392, with a variance accounted for (VAF) of 34.90%, indicating a significant partial mediation effect. Moreover, the directions of the direct and indirect effects are consistent. Therefore, perceived trust plays a complementary mediating role in the relationship between perceived risk and initial willingness to pay. The indirect effect of perceived usefulness on initial willingness to pay through perceived value is 0.039, and the total effect is 0.194, with a VAF of 20.10%, indicating a significant partial mediation effect. Similarly, the directions of the direct and indirect effects are consistent. Thus, perceived value serves as a complementary mediating role in the relationship between perceived usefulness and initial willingness to pay.

Table 4: Mediation Analysis in PLS-SEM

Path	Effects	Estimate	Bootstrap 5000 Times			2.5%-97.5%Percentile		VAF	Conclusion
			S.E.	T	P	Low	Upper		
PR -> PT -> IWTP	Direct Effects	-0.255***	0.046	5.915	0.000	-0.344	-0.163	34.9%	Complementary (Partial Mediation)
	Indirect Effects	-0.137***	0.025	5.517	0.000	-0.188	-0.092		
	Total Effects	-0.392***	0.045	8.750	0.000	-0.479	-0.305		
PU -> PV -> IWTP	Direct Effects	0.155***	0.044	3.543	0.000	0.069	0.239	20.1%	Complementary (Partial Mediation)
	Indirect Effects	0.039***	0.012	3.284	0.001	0.016	0.062		
	Total Effects	0.194***	0.044	4.362	0.000	0.104	0.282		

Notes: *** indicates P < 0.001; IWTP = Initial Willingness to Pay; PR = Perceived Risk; PT = Perceived Trust; PU = Perceived Usefulness; PV = Perceived Value.

Discussion and Conclusion

Theoretical Contributions

From a theoretical perspective, this study combines perceived value theory, perceived risk, trust theory, and the technology acceptance model to build a comprehensive theoretical model aimed at systematically explaining the factors influencing college students' initial willingness to pay for online knowledge. By integrating multiple theories, this study is more comprehensive and systematic in theory, able to delve deeper into the factors affecting initial online knowledge payment. This study conducted empirical research on the initial willingness to pay for college students' online knowledge payment platforms and found that perceived usefulness, perceived value, perceived trust, and perceived risks significantly impact the initial willingness to pay. These factors have been shown to be important determinants of the initial willingness to pay. Previous studies have confirmed the effects of these factors on the willingness to pay in different research contexts, but fewer studies have focused on their combined effects. This research enriches the understanding of perceived value, perceived trust, perceived risk, and the technology acceptance model in the context of online knowledge payment. Moreover, this study found that perceived content quality, perceived service quality, and perceived costs significantly influence the formation of perceived value. This implies that perceived value is a relatively abstract and complex concept, and there are multi-dimensional factors influencing the formation of perceived value. This finding further deepens the understanding of perceived value construction in the context of online knowledge payment. Finally, this study found through the mediating effect that perceived trust and perceived value play a complementary mediation role in the influence of perceived wind and perceived usefulness on the initial willingness to pay. Specifically, perceived risk affects the initial willingness to pay by reducing perceived trust, while perceived usefulness promotes the initial willingness to pay by enhancing perceived value. Therefore, improving users' perceived value and trust in the knowledge payment platform can enhance users' initial willingness to pay. Additionally, although perceived risk has a large impact on the initial willingness to pay, by introducing perceived trust as a mediating variable, the mediation effect is also significant. This indicates that perceived trust plays an important role in mitigating the influence of perceived risk on the initial willingness to pay. This conclusion further deepens the understanding of the relationship between perceived trust and perceived risk in the context of online knowledge payment and helps better explain the intrinsic relationship between perceived trust and perceived risk.

Managerial Implications

From a practical perspective, the above research conclusions have important implications for promoting initial willingness to pay for users of online knowledge payment platforms. Overall, the practical significance of the research is manifested in the following areas. First, from the perspective of users of knowledge payment platforms, the practical contribution of the study is that it reveals the key factors that influence the initial willingness of college student users to pay, including perceived usefulness, perceived value, perceived trust, and perceived risk, etc. These findings can guide the formulation of effective user guidance strategies for knowledge payment platforms, such as strengthening the introduction and recommendation of platform content, improving service quality, and enhancing user privacy protection. At the same time, for college students, these findings can enhance their understanding and trust of knowledge payment platforms, thereby promoting better user participation. Secondly, from the perspective of knowledge producers, the practical contribution of the research lies in clarifying that college students' perception of knowledge value in online knowledge payment platforms is a multi-dimensional process, which not only depends on content quality, but is also affected by service quality and cost. Therefore, knowledge producers on the payment platform should focus on service quality and cost control while providing high-quality content, to enhance users' perceived value of their content. Moreover, knowledge producers can also optimize their knowledge dissemination strategy based on the research results, strengthen the effect and influence of knowledge dissemination, thereby increasing their income. Finally, from the perspective of knowledge payment platform service providers, the research’s practical contribution is to guide its design and optimization of the operation model of the knowledge payment platform. Specifically, service providers can reduce the perceived risk of users and enhance the initial willingness to pay of users by improving the quality of platform content and service quality and establishing stable user trust relationships. In addition, service providers can design differentiated knowledge payment products and services according to different user perception needs and psychology based on the research results and their own actual conditions, improving user satisfaction and loyalty.

Limitations and Directions of Future Research

Despite its contributions, this study has certain limitations that should be acknowledged. Firstly, the sample size was narrow, suggesting the need to broaden the research scope by including a more diverse range of participants. This would enhance the external validity of the findings and provide a comprehensive understanding of factors influencing college students' initial willingness to engage in online knowledge payment. Additionally, it is important to note that the study focused solely on factors influencing initial willingness to pay, without examining the broader context of actual payment behavior. Future research should delve deeper into understanding the determinants of payment behavior, considering individual traits and other relevant factors. While this study selected perceived trust, perceived risk, perceived value, and perceived usefulness as antecedents influencing college students' initial willingness to engage in knowledge payment, it is acknowledged that existing models may not encompass all relevant variables. Therefore, future research should expand and supplement the existing antecedents, particularly in relation to the complex concept of perceived value. Exploring suitable antecedents such as personal emotions and attitudes, continuously refining the existing model, and introducing new variables will contribute to a better understanding of the formation process of initial knowledge payment intentions. Therefore, future research should integrate the development of new technologies and explore trends in online knowledge payment, in order to propose accurate marketing strategies and service models that foster the sustainable development of online knowledge payment platforms.

References

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*, 74–94.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ, US: Prentice-Hall, Inc.

Behr, D. (2017). Assessing the use of back translation: The shortcomings of back translation as a quality testing method. *International Journal of Social Research Methodology*, *20*(6), 573–584.

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, *88*, 588–606. https://doi.org/10.1037/0033-2909.88.3.588

Cai, S., Shi, H., Fu, X., & Chen, X. (2019). A Study on the factors influencing the sales volume of knowledge payment products: Taking Zhihu Live as an example. *Journal of Industrial Engineering and Engineering Management, 33*(3), 71-83. https://doi.org/10.13587/j.cnki.jieem.2019.03.009

Chen, W. (2023). Development strategies for guangdong higher education in the process of China-style modernization. *Higher Education Exploration,* (1), 5-7.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research, 295*(2), 295–336.

China Government Online. (2021). *Scale of China's digital economy*. http://www.gov.cn/xinwen/2021-09/26/content_5639469.htm

Crespo, Á. H., del Bosque, I. R., & de los Salmones Sánchez, M. M. G. (2009). The influence of perceived risk on Internet shopping behavior: A multidimensional perspective. *Journal of Risk Research*, *12*(2), 259–277. https://doi.org/10.1080/13669870802497744

Cronin Jr, J. J., & Taylor, S. A. (1992). Measuring service quality: A reexamination and extension. *Journal of Marketing, 56*(3), 55-68.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319–340.

Dijkstra, T. K., & Henseler, J. (2015). Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics & Data Analysis, 81*, 10–23.

Doty, D. H., & Glick, W. H. (1998). Common methods bias: Does common methods variance really bias results. *Organizational Research Methods*, *1*, 374–406. https://doi.org/10.1177/109442819814002

Du, Z., & Xu, J. (2018). From demand to experience: Influencing factors of user's online knowledge payment behavior. *Journalism and Communication Research, 25*(10), 18-39.

Fang, A., Lu, M., & Li, K. (2018). Empirical study on the willingness of virtual community users to pay for knowledge. *Library and Information Work, 62*(6), 105-115. https://doi.org/10.13266/j.issn.0252-3116.2018.06.013

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS quarterly*, 51-90. https://doi.org/10.2307/30036519

Grönroos, C. (1984). A service quality model and its marketing implications. *European Journal of Marketing, 18*(4), 36–44. https://doi.org/10.1108/EUM0000000004784

Hair Jr, J., Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM).* Sage Publications.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Harrison, M. D., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: A trust building model. *The Journal of Strategic Information Systems*, *11*(3), 297–323. https://doi.org/10.1016/S0963-8687(02)00020-3

He, K. (2021). The Next Decade, the Knowledge-Payment industry may face "Six Major Upgrades.". *Publishing Perspectives,* (22), 42-45. https://doi.org/10.16491/j.cnki.cn45-1216/g2.2021.22.009

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems, 116*(1), 2-20.

Cheong, J. H., & Park, M. (2005). Mobile internet acceptance in Korea. *Internet Research*, *15*(2), 125–140. https://doi.org/10.1108/10662240510590324

Hooton, C. (2019, September 26). *Measuring The U.S. Internet Sector: 2019* [SSRN Scholarly Paper]. Rochester, NY. https://papers.ssrn.com/abstract=3462327

Huang, B., & Tang, W. (2019). On the rise and significance of knowledge payment models. *Publishing Horizons*, (1), 29–32. https://doi.org/10.16491/j.cnki.cn45-1216/g2.2019.01.007.

iResearch Consulting Group. (2022). *China's knowledge payment industry report 2022*. https://www.iimedia.cn/c400/85595.html

Kwong, S. W., & Park, J. (2008). Digital music services: Consumer intention and adoption. *The Service Industries Journal*, *28*(10), 1463–1481. https://doi.org/10.1080/02642060802250278

Li, C., & Shen, C. (2022). The impact of perceived value of membership services on consumption willingness in knowledge payment platforms - Empirical Analysis Based on college Students. *China Publishing*, (12), 22-25.

Li, J. (2019). Enhancing the scientific and technological innovation ability of teachers in private colleges and universities in the context of the Guangdong-Hong Kong-Macao Greater Bay Area. *Science and Technology in Chinese Universities*, (S1), 20-21. https://doi.org/10.16209/j.cnki.cust.2019.s1.006

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *The Journal of Applied Psychology, 86*(1), 114–121. https://doi.org/10.1037/0021-9010.86.1.114

Lu, H., Zhang, X., Xiao, Bi., & Liu, Y. (2021). Influencing factors and moderating variables of online users' willingness to pay for knowledge: A Meta-analysis. *Library and Information Service, 65*(13), 44-54. https://doi.org/10.13266/j.issn.0252-3116.2021.13.005

Lu, Y., & Zhang, M., (2021). Research on the influencing factors of college students' knowledge payment behavior. *Journal of Hangzhou Normal University* (Natural Sciences *Edition), 20*(1), 13–21. https://doi.org/10.19926/j.cnki.issn.1674-232X.2021.01.003

Ming, J., Yu, S., Yang, Y., & Huang, C. (2014). Construction of technology acceptance model for mobile libraries. *Information and Documentation Services*, (5), 49-55.

Murphy, P. E., & Enis, B. M. (1986). Classifying Products Strategically. *Journal of Marketing*, *50*(3), 24–42. https://doi.org/10.2307/1251583

Nunnally, J. C. (1978). *Psychometric theory*. McGraw-Hill.

Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS Quarterly*, *30*(1), 115–143. https://doi.org/10.2307/25148720

Peng, L. (2018). Platform mechanism and user willingness: An analysis of two key elements of knowledge payment. *China Editor*, (11), 11-17.

Ringle, C. M., Sarstedt, M., & Straub, D. W. (2012). Editor's comments: A critical look at the use of PLS-SEM in" MIS Quarterly". *MIS Quarterly*, iii–xiv.

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). SmartPLS 3. https://www.smartpls.com

Shen, J. (2018). Current situation and future prospects of the development of knowledge payment. *The Chinese Editor,* (11), 35-39.

Sullivan, Y. W., & Kim, D. J. (2018). Assessing the effects of consumers' product evaluations and trust on repurchase intention in e-commerce environments. *International Journal of Information Management*, *39*, 199–219.

Sun, X., Zhu, F., & Song, H. (2016). Perceived trust and project performance: The mediating role of organizational commitment. *Management Review, 28*(12), 155-165. https://doi.org/10.14120/j.cnki.cn11-5057/f.2016.12.013

Sun, X., & Ma, Y. (2022). How The Perceived Threat of Covid-19 Aggravates Chinese Employees' Emotional Exhaustion and Turnover Intention in Thailand: The Moderating Role of Affective Commitment. *Creative Business and Sustainability Journal, 44*(1), 1–17. https://so01.tci-thaijo.org/index.php/CBSReview/article/view/258634

Sun, Y., Fang, Y., & Lim, K. H. (2014). Understanding knowledge contributors' satisfaction in transactional virtual communities: A cost–benefit trade-off perspective. *Information & Management*, *51*(4), 441–450.

Tan, C., Wang, X., Diao, F., & Liang, Y. (2023). Research on the mechanism of user's continuous usage Intentions in social Q&A communities based on fsQCA method. *Library and Information Studies*, (1), 74-86. https://doi.org/10.15941/j.cnki.issn1001-0424.2023.01.002

Tehseen, S., Ramayah, T., & Sajilan, S. (2017). Testing and controlling for common method variance: A review of available methods. *Journal of Management Sciences, 4*(2), 142–168. https://doi.org/10.20547/jms.2014.1704202

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Xia, X., Shi, K., & Shi, M. (2010). Trust and risk perception in the network environment. *Microcomputer Information, 26*(30), 45-46.

Xiao, W. (2020). *Introduction and application of statistical analysis: SPSS chinese version + PLS-SEM (SmartPLS) third edition.* Gifi Information.

Xu, Y. (2018). Problems and countermeasures of the knowledge payment platform "Dedao". *Young Journalist*, (30), 81–82. https://doi.org/10.15997/j.cnki.qnjz.2018.30.046

Yang, X., Jiang, Y., & Ma Sirui. (2017). A Study on the influencing factors of consumption willingness of online cultural products. *Journal of Xi'an Jiaotong University (Social Science Edition), 37*(5), 94-103. https://doi.org/10.15896/j.xjtuskxb.201705011

Yin, X., Huang, B., & Lin, Z. (2019). Analysis of the differences in influencing mechanisms of users' willingness to pay for knowledge for the first time and repeatedly: Taking Guangzhou as an example. *New Media Research, 5*(5), 9-11. https://doi.org/10.16604/j.cnki.issn2096-0360.2019.05.003

Yu, Y. (2022). *Study on the influencing factors of user's willingness to pay on online knowledge payment platform* [Master's thesis]. Liaoning University of Technology. https://doi.org/10.27210/d.cnki.glnju.2022.000417

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing, 52*(3), 2–22.

Zhang, W., Xu, M., & Su, R. (2020). *Dancing with structural equation models (Dawn)/ econometric series*. Xiamen University Press.

Zhang, W., & Zhu, J. (2019). The impact of contributors' identity in online knowledge communities on content quality. *Modern Information, 39*(8), 103-110.

Zhang, X. (2019). Comparative study on the models of domestic knowledge payment platforms [Master's thesis]. Zhejiang Media College.

Zhao, S., Chen, L., & Du, Z. (2018). A study on the influencing factors of purchase intention in intelligent communities based on the structural equation model. *Resource Development & Market, 34*(4), 575–581.

Zheng, C., Liu, X., & Yang, X. (2012). Research on the influence of perceived value and personal traits on users' adoption intention of mobile shopping. *Journal of Management Science, 9*(10), 1524–1530.

Zheng, Z. (2016). Research on the causes, connotations, and business models of the sharing economy. *Modern Economic Exploration*, (3), 32–36. https://doi.org/10.13891/j.cnki.mer.2016.03.008

Zhou, T., Lu, Y., & Zhang, J. (2011). Research on the key success factors of mobile business websites. *Management Review, 23*(6), 61-67. https://doi.org/10.14120/j.cnki.cn11-5057/f.2011.06.011

 Creative Business and Sustainability Journal (CBSJ)
Vol.46 No.1 January – June 2024, pp.1-24

Appendix

PCQ1: I believe that paid knowledge platforms provide a variety of information and services.
PCQ2: I consider the services and information I obtain from paid knowledge platforms to be valuable.
PCQ3: I believe that paid knowledge platforms offer the information and services I require.
PSQ1: When I encounter issues with the use of knowledge-based products, the provider responds promptly.
PSQ2: I deem the provider of the paid knowledge platform to be trustworthy.
PSQ3: The provider of the paid knowledge platform promptly and accurately resolves issues.
PC1: I find the pricing of knowledge products to be comparatively high.
PC2: I view high prices as a barrier to the purchase of knowledge products.
PC3: I consider the purchase of knowledge products to require more expenses.
PV1: In comparison to the time invested, I find the purchase of knowledge products to be worthwhile.
PV2: I believe that purchasing knowledge products is worth it when compared to the effort expended.
PV3: I believe that purchasing knowledge products is worthwhile compared to the money spent.
PEU1: I can quickly learn how to use the paid knowledge product I need.
PEU2: I find the website systems of paid knowledge products in general to be stable and smooth to use.
PEU3: I can easily solve problems by using paid knowledge products.
PEU4: Overall, I consider paid knowledge products easy to use.
JR1: In my work/learning process, the paid knowledge platform is important.
JR2: The information provided by the paid knowledge platform is relevant to my needs.
JR3: The information provided by the paid knowledge platform contributes to my learning/work.
SN1: The reviews and evaluations of other users directly influence my initial interest in online knowledge payment.
SN2: Recommendations from friends or influential people directly affect my initial online knowledge payment propensity.
SN3: I think those who are aspiring and excellent are willing to pay for knowledge.
PU1: I consider the use of paid knowledge products to be somewhat beneficial for me.
PU2: I believe that using paid knowledge products can improve efficiency in learning and working.
PU3: Paid knowledge products provide me with a lot of useful information.
PU4: Generally, I find paid knowledge products to be very useful.
PT1: I trust that the paid knowledge platform I use can protect my privacy and financial security.
PT2: I trust that the paid knowledge platform I use is capable of providing quality knowledge product-related services.
PT3: I believe in the quality and services of knowledge products.
PT4: I trust the professionalism of creators of knowledge products.
PR1: When buying knowledge products, I am concerned about the platform's ability to provide content continuously.
PR2: When purchasing knowledge products, I worry about the quality not meeting my expectations.

 Creative Business and Sustainability Journal (CBSJ)
Vol.46 No.1 January – June 2024, pp.1-24

PR3: When purchasing knowledge products, I worry about my inability to stick with the content learning.
IWTP1: When I see online learning resources that I need but require payment, I am willing to pay.
IWTP2: For me, I am more inclined to purchase online learning materials than offline resources.
IWTP3: When I see the online paid information like lectures and courses, I am interested in paying to learn.
IWTP4: When I find quality paid information or knowledge content online, I am inclined to purchase it.