Article

A Study on the Factors Influencing Users' Online Knowledge Paying-Behavior Based on the UTAUT Model

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Abstract: With the explosive growth of information and the increase of people's fragmented time, the knowledge payment industry's market size is growing. However, the heterogeneity between online knowledge payment behavior and traditional consumption gradually comes to the fore. It is of great practical significance to analyze the factors influencing users' online knowledge payment behavior and clarify users' online knowledge payment mechanism. Based on UTAUT theory, this study uses statistics, structural equation modeling, and mediating effect analysis to construct a theoretical model of the influencing factors of users' payment behavior of knowledge payment platform from the user level, knowledge-provider level, and platform level. The findings show that content quality, peer influence, KOL influence, perceived interaction, effort expectation, and perceived trust significantly affect users' willingness-to-pay and have an indirect effect on users' paying behavior through their willingness-to-pay. Perceived cost, perceived interaction, content quality, peer influence, performance expectation, and effort expectation directly and significantly affect user paying behavior. By regulating the above elements, the improvement of customer attraction ability of online knowledge platforms can be realized.

Keywords: paying for knowledge; UTAUT model; user paying behavior; influencing factors

1. Introduction

Paid knowledge is a new industry derived from Internet content consumption [1], with its native industries coming from the education, consulting, and publishing industries. With the popularity of the Internet and the advent of the era of cognitive redundancy, these industries have proliferated on the Internet's express train, eventually giving rise to a series of paid courses, paid channels, paid quizzes, paid communities, and other paid knowledge products [2]. According to the China Knowledge Payment Industry Development's White Paper 2017, knowledge payment refers to producers producing standardized paid products based on their knowledge, integrating books, theoretical knowledge, information, etc., in a systematic and structured manner. The products are then delivered to users through the payment mechanism of knowledge payment platforms. Ultimately, this allows the paying customers to have their needs met to enrich their conversation and improve their cognitive level [3]. Paying for knowledge essentially means that the recipient of knowledge pays money for accessing it. Paying for knowledge allows the recipient of knowledge to pay the disseminators and screeners of knowledge indirectly, rather than allowing those involved in the knowledge distribution chain to receive revenue through other means such as traffic or advertising [4]. The birth of the new Internet industry has further catalyzed the escalation of supply and demand for online knowledge payment. The vast number of knowledge disseminators and screeners drives the exuberant flow of online capital, creating the rapid development of the online knowledge industry.

In 2016, the first year of knowledge payment was ushered in, with Zhihu launching two functional modules, Value Hu and Zhihu Live. In January 2020, WeChat opened

the subscription number payment function, the era of "paid reading" for public numbers officially arrived, which led to the online update of the overseas version of WeChat: the introduction of online knowledge review communities, the realization of paid information resources based on videos, pictures, books and other media, and the sharing of benefits for more people in the knowledge dissemination chain. In 2019, China's knowledge payment industry's market size reached $27.8 billion, and the industry user size reached 360 million people. In the spring of 2020, during the COVID-19 epidemic prevention and control period, the offline real economy suffered a huge impact, while the knowledge payment industry ushered in a new development opportunity [5]. During this period, 63.1% of Chinese users have purchased a paid knowledge product, 88.8% of Chinese online learning users have purchased a paid knowledge product, and about 90% of users said they would purchase a paid knowledge product again [6]. With the general increase in national income and the growing demand for knowledge, the market size is expected to reach 67.5 billion yuan in 2021. There is still a good deal of room for the development of knowledge payment. In developed countries such as the US, the pay-for-knowledge industry started even earlier.

In 2015, the *Times* and other news media gradually began to consider the issue of news pricing, and based on the mobile version of the website, PC version, and other mobile application platforms to build out the prototype of the online knowledge payment platform [5]. Global online education platforms such as Coursera and Udemy began to layout in 2016. In 2018, based on the two dimensions of "social + paid, they received US $20 million in funding, which also marked the rapid development of overseas online knowledge platforms [7].

However, there is still an unbalanced contradiction and gap between the rapid development of the knowledge payment industry and users' willingness-to-pay. From a supply-side perspective, users' demand for the quality of online knowledge has been increasing year by year. However, the vast number of knowledge payment platforms has disrupted the knowledge supply channels and caused qualitative fluctuations in the knowledge dissemination chain, leading to dissatisfaction among users in terms of traffic and advertising revenue [7]. In the long term, online knowledge payment platforms are still relatively small compared to the offline knowledge industry and cultural communication industry, and the current short-term leapfrogging growth of the industry is mainly dependent on the favorable support of the internet industry, even taking advantage of the stagnation period of the knowledge industry brought about by the epidemic crisis. This growth is hollow or tepid. Therefore, the key to the long-term and fundamental development of knowledge payment platforms and the industry as a whole is to master the core demands of users and enhance their stickiness. The core of this demand and stickiness lies in the knowledge platform's clarification of users' willingness-to-pay, and the determination and analysis of the main influencing factors of users' payment behavior, leading the platform to transform and improve its inherent quality actively. Through the development of empathy between platforms and users, the vulnerability and inadequacy of knowledge payment platforms can be reversed to a great extent. This paper will analyze the influencing factors of user paying behavior from three aspects: knowledge recipients, knowledge suppliers, and platforms, to reference the decision-making of knowledge payment platforms and knowledge suppliers and promote the peaceful development of the knowledge payment industry.

2. Literature Review

In the Internet age of "free thinking", unauthorized sharing has become a key constraint for knowledge providers to continue to deliver quality content [7]. To attract customer traffic and other resource information, the online knowledge platform will purchase the copyright of the information in advance for free publication to attract new resources. In this context, the quality of free information cannot be guaranteed. Under the constraint of "content is king," the interests of knowledge providers are the priority of knowledge payment platforms [8]. Therefore, online knowledge platforms integrate the

two major problems of "Internet development" and "knowledge product change". That is, how to use the free-thinking of the Internet to expand and attract consumers rapidly and use the adjustment of knowledge products and the extension of the knowledge dissemination chain to upgrade their interests. Under the impact of both, the question of "You cannot have your cake and eat it, too" soon arose: How to maintain customer attraction to avoid the withdrawal of knowledge providers and the regression of quality caused by knowledge-free products [9].

In the context of current international development, the Internet economy is deeply embedded in people's lives, the value of knowledge is increasingly valued, and online knowledge platforms are gradually gaining prominence in the value, production, and information chains. Therefore, the future information industry cannot ignore the development necessity of online knowledge platforms and cannot ignore users' payment experience and willingness to purchase knowledge to strengthen knowledge revenue [10]. In both cases, online knowledge payment platforms can grasp the influencing factors of users' consumption behavior and optimize and enhance the influencing paths of knowledge providers and users, significantly contributing to the sustainable and high-quality development of the knowledge industry.

In this context, The existing studies already found "the factors influencing users' online knowledge paying behavior. " Based on the connotation and concept of knowledge paying, scholars' understanding of the factors influencing users' behavior can be split into three aspects: the User level (user side), the knowledge-provider level, and the platform level. At the user level, users' usage behavior, paying behavior, and continued usage behavior are explored. Hsiao [11] uses the perceived value as a grounded theory to explore users' willingness-to-pay for content, concluding that perceived value and switching barriers impact users' willingness-to-pay. This perceived value and switching barriers essentially stem from the role of the potential factor expected benefits, with both product quality and supplier reputation only indirectly influencing users' willingness-to-pay through expected benefits [12]. This conclusion, in turn, appears to evolve and change in the context of virtual online knowledge communities.

Under the theory of planned behavior, paying behavior is driven by willingness-to-pay and is ultimately influenced by external expectations at the social level. In other words, the multidimensional environment and the 'other-me' nature of the consumer user will influence their judgment of expected benefits, whether this judgment is positive or negative, and will determine the ultimate purchasing power and extent of the paid knowledge product [13]. This argument establishes the status of 'opinion leaders' in online consumption research: the visibility, expertise, and homogeneity of opinion leaders indirectly contribute to the willingness to continue participating through the perceived value of users [14]. When 'other-me' users dominate the overall community commentary, there is a significant orientation towards purchasing knowledge products that transcend the user's expected benefits and has a decisive impact.

Brian's [15] research confirms that Key Opinion Leader (KOL) visibility enhances consumer trust and that celebrities are more likely to be identified as recommenders of reliable information. At the knowledge-provider level, academics have explored the impact of opinion leaders' knowledge contributions on users among knowledge providers. Essentially, the mechanism by which the knowledge of such supply-oriented opinion leaders affects users' consumption behavior stems from the learning effect [16]. Online knowledge payment platforms provide a learning platform for knowledge suppliers and demanders across geographical boundaries. Knowledge demanders pay knowledge suppliers for learning purposes and to generate their learning benefits [17]. Therefore, users' paying behavior and willingness-to-pay will be influenced by the authority of the knowledge provider [18]. When opinion leaders are formed, users will perceive the quality of knowledge to be superior and more willing to purchase, and more motivated to learn. In a sense, this is when the knowledge payment platform strengthens its traction on users'

consumption behavior and holds the 'core code' of their consumption motivation and influence mechanism.

At the platform level, Vander [19] studied the factors that influence online shopping sites on users' paid purchases and concluded that users' trust in the platform directly influences their willingness to buy. Cai [20] used Zhihu Live, a knowledge payment platform, as the research object to explore the effect of the price of knowledge products on their sales based on a signal theory model. It was eventually found that price hurts sales, but when the number of product reviews increases, the negative effect of price on sales diminishes. It can be seen that users' knowledge paying behavior is closely related to the user level, the knowledge-provider level, and the platform level. Users' willingness-to-pay and their paying behavior should also be judged in the light of these three influencing factors.

Based on exploring the dimensions of the knowledge receiver, knowledge provider, and platform, a framework of factors influencing users' online knowledge payment behavior can be initially mapped out. However, the inner mechanism between the influencing factors and users' behavior still needs to be further explored. In the field of Internet user behavior research, classical models from a variety of perspectives have been produced, with a large number of relevant studies extending on top of the Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), Theory of Rational Action (TRA) and Innovation Diffusion Theory (IDT) [21,22].

From the perspective of technology acceptance, online knowledge payment activities are presented as a process of user acceptance of information costs and information systems, so the theory better explains the determinants of widespread acceptance of information technology and lays a specific theoretical foundation for exploring this paper [23]. The technology acceptance model theory suggests two main factors of information activity, namely perceived usefulness and perceived ease of use [24]. In conjunction with the previous literature summary, perceived usefulness portrays the ultimate performance of the knowledge recipient in terms of independent judgment (expected benefits), 'other-me influence' (opinion leaders or external environmental interference) activities, while perceived ease of use is the ease of use of the knowledge product provided by the knowledge provider and reflects the degree of knowledge quality and authority [25].

From rational behavior theory, users' consumption activities in knowledge payment platforms are driven by their attitudes. The complete process of their purchase intention is the attitude formation process of cognitive information [26], which matches with rational behavior theory. Through the use of this theory, this paper can identify the influencing factors of users' knowledge payment behavior based on rational perspective and expand the formation of logical decision paths to serve the operation optimization strategies of online knowledge platforms [27].

In terms of innovation diffusion theory, online knowledge payment activities are new ideas, new things, and new products and influence mass communication on a social and cultural level. The process of user acceptance is the process of diffusion of communication effects and the integration and absorption of new things [28]. In this process, users are informed, persuaded, and self-persuaded, make decisions, implement and give feedback on the innovation in willingness, behavior, and emotions. With the help of this theory, it is easier to get a clearer picture of the formation mechanism of the influencing factors of users' online knowledge payment and clarify the association between the influencing factors and the final decision [29].

However, there are still problems of isolation and compatibility in the use of the above theories. A research framework under an integrated technology acceptance and use theory can be formed by integrating the above theoretical points. The Unified Theory of Acceptance and Usage of Technology (UTAUT) is a relatively recent development. Still, it has been shown to have a high degree of explanatory power in several research areas [30–32]. The UTAUT model has also been continuously improved and applied to the field of Internet user behavior. In empirical studies, UTAUT theory is often combined with

other theories, or the antecedent variables are reasonably modified to fit the characteristics of the research subject. Min [33] improved the UTAUT model by adding variables such as satisfaction and user characteristics to explore mobile commerce's adoption behavior. Based on the UTAUT model and the Task-Technology Fit model (TTF), Hsiao [11] effectively explains users' adoption behavior towards mobile banking. Yin [34] studied consumer behavior towards using health products based on UTAUT and Protection Motivation Theory (PMT). Zhang [35] conducted an empirical study on the continuous information-sharing behavior of online community users based on the UTAUT and Perceived Value Model (PVM). Zhao [36] added three variables to the UTAUT model to construct a model of factors influencing consumer purchase intention in online group buying. Using UTAUT as a theoretical framework, Li [37] conducted an empirical analysis of older people's willingness and behavior to use WeChat friend circles through structural equation modeling.

The above literature provides ample evidence of the high explanatory power of the UTAUT model for research related to Internet user behavior and the development of knowledge payment platforms as an extension of Internet platforms. However, the theory has not been much studied in the field of knowledge payment, so that this study will analyze the factors influencing the paying behavior of users of knowledge payment platforms based on the UTAUT model.

Throughout the research results at home and abroad, few studies on the willingness-to-pay and paying behavior of users of knowledge payment platforms are based on UTAUT theory. Therefore, this paper will take the theory as the basis and knowledge payment users as the research object and consider the three levels of users, knowledge providers, and platforms comprehensively to conduct an empirical study on users' paying behavior.

3. Theoretical Foundations and Model Assumptions

3.1. Improved Model

The Unified Theory of Acceptance and Usage of Technology (UTAUT) was developed by Venkatesh [38] in 2003 to study consumers' willingness-to-use and usage behavior, as shown in Figure 1. The UTAUT model integrates arguments from eight theories (Technology Acceptance Model (TAM), Theory of Rational Action (TRA), Theory of Planned Behaviour (TPB), Task-Technology Fit Model (TTF), Innovation Diffusion Theory (IDT), Motivation Model (MM), Social Cognitive Theory (SCT) and Model of PC Utilization (MPCU) and condenses the influencing variables into four antecedent variables, namely performance expectation, effort expectation, social impact, and facilitating-condition. Of these, performance expectation, effort expectation, and social impact willingness-to-use, and facilitating condition have a significant impact on usage behavior, and the other four control variables are gender, age, experience, and voluntariness. Because the UTAUT model was proposed later, its application is not as widely used as the TAM model and TPB theory, but many domestic and foreign scholars have empirically proved that the UTAUT model is more effective than any previous model, with an explanatory power of up to 70% [39].

This study retains the performance expectation and effort expectation from the original UTAUT model. Social impact is the attitude of people around the user who are essential to them or whom the user perceives to be important to the knowledge payment product or service [33], similar to the subjective norm in Theory of Planned Behaviour (TPB), which responds to the role of external factors in influencing the user. Subjective norms are divided into peer influence and external influence [12]. However, only human influence exists in social impact, not environmental factors, so the social impact is divided into peer influence and KOL influence, considering that KOL, mostly content producers, play an increasingly important role in social platforms [22]. Peers refer to the user's friends, family, colleagues, superiors, etc., while KOLs refer to the opinion leaders in the knowledge payment platform. Facilitating condition is an illustration of the impact of new technology features. Han conducted a statistical analysis of 161 papers applying the UTAUT model research in China between 2007 and 2016. He found that facilitating conditions had a weak

influence on adoption behavior [40]. Because the current popularity of 4G technology and the development of 5G bring great convenience, facilitating condition was not used as an influencing factor when constructing the model.
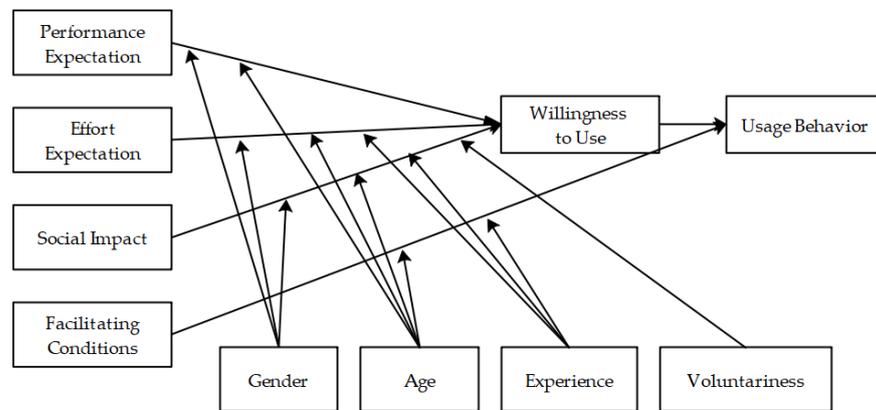

Figure 1. The Unified Theory of Acceptance and Usage of Technology Model (UTAUT) [38].

In addition, knowledge payment platforms are knowledge communities that attach social attributes to knowledge as a product or service. In a knowledge payment platform, there are three primary levels involved. Firstly, the knowledge receiver, i.e., the vast majority of platform users; secondly, the knowledge supplier, i.e., the party that generates the knowledge; and thirdly, the knowledge payment platform. Based on the UTAUT model, this paper expands to add four related variables of content quality, perceived trust, perceived interaction, and perceived cost as influencing factors of users' willingness-to-pay and paying behavior, based on the platform characteristics from these three dimensions combined [41].

3.2. Research Hypotheses

3.2.1. User level

The user's self-perception is often the most direct factor influencing paying behavior. It first appeared in the technology acceptance model theory and was characterized as a perceptual trait. The early scales of this theory were used to delineate and address dimensions such as customer expectations and expected value. In the extension of the theory of planned behavior, perceptual characteristics are associated with the willingness of the actor, i.e., perceptual characteristics are endogenously motivated to influence the subject's willingness to engage in activities, and there is a significant influence path between the two [42].

The performance expectation and effort expectation of the user in the UTAUT model are factors at the user's level. According to the interpretation in the original UTAUT model, social impact is further subdivided into peer influence and KOL influence. Since peers mainly include such people in the user's daily life as friends, family, colleagues, and superiors, peer influence's antecedent variable is also a user-level factor. On this basis, this paper extends the hypothetical mechanisms of the fused technology acceptance model and theory of planned behavior based on the UTATA model. The final hypothesis of performance expectations, effort expectations, and peer influence on the user willingness layer is proposed. The details are as follows:

- Performance Expectation In this paper, performance expectation is defined as the extent to which users perceive an increase in the efficiency of a knowledge payment platform for learning, work, or other personal needs. Performance expectation can be expressed in several ways. Zhang found that the most critical needs of paid knowledge users were task completion and gaining expertise, followed by hobbies, self-improvement, emotional factors, saving time and energy, and social needs, respectively [41]. Research on online learning has shown that if users use a new platform or

technology to improve their work performance, this expectation will increase their willingness-to-use it [43]. From a theoretical perspective, performance is the immediate utility of knowledge product purchases and the immediate goal of users' consumption on knowledge platforms: namely, to enhance their substantive self-efficacy with learning effects. This pure motivation will drive an increase in users' willingness-to-pay. In the context of learning motivation theory, the reinforcing power of performance on goals will act significantly on users' internal activities and is a trigger mechanism for the internal arousal of human behavior [44]. The same is true in knowledge payment platforms, where paid content tends to be of higher quality than other content and is more helpful in improving users' performance and more significant in terms of willingness and behavior to pay. Therefore, the following hypothesis is proposed in this paper.

Hypothesis 1a. *Performance expectations have a positive effect on users' willingness-to-pay.*
Hypothesis 1b. *Performance expectations have a positive effect on users' paying behavior.*

- Effort Expectation In this paper, effort expectation is defined as the ease of operational use of the knowledge payment platform as perceived by the user. Much like the perceived ease of use in the TAM model, Davis found that the ease of using an information system directly affects users' willingness to adopt it [45]. Users want to improve their performance when using a knowledge payment platform and want it to be easy to learn and use. Guided by the theory of the technology acceptance model, the counter-decision of information platforms on users (i.e., influencing users' willingness and inhibiting their use) exists mainly in terms of the experience of using the platform. When the technology is too complex and the barriers to use stand out, users will abandon their use in favor of alternatives, and conversely, they will actively embrace it. Based on this condition, users' willingness and behavior to pay for knowledge payment products will also increase, so the following hypothesis is proposed.

Hypothesis 2a. *Effort expectations have a positive effect on users' willingness-to-pay.*
Hypothesis 2b. *Effort expectations have a positive effect on users' paying behavior.*

- Peer Influence In this paper, peer influence is defined as the knowledge payment platform users' role being influenced by those around them on their willingness-to-pay and their paying behavior. As a further subdivision of social impact, peer influence is similar to the variable of subjective norms in the TPB model. Taylor's study found that significant surrounding people or groups positively influence an individual's intention to make decisions and that behavioral intention, in turn, has a significant effect on actual behavior [46]. Peer influence is an external manifestation of the user resulting from a combination of rational behaviour theory, social cognitive theory and peer effects. In conjunction with the previous literature, it is clear that peers, especially opinion leaders, have a strong influence on the user body and, to a certain extent, on the final willingness-to-pay. Therefore when surrounding peers use or recommend information systems, users will enhance their intentions and behavior towards the system. The following hypothesis is proposed for this purpose:

Hypothesis 3a. *Peer influence has a positive effect on users' willingness-to-pay.*
Hypothesis 3b. Peer influence has a positive effect on users' paying behavior.

3.2.2. Knowledge-Provider Level

Knowledge providers act as content producers for knowledge payment platforms. Among the many knowledge payment platforms, the trend of superiority and inferiority of content has intensified, users change from paying impulsively to paying rationally, and quality content is more prevalent among users [47], so the content quality of the

platform can often reflect the overall good or destructive operation of a platform. KOLs are a minority of people who constitute an essential source of information and influence within a team and can sway the majority's attitudinal tendencies. KOLs often act as content producers in social platforms, and the vast majority of KOLs also act as excellent knowledge providers in paid knowledge platforms and have a strong influence on users' attitudinal tendencies.

The quality of the supply-side product, publicity, is shown to influence the actor by the theory of rational behavior positively, the model theory of technological fitness for the task, the theory of diffusion of innovation, and the theory of PC utilization model. This is essentially a role of perceived appropriateness theory, which reflects the ability of knowledge supply-side information technology to support work tasks. By describing cognitive psychology and cognitive behavior to reveal how information technology acts on an individual's task performance [48], it reflects the logical relationship between information technology and task demands. This logical relationship is the path of influence of content quality and KOL influence on the impact of user knowledge payment in the knowledge supply hierarchy. Therefore the content quality and KOL influence are considered essential factors at the knowledge provider level.

- Content Quality In this paper, content quality is defined as the level of quality of content provided to users in a knowledge payment platform, encompassing the content's relevance, interpretability, accuracy, and timeliness. There are seven main factors distilled from online knowledge paying behavior, of which the quality of information is key to influencing paying behavior [41]. Using UTAUT as a theoretical basis, Siqing analyzed the factors influencing users' willingness-to-use regarding acceptance factors, risk factors, and content factors in a tripartite manner [49]. He used UTAUT as the theoretical basis and introduced three variables, such as information quality, to construct a theoretical model of factors influencing mobile library users' willingness-to-use [50]. Ángel used UTAUT theory as a basis to add three antecedent variables, such as information quality, to study the usage behavior of academic, social networks [51]. Also, numerous studies have shown that users' judgment of content quality is a decisive factor in knowledge paying behavior and suggests that no effort should be spared to improve knowledge payment products [52,53].

  Hypothesis 4a. *Content quality has a positive effect on users' willingness-to-pay.*
  Hypothesis 4b. *Content quality has a positive effect on users' paying behavior.*

- KOL Influence In this paper, KOL influence is defined as the extent to which KOLs influence knowledge payment users on their willingness-to-pay and their paying behavior. The KOLs include celebrities, experts, internet celebrities, and bloggers. Rogers argues that KOLs can exert varying degrees of influence on individual decisions and that KOLs are characterized by innovation, expertise, and high levels of product involvement [54]. The results of a study by Li show that the professionalism, popularity, and homogeneity of KOLs have a significant impact on users' paid spectatorship behavior [22]. This paper, therefore, proposes the following research hypothesis and uses professionalism, visibility, and innovation as indicators of KOL influence.

  Hypothesis 5a. *KOL influence has a positive impact on users' willingness-to-pay.*
  Hypothesis 5b. *KOL influence has a positive impact on users' paying behavior.*

3.2.3. Platform Level

As a medium between users and providers, the platform takes on the role of an exchange of content and fees. As online platforms are virtual platforms with no actual contact behaviors, users' trust, interaction, and payment are based on the knowledge payment platform. The theoretical relationships, social cognitive theory, incentive model, and technology adaptation task model are all well-constructed theoretical frameworks for

knowledge payment platforms and users' paying behavior. The social cognitive theory emphasizes the sustainable learning characteristics of human beings. It covers cognitive factors such as beliefs, memories, expectations, motivation, and self-reinforcement [55]. Still, the realization of these cognitive factors depends on a realistic medium, i.e., society or a specific organization subordinate to society. Clearly, there is some significant relationship between knowledge payment platforms, as knowledge aggregators, which are places where knowledge providers and users exchange and interact with each other in terms of beliefs, memories, and other cognitive elements, laying the groundwork for users' willingness-to-pay and consumption behavior [56].

The incentive model further refines the relationship between the two influences, with incentives determining the level of effort and behavior of the 'human' subject [57] and the direction of this behavior being influenced by the nature of the incentive. At the superficial level, essential utilities such as fees are used as a guide. At the middle level, when the platform generates activity with the user in communication, it shows the platform's recognition of him or her and satisfies his or her psychological needs to some extent. At the top level, a contractual relationship of trust is formed through knowledge payment activities, a relationship that undoubtedly sublimates the user's behavior and willingness and the platform's influence even more [58]. This theoretical perspective is also expressed in the technology adaptation model analyzed earlier. Therefore, at the platform level, the perceived trust, perceived interaction, and perceived cost of users through the platform are considered critical influencing factors of knowledge paying behavior.

- Perceived Trust In this paper, perceived trust is defined as the level of trust users feel when using a knowledge payment platform. Perceived trust contributes to willingness-to-pay and paying behavior, where trust includes trust in the platform, trust in the product, and trust in security. The trust that users perceive from the platform leads to positive behavioral influences in individuals [59]. Yin extended the UTAUT model based on trust perception and risk perception to explore the factors influencing consumers' willingness to purchase drugs online, confirming that trust perception positively and significantly affects purchase intention [60]. Chen integrated the UTAUT and ITM models, introduced trust theory to construct a user acceptance model of WeChat payment, and empirically analyzed user behavior's critical factors using WeChat payment [61]. In health apps, trust is also a key factor influencing users' willingness-to-use and usage behavior [36]. The following research hypothesis is therefore proposed in this paper.

Hypothesis 6a. *Perceived trust has a positive effect on users' willingness-to-pay.*
Hypothesis 6b. Perceived trust has a positive effect on users' paying behavior.

- Perceived Interaction In this paper, perceived interaction was defined as the communication and interaction that users feel with other users through the knowledge payment platform, including comments, likes, content interaction, etc. Knowledge payment platforms have social attributes that allow users' emotions to be satisfied through interaction, thus enabling social networking connections to be made between users [62]. Interaction enhances the user's ability to control the knowledge content and supports the purchase decision by establishing cognitive preferences [63]. In studying user usage behavior of paid knowledge products, Boratto added six additional variables such as interaction motivation to the original UTAUT model [64]. In a study of factors influencing MOOC (Massive Open Online Course) users' persistent use behavior, Li confirmed that social interaction had a significant positive effect on expectation confirmation [65]. Wang studied webcast app usage behavior based on the TAM and UTAUT models and found that perceived interaction positively impacts user usage behavior [66]. In summary, the following hypothesis is proposed in this paper.

Hypothesis 7a. *Perceived interaction has a positive effect on users' willingness-to-pay.*

Hypothesis 7b. *Perceived interaction has a positive effect on users' paying behavior.*

- Perceived Cost In this paper, perceived cost is defined as the user's perception and evaluation of the cost to be paid when using a knowledge payment platform. If the user's perceived cost is more significant than their expected benefit, the willingness-to-pay is low, and conversely, the willingness-to-pay is high. In a channel study of e-commerce, Devaraj found that perceived cost harmed continued willingness-to-use [67]. In a study on the factors influencing users' willingness to use knowledge-paying apps consistently, Zhao also confirmed the negative role of perceived costs [68]. In a study on the intention to continue using mobile communication services, Alexandre concluded that perceived cost's effect on behavioral attitudes was not significant [12]. Based on the above research, this paper will continue to explore the impact of perceived cost on users' willingness-to-pay and paying behavior on knowledge payment platforms and propose the following research hypotheses.

Hypothesis 8a. *Perceived cost has a negative effect on users' willingness-to-pay.*
Hypothesis 8b. *Perceived cost has a negative effect on users' paying behavior.*

In the original UTAUT model, willingness-to-use had a significant effect on usage behavior [33]; In the TPB model, behavioral intention also has a significant positive effect on actual behavior [46]. Therefore, this paper assumes a positive relationship between users' willingness-to-pay and paying behavior and will expand to investigate the mediating effect of willingness-to-pay on each antecedent variable and paying behavior. The following hypothesis is ultimately proposed.

Hypothesis 9: *Willingness-to-pay has a positive effect on users' paying behavior;*
Hypothesis 10: *The mediating effect of users' willingness-to-pay is significant in the relationship between the antecedent variables and paying behavior.*

In summary, based on the UTAUT model, this paper proposes a theoretical model of the factors influencing the paying behavior of users of knowledge payment platforms at the user level, the knowledge-provider level, and the platform level, which is shown in Figure 2.
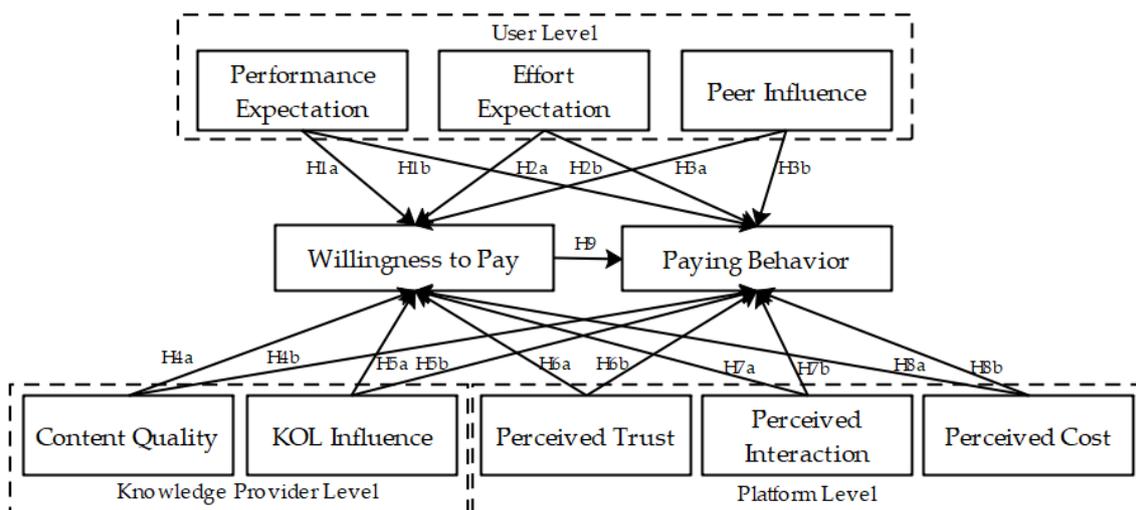

Figure 2. Theoretical model of user paying behavior on knowledge payment platforms.

4. Research Design

4.1. Questionnaire Design

This study used a questionnaire method to collect data to test the constructed theoretical model. A small sample was tested to ensure the validity of the questionnaire before the study was formally conducted. The questionnaire consists of two parts. The first part is the respondents' basic information, including gender, age, education level, occupation, and monthly income, etc. The second part evaluates the measurement indicators of each variable which is also the central part of the questionnaire, containing variable measurement questions of 10 latent variables such as Performance expectation. The scale in this paper is based on the established scales that existed in the previous work, using a five-point Likert scale, and the scales of each variable were appropriately adjusted by combining the characteristics of the knowledge payment platform. Through pre-interview, questionnaire pre-test, and questionnaire revision, the questionnaire's revised scale has a total of 35 questions, of which 30 indicators measure the variables. Table 1 shows the reference sources for the scale design.

Table 1. Scale design references.

Variable Name	Literature Sources
Performance expectation	[33,51]
Effort expectation	[11,33]
Peer influence	[12,39,46]
Content quality	[69,70]
KOL influence	[22,54]
Perceived trust	[71,72]
Perceived interaction	[73–75]
Perceived cost	[76,77]
Willingness-to-pay	[33,78]
Paying behavior	[33,79]

4.2. Data Collection

According to Aurora Big Data, users of knowledge payment apps are mainly between 20 and 24 years old. Among the users of Dedao app, 47.6% are aged 20–24, 53.1% are Zhihu, and 50.2% are Fenda [80], which is just the age range of university students and postgraduates, so a part of the student group was chosen as the survey users in this study. This study's survey mainly used WeChat, QQ, and online communities to distribute questionnaires and finally received 523 questionnaires. After deleting 68 invalid questionnaires, 458 valid questionnaires were obtained, with a sample pass rate of 87.57%.

Descriptive statistical analysis of the demographic variables is shown in Table 2. Males accounted for 49.3%, and females accounted for 50.7%. The age range of 18–25 years old constitutes most of the sample, accounting for 72.5%. The survey respondents' education level was mainly concentrated in college, Bachelor's and Master's degrees or above, occupying 84.9% of the whole sample, and 67.9% of the survey respondents were students by occupation. In terms of monthly income, 89.3% of the survey respondents had a monthly income of less than CNY 6000 (1 CNY ≈ 0.1545 USD).

Table 2. Descriptive statistics for demographic variables.

Variables	Features	Frequency	Percentage (%)
Gender	Male	226	49.3
	Female	232	50.7
Age	<18	2	0.4
	18−25	332	72.5
	26−30	34	7.4
	31−40	32	7.0
	41−50	54	11.8
	>50	4	0.9
Education level	Junior High School and below	22	4.8
	High School or Post-Secondary	47	10.3
	College	79	17.2
	Undergraduate	191	41.7
	Master's and above	119	26.0
Occupation	Students	311	67.9
	State agencies, institutions	74	16.2
	Enterprise employees	57	12.4
	Other occupations	16	3.5
Monthly income	<CNY 1499	84	18.3
	CNY 1500−2999	241	52.6
	CNY 3000−5999	84	18.3
	CNY 6000−9999	33	7.2
	>CNY 10,000	16	3.5

Note: 1 CNY ≈ 0.1545 USD.

5. Data Analysis

5.1. Measurement Model

The Cronbach α coefficient and the composite confidence CR are often used to test the confidence and validity of a scale, and when the α is more significant than 0.7 and the CR is greater than 0.7, the model has good internal consistency. As shown in Table 3 below, all variables' α and CR values were more significant than 0.8, which satisfied the requirements, and the questionnaire had good confidence. Tests of validity include tests of convergent validity and tests of discriminant validity. We observed that the standard factor loadings for all question items were more outstanding than 0.5, and the AVE for each latent variable was even more significant than 0.5, indicating that the model has good convergent validity.

Table 4 below shows the correlation coefficient matrix between the variables, with the square root of the AVE of each variable on the diagonal. As shown in Table 4, the AVE's square root for all latent variables is more significant than their correlation coefficients with other variables, so the model has good discriminant validity.

5.2. Structural Model Testing and Discussion of Results

The model was tested using Amos 22.0 software, and the fit indicators of the model are shown in Table 5. It can be observed that the actual values of all the fitted indicators are more significant than the recommended values, indicating that the model has a good fit.

Table 3. Measurement model confidence and validity analysis.

Dimensionality	Measurement Items	Factor Loadings	Cronbach α	AVE	CR
Performance expectation	PE1 PE2 PE3	0.871 0.722 0.805	0.84	0.64	0.84
Effort expectation	HE1 HE2 HE3	0.896 0.780 0.767	0.85	0.67	0.86
Peer Influence	CA1 CA2 CA3	0.885 0.724 0.804	0.84	0.65	0.85
Content Quality	CQ1 CQ2 CQ3	0.780 0.805 0.863	0.86	0.67	0.86
KOL Influence	OLA1 OLA2 OLA3	0.854 0.790 0.791	0.85	0.66	0.85
Perceived Trust	FT1 FT2 FT3	0.811 0.755 0.803	0.83	0.62	0.83
Perceived Interaction	FI1 FI2 FI3	0.842 0.821 0.806	0.86	0.68	0.86
Perceived Cost	FC1 FC2 FC3	0.928 0.777 0.834	0.88	0.72	0.88
Willingness-To-Pay	UI1 UI2 UI3	0.831 0.787 0.804	0.85	0.65	0.85
Paying Behavior	UB1 UB2 UB3	0.776 0.775 0.797	0.83	0.61	0.83

Table 4. Correlation coefficient matrix and AVE square root values.

Variables	Performance-Expectation	Effort Expectation	Peer Influence	Content Quality	KOL Influence	Perceived Trust	Perceived Interaction	Perceived Cost	Willingness-To-Pay	Paying Behavior
Performance-Expectation	0.802									
Effort Expectation	0.348	0.816								
Peer Influence	0.379	0.345	0.807							
Content-Quality	0.383	0.403	0.338	0.817						
KOL-Influence	0.361	0.324	0.351	0.366	0.811					
Perceived Trust	0.318	0.376	0.380	0.372	0.323	0.790				
Perceived Interaction	0.309	0.334	0.325	0.371	0.315	0.315	0.823			
Perceived Cost	−0.357	−0.342	−0.368	−0.383	−0.379	−0.339	−0.344	0.849		
Willingness-To-Pay	0.438	0.499	0.522	0.549	0.499	0.481	0.488	−0.444	0.808	
Paying Behavior	0.545	0.553	0.582	0.618	0.530	0.522	0.568	−0.600	0.750	0.783

Table 5. Recommended and actual values of model fit indices.

Fit Index	χ^2/df	GFI	AGFI	IFI	CFI	NFI	RMSEA
Recommended value	<3	>0.90	>0.80	>0.90	>0.90	>0.90	<0.08
Actual value	1.314	0.938	0.920	0.986	0.986	0.944	0.026

Note: χ^2/df is the cardinality to degrees of freedom ratio; GFI is the goodness of fit index; AGFI is the adjusted goodness of fit index; IFI is the value-added fitness index; CFI is the comparative fit index; NFI is the non-canonical fit index; RMESA is the root mean square of the approximation error.

The results of the analysis of all paths for AMOS operations are shown in Table 6. We can obtain the results from the graphs that 13 out of all 17 research hypotheses were tested, and four hypotheses were not supported. Among the factors influencing willingness-to-pay, the six factors in order of influence were content quality, peer influence, KOL influence, perceived interaction, effort expectation, and perceived trust, all of which had a positive and significant effect on willingness-to-pay. In contrast, Performance expectation and perceived cost had no significant effect on willingness to pay. Among the factors influencing paying behavior, in order of influence, the six factors are perceived cost, perceived interaction, content quality, peer influence, performance expectation, and effort expectation, all of which have a positive and significant influence except perceived cost, which has a negative influence. In contrast, KOL influence and perceived cost have no significant influence on paying behavior.

Table 6. Structural equation model path coefficients.

Serial Number	Relationship	Path Factor	Significance	T-Value	Test Result
H1a	Performance expectation→willingness-to-pay	0.042	0.369	0.899	Not Support
H2a	Effort expectation→willingness-to-pay	0.164	***	3.534	Support
H3a	Peer influence→willingness-to-pay	0.206	***	4.364	Support
H4a	Content quality→willingness-to-pay	0.24	***	4.837	Support
H5a	KOL influence→willingness-to-pay	0.191	***	4.094	Support
H6a	Perceived trust→willingness-to-pay	0.139	**	2.895	Support
H7a	Perceived interaction→willingness-to-pay	0.183	***	4.049	Support
H8a	Perceived cost→willingness-to-pay	−0.027	0.546	−0.604	Not Support
H1b	Performance expectation→paying behavior	0.128	***	3.629	Support
H2b	Effort expectation→paying behavior	0.088	*	2.46	Support
H3b	Peer influence→paying behavior	0.142	***	3.796	Support
H4b	Content quality→paying behavior	0.163	***	4.102	Support
H5b	KOL influence→paying behavior	0.06	0.098	1.655	Not Support
H6b	Perceived trust→paying behavior	0.064	0.079	1.754	Not Support
H7b	Perceived interaction→paying behavior	0.165	***	4.631	Support
H8b	Perceived cost→paying behavior	−0.191	***	−5.566	Support
H9	Willingness-to-pay→paying behavior	0.327	***	5.289	Support

Note: *** denotes $p \leqq 0.001$ or $T \geqq 3.29$, ** denotes $p \leqq 0.01$ or $T \geqq 2.58$, * denotes $p \leqq 0.05$ or $T \geqq 1.96$.

At the user level, the user-level factors include performance expectation, effort expectation, and peer influence. Among them, effort expectation has a positive effect on both willingness-to-pay and paying behavior. This is in line with the judgment of the Technology Acceptance Model: the quality of the system, i.e., the technical characteristics of the platform itself, affects the user's perception of the usefulness of that platform [81]. This suggests that the stability and payment security of today's knowledge payment platforms generally meet users' acceptance criteria for determining the usefulness and that system quality drives user satisfaction. In addition, the accuracy, completeness, and timeliness of the quality of the knowledge payment products provided by knowledge payment platforms influence users' judgments of the platform's usefulness. This result is consistent with the fact that P2P platforms focus on disseminating and exchanging information. Crucially, the quality of service and the low barrier to entry provided by a P2P platform affect users' judgment of the platform's usefulness to the same extent as the quality of the knowledge product. On this premise, low barriers and high quality of usage satisfaction (effort expectations) drive an increase in users' willingness and behavior to pay. Peer influence has a positive effect on both willingness-to-pay and paying behavior, so hypotheses H2a, H2b, H3a, and H3b all hold.

The above results are in line with social cognitive theory and the judgment of the cohort effect. Combined with the previous analysis, it can be seen that users form the "other-me effect" through their perception of external decisions, the environment, and mainstream users and opinion leaders, which plays a vital role in the completion of individual goals and formation of decisions. Paid users of knowledge platforms are subject to the dominant social perceptions due to their limited knowledge and closed knowledge streams before paying. Being open to decision-making, listening to what others have to say, and based on a lack of self-judgment, users are more willing to reinforce their willingness and behavior to pay.

Performance expectation only has a significant effect on paying behavior and has no significant effect on willingness-to-pay. Hypothesis H1a does not hold, and H1b holds, which suggests that performance expectation directly affects users' paying behavior, without being mediated through willingness-to-pay. This is because the vital performance needs of users are to complete tasks and improve work and learning efficiency [41]. When we are in a hurry to achieve this goal, it tends to trigger paying behavior directly. When we do not have urgent tasks to complete in our daily lives, it is challenging to generate willingness-to-pay even when we see quality content on a knowledge payment platform. Therefore, The above explains the direct effect of knowledge-paying users on paying behavior and the insignificant effect on willingness-to-pay. Besides, we found that of the three influencing factors at the user level, peer influence had the most significant impact on willingness-to-pay and paying behavior.

Observed from the knowledge-provider level, the factors at the knowledge-provider level are content quality and KOL influence. The two research hypotheses of content quality, H4a and H4b, both hold, with the influence of content quality on willingness-to-pay being the most influential factor among the six factors, which indicates that content quality is highly attractive to users. The willingness-to-pay is the basis for paying behavior, so if platforms want to attract more users, they should try to improve the content quality. This is in line with the diffusion of innovation theory: innovation is relative to a particular group of people, and what is commonplace to some groups may be new to another. Knowledge payment platforms and their products are themselves a collection of innovations. At the same time, users are using the platforms to satisfy their understanding of the unknown and unknown content and gain knowledge of the unknown through the act of paying for it, which is also clearly a process of innovation. For the platform, the more significant the advantages of new knowledge products and paid services over existing products, and the less they conflict with existing experience and values, and the less complicated they are to use, the higher the likelihood that they will be accepted. The quality of the content, therefore, determines the willingness of users to pay.

KOL influence has a positive and significant effect on users' willingness-to-pay, while it has no significant effect on paying behavior. KOL influence ranks third among all factors influencing willingness-to-pay, indicating that opinion leaders still strongly influence users' behavioral attitudes. However, KOL has no significant impact on users' paying behavior, reflecting that the era of impulsive consumption by users through receiving recommendations from celebrities and weblebrities has passed. The superiority of content has intensified, and users have shifted from impulsive consumption to rational consumption [47]. Users are more concerned about the content produced by KOLs than the recommendations of KOLs, which suggests that the 'fan economy' still exists, with users being advised by KOL to be willingness-to-pay, but not to consume directly. Fans have been transformed into "sensible fans," but as KOL has a strong influence on willingness-to-pay, some fledgling knowledge payment platforms can attract more users by stationing KOL on their platforms.

From the platform level, the influencing factors at the platform level are perceived trust, perceived interaction, and perceived cost. P+erceived trust has a positive and significant effect on willingness-to-pay and no significant effect on paying behavior, hypothesis H6a is valid, and H6b is not. The above analysis shows that perceived trust positively impacts users' behavioral attitudes and generates a stronger willingness-to-pay, but users do not direct payment because they trust the knowledge payment platform; at present, users are more concerned with the platform's content quality and their demand factors [41]. This supports the application of social cognitive theory to knowledge-based platforms: a person's behavior is determined by his or her perception and processing of social situations. The laws concerning social perception are very similar to those concerning the perception of objects. People often naturally organize their perceptions, thoughts, and beliefs about a social situation into a meaningful but straightforward form. This perception, organization, and interpretation of the environment influence a person's response to social situations. In knowledge payment platforms, as a nascent social context, users' behavior is influenced by their processing of the situation because of their dependence on the online environment. This processing effect is the perceived trust of the self. perceived interaction has a positive effect on both willingness-to-pay and paying behavior.

Social interaction is two-way communication between different subjects [82], and knowledge payment platforms have social attributes attached to them, and users' emotions need to be interacted with to be satisfied [62]. The significant impact of social interaction on willingness-to-pay and behavior is that users are becoming more focused on the experience and emotional factors of use. The hypothesis H8a for perceived cost does not hold, and H8b holds, i.e., the user's perceived cost does not affect willingness-to-pay. In contrast, perceived cost has a direct effect on paying behavior and has the most excellent effect of all the influencing factors on paying behavior. When the fee is lower, the more directly it promotes the user's paying behavior, which reveals to us that price has a direct impact on users, and if the knowledge payment platform wants more people to experience the knowledge payment product, the most effective way is to lower the price of the product directly.

5.3. Indirect Effects Test

This study uses bootstrapping to examine willingness-to-pay's mediating effect, which does not require a customarily distributed sample and has greater statistical power than the traditional Sobel test. The estimates of indirect effects and 95% confidence intervals were derived from 5000 Bootstrap replicate samples following the method proposed by Jocelyn [83], and the results are shown in Table 7. The results show that the confidence intervals of the indirect effect estimates for the paths 'Performance expectation → willingness-to-pay → paying behavior' and 'perceived cost → willingness-to-pay → paying behavior' contain 0, indicating that there is no mediating effect. In contrast, the mediating effects for the other paths are significant. The results show the six variables of effort expectation, peer influence, content quality, KOL influence, perceived trust, and perceived interaction can have an indirect effect on paying behavior through willingness-to-pay. Neither KOL influence nor perceived trust had a significant direct effect on paying behavior, so the mediating

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variable of willingness-to-pay can only influence these two variables. For the remaining four variables, when we observe Table 6, we can see that the path coefficients for the four variables of effort expectation, peer influence, content quality, and perceived interaction are all more significant than the path coefficients for willingness-to-pay, reflecting the fact that these variables are influencing paying behavior through the mediating variable willingness-to-pay. The variables of performance expectation and perceived cost do not play an indirect role on paying behavior through willingness-to-pay, possibly because the previous structural equation modeling analysis concluded that Performance expectation and perceived cost have no significant effect on willingness-to-pay and have a direct effect on paying behavior.

Table 7. Indirect effects of the bootstrapping test.

Indirect Effects	Estimated Value	95%CI		p	Conclusion (with or without Intermediary)
		Lower	Upper		
Performance expectation→willingness-to-pay→paying behavior	0.014	−0.008	0.066	0.184	No
Effort expectation→willingness-to-pay→paying behavior	0.054	0.013	0.133	**	Yes
Peer influence→willingness-to-pay→paying behavior	0.068	0.018	0.152	**	Yes
Content quality→willingness-to-pay→paying behavior	0.079	0.015	0.181	*	Yes
KOL influence→willingness-to-pay→paying behavior	0.062	0.016	0.169	**	Yes
Perceived trust→willingness-to-pay→paying behavior	0.045	0.004	0.15	*	Yes
Perceived interaction→willingness-to-pay→paying behavior	0.06	0.018	0.147	**	Yes
Perceived cost→willingness-to-pay→paying behavior	-0.009	-0.06	0.017	0.352	No

Note: ** means $p \leqq 0.01$, * means $p \leqq 0.05$.

6. Conclusions and Recommendations

Based on UTAUT theory, this study constructs a conceptual model of the factors influencing users' paying behavior, formulates the research hypothesis of this paper, and validates it using structural equation modeling. Fourteen of the 17 research hypotheses in this paper were supported. The significant influences on willingness-to-pay in order of magnitude were: content quality, peer influence, KOL influence, perceived interaction, effort expectation, and perceived trust. Among the significant influences on paying behavior, in order of magnitude, they are perceived cost, perceived interaction, content quality, peer influence, Performance expectation, and effort expectation, of which only perceived cost

shows a significant negative influence and the rest are significant positive influences. There was a significant intermediary effect of willingness-to-pay between the six variables of effort expectation, peer influence, content quality, KOL influence, perceived trust, perceived interaction and paying behavior.

Based on the findings of this paper, the following recommendations are made to promote the development of knowledge payment platforms:

- Focus on platform content management

Content is fundamental to paid knowledge platforms. Online users acquire knowledge, information, and skills through knowledge payment platforms, all of which are based on platform content. Quality content is a scarce knowledge resource and a source of value for the pay-for-knowledge model, manifesting its powerful capabilities in the knowledge economy [84]. In this study, content quality topped the list of factors influencing users' willingness-to-pay and significantly impacted paying behavior, which shows how much users value the quality of content on platforms. Therefore, knowledge payment platforms should pay more attention to the platform's content cultivation, attracting users through quality content and increasing user stickiness to trigger users' continuous usage behavior and create lasting revenue for the platform. Specific measures include: the platform can introduce more KOLs and PGCs that produce quality content, raise the threshold of entry to the platform, segment the professional fields, and improve the reward mechanism for ordinary users to produce quality content.

The current knowledge payment platforms have problems such as single, fragmented content, incomplete courses, uneven knowledge content, and severe homogenization of content across platforms. Much paid knowledge does not have a clear and complete system structure, and knowledge is primarily fragmented, which inevitably causes users to accept information as a kind of paralysis of the self. Paid knowledge is mainly a form of PGC+UGC production. The producer should start from the user's needs and create profound, targeted, and sustainable content. Themes and creative directions are adjusted according to user needs, and knowledge structures and systems are refined according to users' needs for paid knowledge segmentation. Combined with the technology acceptance model and the theory of planned behavior, further implications for managing knowledge payment platforms can be generalized. The main realizations are: starting from the user's heart and core demands, replacing actual behavior with behavioral intentions, and valuing the role of planned activities in the orientation of knowledge consumers. Finally, using arousal theory, environmental stimulation theory, behavioral scenario theory, and push-pull model, the scenario-based construction of user content is formed to achieve a realistic link between professional content and consumers.

- Appropriate use of "price war" strategies

In knowledge payment platforms, knowledge payment products are ultimately a commodity and have price attributes. This paper's results show that perceived cost has no significant effect on willingness-to-pay and no significant mediating effect on paying behavior through willingness-to-pay, but has a significant effect on paying behavior and has the most excellent effect of all the influencing factors on paying behavior, with a negative effect. This further reveals that price is the most direct factor influencing users' paying behavior, and "price reduction" is the most effective method. From a platform strategy perspective, if a knowledge payment platform wants to get more people to experience knowledge payment products in the short term, to have a base of paying-users, or to increase sales of knowledge payment products in the short term, it can adopt a "price war" strategy. Specific measures can be taken such as "Limited Time Offer," "Low price audition," "points to deduct cash activities," etc. Combining the theoretical insights from the technology adaptation task model and the incentive model, it follows that price is often an important factor in lowering the threshold of consumption and stimulating users to pay. The above theories study the adaptation between technical capabilities and task requirements, that is, the ability of information technology to support a task. For

platform managers, it is vital to use price strategies to rationalize the four elements between capabilities and tasks. The first is task characteristics and technical characteristics, which influence the third element, task technology adaptation, which influences the final element behavior or use. Information technology is adopted when and only when its functions can support the behavior of the user. Information systems can only generate efficiency in the use of their resources if users use them. The key to reducing the use of each element, such as behavior, is to drive the flow of elements with a large number of low-priced products in the short term (quality assured) so that the resources are applied and generate benefits.

- Deepening the social impact of users

In the original UTAUT model, social impact refers to the degree to which the group around them influences a user. Here we consider the social influence of a user as the degree to which the user influences the group around them. Of the three influencing factors at the user level in this paper, peer influence plays the largest role in willingness-to-pay and paying behavior, second only to content quality. Peers in this context are the groups around the user in their lives, including friends, family, colleagues, and superiors. This also shows that users greatly influence their peers around them and that spreading the word of users is the most cost-effective publicity strategy. Therefore, in the early stages of the platform's development, it is possible to make full use of users' 'circle of friends' effect and expand its user base and increase their willingness-to-pay. This can be done by encouraging users to share and offering rewards. Furthermore, the results show that perceived interaction is second only to perceived cost in influencing users' paying behavior. Perceived interaction can be seen as interactions between users and their 'surrounding community' within the platform, facilitating communication between users and generating trust and emotional pleasure, leading to continued usage behavior. Knowledge payment platforms themselves have social attributes attached to them, and in recent years, the development of social interaction has become an important strategy and direction for the development of knowledge payment platforms. Therefore, platforms should enhance their users' social features and increase their "social influence" on the platform, increase the proportion of paying users and promote knowledge payment platforms' healthy development.

As knowledge payment enters a cooling-off period, service providers should broaden their core user base and explore the paid market in third, fourth, and fifth-tier cities. Compared to first and second-tier cities, third and fourth-tier cities have a shallow level of class anxiety. As the learning effect and atmosphere for all people increases, the awareness of "self-improvement" will increase, and the penetration rate of the Internet will also increase, which requires producers to design the content and arrange courses for different groups of people to maximize the potential users. Combined with social cognitive theory and innovation diffusion theory, knowledge payment platforms should pay attention to the orientation mechanism of surrounding groups. Consumers' payment for knowledge products originates from individuals making speculations and judgments about the mental states, behavioral motives, and intentions. When groups give conclusive judgments, consumers integrate learning from past experiences and analysis of relevant cues, and then through the thinking activities of cognizers (including information processing, reasoning, classification, and induction). Platform managers should therefore expand their ability to promote the use of new media and resources to form and integrate social networks, and on this basis, expand their ability to radiate to consumers.

- Improving the quality of KOLs and making rational use of the "Netflix economy"

KOLs refer to celebrities, experts, Internet celebrities, bloggers, vloggers, and other opinion leaders in related industries. In the context of knowledge payment platforms, KOLs can also be referred to as "knowledge weblebrities." In this study, the factor with the highest impact on willingness-to-pay is content quality, with KOL being the second most influential. However, the quality of content on platforms is also often sourced from KOL. For example, the recognition and adoption of "Big V" in Zhihu and certified responders in Get are much higher than that of ordinary users.

In summary, the impact of KOL influence on users' willingness-to-pay is the most important, but in this study, KOL influence did not have a direct impact on paying behavior, so the barrier that needs to be broken through is to improve the conversion rate of KOL on users' willingness-to-pay to paying behavior. Therefore, platform operators should improve the quality of KOLs and make reasonable use of the "knowledge weblebrity economy." First, raise the threshold of KOL certification. In the era of Web 3.0, everyone can be a weblebrity, but not everyone can be a "knowledge weblebrity." Knowledge payment platforms are fundamentally different from short video sharing platforms and should be taken seriously, so the standards for KOLs on knowledge payment platforms should be raised. For example, the industry's qualification certificate should be used as the threshold to set the knowledge production cycle, and the answer adoption rate should be used as the performance assessment standard. Second, enhance the incentive mechanism for KOLs to stimulate quality knowledge content production. For example, outstanding KOLs participate in the platform's profit-sharing, and stage cash rewards are given when the KOL adoption rate reaches a fixed value. Excellent "knowledge weblebrities" need better reward mechanisms from the platform, and excellent knowledge deserves more attention and encouragement.

7. Insufficient Research

The article takes users' online knowledge paying behavior as the research object. It integrates the Technology Acceptance Model (TAM), Theory of Rational Behaviour (TRA), Theory of Planned Behaviour (TPB), Technology Adaptation Task Model (TTF), Innovation Diffusion Theory (IDT), Motivation Model (MM), Social Cognitive Theory (SCT) and PC Utilisation Model (MPCU) to form the UTATA model under the framework for research on consumers' willingness-to-use and usage behavior of online knowledge platforms, with an explanation rate of the study exceeding 70%. However, the following shortcomings still exist:

- The limited number of questionnaires, the small number of stratified groups, and the fact that the study is primarily based on a Chinese perspective may make the results non-generalizable. However, this study can still positively serve developing countries' online knowledge payment platforms in their infancy by expanding on the findings and analyzing them. In subsequent studies, we will continue to expand the sample to enable comparisons across countries and draw more generalizable conclusions.
- In the methodology, the SEM structural equation model and the mediating effects model are used. The validity and explanatory power of the models are reasonable, but the overall difficulty is slightly lower, and there is some endogeneity and error in the methods. We will continue to supplement the theoretical and practical models in subsequent studies, combine complex systems theory to solve the error problem and obtain a more realistic and practical hypothesis testing path.

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