sustainability

MDPI

Article

Use of Latent Dirichlet Allocation and Structural Equation Modeling in Determining the Factors for Continuance Intention of Knowledge Payment Platform

Heng Xu [1,*], Menglu Zhang [1], Jun Zeng [1], Huihui Hao [2], Hao-Chiang Koong Lin [3,*] and Mengyun Xiao [1]

[1] School of Management, Henan University of Technology, Zhengzhou 450001, China; lucyzhang@stu.haut.edu.cn (M.Z.); junzeng@stu.haut.edu.cn (J.Z.); xiaomengyun@stu.haut.edu.cn (M.X.)
[2] Faculty of Agribusiness and Commerce, Lincoln University, Lincoln 7647, New Zealand; huihui.hao@lincolnuni.ac.nz
[3] Department of Information and Learning Technology, National University of Tainan, Tainan 700, Taiwan
* Correspondence: xuheng@haut.edu.cn (H.X.); koong@gm2.nutn.edu.tw (H.-C.K.L.)

Abstract: Knowledge payment is a new type of E-learning that has developed in the era of social media. With the influence of the COVID-19 epidemic, the knowledge payment market is developing rapidly. Exploring the influencing factors of users' continuance intention is beneficial for the sustainable development of knowledge payment platforms. Our study took "Himalayan FM" as an example and included two studies: Study 1 used latent dirichlet allocation (LDA) to explore the main factors affecting the users' willingness to continue use, through mining user comment data on the knowledge payment platform; Study 2 constructed the conceptual model by integrating the technology acceptance model (TAM) and IS success model (IS) and carried out empirical analysis by SPSS and AMOS using the data that were collected through the questionnaire. The results show that: (1) perceived usefulness, user satisfaction, and spokesperson identity have a direct positive impact on users' willingness to continuous use, while perceived cost has a direct negative impact on users' willingness to continue use; (2) perceived ease of use, content quality, and system quality of knowledge payment platforms impacted user satisfaction directly, then affected users' willingness to continue use indirectly; (3) users' perceived enjoyment, membership experience, auditory experience, and other factors also directly impacted user satisfaction, affecting users' willingness to continue use indirectly. This study effectively expands the factors influencing knowledge payment users' willingness to continue use and provides a useful reference for the sustainable development of knowledge payment platforms.

Keywords: knowledge payment; continuance intention; latent dirichlet allocation (LDA); review mining; technology acceptance model (TAM); structural equation modeling (SEM)

check for updates

Citation: Xu, H.; Zhang, M.; Zeng, J.; Hao, H.; Lin, H.-C.K.; Xiao, M. Use of Latent Dirichlet Allocation and Structural Equation Modeling in Determining the Factors for Continuance Intention of Knowledge Payment Platform. *Sustainability* **2022**, *14*, 8992. https://doi.org/10.3390/su14158992

Academic Editors: Fernando Almeida, Sébastien Jacques and Abdeldjalil OUAHABI

Received: 5 May 2022
Accepted: 20 July 2022
Published: 22 July 2022

1. Introduction

Traditional education systems have been completely challenged by the COVID-19 pandemic [1]. Simultaneously, advances in digital technology and computer science have transformed the educational mode from traditional face-to-face education to smart learning that is based on E-learning [2]. Jacques et al. [3] also pointed out there are few barriers in the synchronous approach to E-learning. Due to the COVID-19 epidemic, the economic and mental pressure that was faced by the public has increased significantly, resulting in "anxiety to improve themselves to avoid being left behind by society". This kind of anxiety further led to a sharp increase in user demand for knowledge-based products [4]. In this context, the knowledge payment platform has been popularized because it can accurately satisfy the user's diversified, fragmented, and interdisciplinary learning needs and expectations. Furthermore, according to the United Nations 2030 Agenda for Sustainable Development [5], the sustainable development of online learning platforms would have significance for building inclusive and effective learning environments for all and great potential to accelerate the development of knowledge societies [6]. Therefore, the sustainable development of knowledge payment platforms is increasingly important for sustainability in quality education.

The rapid development of the mobile Internet provides a large amount of free information. However, the availability of massive amounts of information makes it difficult and inefficient for knowledge demanders to choose quality content. Facing the exponential growth of Internet information and the scarcity of attention, paying for knowledge helps knowledge consumers acquire valuable information effectively, and incents knowledge providers to produce high-quality content. In the knowledge payment market, knowledge payment platforms bridge the gap between knowledge providers and knowledge consumers. Therefore, knowledge payment is a new type of E-learning that was developed in the era of social media. It means that the knowledge users pay for the knowledge products or services that are processed and packaged by the knowledge provider [7]. For the knowledge providers, with a surplus of cognition and time [8], it is a way to exchange knowledge products or services for commercial value and social value in the knowledge payment platform. As a way of knowledge dissemination, the purpose of the knowledge payment platform is to provide suitable learning conditions and high-quality knowledge products or services for the public.

Differing from traditional education and training modes, demanders of knowledge payment platforms have a solid and active willingness to learn and pay attention to the cost of time and energy, the quality of professional knowledge, and the teaching level of the knowledge providers [9]. Knowledge payment platforms also want to promote user satisfaction and loyalty by providing higher quality knowledge products and better experience [10]. However, the increasingly homogenous competitive situation of payment knowledge platforms has led to the problem of insufficient user retention [11]. Therefore, exploring the key factors that affect users' willingness to continue using paid knowledge can effectively supplement the information system theory, and promote the development of the knowledge economy.

These knowledge products and services are usually spread through the Internet and smart terminals. Users' opinions on knowledge products and payment platforms themselves will be more likely to be published on the Internet [12]. Posting online reviews is a behavior with a high penetration rate [13]. Its content is precisely the user's actual evaluation and emotional expression, which provides favorable conditions to apply text mining methods to explore the potential factors that affect users' willingness to continue to use. Through review mining, we can grasp consumers' demands and expectations on time, which can help the knowledge payment platforms improve product positioning and service models. This is conducive to the sustainable development of knowledge payment platforms and to people's sustainable access to online learning resources, thereby promoting the construction of a lifelong learning system and learning society.

The content of this research and the rest of the paper is the following: Section 2 reviews the literature on continuance intention and research methods. In Section 3, Study 1 applies LDA to explore the influencing factors of continuance intention from users' comment data. In Section 4, Study 2 aims to verify the validity and intrinsic relationships of the factors that were found in the topic identification and carries out an empirical study to examine the factors that affect the continuance intention by expanding the integration of the TAM and IS model and investigates the underlying mechanism that affects users' continued use of knowledge payment platforms. The two methods complement each other, through empirical evidence making up for the lack of manual topic identification and enriching the expansion variables of the knowledge payment field. Section 5 draws conclusions.

2. Literature Review

Continuance intention is an intention or long-term usage of a technology after initial adoption [14]. In recent decades in the domains of information systems or internet products, numerous theoretical models have been developed to predict and explain the users' continued use of Internet products. E-learning is a teaching approach that is also referred to as online learning or electronical learning, which is based on the use of electronic media and devices as tools for improving the availability of training, communication, and interaction [15]. Knowledge payment is one type of E-learning, therefore, the topics that were used for the review were E-learning and its research methodology.

The literature search was conducted in December 2021 using these search terms: E-learning, knowledge payment, continuance intention, user satisfaction, influencing factor, topic identification, TAM, and others. We conducted searches of repositories (e.g., Springer, ScienceDirect, MDPI) and filtered the literature according to the contribution to the development of the research area. Then, we screened the remaining literature once more and mainly kept the literature from the last five years.

2.1. Technology Acceptance Model Perspectives of E-Learning

Davis [16] proposed the technology acceptance model (TAM), which was developed from the theory of reasoned action (TRA) in the fields of information systems and computer technology. It is a widely accepted model and used in E-learning to investigate users' acceptance [16–19]. In TAM, the perceived ease of use (PEOU) and perceived usefulness (PU) are the two main factors that are used to explain differences in user behavioral intention (BI) and actual use (AU) [20].

Different scholars [21–23] introduced the influencing factors in different fields into the TAM to explore the impact of perceived usefulness and perceived ease of use on users. In the context of COVID-19, a number of academic researchers have explored students' acceptance of technology learning [19,24,25], and detected differences in acceptance between the disciplines, enriching and extending the external factors of the TAM that is associated with the E-learning acceptance. Based on TAM, Humida et al. [18] predicted the factors that influence students' behavioral intention to use the E-learning system in Bangladesh, and showed that perceived usefulness and perceived ease of use were positively and significantly influenced by perceived enjoyment.

However, some scholars [10,26] have contended that the TAM investigates human behavior intention only at the cognitive level, neglecting its indicators and directly investigating the external variables and ignoring the relationship between usage attitude and usage intention. Davis [16] also suggested that researchers extend TAM with external variables that are based on different theories in different technology fields.

In order to research a more complete IT acceptance model, an extended TAM with additional external factors was used to investigate the acceptance and usage of online learning. For example, Jiang et al. [27] found that perceived enjoyment and self-efficacy (SE) did not significantly predict the perceived usefulness and perceived ease of use, due to the limitations of online classes and the instability of the internet. In the research of Prendes-Espinosa et al. [28], digital competence poses a great challenge for teachers because they also need to learn new digital technologies, which directly influences their students' training. Salloum et al. [15] summarized TAM's most extensively used external factors concerning the E-learning adoption studies, including computer self-efficacy, subjective/social norm, perceived enjoyment, system quality, information quality, content quality, accessibility, and computer playfulness. Al-Rahmi et al. [26] used extended TAM and IDT to explore the potential factors influencing students' behavioral intentions use of the E-learning system, and proposed that the variables affecting the perceived usefulness and perceived ease of use are the relative advantages, complexity, observability, etc. These variables are applicable to the study of behavior intention to use, but the factors affecting continuance intention needs to be further explored.

E-learning systems are a form of information system that incorporates human factors (i.e., learners and instructors) and non-human factors (i.e., learning management systems). Therefore, it is crucial to examine the factors that are associated with these as external variables to TAM. DeLone and McLean developed the model of IS success [29]. This model comprises of six success factors that measure IS success, namely, organizational impact, individual impact, use, user satisfaction, system quality, and information quality. Mailizar et al. [30] found that to ensure the sustainable use of E-learning during the pandemic and beyond, the quality of the E-learning system is crucial. The updated DeLone and McLean IS success model (IS) has been widely used to investigate the quality factors on usage behaviors in an E-learning system [31], and the integration of TAM and the IS model has also been applied to investigate the intention to use the E-learning system consistently [32,33]. Overall, the integration of the TAM and IS model is suitable to be used to explore intention to use E-learning, but external factors regarding the intention to use E-learning need to be further explored during the epidemic. The text of users comments provides a new source of data for this study to explore external factors.

2.2. Latent Dirichlet Allocation in E-Learning

Unlike traditional learning methods, self-learners can release millions of course-related comments in discussion forums in an E-learning environment, so how to evaluate large volumes of qualitative data that these large online courses generate is a big challenge. The LDA topic models can identify emerging themes from a large collection of documents. Scholars have introduced LDA to E-learning, using natural language processing to capture users' concerns and make suggestions. Table 1 summarizes the related literature on the use of LDA in E-learning. LDA can obtain a topic word distribution matrix and a topic-comment distribution matrix that can describe the topics of the course comments through text mining. Further, utilizing different topics can also establish a comprehensive curriculum evaluation system [12]. Lin et al. [34] put forward a kind of method which can effectively improve the effect of personalized course recommendations that are based on LDA. The results showed that E-learning could have high user satisfaction for training investigators of clinical studies and medical students. In E-learning systems, the LDA model is effective in exploring the interests of users and helps to build an accurate recommendation system for users' interests [35]. Natural language processing may be beneficial in the analysis of large-scale educational courses [35].

Table 1. Summary of related literature.

Author	Method	Research Object	Conclusion
Nilashi et al. (2022) [36]	LDA	Course choice decision in massive open online courses	The data collected from the online platform is evaluated by LDA method and the results show that this method can accurately provide relevant courses for users according to their preferences.
Ray et al. (2020) [37]	LDA-SEM	Values affecting E-Learning adoption	Emotional connection and facilitator quality, are important predictors of user's intention to take up courses from E-learning platforms.
Ray et al. (2021) [38]	LDA-SEM	Gratifications affecting user's choice of different E-learning providers	Users have generally posted comments which relate to trust, anticipation, and joy, and they have an overall positive sentiment towards the providers.
Ray et al. (2022) [39]	LDA-SEM	Barriers affecting E-Learning usage intentions	Value and facilitator issues, tradition, and risk barriers have a notable negative impact on usage-intention.
Nanda et al. (2021) [40]	LDA	Large collections of open-ended feedback from MOOC learners	Content quality, accurate description of prerequisites and required time commitment in course syllabus, quality of assessment and feedback, meaningful interaction with peers and educators, engaging instructor and videos, accessibility of learning materials, and usability of platform significantly affect the learning experience of users.
Lin et al. (2021) [34]	LDA	Personalized educational resource recommendation	Building a user interest model through LDA and calculating the user's preference for the topic can effectively improve the effect of personalized learning resource recommendation.

The current E-learning research was mainly based on TAM, and the selection of influencing factors comes from the theoretical analysis and practice experiences of different fields [15,26,27,30]. There is a growing trend to use text mining methods to explore the influences that are associated with user-generated content (UGC) with the aim of exploring learners' attitudes toward the online courses [12,34]. In addition, knowledge payment is an emerging form that originated from online learning and E-commerce, and there has not been a systematic study of the willingness to continue using knowledge payment. Therefore, this article uses the LDA topic model to analyze the online comments of knowledge paying users and extracts the key factors that affect the users' continuous use intention from the user's perspective. On this basis, we combined this with TAM and IS model to establish a conceptual model of the user's continuous use intention formation mechanism and carried out empirical research to verify these influencing factors.

In general, by learning E-learning experiences from the learners perspective, we can group these aspects to enrich external factors of the TAM based on data that were mined from online comments, improving the effectiveness of the model and compensating for the problems that are caused by empirical data.

3. Study 1: Exploring the Factors Based on Review Mining with Latent Dirichlet Allocation

Using text mining, this section explores the users' comments on a knowledge payment platform to mine topics that the users focus on. Then, we find the key factors affecting users' continuance intention from the users' perspectives, which lays a foundation for constructing a conceptual model of users' continuance intention in the next section.

3.1. Data

This study selects Himalayan FM as a research object. Himalayan FM is a knowledge payment platform that is dedicated to audio sharing that has grown up in the digital economy and includes many knowledge products such as education, humanities, finance, economics, and audiobooks. Another feature of it is the ability of the knowledge providers to deliver knowledge content to users in the form of anchors. The user's comment text of this app in the app store is used as the research data. There are two reasons for the data selection. First, Himalayan FM has been ranked highly for a long time on the iPhone operating system (iOS) and Android application stores [41]. It performs excellently according to evaluations that are based on indexes, such as users' activity, total online time, and startup times [42]. Second, users' comments in the client-side of the knowledge payment platform APP mainly focus on a certain knowledge-based product and service rather than the platform itself. As it takes a higher time-cost in making comments in app stores, users' comments in app stores are often the users' real feelings and evaluations on their overall experience of the products and services. The AppStore is unique to the iOS system, and Huawei mobile phones occupy the highest market share of Android phones in China. Therefore, we collected comment data from Himalayan FM both in the iOS AppStore and HUAWEI AppGallery to ensure the comprehensiveness and validity of the data, and the data are listed in Table 2.

Table 2. Download details of comment data.

App Store	Time Period	Comment Text Volume/Items	Download Time
iOS AppStore	1 January 2018~17 April 2022	87,492	17 April 2022
HUAWEI AppGallery	1 January 2018~17 April 2022	89,236	
Total		176,728	

The data were cleaned by Python 3.8, including ① removing duplicate system default praise text, ② removing comment texts whose length is less than or equal to 3 words, and ③ extracting Chinese comment texts. Finally, 126,718 valid comment texts were obtained, 65,707 for the iOS AppStore and 61,011 for the HUAWEI AppGallery separately.

3.2. Methods

Latent Dirichlet allocation (LDA) is a three-layer Bayesian topic model that was proposed by Blei et al. [43], which discovers the topic-related information that is hidden in the text through the unsupervised learning method aiming to find the implicit semantic dimensions of these "Topic" or "Concept" from the text. Based on the LDA topic model, a framework of user comment mining of the knowledge payment platform is constructed in Figure 1.

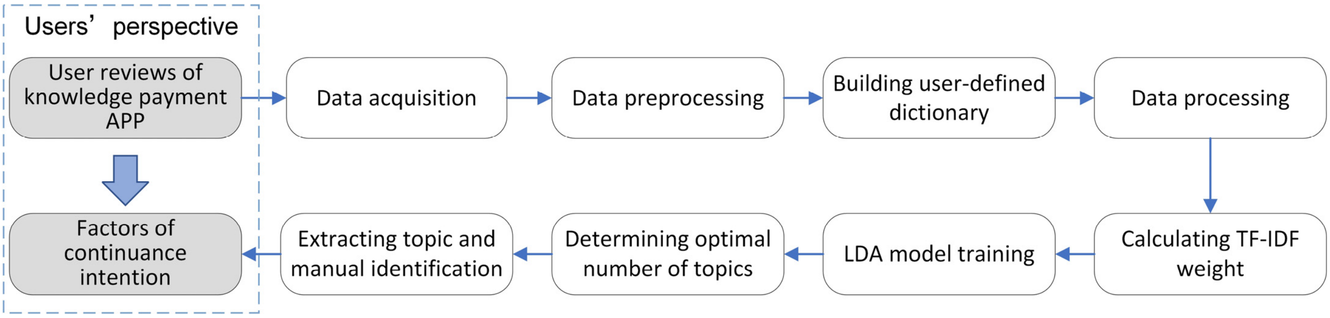

Figure 1. Review mining framework of knowledge payment platform.

(1) Word segmentation and part-of-speech filtering

The absence of clear separation marks between Chinese texts is a significant feature distinguishing Chinese from most other languages [44]. Jieba is a word segmentation library that Python uses exclusively for Chinese word segmentation, which is widely applied due to its excellent word segmentation efficiency [45]. As comment texts are short and unstructured, this study adopts the exact mode of Jieba for word segmentation in the text sets. In addition, the part of speech is tagged in the comment texts, and non-noun texts are filtered by using the posseg function in the Jieba word segmentation library.

(2) Removing stopwords and word frequency statistics

To ensure the comprehensiveness of the stopword dictionary, this research summarizes stopwords in Harbin Institute of Technology, machine intelligence laboratory of Sichuan University and Baidu and stopwords relating to GitHub to obtain a customized stopword dictionary including a total of 2462 stopwords. After removing the stopwords, the word frequency statistics are made on the data with stopwords removed by using the Counter function of Python to verify validity of the results and find noise words.

(3) Data processing

The data are processed again in this study according to the following three steps:

① High-frequency useless comment contents, including advertisements, are manually screened. Anomalous high-frequency words are conducive to finding a lot of advertising comments from comment data. In this study, 2781 invalid comment texts are screened and deleted by manually browsing comment texts.

② A customized word segmentation dictionary is constructed. According to word frequency statistics, the customized word segmentation dictionary is constructed, mainly adding Internet glossary and specialized vocabularies in knowledge payment.

③ The stopword dictionary is supplemented. After filtering part of speech and removing stopwords, there are still a large number of meaningless words that are irreverent to topics. Therefore, the existing stopword dictionary is supplemented according to word frequency statistics. In order to reduce the noise of the comment texts as much as possible, we classified and added the high frequency words with unreasonable segmentation into customized word segmentary dictionary and stopword dictionary based on the results of three word-sorting experiments, thus obtaining the final word frequency statistics in Table 3.

(4) Weighting based on term frequency-inverse document frequency

Term frequency-inverse document frequency (TF-IDF) tends to filter out common words and retain words with a strong ability to predict topics. By utilizing the doc2bow function of Gensim [46] module in Python 3.8, the preprocessed comment data are transformed into the form of word vectors and then the feature words are weighted with the TF-IDF model of Gensim, so as to substitute the data into the LDA model.

(5) LDA model training

For the LDA topic model, the number of topics is an essential factor affecting the quality of text mining. The optimal number of topics is determined by the perplexity in this research [47]. It is generally believed that the lower the perplexity is, the better the model training effects. However, for the LDA topic model, the lower the perplexity is, the more the topics. At the same time, the classification of texts will lose the sense of clustering due to excessive refinement with the increase of the number of topics. Therefore, an inflexion point of the curve relating to the perplexity and the number of topics is selected as the optimal number of topics in this study [43]. Based on the perplexity of topics that were calculated through the math function in Python 3.8, the perplexity curve drops dramatically with the continuing increase in the number of topics. When the number of topics is 10, the perplexity curve is at the lowest point and then rises, so the optimal number of topics is determined as 10.

Table 3. Word frequency statistics (TOP 40).

Word	Frequency	Word	Frequency	Word	Frequency	Word	Frequency
Advertisement	14,363	Learning	2734	Flash back	1742	System	1073
Software	11,791	Mobile phone	2520	Function	1704	English	1068
Member	6964	Free	2451	Customer Service	1688	Children	1059
Game	5944	Money	2163	User	1654	Crosstalk	963
Content	5227	Platform	2086	Version	1507	Radio station	961
Fiction	4792	Network	1971	Music	1360	Wang Yibo	951
Sound	4613	Audio	1937	Eye	1309	Teacher	915
Time	3651	Resource	1898	Comment	1270	Works	796
Book	3364	Knowledge	1823	Anchor	1239	Tone quality	768
Story	2983	Rich in content	1817	Spokesperson	1160	Dubbing	684

3.3. Topic Identification

The number of topics is determined as K = 10 in this research. By setting the hyper-parameter of Dirichlet prior distribution as $\alpha = 1/K$, β as auto (automatic mode) and the number of iterations as 500 (default number), the probability distribution of topics and feature words can be obtained and lexical items ranking top 20 are selected as feature words. Furthermore, the probabilities of each document belonging to different topics are obtained by calculating the probability distribution of documents and topics to calculate the intensity of topics representing the users' degree of attention on a topic in a certain time window [48].

Topic identification is a manual identification process of training results of the topics based on LDA. In the topic-recognition step, Ray et al. [39] identified the useful topics for each construct by analyzing the related terms. The extracted topics are potential influencing factors for users' continuance intention towards the knowledge payment platform. In general, a large number of feature words are not conducive to topic modelling. Considering this, this study selects 10 feature words with a strong ability to express topics from the top 20 feature words of each topic for manually identifying the topic by browsing comment texts and visiting senior users of the knowledge payment platform and experts in the consulting field. By doing so, the topics that were mainly concerned by the users of the knowledge payment platform are identified. The results of topic identification, sorted by intensity, are demonstrated in Table 4.

Table 4. Topic identification and sorting of intensity.

No.	Topic Identification	Intensity of Topics	Feature Words
1	Content quality	0.1123	Content, program, time, function, good book, quality, music, radio, work, sound effect
2	Advertising content	0.1121	Advertisement, cover, fiction, member, unlock screen, comment, content, audio, video, payment
3	Perceived enjoyment	0.1075	Storytelling, life, Deyunshe (A cultural communication Co., Ltd. engaged in professional crosstalk art performance), joke, mood, culture, leisure, software, reading material, radio
4	Resource experience	0.1065	Book, platform, rich in content, reading, lazy person, category, course, classification, comprehensiveness, caption
5	Membership experience	0.1061	Member, story, audio, profession, English, children, customer service, accompany, spending money, earphone
6	Auditory experience	0.0989	Sound, resource, eyes, sound effect, ear, audience, information, dub, pageviews, category
7	Lecturer quality	0.0954	Teacher, product, quality, taping, author, team, album, humanization, network, copyright
8	Spokespersons of platforms	0.0908	Spokesperson, experience, Wang Yibo, endorsement, Yiyang Qianxi (Jackson), interface, friend, habit, mode, fans
9	System quality	0.0894	Mobile phone, version, system, tone quality, button, program, page, account, server, Bluetooth
10	Perceived costs	0.0799	Charge, money, defraudation, waste, hour, recharge, spending money to buy something, standard, Xiaoya (radio of Himalayan FM), cost-free listening

3.4. Results Analysis

As shown in Table 4, there is a certain correlation between the internal lexical items of different topics. For example, the feature words, such as content, good book, work, and quality appear in topics, such as content quality, advertising content, resource experience, and lecturer quality. Feature words relating to the expense including payment, pageviews, and money do not merely exist in the topic of perceived costs. Content quality includes the content quality of knowledge payment products and contains lecturer quality, an abundance of resources, and loading of advertising content. Therefore, considering specific usage situations and the semantic correlation of comment texts of users, the topics including advertising content, resource experience, and lecturer quality are incorporated into the topic of content quality to refine factors affecting users' continuance intention.

In conclusion, through text mining of users' comments on the knowledge payment platform, this study extracts seven influencing factors: content quality, perceived enjoyment, membership experience, auditory experience, spokespersons of the platform, system quality, and perceived costs. Furthermore, based on the TAM and IS, the content quality is used as the explanatory variable of the perceived usefulness, and the topic of system quality is set as the explanatory variable of perceived ease of use. In this way, the external variables of the TAM are enriched in the context of knowledge payment. To verify the objectivity and accuracy of these factors, the empirical method of a questionnaire survey is used in Study 2.

4. Study 2: Empirical Test of Influencing Factors Based on Technology Acceptance Model and Is Success Model

The TAM can predict users' continuance intention in the information system, while external variables need to be added in different research to ensure the applicability of different models [15]. In this study, we retain the existing variables of the TAM, namely the perceived usefulness and the perceived ease of use, and on the basis of IS add the variables of user satisfaction and continuance intention according to the research purpose. Meanwhile, the mining (above) results of the users' comments on the knowledge payment platform are integrated with the TAM. Finally, seven variables are introduced to construct the conceptual model of the users' continuance intention to the knowledge payment platform, namely, quality, system quality, perceived enjoyment, membership experience, auditory experience, sense of identity spokespersons, and perceived costs.

4.1. Conceptual Model Based on Technology Acceptance Model

Based on the topic identification and TAM, this study constructs the conceptual model of users' continuance intention to the knowledge payment platform, as shown in Figure 2. In this model, the perceived usefulness, perceived ease of use, and user satisfaction are mediators. On the one hand, the content quality, system quality, perceived enjoyment, auditory experience, and membership experience represent the user experience or the emotional response to the quality and function of the knowledge payment product. Therefore, we use these five elements as independent variables of user satisfaction. On the other hand, the spokesperson represents the brand promotion strategy, and cost represents the pricing strategy of the knowledge payment product. The above two factors do not directly affect the consumers' perceived quality and the function of the knowledge payment product. Therefore, we take these two elements, spokesperson identity and perceived costs, as independent variables of users' continuance intention.

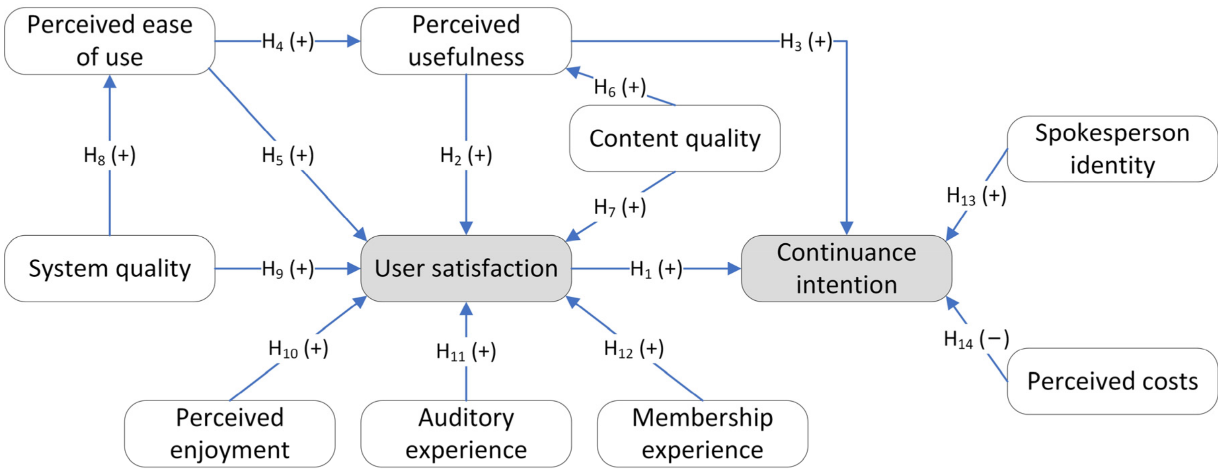

Figure 2. Conceptual model of users' continuance intention to knowledge payment platform.

4.2. Construct Definition and Hypothesis Development

(1) Continuance intention

When a new information system is viewed by enough users, how to retain these users is the key problem for enterprises to consider [14]. In this study, continuance intention (CI) refers to the willingness of users to continue using the knowledge payment platform constantly in a certain period in the future, which can promote the generation of continuous use behaviors of users [49]. For the operators of the knowledge payment platform, mastering influence factors for users' continuance intention to the knowledge payment platform is favorable for establishing the core competitiveness of enterprises and can provide reference suggestions for the management and training of knowledge suppliers.

(2) User satisfaction

User satisfaction (US) refers to the subjective evaluation of users on an information system. In this research, it refers to the users' subjective feelings after using and experiencing the functions and services of the knowledge payment platform. User satisfaction with using the information system positively affects their use attitude [50] and is an important source of shaping continuance intention [51]. Many scholars have also proved the positive effects of satisfaction on continuance intention in the theoretical model of continuance intention to the extended information system [52]. Dai et al. [53], taking the large-scale open online course platform MOOC as the research object, confirmed that user satisfaction plays a crucial role in users' continuance intention. Therefore, the following hypothesis is proposed:

Hypothesis 1. *User satisfaction positively affects users' continuance intention.*

(3) Perceived usefulness

Perceived usefulness (PU), a key variable of the TAM and expectation confirmation model (ECM), is a subjective evaluation of self-promotion that is perceived by the users when using the technology or an information system. Barnes et al. [54] proved the positive effects of perceived usefulness on user satisfaction by studying the users' behaviors. When a knowledge payment platform can meet the demands of the users and bring functional value to the users, the users will be more satisfied with the knowledge payment platform and more willing to continue using the platform. Lee et al. [55] demonstrated that high-perceived usefulness promotes web-based learners' satisfaction and continuance intention. Therefore, the hypotheses are proposed as follows:

Hypothesis 2. *Perceived usefulness positively influences user satisfaction.*

Hypothesis 3. *Perceived usefulness positively affects users' continuance intention.*

(4) Perceived ease of use

The perceived ease of use (PEOU) is the core element of the TAM and positively influences the perceived usefulness and users' attitudes toward the platform [16,56]. In this research, it refers to the perceived ease of users when using the knowledge payment platform [16], such as simple operation, fast search, and sound functions. Previous research has confirmed that the perceived ease of use significantly affected the perceived usefulness [55,57,58]. Furthermore, prior studies showed that the perceived ease of use strongly predicted user satisfaction toward the use of E-learning [59,60]. When the degree of the perceived ease of use is high, the users perceive more help from the knowledge payment platform in improving their performance and satisfaction while perceiving the usefulness of the knowledge payment platform. Therefore, the following hypotheses are put forward:

Hypothesis 4. *Perceived ease of use exerts positive influences on the perceived usefulness.*

Hypothesis 5. *Perceived ease of use has positive effects on user satisfaction.*

(5) Content quality

Content quality (CQ) refers to the quality of the knowledge payment products on the platform, including high-quality knowledge content, abundance of learning resources, teaching level, and service quality. The content quality theme is derived from the identification of the LDA model, which includes rich in content, function, and quality. This theme has a high weighting, and users are more concerned about the content quality. Lin et al. [61] found that the high quality and abundance of course content play a positive role in improving the users' perceived usefulness in the study of online learning. Ozkan et al. [62] in their study highlighted the importance of usefulness of the content, that is, having a positive impact on user satisfaction, and quantitative results proved that interactive content is significant in both blended and online learning. Therefore, the following hypotheses are put forward:

Hypothesis 6. *Content quality positively influences the perceived usefulness.*

Hypothesis 7. *Content quality positively affects user satisfaction.*

(6) System quality

System quality (SQ) means the operation quality of the knowledge payment platform, including indexes, such as ease of use, flexibility, reliability, user-friendliness, and maintainability [63,64]. The system quality is characterized in the model by words such as version, system, tone quality, server, etc. This is one of the criteria that users use to measure the merits of knowledge payment platforms. The system quality obviously has a positive effect on the perceived ease of use [58]. In addition, the research of the information system success model (ISSM) [63] and Petter et al. [65] points out that system quality positively affects user satisfaction. Therefore, the following hypotheses are proposed:

Hypothesis 8. *System quality positively influences the perceived ease of use.*

Hypothesis 9. *System quality exerts positive effects on user satisfaction.*

(7) Perceived enjoyment

Perceived enjoyment (PE) refers to the degree of pleasure and fun that users feel when using technology or an information system [66]. In this study, it implies the fun that is experienced by users when using the knowledge payment platform. The feature words are joke, mood, culture, leisure, etc. In the mobile Internet environment, the users' perceived enjoyment and usefulness for content and services play a positive role in user satisfaction [67,68]. Different from online education platforms, the knowledge payment platform offers knowledge that is acquired to help users improve professional skills and needs to please the users so that they can enjoy subjective pleasure and relieve individual life or work pressure. When the users experience the pleasure of learning, they have positive emotions about learning styles, so the perceived enjoyment is an influencing factor that cannot be ignored. Therefore, the hypothesis is made as follows:

Hypothesis 10. *Perceived enjoyment exerts positive influences on user satisfaction.*

(8) Auditory experience

Knowledge payment in the form of audio is popular because it can liberate users' hands and eyes. Auditory experience (AE) has also become an important experience for users in the knowledge payment platform. The auditory experience theme that was identified from the user review content has an important impact on the user's experience, and the characteristic words of this theme include sound, sound effect, dub, etc. An enjoyable auditory experience means a satisfactory product experience. A well-designed sound product can bring users sensory pleasure, thus positively impacting the overall appreciation of the product [69]. Therefore, the following hypothesis is made:

Hypothesis 11. *Auditory experience has positive effects on user satisfaction.*

(9) Membership experience

Membership marketing plays a vital role in mining value, improving retention, and strengthening users' continuance intention. Membership experience (ME) in this research refers to the users' subjective feelings that are brought by differentiated services after becoming members of the knowledge payment platform, which usually includes content, function, and welfare privileges. This theme contains feature words such as member, profession, customer service, etc. When users can obtain better experience after becoming members, user satisfaction will be improved accordingly. Therefore, the following hypothesis is proposed:

Hypothesis 12. *Membership experience positively affects user satisfaction.*

(10) Spokesperson identity

The sense of identity is a kind of response in which individuals acquire inner cognition and turn the nature or characteristics of identified events into a part of the individual psychological structure [70]. The loyalty of consumers can increase with the enhancement of their sense of identity to a product or an enterprise [71]. The sense of identity of users to spokespersons of the knowledge payment platform is mainly explored in this research. The main focus of users on this topic is celebrity endorsement, with the words Wang Yibo, Yiyang Qianxi, fans. McCracken's [72] model of transference' is designed to explain the process by which celebrity endorsements increase consumer purchase intentions, that is, the public transfers celebrity characteristics to their perception of the product. The greater the match between the spokespersons and the product, the higher the purchasing intention of the consumers. This consistency is an important predictor [73]. A spokesperson is a person who shows brand images and characteristics through statements or behaviors in brand promotion activities [74], and is a key carrier for consumers to establish a relationship with a brand [75]. By analyzing comment data about spokespersons, the users' sense of identity to spokespersons of the knowledge payment platform greatly affects continuance intention. Therefore, the hypothesis is proposed as follows:

Hypothesis 13. *Sense of identity to spokespersons (SI) has positive effects on users' continuance intention.*

(11) Perceived costs

The perceived costs (PC) in this study imply subjective evaluation on payment when the users use the knowledge payment platform. The costs that are incurred by users in the knowledge payment platform are usually reflected in communication costs, purchasing products, purchasing members, and time and energy consumption. Based on the LDA model, we identify the topic containing the feature words charge, recharge, and cost-free listening as perceived costs. Studies on users' continuance intention in the fields of mobile banking [76] and third-generation (3G) services [77] have confirmed that high costs will negatively influence users' continuance intention. As competition intensifies in the market of knowledge payment, homogeneous contents among the platforms lead to low costs for user transfer and users become more sensitive to costs. Therefore, the hypothesis is put forward as follows:

Hypothesis 14. *Perceived costs negatively affect users' continuance intention.*

4.3. Questionnaires and Data

The questionnaire design is shown in Table A1. This study developed questionnaires on the Wenjuanxing platform, using a hyperlink via knowledge payment platform communication groups (including QQ group and WeChat group). The research purpose and the eligibility requirements for participation were clearly presented at the head of the first page of the Wenjuanxing Forms. After informed consent was given, the participants could complete a survey. The inclusion criteria were (1) have the ability to understand the Chinese questionnaire and the meaning of the questions, (2) have used knowledge platforms, and (3) have the ability to pay. The respondents were offered a random financial incentive after completing the questionnaire. The data were collected over a 1-month period (April–May 2022). A total of 532 questionnaires were distributed, of which 494 were valid after excluding invalid questionnaires. Statistical information of the sample description is shown in Table 5, and the usage of the knowledge payment platform of the studied users is demonstrated in Table A2.

Table 5. Descriptive statistical analysis.

Survey Object	Options	Quantity	Percentage (%)
Gender	Male	190	38.5
	Female	304	61.5
Age	Under 18	21	4.2
	18–25	210	42.5
	26–35	190	38.5
	36–45	63	12.8
	Above 45 years old	10	1.9
Education	High school and below	30	6.1
	Specialist	35	7.1
	Undergraduate	275	55.6
	Postgraduate and above	154	31.2
Profession	Student	198	40.1
	Enterprise Employees	133	26.9
	Staff in Government agencies	35	7.1
	Liberal professions	61	12.3
	Others	67	13.6

The questionnaire results show that the proportion of females in the knowledge paying user group is higher than that of men by more than 20%, indicating that women's knowledge demand and autonomous learning ability are relatively stronger. The users that were aged 18–25 account for the largest proportion. This group is more active in learning to complete their studies or acquiring new knowledge. The following age range of most respondents was 26–35. Work and life pressure can easily cause them to have knowledge anxiety, so they are willing to invest in various costs and use the knowledge payment platform. Over 80% of those surveyed have a bachelor degree, indicating that well-educated people have a great demand for knowledge and a high degree of acceptance of online learning.

The reliability and validity statistics are shown in Table 6. In the reliability test of questionnaires, the Cronbach's α value of questionnaires is 0.917 and the Cronbach's α values of each variable are above 0.8. The variables show good internal consistency, indicating that questionnaires are highly reliable. In this study, construct validity is selected as the index for the validity test, measured from two dimensions: exploratory and confirmatory factors. The Kaiser–Meyer–Olkin (KMO) value of questionnaires is 0.929, larger than the optimal critical value of 0.9. The sig value of Bartlett's sphericity test is 0.000. Therefore, it is reasonable to carry out principal component analysis. The interpretation rate for the cumulative variance of the first 11 factors that were extracted is 77.343%, and the load values of each factor are all above 0.7 (Table A3). Moreover, all the factor loadings are smaller than 0.4 after varimax rotation, indicating valid samples. The combined reliability (CR) of all 11 variables is greater than 0.7, and the average variance extracted (AVE) is greater than 0.5, indicating that each variable has good convergent validity and internal consistency.

Table 6. Reliability and validity statistics.

Constructs	Items	Loading	CR	AVE	Cronbach's α
Content quality (CQ)	CQ1	0.808	0.892	0.675	0.888
	CQ2	0.798			
	CQ3	0.760			
	CQ4	0.912			
Perceived usefulness (PU)	PU1	0.819	0.910	0.716	0.840
	PU2	0.806			
	PU3	0.948			
	PU4	0.804			

Table 6. *Cont.*

Constructs	Items	Loading	CR	AVE	Cronbach's α
Perceived ease of use (PEOU)	PEOU1 PEOU2 PEOU3	0.887 0.769 0.791	0.857	0.668	0.879
System quality (SQ)	SQ1 SQ2 SQ3	0.856 0.763 0.778	0.842	0.640	0.817
Perceived enjoyment (PE)	PE1 PE2 PE3	0.869 0.850 0.807	0.880	0.710	0.829
Auditory experience (AE)	AE1 AE2 AE3	0.805 0.753 0.801	0.830	0.619	0.870
Membership experience (ME)	ME1 ME2 ME3	0.793 0.744 0.786	0.818	0.600	0.830
Perceived costs (PC)	PC1 PC2 PC3	0.838 0.753 0.780	0.834	0.626	0.906
Spokesperson identity (SI)	SI1 SI2 SI3	0.890 0.798 0.810	0.872	0.695	0.855
Users' satisfaction (US)	US1 US2 US3	0.843 0.803 0.827	0.864	0.680	0.863
Continuance intention (CI)	CI1 CI2 CI3	0.876 0.720 0.794	0.841	0.639	0.837

The square roots of the AVEs of each factor (bold values along the diagonal) are all larger than the normalized correlation coefficients beyond the diagonal (Table 7), suggesting significant discriminant validity, so it passes the convergent validity test.

Table 7. Discriminative validity.

	CQ	SQ	PE	ME	AE	PC	SI	PU	PEOU	US	CI
CQ	0.822										
SQ	0.391 **	0.800									
PE	0.361 **	0.444 **	0.842								
ME	0.435 **	0.453 **	0.483 **	0.775							
AE	0.429 **	0.477 **	0.418 **	0.422 **	0.787						
PC	−0.255 **	−0.285 **	−0.431 **	−0.307 **	−0.285 **	0.791					
SI	0.404 **	0.425 **	0.407 **	0.492 **	0.393 **	−0.381 **	0.834				
PU	0.342 **	0.375 **	0.414 **	0.420 **	0.376 **	−0.332 **	0.380 **	0.846			
PEOU	0.473 **	0.462 **	0.480 **	0.500 **	0.499 **	−0.316 **	0.450 **	0.330 **	0.817		
US	0.473 **	0.507 **	0.504 **	0.521 **	0.503 **	−0.396 **	0.477 **	0.449 **	0.536 **	0.825	
CI	0.370 **	0.401 **	0.502 **	0.452 **	0.398 **	−0.331 **	0.439 **	0.395 **	0.398 **	0.439 **	0.799

Notes: ** The correlation is significant at the 0.01 level (two-tailed).

4.4. Structural Equation Model Testing

(1) Fitness test of the model

AMOS 24.0 software is used to verify whether the suppositional relationship between the sample data and the conceptual model is fitted. As shown in Table 8, the fitting indexes meet the standard, and the research model is well fitted.

Table 8. Model fitness results.

Index	Indicator	Standard	Estimation Result	Fitness Level
Absolute Fitness Indicator	CMIN/DF	<3.00	1.653	Good Fit
	RMSEA	<0.08	0.036	Good Fit
	GFI	>0.90	0.912	Good Fit
Relative Fitness Indicator	NFI	>0.90	0.920	Good Fit
	IFI	>0.90	0.967	Good Fit
	CFI	>0.90	0.967	Good Fit
Simple Fitness Indicator	PGFI	>0.50	0.760	Good Fit
	PNFI	>0.50	0.812	Good Fit
	PCFI	>0.50	0.853	Good Fit

(2) Hypothesis testing of the model

The model path is verified with the AMOS software and the path coefficient of the structural equation model (SEM) is obtained after additional modification of the initial structural model, as shown in Figure 3.

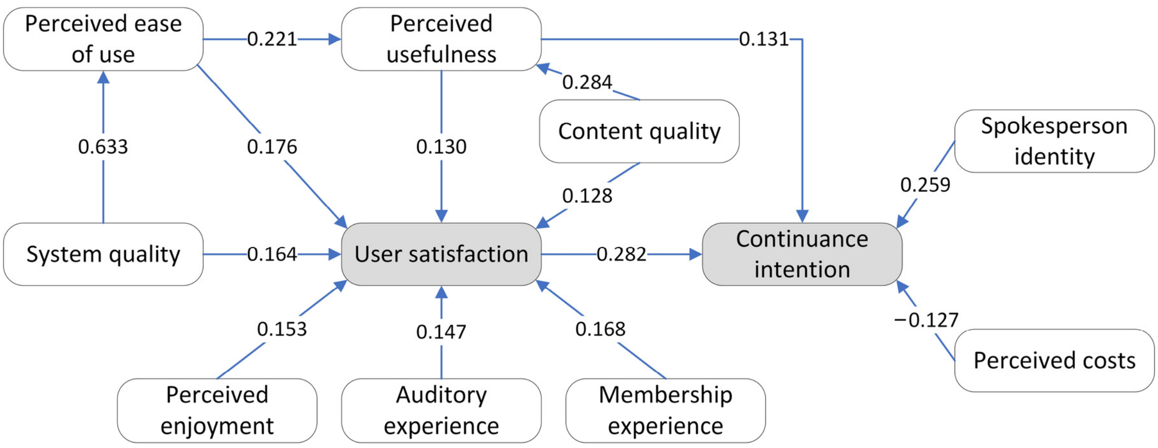

Figure 3. Path coefficient of the structural equation model.

The effects of various variables on continuance intention are demonstrated in Table 9. All hypotheses are true.

(3) Mediating effect test

In this research, the samples are repeatedly sampled 5000 times by utilizing the Bootstrap method that is built in AMOS 24.0 software. The mediating effects are established when the bias-corrected and percentile 95% confidence intervals do not contain zero. The results of Table 10 illustrate that the perceived ease of use partially mediates the relationship between the system quality and user satisfaction. The perceived usefulness partially mediates the relationships of content quality and the perceived ease of use with user satisfaction. Furthermore, user satisfaction completely mediates the relationships of content quality, perceived ease of use, system quality, perceived enjoyment, auditory experience, and membership experience with continuance intention. It also plays a partial mediating role in the relationship between the perceived usefulness and continuance intention.

Table 9. Path coefficient of SEM.

Hypothesis	Relationship	Unstandardized Path Coefficient	S.E.	C.R.	p	Standard Path Coefficient	Supported
H1	CI←US	0.259	0.053	4.887	***	0.282	Yes
H2	US←PU	0.129	0.041	3.180	0.001	0.130	Yes
H3	CI←PU	0.120	0.043	2.785	0.005	0.131	Yes
H4	PU←PEOU	0.219	0.049	4.439	***	0.221	Yes
H5	US←PEOU	0.174	0.054	3.213	0.001	0.176	Yes
H6	PU←CQ	0.319	0.056	5.713	***	0.284	Yes
H7	US←CQ	0.144	0.056	2.587	0.010	0.128	Yes
H8	PEOU←SQ	0.655	0.051	12.744	***	0.633	Yes
H9	US←SQ	0.167	0.078	2.153	0.031	0.164	Yes
H10	US←PE	0.147	0.050	2.918	0.004	0.153	Yes
H11	US←AE	0.164	0.064	2.570	0.010	0.147	Yes
H12	US←ME	0.164	0.058	2.799	0.005	0.168	Yes
H13	CI←SI	0.226	0.050	4.556	***	0.259	Yes
H14	CI←PC	−0.133	0.056	−2.359	0.018	−0.127	Yes

Notes: *** $p < 0.001$.

Table 10. Results of the mediating effect test.

Path	Indirect Effects	Estimate	Bias-Corrected 95%		Percentile 95%		Result
			Lower	Upper	Lower	Upper	
1	CQ—US—CI	0.036	0.008	0.080	0.007	0.078	Significant
2	PU—US—CI	0.037	0.009	0.078	0.007	0.074	Significant
3	PEOU—US—CI	0.050	0.014	0.110	0.009	0.102	Significant
4	SQ—US—CI	0.046	0.010	0.110	0.008	0.102	Significant
5	PE—US—CI	0.043	0.007	0.109	0.004	0.103	Significant
6	AE—US—CI	0.042	0.008	0.094	0.005	0.087	Significant
7	ME—US—CI	0.047	0.011	0.111	0.008	0.104	Significant
8	CQ—PU—US	0.037	0.009	0.079	0.007	0.073	Significant
9	PEOU—PU—US	0.029	0.008	0.062	0.005	0.057	Significant
10	SI—PEOU—US	0.112	0.027	0.215	0.024	0.210	Significant

4.5. Results Analysis

(1) Correlations of content quality, system quality, perceived usefulness, and perceived ease of use with user satisfaction

As displayed in Table 9, the normalized path coefficients for the relationships of content quality, system quality, perceived usefulness, and perceived ease of use with user satisfaction are 0.128, 0.164, 0.130, and 0.176, respectively. This suggests that content quality, system quality, perceived usefulness, and the perceived ease of use are significantly positively correlated with user satisfaction. The results demonstrate that the knowledge payment platform should improve the diversity and high-quality of resources and teaching quality of lecturers and reduce advertising content in terms of the content quality and increase system fluency, indirectivity of navigation, and comfort of the page layout with respect to system quality. The users' perceived usefulness and the perceived ease of use would be enhanced by improving the content quality and system quality.

(2) Correlations of perceived enjoyment, auditory experience, and membership experience with user satisfaction

The normalized path coefficients for relationships of the perceived enjoyment, auditory experience, and membership experience with user satisfaction separately are 0.153, 0.147, and 0.168. This indicates that the perceived enjoyment, auditory experience, and membership experience show significant positive correlations with user satisfaction. Membership experience affects the users' continuance intention through its influences on user satisfaction.

The positive effects of perceived enjoyment on user satisfaction are consistent with previous research results. It is worth noting that users' consumption on the knowledge payment platform is an online learning activity, which is quite different from the consumption of entertainment content, such as listening to music, watching videos, and playing games. As learning behavior users on the knowledge payment platform often lack supervision and constraint mechanisms, users will even reduce their learning enthusiasms when they perceive low entertainment, finally affecting user satisfaction with the knowledge payment platform. Therefore, the content quality of the knowledge payment platform should be both professional and interesting, and the teaching process of knowledge producers should be more relaxed and pleasant.

Furthermore, because users of the knowledge payment platform tend to be in a more private learning space, an excellent auditory experience can help users enter into an immersive learning atmosphere, thus improving user satisfaction. Membership systems can also bring customized services and differentiated user experience, which ultimately positively influence users' continuance intention.

(3) Correlations of perceived usefulness, perceived costs, sense of identity to spokespersons, and user satisfaction with continuance intention

The normalized path coefficient for the relationship between the perceived usefulness and continuance intention is 0.131, indicating that the two variables are significantly positively correlated. The normalized path coefficient for the relationship between the perceived costs and continuance intention is -0.127, suggesting that high perceived costs can reduce users' continuance intention. For users who prefer to obtain free knowledge through the Internet, the pricing strategy of the knowledge payment platform is particularly important. Adopting multiple pricing methods can strengthen users' continuance intention while guaranteeing profits.

The normalized path coefficient for the relationship between the sense of identity to spokespersons and continuance intention is 0.259, which indicates a significant positive correlation between the two variables. On the one hand, the main customer group for the knowledge payment platform is young people from 18 to 35 years old, that are susceptible to celebrity effects and even the derivation of fan culture and economy of fans. They are willing to pay for and actively promote products that are endorsed by their idols; otherwise, they reject the brands or products that are endorsed by an artist because of distaste for the artist. On the other hand, due to the particularity of products and services that are provided by the knowledge payment platform, spokespersons of the platform are usually considered to represent the platform's overall knowledge and culture level. A common sense of identity to the individual knowledge and culture level of spokespersons will directly result in doubt of users' perceived usefulness of the knowledge payment platform, thus constantly reducing continuance intention. Therefore, the selection of spokespersons for the knowledge payment platform should comprehensively consider the market and cultural influences.

The normalized path coefficient for the relationship between user satisfaction and continuance intention is 0.282, the largest among the four factors directly affecting the users' continuance intention. This indicates that user satisfaction has important effects on continuance intention and the improvement of user satisfaction is the fundamental strategy for the knowledge payment platform to retain customers.

5. Conclusions

This study shifts the research on users' continuance intention to the critical issues that are concerned by users. Based on the literature review and theoretical deduction, the LDA topic model is introduced to explore key influence factors for users' continuance intention towards the knowledge payment platform from accurate comments of users. Through literature support and empirical analysis, these factors are reliable and valid, and the validity of the results of topic identification is tested again. The combination of text mining and empirical analysis strengthens the validity and robustness of the research conclusions and provides a new idea for traditional empirical studies.

5.1. Academic Contributions

(1) Taking users' comments on the knowledge payment platform, namely Himalayan FM, as the data source, ten topics were primarily concerned by users on the knowledge payment platform are explored using the LDA topic model. Furthermore, considering the correlations of internal lexical items of different topics, ten topics are summarized into seven influence factors: content quality, perceived enjoyment, membership experience, auditory experience, spokespersons of the platform, perceived costs, and system quality. This provides a reference for analyzing users' continuance intention to the knowledge payment platform.

(2) Through the external variables that are introduced by topic identification, such as membership experience, auditory experience, and spokesperson identity, based on the TAM and IS integration, the conceptual model for formation mechanisms of the users' continuance intention to knowledge payment is constructed. The model's validity is verified through the structural equation, which verifies the validity of topic identification, thus making up for the shortcomings of external variables of the TAM, extending TAM and IS integration, and enriching the theory of continued usage of the information system by users.

(3) Factors including the perceived usefulness [55], user satisfaction [52,53]), and sense of identity to spokespersons [73] directly positively affect users' continuance intention, while the perceived costs [76,77] directly negatively influence users' continuance intention. The perceived ease of use, as well as the content quality and system quality of the knowledge payment platform, indirectly affect the users' continuance intention through user satisfaction [30]. Meanwhile, the content quality and system quality of the knowledge payment platform have direct positive effects on the perceived usefulness and ease of use [58]. In addition, factors such as perceived enjoyment [67], membership experience, and users' auditory experience exert indirect influences on users' continuance intention through user satisfaction.

5.2. Implications for Practice

Users' continuance usage is fundamental for the long-term development of the knowledge payment platform. In the post-epidemic period, how to promote the formation of users' continuance intention towards the knowledge payment platform is particularly important for the sustainable development of the knowledge payment industry. To this end, the following management implications are proposed:

(1) Improving content quality and system quality

The perceived usefulness and perceived ease of use are core elements for the TAM and core demands for users of the knowledge payment platform. Based on the research conclusions, the two exert positive effects on user satisfaction and continuance intention. Therefore, in the pan-entertainment Internet environment, the key to the sustainable development of the knowledge payment platform is the continuous improvement of content quality and the optimization of system quality. Firstly, as an intermediary between knowledge suppliers and consumers, the knowledge payment platform should strengthen the training, service, and supervision of knowledge producers and check the knowledge payment products and services that are provided, thus strictly controlling the content quality from the source of knowledge, while ensuring the professionalism and high-quality of knowledge payment products, the users' perceived usefulness can be improved. Secondly, users will have different knowledge needs in different periods, and it is difficult for a single resource category to meet the changing needs of users, resulting in transfer behaviors of users. Therefore, knowledge payment platforms should introduce knowledge producers from different fields to enrich content resources and ensure the introduction of continuous number of users. In addition, with the growing number of users and continuous improvement of users' experience on the platform, it is necessary to strengthen the system construction of the platform and optimize system quality of the knowledge payment platform from the aspects, such as stability, simplicity, and aesthetics. This ensures the users' operation comfort and improves the users' perceived ease of use and satisfaction.

(2) Paying attention to influences of spokespersons

Based on the users' comments relating to spokespersons of the knowledge payment platform, the recognition of users to spokespersons of the platform can directly affect users' continuance intention. On the one hand, most users of the knowledge payment platform are new generations that are born after 2000 and 1990. This group is widely fanatical about online celebrities with a huge fan base. Individuals tend to ignore the actual effectiveness of products or services, thus simply paying energy and financial resources for products that are endorsed by their idols. On the other hand, as the knowledge payment platform is labeled as culture by the public, the spokespersons are the embodiment of the cultural level of the platform for users. Unlike traditional celebrity endorsements, spokespersons without cultural labels generally make users doubt the content quality and operation mode of the knowledge payment platform, thus having the intention to transfer. Therefore, for the knowledge payment platform, it is necessary to strike a balance between culture and celebrity, so that spokespersons can have a positive influence on the formation of users' continuance intention.

(3) Improving the management system of members

As a classic marketing strategy, a membership system can effectively promote the loyalty of consumers. Based on research conclusions, users of the knowledge payment platform pay more attention to the membership experience and hope to enjoy more resources and services at a reasonable member price. For non-member users, the knowledge payment platform should strengthen the marketing of membership experience. For users as members, the existing membership experience should be improved from the aspects of content, function, and welfare privileges to promote users' continuance intention.

(4) Improving auditory experience of users

The paid audio knowledge is widespread because audio liberates the eyes and hands of users. The auditory experience, as the users' primary experience, can directly affect user satisfaction. Therefore, the knowledge payment platform should improve audio products in a new manner, formulate strict recording and broadcasting indicators, and strengthen the construction of content quality from aspects of sound, speed, sound effect, and emotion. Moreover, it should meet the emotional value of users by listening and provides a better auditory experience from the physiological, emotional, and cognitive dimensions.

5.3. Limitations and Further Study

Due to the difference of knowledge payment platforms, the influencing factors for continuance intention may be different. The construct of auditory experience and spokesperson identity are applicable in the context of this study, but whether it is applicable to different types of knowledge payment platforms needs to be explored. In future research, contextual variables of different knowledge payment platforms should be explored, such as Massive Open Online Courses (MOOCs), real-time voice Q & A platform, and knowledge service platform. The coverage of the studied samples should be expanded to enrich influencing factors and action mechanisms for users' continuance intention towards knowledge payment platforms. Other data collection methods, such as experimental methods, can be considered to further improve the conclusions of this study.

Author Contributions: H.X. contributed to conceptualization, methodology, and supervision; M.Z. contributed to the investigation, formal analysis, and writing and editing of the original draft; J.Z. contributed to writing and editing of the original draft; M.X. contributed to the investigation and formal analysis; H.H. contributed to data acquisition, validation and editing; H.-C.K.L. contributed to review. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects that were involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: The authors would like to thank the anonymous reviewers for their valuable comments.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Scale items.

Constructs	Items	Measures	References
Content quality (CQ)	CQ1	The knowledge payment platform contains diverse programs and abundant resources.	Delone et al. (1992) [29] Ozkan et al. (2009) [62] Wang et al. [78]
	CQ2	The quality of teaching contents on the knowledge payment platform is reliable.	
	CQ3	The teaching quality of course instructors on the knowledge payment platform is high.	
	CQ4	The course chapters of the knowledge payment platform are set up scientifically and rationally.	
Perceived usefulness (PU)	PU1	The knowledge payment platform can provide useful information or knowledge for me in many aspects.	Davis (1989) [79] Agarwal et al. (2000) [80] Teo et al. (2001) [81]
	PU2	The knowledge payment platform allows me to make full use of spare time.	
	PU3	The knowledge payment platform can improve my learning ability.	
	PU4	The knowledge payment platform can improve my skill ability.	
Perceived ease of use (PEOU)	PEOU1	I think it is very easy to learn to use the knowledge payment platform.	Davis (1989) [79] Thong et al. (2006) [82] Venkatesh et al. (2003) [83]
	PEOU2	I think the operation steps of the knowledge payment platform are simple and easy to learn.	
	PEOU3	I consider it is easy to access the knowledge payment platform anytime and anywhere.	
System quality (SQ)	SQ1	The knowledge payment platform starts quickly, works well and breaks down infrequently.	Mailizar et al. [30] Ozkan et al. (2009) [62]
	SQ2	The knowledge payment platform can quickly respond to users' requests.	
	SQ3	The knowledge payment platform has reasonable interface layout, and clear navigation that conforms to users' habits.	
Perceived enjoyment (PE)	PE1	Time flies when using the knowledge payment platform.	Moon et al. (2001) [84] Lee et al. (2005) [68]
	PE2	It is relaxed and pleasant to use the knowledge payment platform.	
	PE3	I think it is interesting to acquire knowledge through the knowledge payment platform.	
Auditory experience (AE)	AE1	The video and audio lecturers/anchors on the knowledge payment platform have vivid voice, clear speech and moderate speaking speed.	Chen et al. (2019) [85] Ye et al. (2018) [86]
	AE2	The audio of the knowledge payment platform is smooth without buffering.	
	AE3	The knowledge payment platform has rich and vivid sound effects.	

Table A1. *Cont.*

Constructs	Items	Measures	References
Membership experience (ME)	ME1	I can obtain more content privileges after becoming the member of the knowledge payment platform.	Wang et al. (2019) [87]
	ME2	I can enjoy more function privileges after becoming the member of the knowledge payment platform.	
	ME3	I can enjoy more welfare privileges after becoming the member of the knowledge payment platform.	
Perceived costs (PC)	PC1	I consider that the price of paid information on the knowledge payment platform is high.	Kuo et al. (2009) [77]
	PC2	I believe that the knowledge payment platform costs a lot of data traffic.	
	PC3	I believe that irrelevant contents on the knowledge payment platform waste much of unnecessary time and energy.	
Spokesperson identity (SI)	SI1	I think that the spokespersons of the knowledge payment platform have excellent characteristics.	Wu et al. (2007) [71]
	SI2	I believe that the spokespersons of the knowledge payment platform conform to the image of the platform.	
	SI3	I will pay attention to the latest development of the spokespersons of knowledge payment platform.	
User satisfaction (US)	US1	I am very satisfied with my experience on the knowledge payment platform.	Bhattacherjee et al. (2001) [14] Chen et al. (2017) [88]
	US2	I am very satisfied with the learning effects through the knowledge payment platform.	
	US3	I am very satisfied with the overall functions and services of the knowledge payment platform.	
Continuance intention (CI)	CI1	I would like to continue to use this knowledge payment platform.	Bhattacherjee et al. (2001) [14] Chen et al. (2017) [88]
	CI2	I would like to recommend the knowledge payment platform to others.	
	CI3	I make positive comments on the knowledge payment platform.	

Notes: The five-point Likert scale is used, and the questions for screening are set in the questionnaire to exclude the respondents who do not have usage experience of the knowledge payment platform. The questionnaire includes two parts: basic information of the respondents and variable measurement items.

Table A2. Usage of various knowledge payment platforms.

Knowledge Payment Platforms	Response		Percentage of Cases (%)
	Number of Cases	Percentage (%)	
Himalaya FM	322	22.80	65.20
Iget	74	5.20	15.00
Fandengread	87	6.10	17.60
Dragonfly FM	60	4.20	12.10
Zhihu University (Including Zhihu Live)	187	13.20	37.90
LAIX	113	8.00	22.90
Qlchat	13	0.90	2.60
Hundun Academy	12	0.80	2.40
Cloud classroom of Netease	119	8.40	24.10
Netease CloudMusic (Paid radio)	252	17.80	51.00
Douban Time	25	1.80	5.10
Zaih	4	0.30	0.80
Lizhiweike	31	2.20	6.30
Lifeweek Zhongdu	1	0.10	0.20
Kaishu Story	40	2.80	8.10
Mtedu	4	0.30	0.80

Table A2. *Cont.*

Knowledge Payment Platforms	Response		Percentage of Cases (%)
	Number of Cases	Percentage (%)	
Others	71	5.00	14.40
Total	1415	100.00	286.40

Notes: (1) Percentages and totals are based on responders, and the value 1 is used to tabulate the two groups. (2) The survey results show that the top five knowledge payment APPs in China are Himalayan FM, Netease cloud music (Paid radio), Zhihu University, LAIX, and Fandengread. Himalayan FM has a high market share, which also shows the reliability and universality of the subject extraction results in this paper.

Table A3. Interpretation of total variance.

Component	Initial Eigenvalues			Extraction Sums of Squared Loading			Rotation Sums of Squared Loading		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.671	36.202	36.202	12.671	36.202	36.202	3.320	9.486	9.486
2	2.250	6.427	42.630	2.250	6.427	42.630	3.218	9.195	18.682
3	1.935	5.530	48.160	1.935	5.530	48.160	2.378	6.793	25.475
4	1.661	4.744	52.904	1.661	4.744	52.904	2.368	6.766	32.241
5	1.494	4.269	57.173	1.494	4.269	57.173	2.366	6.761	39.001
6	1.449	4.141	61.314	1.449	4.141	61.314	2.331	6.661	45.663
7	1.277	3.649	64.964	1.277	3.649	64.964	2.296	6.560	52.223
8	1.220	3.485	68.448	1.220	3.485	68.448	2.285	6.530	58.752
9	1.078	3.080	71.528	1.078	3.080	71.528	2.268	6.481	65.234
10	1.025	2.929	74.456	1.025	2.929	74.456	2.122	6.063	71.297
11	1.010	2.887	77.343	1.010	2.887	77.343	2.116	6.047	77.343
12	0.519	1.483	78.827						
					……				
35	0.147	0.421	100.000						

Notes: The extraction method is principal component analysis.

References

1. Kanetaki, Z.; Stergiou, C.; Bekas, G.; Jacques, S.; Troussas, C.; Sgouropoulou, C.; Ouahabi, A. Grade Prediction Modeling in Hybird Learning Environments for Sustainbale Engineering Engineering Education. *Sustainability* **2022**, *14*, 5205. [CrossRef]
2. González-Calatayud, V.; Prendes-Espinosa, P.; Roig-Vila, R. Artificial Intelligence for Student Assessment: A Systematic Review. *Appl. Sci.* **2021**, *11*, 5467. [CrossRef]
3. Jacques, S.; Ouahabi, A.; Lequeu, T. Synchronous E-learning in Higher Education during the COVID-19 Pandemic. In Proceedings of the 2021 IEEE Global Engineering Education Conference (EDUCON), Vienna, Austria, 21–23 April 2021; pp. 1102–1109. [CrossRef]
4. Zhang, X.; Chang, J.; Zhou, Y. The Study of Charging Mechanism of Knowledge Payment Platform Based on Tripartite Game Model. *Enterp. Inf. Syst.* **2020**, *16*, 1846791. [CrossRef]
5. United Nations Trust Fund for Human Security. AGENDA 2030. Available online: https://www.un.org/humansecurity/agenda-2030/ (accessed on 11 June 2022).
6. Xu, H.; Wang, J.; Tai, Z.; Lin, H.-C. Empirical Study on the Factors Affecting User Switching Behavior of Online Learning Platform Based on Push-Pull-Mooring Theory. *Sustainability* **2021**, *13*, 7087. [CrossRef]
7. Zhang, J.; Zhang, J.; Zhang, M. From free to paid: Customer expertise and customer satisfaction on knowledge payment platforms. *Decis. Support. Syst.* **2019**, *127*, 113140. [CrossRef]
8. Matei, S.A. Cognitive surplus. *Inform. Soc.* **2012**, *28*, 128–130. [CrossRef]
9. Zhao, Y.; Yuan, X.; Zhou, R. How knowledge contributor characteristics and reputation affect user payment decision in paid Q&A? An empirical analysis from the perspective of trust theory. *Electron. Commer. Res. Appl.* **2018**, *31*, 1–11. [CrossRef]
10. Yu, L.; Chen, Z.; Yao, P.; Liu, H. A Study on the Factors Influencing Users' Online Knowledge Paying-Behavior Based on the UTAUT Model. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 1768–1790. [CrossRef]
11. Huo, H.; Li, Q. Influencing Factors of the Continuous Use of a Knowledge Payment Platform—Fuzzy-Set Qualitative Comparative Analysis Based on Triadic Reciprocal Determinism. *Sustainability* **2022**, *14*, 3696. [CrossRef]
12. Qi, C.; Liu, S. Evaluating On-Line Courses via Reviews Mining. *IEEE Access* **2021**, *9*, 35439–35451. [CrossRef]

13. Malloch, Y.Z.; Zhang, J. Seeing Others Receive Support Online: Effects of Self-Disclosure and Similarity on Perceived Similarity and Health Behavior Intention. *J. Health Commun.* **2019**, *24*, 217–225. [CrossRef] [PubMed]
14. Bhattacherjee, A. Understanding Information Systems Continuance: An Expectation-confirmation Model. *Manag. Inf. Syst. Q.* **2001**, *25*, 351–370. [CrossRef]
15. Salloum, S.A.; Alhamad, M.Q.A.; Al-Emran, M.; Monem, A.A.; Shaalan, K. Exploring Students' Acceptance of E-Learning Through the Development of a Comprehensive Technology Acceptance Model. *IEEE Access* **2019**, *7*, 128445–128462. [CrossRef]
16. Davis, F.D.; Bagozzi, R.P.; Warshaw, P.R. User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Manag. Sci.* **1989**, *35*, 982–1003. [CrossRef]
17. Zardari, B.A.; Hussain, Z.; Arain, A.A.; Rizvi, W.H.; Vighio, M.S. Development and Validation of User Experience-Based E-Learning Acceptance Model for Sustainable Higher Education. *Sustainability* **2021**, *13*, 6201. [CrossRef]
18. Humida, T.; Al Mamun, M.H.; Keikhosrokiani, P. Predicting behavioral intention to use e-learning system: A case-study in Begum Rokeya University, Rangpur, Bangladesh. *Educ. Inf. Technol.* **2022**, *27*, 2241–2265. [CrossRef]
19. Sukendro, S.; Habibi, A.; Khaeruddin, K.; Indrayana, B.; Syahruddin, S.; Makadada, F.A.; Hakim, H. Using an extended Technology Acceptance Model to understand students' use of E-learning during COVID-19: Indonesian sport science education context. *Heliyon* **2020**, *6*, e05410. [CrossRef]
20. Kanwal, F.; Rehman, M. Factors Affecting E-Learning Adoption in Developing Countries–Empirical Evidence from Pakistan's Higher Education Sector. *IEEE Access* **2017**, *5*, 10968–10978. [CrossRef]
21. David, G. TAM or Just Plain Habit: A Look at Experienced Online Shoppers. *J. Organ. End User Comput.* **2003**, *15*, 1–13.
22. Kim, J.H.; Ha, K.S. The Study of the Effects of the Enterprise Mobile Social Network Service on User Satisfaction and the Continuous Use Intention. *J. Digit. Converg.* **2012**, *10*, 135–148. [CrossRef]
23. Mijin, N.; Jang, H.; Choi, B.; Khongorzul, G. Attitude toward the use of electronic medical record systems: Exploring moderating effects of self-image. *Inf. Dev.* **2019**, *35*, 67–79. [CrossRef]
24. Vladova, G.; Ullrich, A.; Bender, B.; Gronau, N. Students' Acceptance of Technology-Mediated Teaching—How It Was Influenced During the COVID-19 Pandemic in 2020: A Study from Germany. *Front. Psychol.* **2021**, *12*, 636086. [CrossRef] [PubMed]
25. Alyoussef, I.Y. E-Learning Acceptance: The Role of Task–Technology Fit as Sustainability in Higher Education. *Sustainability* **2021**, *13*, 6450. [CrossRef]
26. Al-Rahmi, W.; Yahaya, N.; Aldraiweesh, A.A.; Alamri, M.M.; Aljarboa, N.A.; Alturki, U.; Aljeraiwi, A.A. Integrating Technology Acceptance Model with Innovation Diffusion Theory: An Empirical Investigation on Students' Intention to Use E-Learning Systems. *IEEE Access* **2019**, *7*, 26797–26809. [CrossRef]
27. Jiang, M.Y.; Jong, M.S.; Lau, W.W.; Meng, Y.; Chai, C.; Chen, M. Validating the General Extended Technology Acceptance Model for E-Learning: Evidence from an Online English as a Foreign Language Course Amid COVID-19. *Front. Psychol.* **2021**, *12*, 671615. [CrossRef]
28. Prendes-Espinosa, P.; Solano-Fernández, I.M.; García-Tudela, P.A. EmDigital to Promote Digital Entrepreneurship: The Relation with Open Innovation. *J. Open Innov. Technol. Mark. Complex.* **2021**, *7*, 63. [CrossRef]
29. DeLone, W.H.; McLean, E.R. Information systems success: The quest for the dependent variable. *Inf. Syst. Res.* **1992**, *3*, 60–95. [CrossRef]
30. Mailizar, M.; Burg, D.; Maulina, S. Examining university students' behavioural intention to use E-learning during the COVID-19 pandemic: An extended TAM model. *Educ. Inf. Technol.* **2021**, *26*, 7057–7077. [CrossRef]
31. Cheng, Y.M. Why do users intend to continue using the digital library? An integrated Perspective. *Aslib. J. Inform. Manag.* **2014**, *66*, 640–662. [CrossRef]
32. Wu, B.; Zhang, C. Empirical study on continuance intentions towards E-Learning 2.0 systems. *Behav. Inform. Technol.* **2014**, *33*, 1027–1038. [CrossRef]
33. Al-Adwan, A.S.; Albelbisi, N.A.; Hujran, O.; Al-Rahmi, W.M.; Alkhalifah, A. Developing a Holistic Success Model for Sustainable E-Learning: A Structural Equation Modeling Approach. *Sustainability* **2021**, *13*, 9453. [CrossRef]
34. Lin, Q.; He, S.; Deng, Y. Method of personalized educational resource recommendation based on LDA and learner's behavior. *Int. J. Electr. Eng. Educ.* **2021**. [CrossRef]
35. Borakati, A. Evaluation of an international medical E-learning course with natural language processing and machine learning. *BMC Med. Educ.* **2021**, *21*, 181. [CrossRef] [PubMed]
36. Nilashi, M.; Minaei-Bidgoli, B.; Alghamdi, A.; Alrizq, M.; Alghamdi, O.; Nayer, F.K.O.; Aljehane, N.; Khosravi, A.; Mohd, S. Knowledge discovery for course choice decision in Massive Open Online Courses using machine learning approaches. *Expert Syst. Appl.* **2022**, *199*, 117092. [CrossRef]
37. Ray, A.; Bala, P.K.; Dwivedi, Y.K. Exploring values affecting e-Learning adoption from the user-generated-content: A consumption-value-theory perspective. *J. Strateg. Mark.* **2020**, *29*, 430–452. [CrossRef]
38. Ray, A.; Bala, P.K.; Kumar, R. An NLP-SEM approach to examine the gratifications affecting user's choice of different e-learning providers from user tweets. *J. Decis. Syst.* **2021**, *30*, 439–455. [CrossRef]
39. Ray, A.; Bala, P.K.; Dwivedi, Y.K. Exploring barriers affecting eLearning usage intentions: An NLP-based multi-method approach. *Behav. Inform. Technol.* **2022**, *41*, 1002–1018. [CrossRef]
40. Nanda, G.; Douglas, K.A.; Waller, D.R.; Merzdorf, H.E.; Goldwasser, D. Analyzing large collections of open-ended feedback from MOOC learners using LDA topic modeling and qualitative analysis. *IEEE Trans. Learn. Technol.* **2021**, *14*, 146–160. [CrossRef]

41. Kuchuan. Himalaya APP「Listening Community」Radio Audiobooks Comic Book Reviews丨iOS丨Real-Time Rankings丨Help Companies Get More Customers-Kuchuan. Available online: https://ios.kuchuan.com/page/appInfo?infoId=596&site=0&market=xiaomi#rank (accessed on 17 December 2021).
42. BigData-Research. China Paid Knowledge Industry Market Research Report, 1Q 2018. Available online: http://www.bigdata-research.cn/content/201806/705.html (accessed on 19 June 2018).
43. Blei, D.M.; Ng, A.Y.; Jordan, M.I. Latent dirichlet allocation. *J. Mach. Learn. Res.* **2003**, *3*, 993–1022.
44. Huang, C.N. The problem of word separation in Chinese information processing. *Lang. Text. Appl.* **1997**, *1*, 74–80. (In Chinese)
45. Dai, D.; Ma, Y.; Zhao, M. Analysis of big data job requirements based on K-means text clustering in China. *PLoS ONE* **2021**, *16*, e0255419. [CrossRef]
46. Nielsen, F.A. Wembedder: Wikidata entity embedding web service. *Mach. Learn.* 2017. [CrossRef]
47. Wang, B.; Liu, S.; Ding, K.; Liu, Z.; Xu, J. Identifying technological topics and institution-topic distribution probability for patent competitive intelligence analysis: A case study in LTE technology. *Scientometrics* **2014**, *101*, 685–704. [CrossRef]
48. Jian, F.; Wang, Y.; Ding, Y. Microblog topic evolution computing based on LDA algorithm. *Open Phys.* **2018**, *16*, 509–516. [CrossRef]
49. Limayem, M.; Hirt, S.G.; Cheung, C.M.K. How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance. *Manag. Inf. Syst. Q.* **2007**, *31*, 705–737. [CrossRef]
50. Liao, C.; Palvia, P.; Chen, J.L. Information technology adoption behavior life cycle: Toward a Technology Continuance Theory (TCT). *Int. J. Inf. Manag.* **2009**, *29*, 309–320. [CrossRef]
51. Oliver, R.L. *Sati Sfaction: A Behavioral Perspective on the Consumer*; Irwin/McGraw-Hill: New York, NY, USA, 1997.
52. Bhattacherjee, A.; Perols, J.; Sanford, C. Information Technology Continuance: A Theoretic Extension and Empirical Test. *J. Comput. Inf. Syst.* **2007**, *49*, 17–26. [CrossRef]
53. Dai, H.M.; Teo, T.; Rappa, N.A.; Huang, F. Explaining Chinese university students' continuance learning intention in the MOOC setting: A modified expectation confirmation model perspective. *Comput. Educ.* **2020**, *150*, 103850. [CrossRef]
54. Barnes, S.J.; Vidgen, R.T. Technology socialness and Web site satisfaction. *Technol. Forecast. Soc. Chang.* **2014**, *89*, 12–25. [CrossRef]
55. Lee, M.C. Explaining and predicting users' continuance intention toward E-learning: An extension of the expectation–confirmation model. *Comput. Educ.* **2010**, *54*, 506–516. [CrossRef]
56. Hung, S.Y.; Liang, T.P.; Chang, C.M. A meta-analysis of empirical research using TAM. *Inf. Manag.* **2005**, *12*, 211–234.
57. Lin, K.M. E-Learning continuance intention: Moderating effects of user e-learning experience. *Comput. Educ.* **2011**, *56*, 516–526. [CrossRef]
58. Calisir, F.; Gumussoy, C.A.; Bayraktaroglu, A.E.; Karaali, D. Predicting the Intention to Use a Web-Based Learning System: Perceived Content Quality, Anxiety, Perceived System Quality, Image, and the Technology Acceptance Model. *Hum. Factors Ergon. Manuf.* **2014**, *24*, 515–531. [CrossRef]
59. Joo, Y.J.; Lim, K.Y.; Kim, E.K. Online university students' satisfaction and persistence: Examining perceived level of presence, usefulness and ease of use as predictors in a structural model. *Comput. Educ.* **2011**, *57*, 1654–1664. [CrossRef]
60. Sun, P.C.; Tsai, R.J.; Finger, G.; Chen, Y.Y.; Yeh, D. What drives a successful e-Learning? An empirical investigation of the critical factors influencing learner satisfaction. *Comput. Educ.* **2008**, *50*, 1183–1202. [CrossRef]
61. Lin, W.S.; Wang, C.H. Antecedence to Continued Intentions of Adopting E-learning System in Blended Learning Instruction: A Contingency Framework Based on Models of Information System Success and Task-technology Fit. *Comput. Educ.* **2012**, *58*, 88–99. [CrossRef]
62. Ozkan, S.; Koseler, R. Multi-dimensional students' evaluation of e-learning systems in the higher education context: An empirical investigation. *Comput. Educ.* **2009**, *53*, 1285–1296. [CrossRef]
63. William, H.D.; Ephraim, R.M. The DeLone and McLean model of information systems success: A ten-year update. *J. Manag. Inf. Syst.* **2003**, *19*, 9–30.
64. Rivard, S.; Poirier, G.; Raymond, L.; Bergeron, F. Development of a measure to assess the quality of user-developed applications. *ACM SIGMIS Database* **1997**, *28*, 44–58. [CrossRef]
65. Petter, S.; Delone, W.; Mclean, E. Measuring information systems success: Models, dimensions, measures, and interrelationships. *Eur. J. Inform. Syst.* **2008**, *17*, 236–263. [CrossRef]
66. Davis, F.D.; Bagozzi, R.P.; Warshaw, P.R. Extrinsic and Intrinsic Motivation to Use Computers in the Workplace. *J. Appl. Soc. Psychol.* **2010**, *22*, 1111–1132. [CrossRef]
67. Lin, C.S.; Wu, S.; Tsai, R.J. Integrating perceived playfulness into expectation-confirmation model for web portal context. *Inf. Manag.* **2005**, *42*, 683–693. [CrossRef]
68. Lee, I.; Kim, J.; Kim, J. Use Contexts for the Mobile Internet: A Longitudinal Study Monitoring Actual Use of Mobile Internet Services. *Int. J. Hum. Comput. Interact.* **2005**, *18*, 269–292. [CrossRef]
69. Schifferstein, H.N.J.; Otten, J.J.; Thoolen, F.; Hekkert, P. The experimental assessment of sensory dominance in a product development context. *J. Des. Res.* **2010**, *8*, 119–144. [CrossRef]
70. Kagan, J. The concept of identification. *Psychol. Rev.* **1958**, *65*, 296–305. [CrossRef]
71. Wu, W.Y.; Tsai, C.H. The Empirical Study of CRM: Consumer Company Identification and Purchase Intention in the Direct Selling Industry. *Int. J. Commer. Manag.* **2007**, *7*, 194–210. [CrossRef]
72. McCrackern, G. Who is the celebrity endorser? Cultural foundations of the endorsement process. *J. Consumer Res.* **1989**, *16*, 310–321. [CrossRef]

73. Hanna, P.; Kantenbacher, J.; Cohen, S.; Gössling, S. Role model advocacy for sustainable transport. *Transp. Res. Part D Transp. Environ.* **2017**, *61*, 1361–9209. [CrossRef]
74. Elberse, A.; Verleun, J. The Economic Value of Celebrity Endorsements. *J. Advert. Res.* **2012**, *52*, 149–165. [CrossRef]
75. Ilicic, J.; Webster, C.M. Celebrity co-branding partners as irrelevant brand information in advertisements. *J. Bus. Res.* **2013**, *66*, 941–947. [CrossRef]
76. Luarn, P.; Lin, H.H. Toward an understanding of the behavioral intention to use mobile banking. *Comput. Hum. Behav.* **2005**, *21*, 873–891. [CrossRef]
77. Kuo, Y.F.; Yen, S.N. Towards an understanding of the behavioral intention to use 3G mobile value-added services. *Comput. Hum. Behav.* **2009**, *25*, 103–110. [CrossRef]
78. Wang, W.T.; Wang, Y.S.; Liu, E.R. The stickiness intention of group-buying websites: The integration of the commitment-trust theory and E-commerce success model. *Inf. Manag.* **2016**, *53*, 625–642. [CrossRef]
79. Davis, F.D. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Manag. Inf. Syst. Q.* **1989**, *13*, 319–339. [CrossRef]
80. Agardwal, R.; Karahanna, E. Time Flies When You're Having Fun: Cognitive Absorption and Beliefs about Information Technology Usage. *Manag. Inf. Syst. Q.* **2000**, *24*, 665–694. [CrossRef]
81. Teo, T.S.H. Demographic and motivation variables associated with Internet usage activities. *Internet Res.* **2001**, *11*, 125–137. [CrossRef]
82. Thong, J.; Hong, Y.L.; Tam, K.Y. The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *Int. J. Hum. Comput. Stud.* **2006**, *64*, 799–810. [CrossRef]
83. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User Acceptance of Information Technology: Toward a Unified View. *Manag. Inf. Syst. Q.* **2003**, *27*, 425–478. [CrossRef]
84. Moon, J.W.; Kim, Y.G. Extending the TAM for a World-Wide-Web context. *Inf. Manag.* **2001**, *38*, 217–230. [CrossRef]
85. Chen, J.; Zhu, H.H. User experience scale development and validity testing from customer perspective. *Stat. Decis. Mak.* **2019**, *35*, 60–64. (In Chinese)
86. Ye, Y.; Wang, H. Research on factors influencing users' willingness to pay for content on audiobook platforms. *Librariansh. Res.* **2018**, *1*, 82–88. (In Chinese)
87. Wang, Y. Empirical analysis of factors influencing the willingness to pay for e-commerce membership system. *Bus. Econ. Res.* **2019**, *23*, 93–96. (In Chinese)
88. Chen, X.; Li, S. Understanding Continuance Intention of Mobile Payment Services: An Empirical Study. *J. Comput. Inform. Syst.* **2017**, *57*, 287–298. [CrossRef]