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Influencing Factors of Usage Intention of Metaverse Education Application Platform: Empirical Evidence Based on PPM and TAM Models

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Abstract: We explored the influencing factors of the usage intention of a metaverse education application platform that directly influence the optimization of its service function, improve the usage intention, and realize the promotion and application of metaverse technology in the education domain. Based on the characteristics of the metaverse education application platform, we integrated the PPM (push–pull–mooring) model and the TAM (technology acceptance model) to construct the model of influencing factors of usage intention. Ultimately, 275 valid questionnaires were collected through expert demonstration, pre-investigation, formal investigation, and other processes. In addition, our paper used the SEM (structural equation model) and fsQCA (fuzzy-set qualitative comparative analysis) to analyze the influencing factors of user willingness and their configuration paths. The study found that personalized learning, contextualized teaching, perceived usefulness, perceived ease of use, social needs, and social impact play significant positive roles in the willingness to use the metaverse education platform. Meanwhile, the obtained findings show that the experience-led community-driven mode, personality-led community-driven mode, and social-led utility-driven mode serve as potential guidelines for usage intention enhancement.

Keywords: metaverse; educational application platform; usage intention; PPM model; TAM model

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1. Introduction

The outbreak of COVID-19 has promoted the rapid development of virtual education content, and the digitalization of offline education scenes has become a necessary development trend [1]. During this period, online classes, online graduation ceremonies, and virtual conferences appeared in large numbers. However, due to the limitations of technical conditions, infrastructure, software applications, and other factors, the effect of online education could have been better. Many problems emerged, such as the lack of context, low interactivity, and a weak sense of participation, which urgently need improvement in online teaching [2,3]. Nevertheless, in recent years, the rapidly developing metaverse technology has had outstanding advantages in online education [4,5].

Edu-Metaverse is the application of metaverse technology in the field of education. It is the twin of the actual educational world, giving teachers, students, managers, and other personnel a virtual identity. They achieve seamless connection and virtual integration between the virtual world and the actual teaching environment in the Edu-Metaverse and obtain a new experience in the social communication space, creating and sharing freedoms, high immersion, and virtualization [4–6]. The metaverse education application platform is a specific application of the educational metaverse [7]. Meta, Roblox, Zepeto, and other enterprises have started to develop the metaverse education platform. They integrate the metaverse into the teaching project practice and bring a better experience to users. However, the application of metaverse technology in the education industry has a “false name” phenomenon. For example, in the development of the education application platform, there is a significant deviation between the product software and the needs of user groups [8]. According to the policy statement issued by the Brookings Institution of the United States, only 7 of the 80,000 educational application platforms that users can download through the mobile app store get approved by users, and the rating of free platforms is even worse. Willingness to use is the premise of user behavior and satisfaction [9,10]. Therefore, exploring the influencing factors of user intent on the application platform will help solve the problem of mismatch between the supply of educational technology and users’ demand, and truly bring users into the metaverse education ecosystem.

Firstly, research on the willingness to use educational technology application platforms has been discussed previously. Relevant research mainly involves e-learning systems [11], mobile learning [12], learning management systems [13], AR/VR technologies [14,15], and social media services [16,17]. However, due to the differences in technical equipment, educational content, educational purpose, technical support, application fields, and user groups, the research results based on the influencing factors of other educational technology users’ willingness to use technology do not apply to the field of meta cosmic educational technology [4,18]. Therefore, the influencing factors of users’ willingness to use the metaverse education application platform have specific research significance.

Secondly, the models used in previous educational technology research are the TAM model or the TAM model combined with TTF, IDT, ISSM, ECT, and other models [16,19–21]. The PPM model (push–pull–mooring) was first used in population migration research and later used to explain user behavior transfer [22]. Its applicability in educational technology has also been verified [11,23]. The TAM model and PPM model highly correlate with the research on willingness to use educational technology [9,11].

Finally, looking at the empirical research on the user intent of educational technology, we can find that most of the analysis methods use the SEM (structural equation model). No research has been found in which SEM and fsQCA (fuzzy-set qualitative comparative analysis) methods are combined. Many factors influence the willingness to use [9]. FsQCA is mainly adopted to explain possible configurations in complex causal relationships [24]. In this context, the following questions are brought out in this study:

1. What are the key factors influencing the use intention of the users of the metaverse education application platform?
2. What antecedent configurations trigger the user’s willingness to use the metaverse education application platform?
3. Is the composite model integrating the TAM and PPM models valuable?

This research integrates the PPM model and TAM model and takes the usefulness and ease of use of the TAM model as an essential sub-dimension to play the pull effect in the PPM model. From an integrated perspective, it constructs a model of factors affecting the use intention of users of the metaverse education application platform. The questionnaire survey obtained the data needed for the study. The SEM implemented data analysis and model validation. The study used fsQCA to conduct configuration analysis on the antecedents that trigger the user’s willingness to use the metaverse education application platform. The research results can provide more guiding suggestions for the scene design and practical application of the metaverse education application platform, and further promotes the metaverse education application platform to provide users with satisfactory services and optimize the platform.

The remainder of the article is structured as follows. Section 2 is the literature review and theoretical foundation. Section 3 introduces the research hypothesis, fuses the PPM and TAM models, and constructs the research model of factors influencing usage intention. The structural equation modeling is analyzed in Section 4. Section 5 is the quantitative comparative analysis of fuzzy sets. Finally, Section 6 is the conclusion, discussion, and outlook on future research.

2. Literature Review and Theoretical Foundation

2.1. Literature Review

2.1.1. Research on the Education of the Universe

The unique advantages of the metaverse in the educational application have triggered a research upsurge of scholars at home and abroad. Relevant research mainly includes: (1) The definition of a metaverse in the field of education: metaverse education can be defined as a new educational environment formed under the promotion of metaverse technology [25], which contains four types: augmented reality, life logging, mirror world, and virtual reality [5]. (2) Characteristics of the metaverse in the field of education: Ko et al. [26] proposed that the metaverse has 5C characteristics (Canon, Creator, Currency, Continuity, Connectivity). Zhang et al. [25] found that metaverse education has a high degree of freedom and low restriction in time and space through comparison of in-person learning, screen-based remote learning, and metaverse-based learning; with the characters of solid sociability, strong virtual identity, immersive experience, open and accessible creation, strong interaction, and comprehensive teaching evaluation. (3) The key technologies and tools of the universe in the field of education: Tlili et al. [6] divided the technologies and tools into seven categories: immersive, artificial intelligence (AI), game applications, education, modeling and simulation, mobile, sensors and wearable devices. Gastón et al. [27] emphasized the supporting role of graphics processing units (GPUs), photographic 3D engines, artistic intelligence, cloud computing, 5G, blockchain, extended reality (XR), virtual reality (VR), augmented reality (AR), and brain–computer interfaces (BCI) in the development of metaverse education. (4) The role and influence of the metaverse in the field of education: Lin et al. [4] expound on the positive influence of the metaverse in the field of education from seven aspects, such as helping to enhance the visualization of learning content, improve learning efficiency, break the restriction of educational resources, and reduce educational costs and risks. Kye et al. [5] believed that applying the metaverse in education has brought students greater autonomy and creative freedom. (5) Application scenario and effect evaluation of the universe in the field of education: Hu et al. [28] summarized five potential educational application scenarios, including a learning platform, immersive curriculum, virtual school, twin campus, and open university, based on cases. Lee et al. [29] verified the advantages of the metaverse in terms of ease of use, interactivity, immersion, and interest in educational applications through the user's analysis of the use effect of the spatial system learning platform. Aleksandar et al. [30] investigated the effect of collaborative learning activities in the virtual environment. (5) Risks and challenges of the metaverse in the field of education: Bermejo et al. [31] found that there would be privacy infringement and moral hazards in the application of metaverse technology in education. Challenges such as the feasibility of applying technology, threats to learners' physical and mental health, and insufficient computing power must be considered seriously [28].

2.1.2. Intention to Use the Metaverse Education Application Platform

Before the rise of the metaverse, research on the willingness to use educational application platforms can be categorized according to the following three aspects: (1) From the perspective of research objects, it mainly includes the research on e-learning systems such as e-learning platforms and e-learning environments [32,33]; mobile learning research based on tablet computer and mobile device technology [34,35]; research on learning management systems such as Blackboard and Moodle [36,37]; research based on social media service platforms such as WeChat and Facebook [17,38]; and based on AR&VR technology research [14,39]. (2) From the research model, the TAM model [9], IDT model [10], ISSM [19], UTAUT model [40,41], and the UTAUT2 model [42]. In addition, there are also studies combining the TAM model with TTF, IDT, ISSM, ECT, and other models [19]. (3) From the perspective of analysis methods, the structural equation model analysis method is mainly used in existing studies [14,19].

With the further promotion of the depth and breadth of the metaverse application, the research on the influencing factors of the use intention has received attention. For example, Teng et al. [43], based on the extended UTAUT model, used SEM analysis to study the influencing factors of learners' adoption of the educational metaverse platform. Based on the TAM model and multiple regression analysis, Kim et al. [44] studied the influence mechanism of the perceived value of undergraduate students in higher education on the intention of the metaverse learning environment. Akour et al. [45], using the extended TAM model and the SEM-ANN method, studied college students' views on metaverse education. With the TAM model and SEM-ML method, Almarzouqiet et al. [46] predicted college students' views of using the metaverse in medical education. Maryam et al. [47] studied the influencing factors of medical students' willingness to use the metaverse in medical training by combining the TAM model and the SEM method.

In summary, the research on metaverse education focuses more on the applicability, conception, and design of application scenarios. Alternatively, it takes a metaverse education application platform as an example to evaluate its implementation effect. The research results provide ideas for implementing a metaverse education application platform. However, on the whole, the research results are not universal and lag, and cannot provide a reliable basis for platform design promptly, which may lead to a waste of resources and loss of customers. Furthermore, most of the analysis methods used in the existing research are qualitative, which are difficult to effectively provide practical suggestions for the scene design and application of the metaverse education application platform. User willingness is a critical factor that affects the implementation of the platform. However, the research on the user's willingness to use the metaverse education application platform mainly focuses on student groups using SEM analysis methods. At the same time, they ignore the complexity of the user's willingness. The influence of the mechanism between the influencing factors on user intent is yet to be studied. Therefore, it is necessary to use a variety of models and research methods to conduct empirical research on the influencing factors of users' willingness to use from the perspective of the demand side.

2.2. Theoretical Foundation

2.2.1. PPM Model

The push–pull–mooring (PPM) model was first used in the study of population migration. Later, Bansal [22] used the PPM model to explain the transfer of consumer behavior. In the PPM model, the influencing factors were divided into three aspects: the thrust factor, the pull factor, and the mooring factor. Among them, the thrust factor refers to the factor that pushes the user away from the original product, and the pull factor refers to the factor that pulls the user to accept the new product. Finally, the anchor factor refers to the personal/social factor that can hinder or promote the transfer behavior of the user [48]. Scholars have conducted a wealth of research using the PPM model and achieved fruitful results. Lisana [12] used the PPM model to study the influencing factors of college students turning to mobile learning. Nayak et al. [11] explored the influencing factors of students turning to online learning during the epidemic based on the PPM model. Jin et al. [49] used the PPM model to study the influencing factors of students' transfer from traditional learning to e-learning.

In this paper, transfer behavior refers to the transfer process of users from the traditional education application platform to the metaverse education application platform. The push factor refers to the factors that push users away from the traditional education application platform, the pull factor refers to the factors that pull users to accept the metaverse education application platform, and the anchor factor refers to the personal/social factors that affect the transfer of users from the traditional education application platform to the metaverse education application platform.

2.2.2. TAM Model

The technology acceptance model (TAM) is proposed by Davis [50], and is based on rational behavior theory. It was initially used to explore the decisive factors that led to the wide acceptance of computers. This model explores the relationship between user attitude, behavior intention, and system use through perceived usefulness, perceived ease of use, and external variables. The TAM model proposes two main decisive factors: perceived usefulness and perceived ease of use. Perceived usefulness mainly reflects the degree to which a person thinks that using a certain system will improve his or her work performance, and perceived ease of use mainly reflects the degree to which a person thinks it is easy to use a certain system [51]. With the continuous deepening of scholars' research on the TAM model, the TAM model has matured and has been applied to many fields, and has been explored in combination with other models to solve complex system problems. In the field of education, Callum et al. [52] used the TAM model to study the influencing factors of teachers' adoption of mobile learning. Furthermore, Al-Rahmi et al. [38], based on the integrated model of TAM and IDT, constructed the influencing factors of college students' adoption of e-learning technology. Finally, Prasetyo et al. [19], based on the integrated model of TAM and ISSM, analyzed the influencing mechanism of high school students' acceptance of e-learning platforms in the context of the COVID-19 epidemic.

In this paper, perceived usefulness refers to the degree to which users use the metaverse education application platform to improve their learning effect, and perceived ease of use refers to the ease with which users use the metaverse education application platform.

3. Research Hypotheses and Conceptual Model

3.1. Hypothesis of Influencing Factors of Users' Willingness to Use the Metaverse Education Application Platform

3.1.1. Influence of Push Factors on Users' Willingness to Use the Metaverse Education Application Platform

According to the PPM model, the push factor refers to the factor that pushes users away from the traditional education application platform [53]. In combination with the purpose and demand of this study, personalized learning and situational teaching are taken as the thrust factors of users' willingness to use the metaverse education application platform. Personalized learning means that users can formulate their own learning plans through the metaverse education application platform. Ma et al. [54] studied the key factors affecting personalized learning and resource recommendation by taking the intelligent learning environment as the research object. Lv et al. [55] believed that in the era of artificial intelligence, personalized learning is the mainstream of future development, and the platform should provide users with a stronger independent learning environment. Xiao et al. [56] verified the impact of personalized demand on the application of library virtual reality technology. Situational teaching means that the metaverse education application platform can provide users with an immersive, vivid, and interactive teaching mode. Liu et al. [57] found through teaching experiment research that an immersive virtual environment can promote users' understanding and application. Yuan et al. [58] took the academic virtual community as the research object and analyzed the positive impact of interaction intensity on users' perceived learning. Based on the above analysis, the following research hypotheses are proposed:

H1a. *Personalized learning has a positive impact on users' use intention of the metaverse education application platform.*

H1b. *Situational teaching has a positive impact on users' use intention of the metaverse education application platform.*

3.1.2. Influence of Pulling Force on Users' Willingness to Use the Metaverse Education Application Platform

According to the PPM model, the pull factor refers to the factor that pulls users to accept the metaverse education application platform [59]. Integrating the TAM model, the three factors of perceived usefulness, perceived ease of use, and social needs are taken as the pull factors of users' willingness to use the metaverse education application platform. Perceived usefulness refers to the user's expectation of obtaining benefits from using the metaverse education application platform. Eksail et al. [60] pointed out that perceived usefulness positively impacts the willingness to use online learning. Chen and Keng [61] analyzed the conversion intention of the English teaching platform and believed that if the user's teaching platform were applicable, it would strengthen the user's conversion intention. Perceived ease of use refers to how easy it is for users to master the metaverse education application platform. Balakrishnan et al. [62] focused on the use of social media and believed that ease of use positively impacts social media learning transfer behavior. Huang et al. [63] emphasized the positive impact of ease of use on the willingness to use online learning. Social demand refers to the social expectation of users on the metaverse education application platform. Xie [64] took the tourism virtual community as the research object and verified that social demand is the core element that affects the interaction of members of the tourism virtual community. Hou et al. [65] believe that in the virtual community, social demand will have a positive impact on competitive behavior. Based on the above analysis, the following research hypotheses are proposed:

H2a. *Perceived usefulness has a positive impact on users' willingness to use the metaverse education application platform.*

H2b. *Perceived ease of use has a positive impact on users' willingness to use the metaverse education application platform.*

H2c. *Social needs have a positive impact on users' willingness to use the metaverse education application platform.*

3.1.3. Influence of Mooring Factors on Usage Intention of the Metaverse Education Application Platform

According to the PPM model, the mooring factors refer to the personal/social factors that affect the transfer of users from the traditional education application platform to the metaverse education application platform [66]. At the same time, considering the needs of this study, the technology maturity, perceived privacy risk, and social impact are taken as the mooring factors of the users' willingness to use the metaverse education application platform. Technology maturity refers to the service quality and system quality of the metaverse education application platform. Tan et al. [67] believe that the service quality of WeChat official accounts has a positive impact on the confirmation of users' expectations. Yuan et al. [66] found through empirical research that system quality has a significant impact on mobile government app users' behavior. Perceived privacy risk refers to the risk loss of personal privacy information caused by uncertain factors when users use the metaverse education application platform. Yuan et al. [68] found that perceived privacy is a key factor affecting the non-sustainable use behavior of users in online health communities. Deng et al. [69] believe that both privacy social risk and privacy information risk have an impact on the personal information disclosure behavior of social platforms, and the impact of privacy social risk is greater. Social impact refers to users being affected by friends, classmates, public opinion, news, or other factors when using the metaverse education application platform. Zhou et al. [59] found through empirical analysis that social impact has a significant positive impact on the transfer behavior of social media users. Wang et al. [70] carried out research on live streaming apps and believed that social impact factors have a positive effect on the user's use intention, thus affecting the user's use behavior. Based on the above analysis, the following research hypotheses are proposed:

H3a. *Technology maturity has a positive impact on users' use intention of the metaverse education application platform.*

H3b. *Perceived privacy risk has a positive impact on users' willingness to use the metaverse education application platform.*

H3c. *Social impact has a positive impact on users' use intention of the metaverse education application platform.*

3.2. Influence Factor Model of Use Intention on Metaverse Education Application Platform

On the basis of the above analysis, inspired by Lin [23] and Jin [71], the study considers the simultaneous use of PPM models and TAM models to construct a research model from an integrated perspective. The factors affecting the willingness of metaverse education application platform users are analyzed in three dimensions: push factors, pull factors, and mooring factors, in which the push factors are divided into personalized learning and contextualized teaching; perceived usefulness and perceived ease of use are derived from the TAM model, which has been applied in various studies regarding the willingness to use educational technologies [9]. They are taken as important sub-dimensions to exert the pull effect in the PPM model, combining with social needs. Mooring factors take technical maturity, perceived privacy risk, and social influence as the main aspects. Based on this, this study constructs a conceptual model of factors influencing usage intention of the metaverse education application platform, as shown in Figure 1.

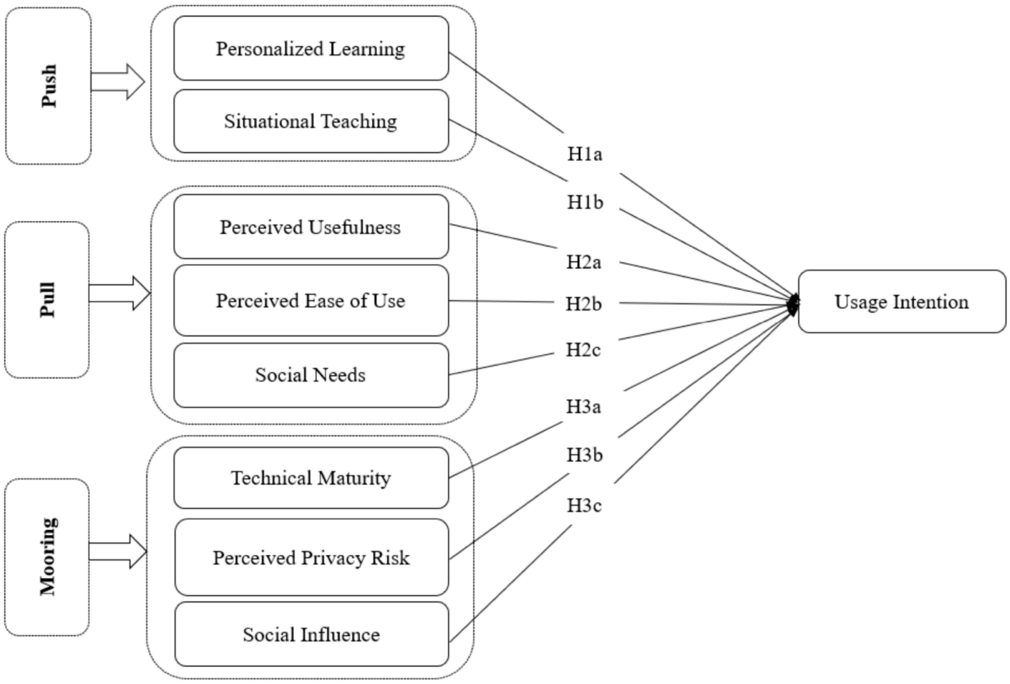

Figure 1. Conceptual Model of Influencing Factors of Usage Intention of Metaverse Education Application Platform.

3.3. Questionnaire Design

Based on the above research hypotheses and conceptual models, and with reference to the research scales of domestic and foreign scholars, a measurement scale of factors affecting the use intention of users of the metaverse education application platform is designed. The contents of this research questionnaire can be divided into two parts. First, the basic information of the respondents mainly included gender, age, education level, occupation, monthly income, and the way to learn about the metaverse education application platform. Second, as shown in Table 1, the factors that affect the user's willingness to use the metaverse education application platform include 9 measurement variables and 34 measurement items. The items are in a declarative sentence structure, and each item includes five response options, namely, "strongly disagree", "disagree", "general", "agree" and "strongly agree". Before the large-scale distribution of the questionnaire, the research group first invited six industry experts (three from the academic community and three from the industry) to review the content of the questionnaire and the setting of the questions. After confirming that there were no problems in the questionnaire, a presurvey was conducted with college students. A total of 56 questionnaires were collected. The contents of the questionnaire were corrected by analyzing the results of the presurvey, such as unclear items, difficult-to-understand items, and repetitive and overlapping items. Finally, formal questionnaire collection was started.

Table 1. Measurement Scale of Influencing Factors of Usage Intention of Metaverse Education Application Platform.

Construct	Item		Sources
Personalized Learning (PL)	PL1	I think I can get the learning resources I need on the metaverse education application platform	Ma et al. [54] Xiao et al. [56]
	PL2	I think on the metaverse education application platform, I can make plans according to my own needs	
	PL3	I think the metaverse education application platform can effectively strengthen its own weak points	
	PL4	I think I can find a learning method that suits me on the metaverse education application platform	
Situational Teaching (ST)	ST1	I think the classroom content of the metaverse education application platform is easier to understand	Li [72] Zhu [73] Liu et al. [57]
	ST2	I think the classroom forms of the metaverse education application platform are more diverse	
	ST3	I think the classroom context of the metaverse education application platform is more vivid	
	ST4	I think metaverse education application platforms can create different roles	
	ST5	I think the metaverse education application platform can be entertaining and educational	
Perceived Usefulness (PU)	PU1	I think the metaverse education application platform can learn more high-quality courses	Eksail et al. [60] Chen et al. [61]
	PU2	I think the metaverse education application platform can make up for the lack of knowledge in the classroom	
	PU3	I think the metaverse education application platform can provide me with more learning resources	
	PU4	I think the metaverse education application platform can expand the scope of my knowledge	
Perceived Ease of Use (PE)	PE1	I think it is not difficult to use the metaverse education application platform	Callum et al. [52] Huang et al. [63]
	PE2	I think the metaverse education application platform is cheap and affordable	
	PE3	I think the metaverse education application platform will benefit students	
Social Needs (SN)	SN1	I will experience the metaverse education application platform with friends/classmates	Xie et al. [64] Hou et al. [65] Huang et al. [74]
	SN2	I will communicate with friends/classmates on the metaverse education application platform	
	SN3	I will make more friends on the metaverse education application platform	
	SN4	I will share the information obtained on the metaverse education application platform with friends/classmates	
Technical Maturity (TM)	TM1	I don't think the current metaverse technology is mature enough	Tan et al. [67] Kye et al. [5]
	TM2	I think the current metaverse education application platform is biased towards entertainment	
	TM3	I think the current metaverse education application platform is not yet universal	

Table 1. *Cont.*

Construct	Item		Sources
Perceived Privacy Risk (PR)	PR1	I'm concerned that metaverse education application platforms collect too much personal information	Yuan et al. [68] Chen et al. [75] Zhu et al. [69] Teng et al. [43]
	PR2	I am concerned about leaking personal privacy when using the metaverse education application platform	
	PR3	I am concerned that personal information is being used illegally by the metaverse education application platform	
	PR4	I am concerned that third parties collect user information through the metaverse education application platform	
Social Influence (SI)	SI1	I will be influenced by my friends/classmates to use the metaverse education application platform	Bansal [22] Zhou et al. [59] Wang et al. [70]
	SI2	I will be influenced by public opinion/news and use the metaverse education application platform	
	SI3	I will show off my virtual identity on the metaverse education application platform to my friends/classmates	
Intention to Use (IU)	IU1	I am willing to use the metaverse education application platform	Wang et al. [70] Zainab et al. [76]
	IU2	I will continue to pay attention to the products related to the metaverse education application platform	
	IU3	I will spend more time on the metaverse education application platform	
	IU4	I will share the metaverse education application platform with friends/classmates	

4. Structural Equation Model Analysis

4.1. Sample and Data Collection

Affected by the "COVID-19 epidemic", the research group decided to adopt online and offline research methods and collect data through online questionnaires, on-site interviews and symposiums on the premise of complying with epidemic prevention and control policies. To ensure the validity of the data, this study is based on the actual situation in the region, through virtual experience (before implementing the survey, the research team sent the interviewees "Metaverse of Education and Learning Scenarios"(https://www.bilibili.com/video/BV1hL411375k?spm_id_from=333.337.search-card.all.click) (accessed on 1 March 2022), which constructs an intuitive visualization and interactive virtual scene through interactive technology, artificial intelligence, 3D vision, etc., to let respondents know the overall shape of the metaverse education platform better) to obtain information about usage intention and provide pavement and guidance for the subsequent real platform design and scene construction. Then, by sharing the QR code and website of the questionnaire, the respondents were encouraged to scan the code or click the website to enter the questionnaire response page in the form of a red packet lottery. The questionnaire was conducted anonymously. After one month (21 April 2022–20 May 2022) of investigation, 339 questionnaires were received in Henan province. According to the principles of short response time, incomplete answers, and the same answers completed in all questionnaires, 275 valid questionnaires were obtained after excluding invalid questionnaires. Table 2 shows the basic characteristics of the interviewees. Among them, 72.36% of the interviewees were under 35 years old, which basically conforms to the age portrait of the audience on the metaverse education platform. Therefore, the sample of this survey is fairly representative.

Table 2. Basic Characteristics of Samples.

Description		Frequency	Percentage (%)
Gender	Man	130	47.20
	Woman	145	52.80
Age	Less than 22 years	94	34.18
	Between 22–35 years old	105	38.18
	Between 36–50 years old	55	20.00
	More than 50 years	21	7.64
Level of education	Lower than High School	25	9.09
	College	50	18.18
	University	137	49.82
	Postgraduate or Above	63	22.91
Occupation	Student	105	38.18
	Civil Servants or Public Institutions	86	31.27
	Enterprise	52	18.91
	Self Employed or Others	32	11.64
Monthly income (Monthly living expenses)	Less than 2000 yuan	92	33.45
	2001~5000 yuan	65	23.64
	5001~7000 yuan	86	31.27
	More than 7000 yuan	32	11.64
Ways to learn about the application platform of metaverse education	News	57	20.73
	WeChat, Weibo, Wechat Moments, etc.	135	49.10
	Advertising	24	8.72
	Friends and Family	33	12.00
	Others	26	9.45

4.2. Reliability and Validity Tests

There are many analysis software programs with a structural equation model (SEM), and the common ones include Amos 26, Mplus, and Smart PLS 3.0. SmartPLS 3.0 is selected for this study. This software is based on the logic of variance-based partial least squares structural equation modeling and has no more restrictions on data distribution and sample size. In addition, there is a bootstrapping function, which can create a new sample representative of the distribution characteristics of the mother by repeatedly extracting samples, which is easy to operate and has rich functions.

Because this study collected data through a questionnaire survey, first, a Harman single-factor test was conducted to check whether there was a common method deviation in the scale. The analysis found that the interpretation percentage of the first common factor was less than 40%, indicating that there was no serious common method variance. Second, the reliability and validity of the constructed index system were tested by indicators such as factor loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and variance inflation factor (VIF). It was found that the load of all factors was greater than 0.7, the CR was greater than 0.7, the AVE was greater than 0.5, the Cronbach's alpha was greater than 0.7, and the VIF was less than 5, indicating that all the indicators of this study met the relevant requirements [77]. Table 3 presents the result of the reliability analysis.

Table 4 shows that the correlation coefficient between each latent variable and other latent variables is less than the square root of the latent variable AVE, which indicates that the discrimination validity of this study model is good [77].

Table 3. Reliability Analysis.

Construct	Item	Factor Loading	Cronbach's Alpha	CR	AVE
Personalized Learning (PL)	PL1	0.876	0.898	0.929	0.765
	PL2	0.864			
	PL3	0.859			
	PL4	0.899			
Situational Teaching (ST)	ST1	0.874	0.915	0.936	0.746
	ST2	0.856			
	ST3	0.861			
	ST4	0.885			
	ST5	0.842			
Perceived Usefulness (PU)	PU1	0.891	0.916	0.941	0.799
	PU2	0.899			
	PU3	0.913			
	PU4	0.871			
Perceived Ease of Use (PE)	PE1	0.846	0.818	0.892	0.733
	PE2	0.872			
	PE3	0.850			
Social Needs (SN)	SN1	0.899	0.919	0.942	0.804
	SN2	0.912			
	SN3	0.899			
	SN4	0.876			
Technical Maturity (TM)	TM1	0.895	0.707	0.818	0.607
	TM2	0.578			
	TM3	0.829			
Perceived Privacy Risk (PR)	PR1	0.864	0.928	0.948	0.819
	PR2	0.918			
	PR3	0.912			
	PR4	0.926			
Social Influence (SI)	SI1	0.840	0.779	0.872	0.694
	SI2	0.880			
	SI3	0.777			
Intention to Use (IU)	WU1	0.790	0.854	0.902	0.697
	WU2	0.875			
	WU3	0.820			
	WU4	0.851			

Table 4. Differentiate Validity Results of Model.

	PL	ST	PU	PE	SN	TM	PR	SI	IU
PL	0.875								
ST	0.684	0.864							
PU	0.538	0.638	0.894						
PE	0.463	0.370	0.487	0.856					
SN	0.523	0.586	0.484	0.381	0.897				
TM	0.227	0.227	0.239	0.043	0.237	0.779			
PR	0.220	0.366	0.258	0.077	0.213	0.519	0.905		
SI	0.249	0.556	0.419	0.375	0.439	0.082	0.070	0.833	
IU	0.604	0.623	0.622	0.635	0.646	0.202	0.189	0.556	0.835

Note: Numbers in diagonal are the square root values of the latent AVE.

4.3. Model Fitting Tests

The use of SmartPLS in this study involves SRMR, d ULS, d_G, Chi-Square, NFI, and RMS_theta. They are generally used to evaluate the fitting of the model [78]. SRMR is the absolute goodness of fit index [79], which requires it to be lower than 0.08 [80], and the standard adaptation index NFI is above 0.9 [77]. However, NFI changes when the parameters change [81], which does not apply to the evaluation model fitting [79]. D_ULS, d_G is the complete adaptation standard, which helps find any difference between the empirical covariance matrix and the covariance matrix understood by the composite factor model [79,82]. RMS_theta is used to evaluate the correlation of external model residuals, mainly used in reflective models [83]. The closer the value is to 0, the better the model is, and less than 0.12, the better the goodness of fit [84]. Hair et al. [79] believed that the estimation model mainly considered the overall impact and model structure, while the saturation model evaluated all structures' relationships.

As seen from Table 5, the RMS_theta is 0.108, indicating the effectiveness of the global PLS model.

Table 5. Model Fit Indicators.

Criteria	Complete Model	
	Saturated Model	**Estimated Model**
SRMR	0.068	0.068
d_ULS	2.786	2.893
d_G	1.166	1.261
Chi-Square	1160.208	1160.208
NFI	0.757	0.757
RMS Theta	0.108	

4.4. Hypothesis Tests

Based on the above reliability, effectiveness, and suitability measurement models, the next step is the structural model [85]. The hypothesis was tested by the bootstrap test (5000 samples). The model has been proved to have high predictive power [86], and the variance percentage of use intention being 69.8%. The results are shown in Figure 2. Personalized learning (β $= 0.132$, $p < 0.05$), situational teaching (β $= 0.154$, $p < 0.05$), perceived usefulness (β $= 0.109$, $p < 0.10$), perceived ease of use (β $= 0.296$, $p < 0.001$), social needs (β $= 0.226$, $p < 0.05$), and social impact (β $= 0.219$, $p < 0.001$) have a significant positive impact on the use intention of users of the metaverse education platform, supporting H1a, H1b, H2a, H2b, H2c, and H3c. Technology maturity (β $=0.013$, $p > 0.05$) and perceived privacy risk (β $=-0.018$, $p > 0.05$) have no significant impact on the use intention of users of the metaverse education platform and do not support H3a and H3b. This indicates that users like to try new things, and trust in emerging technologies has gradually become a habit. Although the metaverse education platform, as an emerging technology, may have problems in terms of technology maturity and user perceived privacy risk, it will not affect the users' willingness to use the metaverse education platform.

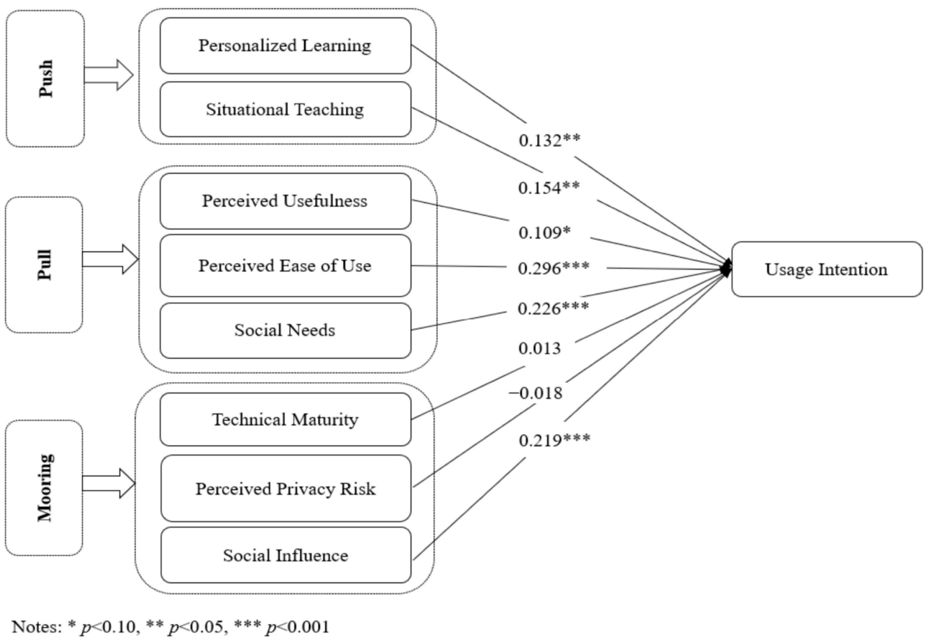

Figure 2. Structural Equation Model Path Analysis.

5. Qualitative Comparative Analysis of Fuzzy Sets

5.1. Variable Selection and Calibration

There are complex relationships among the factors that affect the user's willingness to use the metaverse education application platform. Although SEM analysis has verified which factors affect the user's willingness to use the metaverse education application platform, it remains to be confirmed whether these influencing factors are the result of a single contribution to the user's willingness to use the metaverse education application platform or the interaction of multiple influencing factors. Fuzzy-set qualitative comparative analysis (fsQCA) is mainly used to explain the possible configuration in complex causality, which can make up for the defect that SEM mainly focuses on net benefit [24,87]. This study combines the SEM and fsQCA methods, first verifies the model hypothesis, and then takes the personalized learning, situational teaching, perceived usefulness, perceived ease of use, social needs, and social impact potential variables as antecedent variables and the use intention of the metaverse education platform as the outcome variable. The fsQCA method is used to explore the configuration effect among the factors that affect the user's willingness to use the metaverse education application platform to improve the descriptive power, predictive power, and explanatory power of the theoretical model of this study [88]. Figure 3 shows the fsQCA research framework.

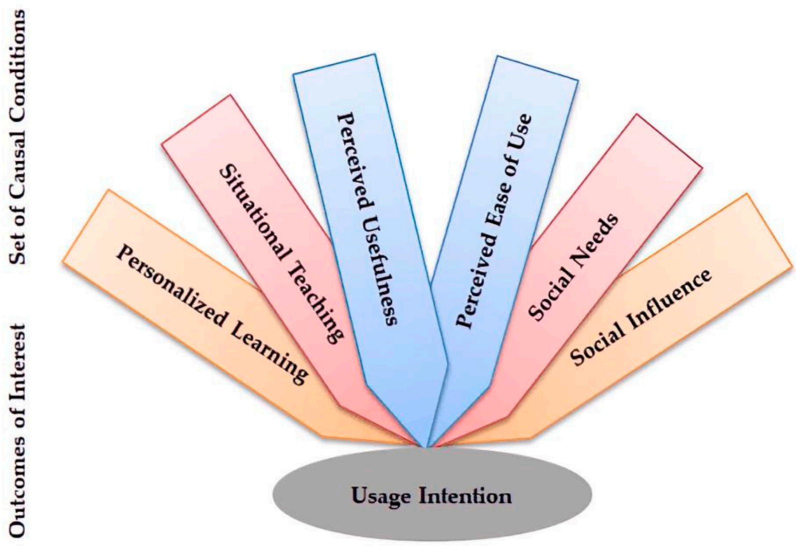

Figure 3. FsQCA Research Framework.

Before the configuration analysis, the dependent variable before calibration was calibrated according to the standard (95%, 50%, 5%) [24]. When an integer is encountered, the case classification problem is solved by adding a tiny number (0.001).

5.2. Necessity Analysis of Conditions

After data calibration, this study conducted a necessity analysis of the antecedent variables and found that the consistency of all antecedent variables was less than 0.90 [12]. To judge the necessity of antecedent variables more accurately, the NCA package of R software was used for in-depth analysis, and it was found that the effect size of all antecedent variables was less than 0.3, indicating that a single antecedent variable cannot form the user's intention to use the metaverse education application platform, and it needs to be formed by the mutual dependence and interaction of multiple antecedent variables [89]. Table 6 presents the result of necessity analysis of precedent variables.

Table 6. Necessity Analysis of Precedent Variables.

Conditional Variable	Consistency	Coverage
Personalized Learning	0.785	0.782
~Personalized Learning	0.798	0.801
Situational Teaching	0.883	0.734
~Situational Teaching	0.706	0.868
Perceived Usefulness	0.834	0.772
~Perceived Usefulness	0.773	0.835
Perceived Ease of Use	0.801	0.809
~Perceived Ease of Use	0.826	0.819
Social Needs	0.822	0.805
~Social Needs	0.816	0.833
Social Influence	0.829	0.750
~Social Influence	0.745	0.826

Note: "~" represents the absence of conditions.

5.3. Sufficiency Analysis of the Conditional Configuration

When discussing the configuration sufficiency of the factors influencing the user's willingness to use the metaverse education application platform, the case frequency threshold is set to 1, more than 80% of the total number of cases are kept, the minimum standard value of original consistency is set to 0.8, and the minimum threshold value of PRI consistency is set to 0.75. The configuration analysis results of the influencing factors and conditions are shown in Table 7. Generally, three solutions (complex solution, intermediate solution and simple solution) are obtained by fsQCA. Considering that the intermediate solution contains both observation samples and logical residuals, its explanatory power is relatively scientific. Here, the intermediate solution is selected to explain the configuration results. Table 7 shows that the coverage of the solution is 0.733 and the consistency of the solution is 0.917, which indicates that the model has good explanatory power.

Table 7. Analysis Results of the Condition Configuration of the Factors Affecting Usage Intention of Metaverse Education Application Platform.

Condition	Usage Intention			
	S1	S2	S3	S4
Personalized learning		✱	✱	•
Situational Teaching	•	•	•	•
Perceived Usefulness	•	•		•
Perceived Ease of Use	✱		•	✱
Social Needs		•	•	✱
Social Influence	✱	✱	✱	
Original Coverage	0.578	0.555	0.508	0.534
Unique Coverage	0.097	0.074	0.027	0.053
Consistency	0.949	0.945	0.962	0.950
Consistency of the solution	0.917			
Coverage of the solution	0.733			

Note: "✱" represents the core condition that appears, "•" represents the presence of an edge condition, "blank" represents the condition may or may not occur.

FsQCA results show that there are four condition configurations that form the user's intention to use the metaverse education application platform. In this paper, the configurations with the same core conditions are summarized into one mode. According to the utility requirements reflected by the core conditions, they can be divided into the experience-driven community-driven type (S1), personality-driven community-driven type (S2 and S3), and social-driven utility-driven type (S4).

5.3.1. Experience-Driven Community-Driven Type

The antecedent configuration of configuration S1 is "perceived ease of use ✱ social influence ✱ perceived usefulness • situational teaching". The core conditions that trigger users' willingness to use the metaverse education platform are perceived ease of use and social impact. When the user perceives that the metaverse education platform is easy to operate and driven by friends and classmates with common interests or public opinion news related to the metaverse education platform, and feels that the metaverse education platform is useful and integrated into the situational teaching mode, the user will be triggered to use it. In this kind of mode, users pay more attention to their experience utility; that is, users are more inclined to perceive ease of use and social impact, and the simultaneous existence of perceived usefulness and social impact will trigger users' use intention.

5.3.2. Community-Driven Type under Personality Guidance

The core conditions of this trigger type are personalized learning and social impact, and there are two sub-modes. Among them, the edge conditions of configuration S2 are situational teaching, perceived usefulness and social needs, and the edge conditions of configuration S3 are situational teaching, perceived ease of use, and social needs. That is, when users feel high personalized learning and social impact, or when situational teaching, perceived usefulness, and social demand are high, or when situational teaching, perceived ease of use and social demand are high, users' willingness to use the metaverse education platform will be triggered. This kind of mode essentially represents the concern of the users of the metaverse education platform for personalized-oriented situational teaching, perceived usefulness and social needs, as well as situational teaching, perceived ease of use, and social needs.

5.3.3. Utility-Driven Type under Social Guidance

The antecedent configuration of configuration S4 is "social needs, perceived ease of use, personalized learning, perceived usefulness, perceived ease of use", The core conditions that trigger the user's willingness to use the metaverse education platform are social needs and perceived ease of use. When users have high social needs and perceived ease of use and perceive that the metaverse education platform has high personalized learning and perceived usefulness, the will to use will be triggered. This kind of mode essentially represents the driving force of users' equal use of personalized learning and perceived usefulness under the guidance of social interaction.

5.4. Robustness Test

There are many methods to check the robustness of QCA. The commonly used method is to adjust the calibration basis, the consistency threshold, and other parameters to compare whether the analysis results have substantial changes before and after the parameter adjustments. If there is no change, the analysis results are robust [90]. By adjusting the consistency threshold and the minimum case frequency, this study found that components such as the configuration path, core condition, and edge condition, as well as the consistency, coverage, and other indicators, did not change, and the analysis results are relatively reliable.

6. Conclusions and Discussion

6.1. Research Conclusion

Combining the metaverse technology with education, with a view toward exploring the user's willingness to use the metaverse education platform, this research integrates the PPM and TAM models and builds an index system of influencing factors on the user's willingness to use the metaverse education platform. Through expert demonstration, pre-investigation, formal investigation, and other methods to collect survey data, and based on the structural equation model and the fuzzy-set qualitative comparative analysis method, the scientificity of the index system construction and the feasibility of the hypotheses are verified, and the configuration analysis between antecedent variables that trigger users' willingness to use the metaverse education platform is discussed. The specific analysis results are as follows:

First, the empirical results of the structural equation model show that personalized learning, situational teaching, perceived usefulness, perceived ease of use, social needs, and social impact have a significant positive impact on the use intentions of users of the metaverse education platform. However, technology maturity and perceived privacy risk have no significant impact on the usage intention of the metaverse education platform. Among the pushing factors, situational teaching has a more significant impact. Among the pull factors, perceived ease of use and social needs are more influential than perceived usefulness. Finally, among mooring factors, only social influence significantly influences the intention to use.

In the research model, perceived usefulness and perceived ease of use have both been verified to have a significant positive impact on the user's willingness to use the metaverse education platform, which is consistent with previous research [44–47]. At the same time, the influence coefficient of usability is higher. The technology maturity and perceived privacy risk have yet to be reverse-verified in the model. Only social impact significantly impacts the use intention, which is different from the conclusion that perceived risk has a reverse impact on the use of education intention proposed by Teng et al. [43]. The metaverse education platform is a new technology product. Although it has hidden dangers regarding technology maturity and user-perceived privacy risks, users have a higher tolerance and reasonable psychological expectations for its technology maturity. Therefore, technology maturity and perceived privacy risk have no marked impact on the intention to use.

The results of qualitative comparative analysis of fuzzy sets show that the three modes of experience-driven community-driven, personality-driven community-driven, and social-driven utility-driven can trigger users' willingness to use the metaverse education platform. Among them, the coverage rate of the community-driven model under the guidance of personality is higher than that of the other models, which indicates that this model has greater explanatory power for the user's use intention.

Finally, a more specific research framework and a more hierarchical integration model have been constructed through the integration of PPM and TAM models. It is more conducive to exploring the key factors that affect the use intentions of the metaverse education application platform and can deduce the main types of antecedent configurations that trigger the use intentions of users. In addition, the model provides direction and reference for governments, enterprises, and other institutions in specific policies and practices.

6.2. Theoretical Contribution and Practical Enlightenment

Theoretical Contribution: First, in the context of a metaverse+ education environment, a model of factors influencing usage willingness is constructed from the demand side, which enriches the empirical research in the field of metaverse education in academia. At the same time, the applicability and theoretical value of the integrated model get validated. Second, this paper integrates the PPM and TAM models from an integrated perspective. It introduces two variables in the TAM model into the pull factors in the PPM model to provide a more specific and hierarchical research framework, which gives the research results better theoretical guidance. Third, we introduce social needs, personalized learning, situational teaching, and other variables to better reflect the user's use intention of the metaverse education platform. Meanwhile, it also has a particular reference significance in exploring the influencing factors of usage intention in the metaverse library and the metaverse museum. Fourth, combining SEM and fsQCA methods, the key influencing factors of users' willingness to use the metaverse education platform are revealed. Fourth, the configuration paths that trigger users' willingness to use the metaverse education platform are explored, and the characteristics and core leading factors of different dominant modes are summarized. Fifth, in the context of the normalization of COVID-19, this study provides more possibilities for crisis management in the education industry.

In terms of practical enlightenment: (1) At the top design level, (a) based on the significant positive effect of social impact on the user intention, the government departments should create a loose and stable business environment for the healthy and orderly development of the metaverse education industry. Furthermore, considering the security of the metaverse education application platform, the government needs to give full play to the public opinion guidance and render the characteristics and advantages of the metaverse technology. Thus, it can enhance users' willingness to use the metaverse education platform. (b) Although the impact of technology maturity and perceived privacy risk on the willingness to use the platform has shown insignificant results, it still needs to be addressed in the development process. Technology and security play a fundamental role in the digital transformation process of the education industry. Therefore, the government should provide financial and policy support for upgrading industry technology and legal protection for the network security of the metaverse platform. (2) Middle-level planning: community-driven mode dominated by personality and utility-driven mode dominated by social interaction have a more decisive influence on users' use intention. Therefore, platform operators should consider subdividing user groups and adopt appropriate marketing strategies for dominant types of users. (a) Create content IP, establish connections with audience groups, trigger users' spontaneous UGC, drive communication with content, and trigger community marketing fission. (b) The platform operator should strengthen cooperation with the government and social platforms and carry out a personalized push for the audience so that users can accurately obtain the information and services they are interested in. (3) At the bottom operational level: (a) Perceived ease of use has a higher impact on user use intention than perceived usefulness. Therefore, platform designers should pay more attention to the ease of operation in the development process, enhance the availability of high-quality learning resources, and consider the cost performance of platform services. (b) Personalized learning and social needs are the core factors that affect users' use of the metaverse education platform. Therefore, in terms of setting the main functions of the platform, more attention should be paid to diversification and personalization. Moreover, it requires efforts to create a new social communication space that spans time and space to meet users' broader and deeper social needs.

6.3. Future Outlook

Due to factors such as the workforce and COVID-19, the questionnaire collection in this study had time and regional limitations. As a new technology, the user intent will change with the development and promotion of the metaverse. In the future, systematic research can be carried out according to a certain time interval to explore the evolution trend of the influencing factors of users' willingness to use the metaverse education application platform at different stages. Due to regional limitations, this region's physical construction of the metaverse education technology platform is in the exploration stage. There is a shortage of platforms formally placed in service, and the actual testing of real scenarios could not be conducted during the questionnaire collection process. In addition, with the global application and promotion of the metaverse education platform, users in different countries may be affected by income differences, cultural differences, and other factors. Their willingness to use the metaverse education platform may also be different. In the future, users in multiple countries may be selected for research to compare users' cognitive differences in using the metaverse education platform among countries.

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