Determinants of Undergraduates' Behavioral Intention Toward Online Learning: A Case Study in Sichuan, China

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Abstract

Purpose: This paper aims to analyze the factors affecting the behavioral intentions of undergraduate students in Sichuan, China, towards adopting online learning. The study examined several key constructs to determine their impact on students' intentions to engage in online learning at universities in Sichuan. These constructs included Perceived Ease of Use (PEU), Perceived Enjoyment (PE), Technology Anxiety (TA), Compatibility (CP), Perceived Usefulness (PU), Social Influence (SI), and Behavioral Intention (BI). **Research design, data, and methodology:** Each factor was assessed to understand its significance in shaping students' online learning behavior. The researchers employed a questionnaire survey method and selected 500 participants from three target universities to distribute the quantitative questionnaire. A multistage sampling strategy was utilized in this survey to gather data from the respondents. **Results:** The data underwent rigorous analysis through Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM), methodologies that confirmed all hypotheses and effectively accomplished the study's objectives. Among the various elements assessed, social influence was identified as the most significant direct determinant of behavioral intentions. **Conclusions:** University administrators and educators should consider the critical factors influencing online learning behaviors and make appropriate optimizations and adjustments accordingly to enhance students' acceptance of online education and effectively improve their capabilities through this learning mode.

Keywords: Online Learning, Technology Anxiety, Perceived Usefulness, Social Influence, Behavioral Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Online learning, alternatively referred to as e-learning, refers to accessing educational content through the Internet, which enables learners to engage with instructional materials, resources, and interactions from virtually anywhere. As the global digital landscape advances and the demand for more sophisticated educational experiences grows, online education has seen a marked increase in popularity among domestic and international students. Da and Gecer (2009) provide the following definition of online education. They believe online education involves using the Internet to deliver materials, access resources, and interact with teachers and peers. This approach not only encompasses the delivery of content but also emphasizes the importance of support

mechanisms designed to enhance the learning process. Online education offers a comprehensive learning opportunity, allowing everyone to acquire, develop, and refine their knowledge and skills, contributing to their academic and personal growth.

Online learning in China has undergone a remarkable evolution. With the rise of the Internet and technological progress, online learning emerged as a practical alternative to traditional classroom education. The early 2000s marked a significant turning point, as higher bandwidth, improved software, and the proliferation of personal computers enabled more interactive and sophisticated online learning platforms. The rise of Massive Open Online Courses (MOOCs) in the 2010s further revolutionized the field, making education more accessible by offering free or low-

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cost courses from renowned institutions to learners worldwide. Online education continued to evolve, integrating multimedia content, virtual classrooms, and real-time communication tools, allowing for a more engaging and interactive learning experience. The COVID-19 pandemic in 2020 served as a catalyst, compelling educational institutions globally to quickly transition to online formats, thereby speeding up the adoption of digital learning tools and methods. Today, it offers flexible and accessible learning opportunities, catering to diverse needs and fostering a vibrant digital education ecosystem in China. The importance of studying online learning arises from its ever-growing prevalence and profound influence on education systems across the globe. As technology advances, online learning has become essential to modern education.

Moreover, this research is crucial in influencing college students' willingness to participate in online learning, offering valuable insights into the factors that encourage or discourage their engagement in virtual education. Understanding students' motivations, challenges, and perceptions through empirical studies allows educators, administrators, and policymakers to design more effective and engaging online learning environments. This research is essential for improving learning outcomes boo, sting student satisfaction, and potentially transforming how we approach education. By uncovering the primary drivers and obstacles of online learning, educators and policymakers can make well-informed decisions to support students in their online education more effectively. Moreover, by continuously investigating and understanding these dynamics, this study improves the standard and efficiency of digital education. It cultivates a more favorable mindset among learners, boosting their readiness to adopt and excel in virtual learning settings. This analysis is crucial for realizing the complete potential of e-learning and reshaping the future of education.

Despite the increasing research to understand the factors influencing online learning behavioral willingness, significant gaps still need to be discovered, particularly concerning the context of Sichuan college students. Existing studies often generalize findings from broader or different populations, neglecting the unique cultural, economic, and educational circumstances specific to students in Sichuan. This oversight can lead to less need for more relevance in interventions designed for this demographic. Furthermore, there is a notable scarcity of behavioral intention (BI) evaluations within this context. Introduced by Fishbein and Ajzen in 1975, BI is a concept that measures an individual's inclination or preparedness to undertake a specific action. It is a valuable metric for assessing the likelihood of performing specific behaviors, offering insights into the motivations, attitudes, and beliefs that drive an individual's decision-making process. Investigating the factors that influence BI can illuminate the underlying reasons behind students' engagement or reluctance, thereby guiding improvements in online education. Understanding BI is crucial for tailoring educational strategies to meet the needs of specific student groups.

Allen et al. (1998) emphasized that BI directly impacts actual behavior, a notion later reinforced by Shonola and Joy (2014). This relationship underscores BI's importance in shaping attitudes and subsequent behaviors. Williams et al. (2015) further assert that BI represents an individual's firm commitment to a particular course of action, marking it as a vital determinant in educational settings. By focusing on BI, educators, and institutions can better understand the elements that motivate or hinder student engagement in online learning environments. To address these gaps, more research is needed that specifically examines the BI of Sichuan college students. Such research should consider local cultural norms, socio-economic factors, and educational practices that may influence students' online learning behaviors. For instance, factors such as regional attitudes toward technology, access to digital resources, and the support provided by educational institutions in Sichuan can significantly affect students' willingness to engage in online learning. By exploring these context-specific elements, researchers can provide more tailored recommendations for enhancing online learning experiences. This targeted approach will help educators design more effective, engaging, and supportive online learning environments that resonate with Sichuan college students' unique needs and preferences, ultimately improving their educational outcomes and overall satisfaction with online education.

Building on a strong foundation of previous research, this study explores the key factors that profoundly impact the behavioral intentions of undergraduate students in Sichuan, China, regarding online learning. The analysis thoroughly investigates how various factors influence students' willingness to participate in this mode of education. Given the complexity of these factors, it is essential to conduct a rigorous and quantifiable investigation into the behavioral intentions of undergraduates in Sichuan. This study thoroughly analyzes students' perceptions and attitudes toward online learning, concentrating on six pivotal factors. In doing so, it aims to reveal the underlying motivations, beliefs, and attitudes influencing students' online education participation. This insight will contribute to the creation of more efficient and engaging digital learning platforms and strategies specifically tailored to the distinct cultural and educational landscape of Sichuan Province.

2. Literature Review

2.1 Perceived Ease of Use

Perceived ease of use indicates the degree to which a person thinks that employing a specific method or mechanism will be effortless. This concept encompasses physical and psychological dimensions of effort, suggesting that the easier a system is perceived, the more likely an individual is to adopt it. The idea is grounded in the assumption that systems or strategies requiring less effort are more readily embraced, as they are seen as more convenient and less burdensome to use. According to Davis (1989), perceived ease of use is critical in determining a system's acceptance and continued use, influencing how individuals interact with and assess new technologies or methods. Perceived Ease of Use (PEU) constitutes a fundamental construct within this study, capturing the degree of convenience a system affords its users (Venkatesh & Davis, 2000). Venkatesh et al. (2003) delved deeper into the concept of Perceived Ease of Use (PEU), a term initially coined by Szajna and Scamell (1993) to describe a person's assessment of the simplicity and straightforwardness linked to interacting with a technological system. They viewed PEU as a critical determinant of user acceptance and engagement, emphasizing the importance of a system's perceived ease of interaction. This definition emphasizes the importance of how users view the simplicity of a technology. It underscores the pivotal role of user perception in determining whether a technology is simple. It highlights that the simplicity or complexity of a system is not solely determined by its objective features but also by how users perceive those features. Multiple factors influence this perception. One significant factor is the user's previous exposure to comparable technologies, which can greatly affect how they view a new system. Another key element is the user's level of technical expertise, which is crucial in determining how easy or difficult they find the technology to use. Additionally, the specific context in which the technology is applied contributes to shaping the user's view of its simplicity. Prior experience can influence how easily users adapt to new technologies, while technical proficiency affects their ability to navigate and utilize these tools effectively.

Within the framework of online learning, Perceived Ease of Use (PEU) plays a crucial role. It represents the subjective judgments that students make about their interaction with an online learning platform or tool. This concept captures how students perceive the simplicity and user-friendliness of the technology they are using. As highlighted by Hamidi and Jahanshaheefard (2019), Performance Expectancy (PEU) reflects students' personal views on how straightforward and effortless it is to navigate, utilize, and interact with an online learning environment. In the realm of online education, this concept becomes especially vital, as the effectiveness of the learning experience is often determined by the ease with which the platform can be navigated. When students find an online learning tool to be user-friendly, they are more inclined to feel confident and motivated to engage with the content, which in turn enhances their learning outcomes. Moreover, PEU is not merely a measure of the technical simplicity of the platform but also encompasses the overall user experience, including factors such as the clarity of instructions, the intuitiveness of the interface, and the accessibility of support resources. By examining these different dimensions, educators and platform developers can gain important insights into methods to enhance the online learning experience for students. This deeper understanding allows them to design a more engaging and efficient learning setting. Tailoring the platform to align with the needs and preferences of users becomes possible, leading to a more personalized and impactful educational experience.

H1: Perceived ease of use has a significant impact on perceived usefulness.

H5: Perceived ease of use has a significant impact on behavioral intention.

2.2 Perceived Enjoyment

Perceived Enjoyment (PE), as articulated by Humida et al. (2022), denotes the profound and subjective emotional response that individuals experience when engaging in various activities, specifically emphasizing online education. This concept encompasses the delight, contentment, and gratification of interacting with the learning material and the online platform. It investigates the emotional aspects of the learning process, including aspects such as interest in the content, active engagement, and overall satisfaction derived from educational activities (Tsourela & Roumeliotis, 2015).

In online education, Perceived Enjoyment is pivotal in influencing students' engagement, motivation, and general effectiveness of the learning experience. When students find the learning content engaging and enjoyable, marked by elements of interest, challenge, and satisfaction, they are more inclined to engage actively in the educational process. This increased engagement often leads to better learning outcomes and a more positive educational experience (Lwoga & Komba, 2015). For instance, when students encounter content that captures their attention and presents intellectually stimulating challenges, their motivation to continue learning and exploring the subject matter is significantly enhanced. To cultivate a high level of Perceived Enjoyment, it is crucial to establish a setting that offers diverse and appealing learning resources and activities. This includes incorporating interactive elements, multimedia content, and opportunities for collaboration that can make the learning experience more dynamic and enjoyable

(Shonola & Joy, 2014). An environment rich in stimulating and varied content helps maintain students' interest and enthusiasm, which is crucial for sustaining their motivation over time.

Furthermore, understanding and promoting Perceived Enjoyment is crucial for designing online learning experiences that resonate with students' intrinsic motivations. When educational activities are aligned with what students find enjoyable and fulfilling, they contribute to a more enriching educational journey. This approach enhances students' immediate learning experiences and fosters long-term engagement and commitment to their educational pursuits (Hamidi & Chavoshi, 2018).

Perceived Enjoyment is a vital online learning component that affects how students interact with educational materials and platforms. By focusing on creating enjoyable and engaging learning experiences, educators and platform developers can enhance student motivation, participation, and overall learning effectiveness. This involves recognizing the importance of emotional responses and ensuring that learning environments are designed to provide satisfaction and Enjoyment, ultimately resulting in a more successful and impactful educational experience.

H2: Perceived enjoyment has a significant effect on perceived usefulness.

2.3 Technology Anxiety

The concept of "technology anxiety" is rooted in earlier studies on "computer anxiety," which explored the emotional responses individuals experience when interacting with computer-related tasks. Venkatesh et al. provided a foundational definition of computer anxiety, emphasizing the various emotional reactions that individuals might have when faced with computer-related activities. These reactions can include fear, discomfort, or unease when performing tasks on a computer or using technology more broadly. Such emotional responses are not merely peripheral but can significantly affect individuals' readiness and capability to adopt and use technology effectively, particularly in contexts such as e-learning (Adnan & Anwar, 2020). Building on this understanding, Alenezi (2012) underscores the profound impact of computer anxiety on integrating online education within higher education. This view is supported by Cheng (2015), who highlights that anxiety related to technology can be a barrier to the effective integration of online learning tools. In the domain of online education, technology anxiety encompasses the nervousness, anxiety, and discomfort that students might feel when using technology or engaging with digital learning tools and platforms (Almaiah et al., 2016). This unease frequently stems from several factors, including unfamiliarity with new technologies, confusion about their operation, and concerns about potential technical issues.

For students, technology anxiety can significantly shape their online learning experiences. The anxiety and stress associated with technology use can undermine their confidence and motivation, making them less likely to engage fully with online learning platforms. For instance, students anxious about encountering technical glitches may hesitate to explore and use new features or resources offered by an online learning system. This reluctance can diminish their learning experience and hinder their overall academic performance. Addressing technology anxiety is essential for developing a supportive online learning environment. Educators and developers can implement strategies to alleviate these concerns by understanding the roots and manifestations of technology anxiety. This might include providing comprehensive training and support for students, ensuring that technology tools are user-friendly and reliable, and creating resources to help students navigate and troubleshoot common technical issues. Additionally, fostering an environment that encourages open communication about technical challenges can help reduce feelings of isolation and frustration among students.

Ultimately, creating an environment that minimizes technology anxiety involves addressing the technical aspects and acknowledging and supporting the emotional dimensions of technology use. Educators and developers can use this approach to enhance students' confidence and engagement with online learning tools, adding to a more positive and successful academic experience. Understanding and mitigating technology anxiety is crucial for ensuring that online learning settings benefit students' academic growth and overall well-being.

H3: Technology anxiety has a significant effect on perceived usefulness.

2.4 Compatibility

Compatibility is key to online learning platforms' efficacy and user experience. It denotes the degree to which the online education system aligns with students' devices, browsers, and operating systems (Venkatesh, Morris et al., 2003). This concept encompasses how well the platform can adapt to different technological environments to ensure students can access and utilize it seamlessly across various devices and systems.

Recent research underscores the pivotal role of compatibility in shaping students' attitudes and intentions toward online learning. Songkram, Chootongchai et al. (2023) stress that a platform's seamless operation across different devices and operating systems is crucial for a positive user experience. When a platform is compatible with a variety of devices and operates effectively across various browsers and operating systems, it significantly reduces barriers to access and usage, thereby fostering a more fluid

learning process. Shin and Lee (2015) further emphasize that compatibility significantly influences students' attitudes toward online learning. Their study reveals that when students perceive an online learning platform as aligned with their current technological setup, they are more likely to develop favorable attitudes and intentions toward using the platform. This positive perception is critical, as it influences how students engage with the platform and their overall satisfaction with the online learning experience. Similarly, research by Shankar and Datta (2018) supports the notion that good compatibility enhances student satisfaction. When students can interact with the platform without technical difficulties, they are more likely to actively participate in learning activities. Compatibility ensures that features such as course materials, video playback, and interactive elements function correctly, which contributes to a more engaging and effective learning environment.

Compatibility issues can significantly impact students' online learning experience. Students expect to access teaching materials, view course videos, and participate in learning activities without encountering technical issues. Kucuk et al. (2020) highlight that when students encounter issues such as slow page loading, video playback issues, or feature malfunctions due to compatibility problems, their learning experience is negatively impacted. These issues can lead to frustration, decreased motivation, and a reluctance to use the platform, ultimately affecting their learning outcomes. Thus, ensuring compatibility is crucial for the effectiveness of online learning platforms. It directly influences how students interact with and perceive the platform, impacting their engagement, satisfaction, and overall learning experience. By addressing compatibility issues and ensuring that the platform functions effectively across various devices, browsers, and operating systems, educators and developers can generate a more accessible and user-friendly learning environment. This approach helps to minimize technical barriers, enhance student engagement, and support more effective and enjoyable online learning experiences.

H4: Compatibility has a significant impact on perceived usefulness

2.5. Perceived Usefulness

Davis (1989) assertion that perceived usefulness is vital in shaping attitudes toward information systems is a foundational concept in technology acceptance and implementation. Perceived usefulness denotes the degree to which individuals think that employing a specific technology will boost their performance or increase the effectiveness of their tasks. This concept emphasizes that users are more inclined to embrace and actively engage with technology if they view it as advantageous in enhancing their effectiveness or streamlining their work processes (Raffaghelli &

Rodríguez, 2022). Perceived usefulness is important because of its capacity to influence user attitudes and behaviors. When individuals recognize that technology can make their tasks easier, more efficient, or more productive, they are more inclined to incorporate it into their daily practices and rely on it to achieve their goals. This notion of perceived usefulness is integral to understanding technology acceptance, as it highlights the importance of perceived value in the decision-making procedure regarding technology adoption. In the context of online learning, Bhattacherjee and Premkumar (2004) apply this concept of perceived usefulness to educational technologies. They argue that perceived usefulness remains consistent within this specific realm with its broader conceptual framework. For students, perceived usefulness relates to how effectively they believe an online learning platform or tool will support them in achieving their educational objectives. If students perceive that a particular online learning tool will assist them in achieving their academic objectives more effectively, they are more inclined to embrace and use it.

This alignment underscores that the perceived utility of technology is a crucial determinant of its acceptance in educational settings. When students view an online learning platform as a valuable resource that can aid their studies and enhance their learning experience, their willingness to engage with it increases. This perception of usefulness, therefore, plays a pivotal role in fostering favorable perceptions of online learning tools and encouraging their widespread use in educational contexts. This concept encompasses the belief that technology will support their learning processes and enhance their academic performance and efficiency. When students view an online learning tool as a valuable asset for achieving their learning objectives, they are more likely to embrace and utilize the platform to its full potential, optimizing their educational experience. Indeed, Davis et al. (1989) observations align with the notion that when students perceive online learning tools to align with their learning objectives, provide high-quality resources, and enhance learning outcomes, they are more likely to engage with them actively.

Indeed, perceived usefulness is a cornerstone of students' engagement and success in online learning. When students believe that an online learning platform or tool can significantly improve their learning outcomes, facilitate their academic progress, and assist them in attaining their educational goals, they are more likely to feel motivated to engage with it. This perception of the platform's effectiveness directly influences their willingness to invest time and effort into their studies. Perceived usefulness thus becomes a crucial determinant within the domain of online learning. It shapes students' engagement by aligning with their convictions about the value and benefits of utilizing technology to improve their educational experience. The

more students view a tool as beneficial and supportive of their academic objectives, the more likely they will actively utilize it and commit to their educational activities. Higher perceived usefulness can stimulate students' interest and initiative, leading to better learning outcomes. Conversely, if individuals perceive lower usefulness in an information system, they are less inclined to adopt or utilize it. Thus, the benefits of using computers and technology lie in their potential to enhance individuals' performance and work outcomes.

H6: Perceived usefulness has a significant effect on behavioral intention.

2.6 Social Influence

Social influence is powerful in shaping individuals' decisions, including their willingness to adopt new technologies or systems. When individuals perceive that important people, such as peers, family members, or authoritative figures, believe that certain actions are appropriate or necessary, they are more likely to align their behaviors with these perceptions (Mailizar, Burg et al., 2021). This influence is rooted in the concept that individuals often look to those around them to guide their choices, especially when deciding about new technologies or practices. Wang et al. (2016) elaborate on this by describing social influence as the effect of others' opinions or statements on a person's decisions, particularly within the framework of technology adoption. This perspective helps to explain how endorsements or recommendations from influential figures can sway individuals toward adopting new technology systems (Akram et al., 2022). The influence of others can manifest through direct encouragement, social norms, or perceived expectations, significantly affecting an individual's decision to engage with an innovative technology. Research by Barrane et al. (2018), Chao (2019), Dwivedi et al. (2019), and Tao (2011) further reinforces the importance of social factors in shaping technology adoption. These studies collectively highlight how social dynamics—such as group norms, peer pressure, and social support—can be crucial in shaping individuals' intentions to implement specific technologies. The findings underscore that understanding technology adoption requires a comprehensive examination of the social setting in which these decisions occur.

Social factors become even more pronounced in educational settings, where interactions between students, teachers, and administrators are frequent and influential. Social influence in this context includes peer interactions, family support, teacher guidance, and societal expectations, all of which can impact students' attitudes toward online learning technologies. Lwoga and Komba (2015) emphasize that understanding these intricate social dynamics is crucial

for grasping the factors driving technology adoption and acceptance within educational environments. The social nature of educational settings means that the perspectives and actions of people are often shaped by the social context and interactions they experience.

Although current studies offer useful insights into the function of social influence in influencing technology acceptance, it is crucial to integrate findings from diverse sources to gain a more thorough grasp of these dynamics. Exploring various facets of social influence, such as peer pressure, family support, and institutional guidance, can provide a richer perspective on how these factors affect technology acceptance and utilization, especially in digital education. This comprehensive approach ensures a robust understanding of how social contexts shape individuals' decisions to embrace new technologies.

H7: Social influence has a significant effect on behavioral intention.

2.7 Behavioral Intention

Fishbein and Ajzen (1975) Theory of Reasoned Action (TRA) argues that a person's intention to engage in a specific action is primarily shaped by two main factors: their evaluations of the action and their perceived social expectations. According to TRA, evaluations represent a person's overall assessment of the action, including their beliefs about the possible results of participating in that action. This assessment can be positive or negative, based on whether the person views the outcomes as beneficial or detrimental. Alongside evaluations, TRA highlights the influence of perceived social expectations, which involve the perceived pressures or anticipations from important individuals—such as family, friends, coworkers, or societal norms—that affect a person's choice to pursue or avoid a certain action. These norms represent the social context and the extent to which individuals feel compelled to conform to the expectations of those around them. By integrating personal evaluations and social influences, TRA offers a comprehensive framework for understanding how behavioral intentions are formed. It suggests that individuals are motivated to act based on how they evaluate the potential outcomes of their actions and the extent to which they feel social pressure to conform to the behavior. Thus, TRA highlights the interplay between personal beliefs and social context in shaping an individual's intentions and subsequent behaviors. TRA suggests that personal evaluations and social influences play crucial roles in shaping an individual's behavioral intentions. Allen et al. (1998) and Shonola and Joy (2014) further validated the importance of behavioral intention in predicting actual behavior, emphasizing its central role in understanding, and predicting human actions. This is because behavioral intention reflects an individual's

preparedness and willingness to undertake a particular action, considering their personal beliefs and attitudes and the social context in which they operate. Within online learning, behavioral intention pertains to students' commitment and eagerness to actively engage in and sustain their usage of online learning platforms. This intention reflects their stance and anticipations toward online learning, signifying their willingness to invest time and effort into utilizing these platforms for educational purposes. Thomas et al. (2020) highlight, behavioral intention is vital to actual conduct, particularly in online learning. Students who demonstrate an optimistic behavioral intention towards online learning are significantly more likely to engage proactively with the course materials, actively participate in online discussions, and complete their assignments with greater diligence. Furthermore, their intention positively influences their interaction with peers and instructors, leading to a more enriched and collaborative learning experience. This proactive engagement is essential for achieving academic success and maximizing the benefits of online education.

Behavioral intention plays an essential role in influencing students' online learning experiences and effectively predicts their level of engagement (Humida et al., 2022). A positive behavioral intention indicates that students value online learning, are motivated to participate in learning activities, explore and utilize learning resources, overcome obstacles, and achieve learning outcomes (Hamidi & Jahanshaheefard, 2019). Conversely, a negative behavioral intention suggests that students may lack positive attitudes and motivation towards online learning, resulting in a reluctance to engage in learning activities or commit over a sustained period.

Understanding behavioral intention is essential for evaluating students' commitment and engagement in online learning environments. It offers valuable insights into how likely students are to engage actively in and persist with their online courses. By gauging students' intentions, educators and developers can better understand their motivation levels and predict their involvement in various learning activities. This understanding enables the creation of more tailored and supportive learning experiences, addressing potential barriers and enhancing overall engagement. Effective strategies can then be implemented to foster a more interactive and sustained educational experience, ultimately leading to improved educational outcomes.

3. Research Methods and Materials

3.1 Research Framework

Humida et al. (2022) and AlAjmi et al. (2021) emphasize the critical need for developing a comprehensive conceptual framework that builds on established theories and models,

ensuring alignment with the conceptual foundations of technology acceptance. This paper proposes a framework that integrates the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), grounded in previous theoretical research.

The comprehensive conceptual framework, illustrated in Figure 1, integrates these variables to offer a detailed and cohesive perspective on technology adoption and usage. Specifically, it examines how PEU, PE, TA, and CP shape users' perceived usefulness. Additionally, PEU, PU, and SI are considered in how they affect users' behavioral intentions. By analyzing these interconnected factors, the framework offers a significant understanding of the complex dynamics that propel technology use and acceptance, offering guidance for designing more effective and user-centered technological solutions.
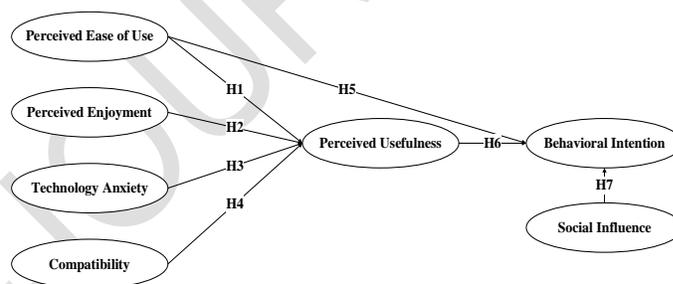

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant impact on perceived usefulness.
H2: Perceived enjoyment has a significant effect on perceived usefulness.
H3: Technology anxiety has a significant effect on perceived usefulness.
H4: Compatibility has a significant impact on perceived usefulness
H5: Perceived ease of use has a significant impact on behavioral intention.
H6: Perceived usefulness has a significant effect on behavioral intention
H7: Social influence has a significant effect on behavioral intention.

3.2 Research Methodology

The goal of this study is to thoroughly explore the factors influencing the behavioral intentions of undergraduate students in Sichuan, specifically those enrolled at Sichuan University (SCU), the University of Electronic Science and Technology of China (UESTC), and Southwest Jiaotong University (SWJTU). This research aims to identify the various elements that affect students' readiness and willingness to engage with online learning platforms, offering

valuable insights into how these factors shape their intentions and behaviors within the context of these prominent institutions. AA's quantitative survey approach was used to achieve this by collecting data from a wide range of participants and employing structured questionnaires. This approach involved selecting representative samples from the extensive dataset to ensure comprehensive and accurate analysis. The model developed for this study is grounded in the relationships among seven key latent variables: Perceived Ease of Use (PEU), Perceived Enjoyment (PE), Technology Anxiety (TA), Compatibility (CP), Perceived Usefulness (PU), Social Influence (SI), and Behavioral Intention (BI). By analyzing these variables, the study will reveal the direct and interdependent influences on Sichuan college students' online learning behavior intentions. The model's design allows for an in-depth examination of how each factor contributes to students' willingness to engage in online learning and how these factors shape their overall behavioral intentions. This research provides a detailed grasp of the complex dynamics affecting online learning intention, offering actionable understanding for educators and policymakers to improve digital learning experiences and tackle the requirements and obstacles students in Sichuan encounter.

3.3 Population and Sample Size

The survey was meticulously designed for undergraduate students enrolled in three esteemed public universities in Sichuan Province. The importance of sample size in quantitative research is underscored by Noordzij et al. (2010), who highlight its critical role in achieving valid and reliable research outcomes. According to Smithson (2001), an appropriately determined sample size is essential for establishing statistical power and ensuring the generalizability of research findings. We employed a rigorous screening and quota selection process to refine our participant pool in line with these guidelines. From an initial pool of 13,600 potential respondents, a final sample size of 500 students was meticulously chosen. This process was strategically designed to ensure that the sample accurately reflects the broader student population at the three universities, thereby enhancing the reliability and validity of the research findings. The chosen sample of 500 students is sufficiently large to offer significant insights into the research inquiries while also ensuring that the results can be generalized to the larger population of undergraduate students at the targeted institutions. By adhering to established methodologies for determining sample size, our study aims to offer robust and credible data that can contribute significantly to understanding the factors influencing online learning behaviors among students in Sichuan Province. This careful approach to sample selection underscores the commitment to achieving high-quality

research outcomes and providing a valuable understanding of the dynamics of online education within a specific educational context.

3.4 Sampling Technique

To ensure a representative sample for this study, we specifically targeted undergraduate students with prior experience with online education at three prestigious universities in Sichuan, China. From this targeted population, a meticulous selection process led to the identification of 500 respondents who were asked to participate in a comprehensive questionnaire survey. The study was crafted to capture detailed insights into online education experiences and perceptions. To maintain the accuracy and dependability of the data, stringent quality control measures were implemented throughout the data collection process. Consequently, upon completing the survey and subsequent data compilation, all 500 responses were thoroughly reviewed and validated, ensuring that all valid and complete data was included in our analysis. This rigorous approach not only strengthened the reliability of our findings but also ensured that the conclusions drawn from this study were grounded in solid empirical evidence.

Table 1: Sample Units and Sample Size

Target Public Universities	Grade	Judgmental Size Total	Proportional Sample Size Total
Sichuan University	Freshman	1030	38
	Sophomore	1082	39
	Junior	1088	39
	Senior	1100	40
University of Electronic Science and Technology of China	Freshman	1900	70
	Sophomore	1786	68
	Junior	1987	73
	Senior	1927	71
Southwest Jiaotong University	Freshman	433	16
	Sophomore	425	15
	Junior	442	17
	Senior	400	14
Total		**13,600**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Table 2 provides a comprehensive summary of the demographic characteristics of the 500 survey respondents, offering a detailed breakdown of their gender, university affiliation, and academic year. The gender distribution among

the participants reveals that 44.80% were male and 55.20% were female, highlighting a somewhat greater proportion of female participants within the sample. In terms of university affiliation, the data indicates that 31.20% of the respondents were enrolled at Sichuan University (SCU), 56.20% were students at the University of Electronic Science and Technology of China (UESTC), and 12.60% were affiliated with Southwest Jiaotong University (SWJTU). This distribution reflects a greater concentration of UESTC respondents than other institutions. Additionally, the survey categorized the respondents based on their academic year: 33.20% were in their first year, 33.40% were second-year students, and 33.40% were third-year students. This even distribution across academic years ensures a balanced representation of students at different stages of their undergraduate studies.

Table 2: Demographic Profile

Demographic Information (n=500)		Frequency	Percentage
Gender	Male	224	44.80%
	Female	276	55.20%
University Belong	SCU	156	31.20%
	UESTC	281	56.20%
	SWJTU	63	12.60%
Academic Year	1st Year	166	33.20%
	2nd Year	166	33.40%
	3ed Year	168	33.40%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is an advanced statistical method used within the context of Structural Equation Modeling (SEM) to evaluate the accuracy of a proposed measurement model thoroughly. Unlike exploratory factor analysis, which identifies potential underlying factors without preconceived notions, CFA tests whether a specific factor structure, based on theoretical expectations, accurately reflects the relationships among observed variables. In CFA, researchers start with a hypothesized model that outlines the expected relationships between observed variables and latent (unobserved) factors. For instance, a model might propose that certain survey items (observed variables) are indicators of broader constructs like "job satisfaction" or "student engagement" (latent factors). CFA evaluates how well the actual data conforms to this hypothesized structure by analyzing the alignment between the observed data and the proposed factor structure. The core of CFA involves assessing the goodness-of-fit between the observed data and the model. This is done through various statistical indices that quantify how closely the model's predictions match the observed data. In addition to these indices, CFA examines factor loadings, illustrating the intensity of the associations between measured variables and their respective latent factors. Strong factor loadings (usually above 0.50) indicate that the measured variables effectively indicate the latent factors.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Ease of Use (PEU)	Vululleh (2018)	4	0.921	0.823-0.910	0.922	0.748
Performance Expectancy (PE)	Mtebe and Raisamo (2014)	4	0.814	0.681-0.746	0.815	0.524
Technology Anxiety (TA)	Wen et al., (2022)	4	0.814	0.667-0.763	0.816	0.526
Compatibility (CP)	Venkatesh et al., (2003)	3	0.817	0.707-0.827	0.820	0.604
Perceived Usefulness (PU)	Vululleh (2018)	4	0.905	0.807-0.876	0.906	0.708
Social Influence (SI)	Mtebe and Raisamo (2014)	5	0.929	0.825-0.889	0.929	0.724
Behavioral Intention (B)	Shonola and Joy (2014)	4	0.983	0.942-0.988	0.983	0.936

Table 4 provides a detailed comparison of various goodness-of-fit indices employed to evaluate the effectiveness and precision of the model employed in this research. This includes a range of fit indices such as the Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), Degrees of Freedom Ratio (CMIN/DF), Normed Fit Index (NFI), Adjusted Goodness of Fit Index (AGFI), Goodness of Fit Index (GFI), and the Approximate Root Mean Square Error of Approximation (RMSEA).

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
TLI	> 0.90 Bentler and Bonett (1980)	0.964
CFI	> 0.90 Hair et al. (2006)	0.969
CMIN/	< 3.00 Hair et al. (2006)	2.102

Fit Index	Acceptable Criteria	Statistical Values
DF		
NFI	> 0.90 Hair et al. (2006)	0.942
AGFI	> 0.80 Sica and Ghisi (2007)	0.887
GFI	> 0.85 Sica and Ghisi (2007)	0.909
RMSEA	< 0.08 Pedroso et al. (2016)	0.047
Model Summary		Acceptable Model Fit

Remark: TLI = Tucker Lewis index, CFI = comparative fit index, CMIN/DF = The ratio of the chi-square value to degree of freedom, NFI = normalized fit index, AGFI = adjusted goodness-of-fit index, GFI = goodness-of-fit index, and RMSEA = root mean square error of approximation

Table 5 presents a detailed analysis of discriminant validity, which is crucial for verifying that the constructs in the research are adequately separate from each other. In the

table, the diagonal figures indicate the square roots of the Average Variance Extracted (AVE) for each construct. These values are essential indicators of how well the constructs capture their intended content. For effective discriminant validity, the square roots of AVE must exceed the correlations between any two latent variables. In this table, most of the correlations between pairs of latent variables are below the threshold of 0.80.

Table 5: Discriminant Validity

	PEU	PE	TA	CP	PU	SI	BI
PEU	0.560						
PE	0.227	0.274					
TA	0.362	0.397	0.276				
CP	0.385	0.451	0.459	0.364			
PU	0.538	0.288	0.364	0.396	0.501		
SI	0.567	0.319	0.269	0.388	0.319	0.524	
BI	0.626	0.491	0.534	0.603	0.584	0.543	0.877

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

Table 6 presents the results of the SEM phase, showing that after adjustment using AMOS 24 software, several key goodness-of-fit indices meet the established acceptable thresholds. Specifically, the CFI, TLI, NFI, GFI, AGFI, CMIN/DF, and RMSEA align with acceptable standards. These metrics collectively suggest that the structural equation model appropriately matches the data, confirming its validity and accuracy in representing the complex relationships among the variables studied. The successful alignment of these metrics demonstrates that the model represents the data well and supports the robustness and reliability of the research findings.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
TLI	> 0.90 Bentler and Bonett (1980)	0.948
CFI	> 0.90 Hair et al. (2006)	0.941
CMIN/DF	< 3.00 Hair et al. (2006)	0.922
NFI	> 0.90 Hair et al. (2006)	0.875
AGFI	> 0.80 Sica and Ghisi (2007)	0.847
GFI	> 0.85 Sica and Ghisi (2007)	2.805
RMSEA	< 0.08 Pedroso et al. (2016)	0.060
Model Summary		Acceptable Model Fit

Remark: TLI = Tucker Lewis index, CFI = comparative fit index, CMIN/DF = The ratio of the chi-square value to degree of freedom, NFI = normalized fit index, AGFI = adjusted goodness-of-fit index, GFI = goodness-of-fit index, and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

The findings in Table 7 confirm the rationality of our hypothesis. Among them, PU strongly influences BI, and its standardized path coefficient is 1.485 (T-Value is 7.886***). Secondly, the influence of PEU on PU is also significant, and its standardized path coefficient is 0.825 (T-value is 9.723***). Thirdly, PEU has a close second effect on BI, and its standardized path coefficient is 0.822 (T-Value is 4.090***). Fourthly, CP has a close second effect on PU, and its standardized path coefficient is 0.519 (T-Value is 4.903***). Fifthly, SI has a close second effect on BI, and its standardized path coefficient is 0.205 (T-Value is 4.786***). Sixly, TA has a close second effect on PU, and its standardized path coefficient is 0.161 (T-Value is 4.519***). Finally, PE has a close second effect on PU, and its standardized path coefficient is 0.154 (T-Value is 4.456***).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PEU→PU	0.825	9.723***	Supported
H2: PE→PU	0.154	4.456***	Supported
H3: TA→PU	0.161	4.519***	Supported
H4: CP→PU	0.519	4.903***	Supported
H5: PEU→BI	0.822	4.090***	Supported
H6: PU→BI	1.485	7.886***	Supported
H7: SI→BI	0.205	4.786***	Supported

Note: *** $p<0.001$
Source: Created by the author

Upon reviewing the results detailed in Table 7, it is evident that hypothesis H1 is supported by the standardized path coefficient of 0.825, which signifies a significant influence of Perceived Ease of Use (PEU) on Perceived Usefulness (PU). This finding underscores PEU's critical role in shaping users' views on the utility of a technology. Numerous studies have corroborated this relationship, consistently demonstrating that the simplicity users can use with technology significantly impacts their perception of its usefulness. For instance, research conducted by Chen et al. (2007), Kim et al. (2007), Heijden et al. (2003), Wang et al. (2003), and Nagy (2018) have consistently highlighted the strong linkage between PEU and PU. These studies emphasize the significance of intuitive interfaces and interactions in enhancing the perceived value of technological innovations. The alignment of these findings with existing literature reinforces that factors such as Perceived Enjoyment and Social Influence are integral to understanding technology adoption and usage.

For hypothesis H2, the standardized path coefficient of 0.154 confirms that Perceived Ease of Use (PE) significantly and directly affects Perceived Usefulness (PU). This finding is consistent with the Unified Theory of Acceptance and Use of Technology (UTAUT), as articulated by Teo (2010),

which identifies Performance Expectancy (PE) and Perceived Usefulness (PU) as pivotal elements that influence users' behavioral intentions and subsequent adoption of technology. According to the UTAUT model, PE and PU play crucial roles in shaping an individual's inclination to use technology, subsequently influencing their usage behavior. This theoretical viewpoint is corroborated by previous research conducted by Venkatesh and Davis (2000), Davis (1989), Tarhini et al. (2014), and Venkatesh et al. (2003), which underscores the importance of Perceived Enjoyment and Social Influence in the context of technology adoption. These studies collectively highlight how Perceived Enjoyment and Social Influence significantly affect individuals' perceptions of technology and their willingness to adopt it, reinforcing PE and PU's relevance in shaping technology adoption behavior.

For hypothesis, H3, the standardized path parameter threshold of 0.161 suggests that Perceived Ease of Use (PE) has a modest yet notable influence on Perceived Usefulness (PU) within the framework of the Technology Acceptance Model (TAM). The TAM posits that Perceived Usefulness is a critical determinant that significantly impacts an individual's intention to embrace and utilize a specific technology. This model further illustrates that when technological anxiety disrupts an individual's perception of usefulness, it can adversely affect their intention to engage with the technology. This concept is supported by research from Tosuntaş (2015), Vladova et al. (2021), and Venkatesh and Morris (2000), which provides empirical evidence that technology anxiety can diminish perceived usefulness, thereby influencing the user's behavioral intentions. These findings align with TAM's assertion that the perceived ease of use and perceived usefulness are integral factors in determining technology adoption. The influence of technological anxiety on perceived usefulness highlights the importance of addressing user concerns and providing support to mitigate anxiety, thereby enhancing the perceived value and usability of the technology.

For hypothesis H4, the standardized path parameter threshold of 0.519 reveals a significant relationship between Compatibility (CP) and Perceived Usefulness (PU). This finding underscores how well technology aligns with users' work practices and personal values. Research consistently demonstrates that when technology is perceived as compatible with a user's established methods and preferences, it is more likely to be considered useful. This compatibility facilitates a smoother technology integration into the user's routine, enhancing their perception of its utility. Venkatesh and Davis (2000) support this notion by highlighting that a technology's ability to fit seamlessly with existing workflows and values can positively influence its perceived

usefulness. The more a technology is perceived as congruent with a user's current practices, the more probable it will be embraced and used effectively. This relationship emphasizes the critical role of compatibility in shaping users' evaluations of new technologies, reinforcing the idea that ease of integration and alignment with established practices significantly impact users' perceptions of usefulness.

For hypothesis H5, the standardized path parameter threshold of 0.822 underscores the significant impact of Perceived Ease of Use (PEU) on Behavioral Intention (BI). This relationship is integral to the Technology Acceptance Model (TAM) and related theoretical frameworks, which posit that PEU is a pivotal determinant influencing users' attitudes and intentions regarding technology adoption. According to TAM, perceived ease of use is pivotal in influencing an individual's readiness to use technology. Specifically, it pertains to how much a person believes using the technology will require minimal effort, impacting their overall intention to use it. Davis (1989) originally introduced this concept, and it has been further elaborated by researchers such as Agarwal and Prasad (1997) and Venkatesh and Davis (2000). Their research underscores that when users view a technology as user-friendly, they are more inclined to have a favorable attitude toward it and, as a result, a stronger intention to engage with it.

For hypothesis, H6, the standardized path parameter threshold of 1.485 validates that Perceived Usefulness (PU) exerts a direct and significant effect on Behavioral Intention (BI). This relationship is a cornerstone in the Technology Acceptance Model (TAM) and related theoretical frameworks. According to the original TAM model introduced by Davis (1989), perceived usefulness is defined as the degree to which a person thinks using a specific technology will boost their effectiveness or efficiency. This idea is crucial in influencing users' perceptions of and intention to utilize the technology. The model suggests that when users view technology as advantageous and likely to enhance their results, their willingness to embrace and interact with it rises accordingly. This insight is supported by extensive research, including Davis (1989) and studies by Agarwal and Prasad (1997), which reinforce the idea that perceived usefulness is a key determinant of behavioral intention. These findings emphasize the critical role of perceived usefulness in driving technology acceptance and user engagement, highlighting the necessity for technologies to deliver tangible benefits to foster higher adoption rates.

For hypothesis H7, the standardized path parameter threshold of 0.205 confirms that Social Influence (SI) directly and substantially affects Behavioral Intention (BI). This relationship highlights the substantial impact of social factors in influencing individuals' technology adoption

decisions. In the context of technology adoption, social influence extends beyond mere consumer behavior and organizational environments, influencing various facets of technology use. For instance, within social media platforms, users are often more inclined to engage with an application or service if it is perceived to be popular or widely used within their social networks. The decision to adopt and consistently use new digital platforms is heavily swayed by the perceptions and recommendations of friends, family, and online communities. This effect underscores the importance of social validation and peer influence in technology acceptance, as Venkatesh and Davis (2000) demonstrated. Their research illustrates that individuals' readiness to engage with and utilize emerging technologies can be significantly shaped by the attitudes and behaviors of those around them.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study explored the factors influencing undergraduate students' behavioral intention to adopt online learning in Sichuan, China. A conceptual framework was meticulously crafted to achieve this, drawing on established theoretical models, notably the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). This framework was designed to investigate the various determinants that impact students' willingness to engage in online learning. It incorporates seven hypotheses aimed at dissecting the intricate relationships between perceived ease of use, perceived enjoyment, technology anxiety, compatibility, perceived usefulness, social influence, and behavioral intention toward online learning among undergraduate students in Sichuan.

To operationalize this investigation, the researchers employed a quantitative survey method. This research focused on a sample of 500 students from three leading universities in Sichuan to investigate the underlying connections between the identified variables. A questionnaire survey was instrumental in uncovering significant patterns and correlations, thus offering important insights into the factors driving students' use of online learning platforms. To ensure the accuracy and credibility of the data, the researchers applied Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) techniques. These methods allowed for a robust evaluation of the relationships among the variables and the validation of the conceptual model.

The results from this study affirm that the developed conceptual model is both analytically and explanatorily powerful, providing a detailed understanding of the factors affecting undergraduates' behavioral intentions toward online learning in Sichuan. To create a more supportive online education setting and empower students to benefit from its advantages fully, university administrators and educators must concentrate on these critical factors. By addressing the key determinants identified in the study, they can make targeted improvements to their online learning platforms and strategies. Such optimizations will likely enhance students' acceptance of online education and ultimately improve their learning experiences and outcomes.

5.2 Recommendation

This study explores factors influencing online learning intentions among Sichuan college students. Using quantitative findings, researchers propose practical recommendations for enhancing future online education in the region.

This research shows that social influence is pivotal in shaping students' online learning behaviors. The influence of a positive social environment sways numerous students' choice of online education. As such, academic institutions should proactively cultivate and implement a favorable social climate for online education, thereby inspiring a larger pool of students to embrace this learning platform. By doing so, students will feel more energized and supported, and the overall effectiveness and acceptance of online education within academia will also undergo a notable uplift.

Secondly, from the perspective of perceived enjoyment, promoting it in online education can be achieved through rich and diverse teaching content, engaging multimedia elements, interactive and participatory learning activities, and personalized learning recommendation and reward mechanisms. These measures can stimulate students' interest in learning, enhance the fun and satisfaction of the learning process, and thus enhance students' overall enjoyment of online education.

Thirdly, the perceived ease of use can be achieved by simplifying user interface design, providing intuitive navigation and operation flow, optimizing platform performance to ensure a smooth and unobstructed user experience, and providing detailed online help and instant technical support. These measures are aimed at lowering the learning barrier for users, enabling them to easily get started and effectively use online education platforms, thereby improving their perceived ease of use.

Fourthly, from the perspective of technology anxiety, to reduce it, we can in the following ways: first, provide detailed technical support to ensure that students can quickly get help when they encounter technical difficulties; Secondly, a simple and intuitive user interface is designed to reduce complex operations and reduce learning costs; Finally, encourage the use of strong compatibility, high stability of

the technology platform, reduce the learning interruption caused by technical problems. These measures have helped ease students' concerns and anxieties about the technological aspects of online education.

Fifthly, from the perspective of the perceived usefulness, to improve it, we can start from the following aspects: Initially, make certain that the instructional material is directly connected to the learning goals and addresses the specific requirements of the students. Secondly, high-quality teaching resources and interactive platforms should be provided to promote the effective transfer and absorption of knowledge. Finally, through regular assessment and feedback mechanisms, students experience significant improvements in learning outcomes. Together, these measures can significantly improve students' perceived usefulness of online education.

Sixthly, from the compatibility perspective, you can start from the technical level and user experience to improve it. At the technical level, it is necessary to ensure that the platform supports multiple operating systems, browsers, and devices, adopts a standardized technology stack, conducts extensive compatibility testing, and is continuously optimized to adapt to new technology developments. Regarding user experience, it is crucial to prioritize the content's accessibility and user-friendliness, ensuring that the educational material is easily viewable across various devices and offering adaptable learning choices to accommodate diverse learners' needs. By implementing these strategies, the compatibility of online education can be substantially enhanced, thereby offering a seamless and enjoyable learning experience to a broader spectrum of learners.

In summary, when considering the perceived ease of use, enjoyment, technology anxiety, compatibility, perceived usefulness, and social influence of online education, students' behavior toward utilizing this learning mode will likely experience a positive enhancement, which can further elevate their capabilities.

5.3 Limitation and Further Study

The present study is constrained by its focus on a relatively narrow population and sample, specifically examining three exemplary public universities in Sichuan, China, and selecting only seven latent variables within its conceptual framework. This limitation highlights the need for broader exploration in future research to enhance generalizability and depth. To address these limitations and broaden the scope of future investigations, more in-depth research can be conducted from the two key perspectives below.

Firstly, extending the research perimeter to encompass a broader range of regions across China would significantly enhance the study's comprehensiveness. By including universities from various provinces and cities, researchers could capture diverse student experiences and perceptions of online learning. This geographical diversification would offer a deeper understanding of regional differences in technology adoption and online learning behaviors. It would also account for variations in educational infrastructure, cultural attitudes, and economic conditions, which could influence students' behavioral intentions and engagement with online learning platforms.

Secondly, there is a need to enhance the theoretical framework by incorporating additional technology acceptance theories beyond those currently employed. While the study utilizes established models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), incorporating other relevant theories could significantly strengthen the research design and improve its explanatory power. For instance, the Theory of Planned Behavior (TPB) and the Theory of Reasoned Action (TRA) provide important insights into the cognitive and social elements that affect behavioral intentions. Integrating these theories with TAM and UTAUT could offer a more thorough perspective on the psychological and situational factors affecting online learning adoption. By considering these additional theoretical perspectives, researchers can better understand the complex interplay between individual attitudes, perceived behavioral control, and external influences.

Future research that continues to explore both of these extended avenues may uncover more effective strategies to boost student interest in online learning, thereby enhancing its overall effectiveness.

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