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Factors Influencing Behavioral Intentions of College Students in Smart Campus Face Recognition System in Chengdu

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Abstract

Background and Aim: The integration of face recognition systems with smart campuses improves the efficiency of identity authentication, attendance management, and access control, and realizes the modernization of education. However, factors such as personal privacy and data ethics affect college students' behavioral intentions and pose challenges to the successful adoption of these systems. This study aims to identify the key determinants that affect students' acceptance and use of smart campus face recognition systems and provide a decision-making basis for student information protection and university informatization promotion.

Materials and Methods: A quantitative research design was adopted, focusing on seven key variables that influence behavioral intentions and usage behaviors. An online survey was conducted on 500 students from four colleges of Xihua University, and descriptive statistics were analyzed using frequency, percentage, mean, and standard deviation. Confirmatory factor analysis and structural equation modeling were used to analyze the data to assess the fit of the model and examine the relationship between variables.

Results: The results showed that perceived usefulness, perceived ease of use, social influence, habit, risk belief, and trust belief had significant direct effects on behavioral intention. Perceived usefulness and risk belief emerged as the most important determinants of students' behavioral intention toward face recognition systems. Among them, students' risk beliefs hurt the behavioral intention of technology acceptance (β=-0.402, $p < .001$), which means that universities must reduce the perceived risk of the system; in addition, the trust belief and perceived usefulness of the system have a significant positive impact on the behavioral intention (β=0.279, $p <0.001$, β=0.234, $p <0.001$).

Conclusion: The study emphasizes that universities need to prioritize the practicality and ease of use of facial recognition systems while addressing issues related to risk and trust, adopting security protocols and strict data protection policies in technology, and forming relevant safeguards laws, and regulations through multiple channels to alleviate concerns about olefins and enhance trust to increase the adoption rate of facial recognition systems and promote the in-depth application of technology in the digital transformation of education. These insights can also provide references for policy decisions and system design strategies, ultimately promoting smarter campus management and enhancing the decision-making process.

Keywords: Smart Campus; Face Recognition System; Behavioral Intention

Introduction

In recent years, the widespread adoption of face recognition technology (FRT) has gained momentum globally, finding applications in various sectors, including law enforcement, retail, and education. As one of the most commonly used biometric identification methods, FRT has become integral to modern security and identity management systems. (Adjabi et al., 2020; Hardianti et al., 2018; Hsu & Hung, 2020; Rukhiran et al., 2023). Particularly in educational environments, FRT is being incorporated into smart campuses to streamline operations, enhance security, and improve the student experience. (Wu et al., 2020; Zhou, 2020). This technological trend aligns with broader global advancements in artificial intelligence, the Internet of Things (IoT), and big data, which have significantly influenced education.

China, a forerunner in adopting smart campus technologies, has embraced FRT in its universities, allowing students to complete administrative tasks, such as payment and dormitory selection, using facial recognition systems (Hsu & Hung, 2020). Moreover, FRT is employed for attendance tracking, classroom monitoring, and access control, making it an integral part of campus life. This high level of integration has sparked significant interest in understanding the factors that influence students' acceptance of FRT in

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educational settings, particularly in Chinese universities where smart campuses are expanding rapidly (Zhou, 2020). However, despite its advantages, the growing application of FRT raises concerns about privacy, data security, and potential misuse. In contrast to Western countries, where privacy concerns often dominate discussions about FRT, Chinese students tend to view the technology more favorably, citing its convenience and security benefits. Nonetheless, scholars have pointed out that unchecked FRT use can lead to privacy infringements and data misuse, heightening the public's sense of risk and mistrust toward this technology (Roussi, 2020).

In the context of education, FRT adoption has been met with mixed reactions. Some see it as a tool to enhance campus efficiency and security, while others are wary of its ethical and privacy implications, especially in light of studies highlighting concerns related to potential data misuse and surveillance (Maerz et al., 2021). For example, foreign studies have reported public resistance to FRT in schools and public spaces due to concerns about racial bias, privacy violations, and government overreach (Perkowitz, 2020). In contrast, research in China suggests a generally positive public attitude towards FRT, with many viewing it as a necessary tool for improving campus security and efficiency (South China Morning Post, 2020). While previous studies have examined the public's behavioral intentions toward FRT adoption, they often simplify the complexities of individual perceptions and fail to account for the influence of specific usage contexts (Kostka et al., 2021). Lai and Rau (2021) argued that different public perceptions of FRT misuse in specific scenarios could significantly affect its deployment. Given the rapid expansion of FRT in Chinese educational environments, it is essential to explore how students' privacy concerns, trust, and risk beliefs influence their intention to use FRT on smart campuses.

The primary aim of this study is to examine the key factors affecting students' behavioral intention to use FRT in smart campuses in China. Specifically, it seeks to evaluate the role of perceived usefulness, perceived ease of use, social influence, habit, risk belief, and trust belief in shaping students' attitudes and intentions. This study expands the traditional Technology Acceptance Model (TAM) by incorporating variables related to risk and trust, offering a more comprehensive framework for understanding student behavior in the context of FRT. This research contributes to the growing body of literature on technology acceptance in education by extending the TAM framework with trust and risk beliefs, providing new insights into how these factors influence behavioral intention in high-sensitivity technologies like FRT (Dowling & Staelin, 1994; Rukhiran et al., 2023). In doing so, the study not only verifies the relevance of TAM in smart campus environments but also offers a theoretical foundation for addressing the concerns surrounding privacy and trust in FRT applications. On a practical level, the findings provide valuable guidance for universities in promoting and managing FRT. By understanding the factors that influence students' intention to use FRT, educational institutions can implement strategies to enhance its perceived usefulness and ease of use. Additionally, this study emphasizes the importance of addressing students' concerns about privacy and data security, proposing that universities establish transparent data management practices to build trust and ensure successful adoption.

Objectives

The purpose is to clarify the causal relationship between the key factors that affect the behavioral intention of college students in Chengdu towards the smart campus face recognition system and their usage behavior.

Literature Review

Trust beliefs

Trust beliefs (TB) are understood as the extent to which individuals perceive a company as reliable in safeguarding consumer personal data (Gefen et al., 2003; Malhotra et al., 2004). Specifically, TB refers to users' perceptions of how online companies will handle their personal information securely (Harborth & Pape, 2020). This confidence is built upon a company's demonstrated ability, goodwill, integrity, and reliability in managing user information (Koohang et al., 2018). Gefen et al. (2003) identified a significant

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positive correlation between trust beliefs—encompassing a vendor's integrity, concern for customers, and reliability—and an individual's willingness to share personal information to complete an online transaction. In the context of facial recognition technology, a type of biometric technology, the trust between users and the system is particularly important due to the sensitive nature of the personal data involved. The International Standards Organization (2009) specifies that biometric platforms must provide "protection against theft and misuse of secrets held in the biometric system"(International Standards Organization, 2009) and ensure that these systems are secure and reliable. For users to trust biometric technology, including facial recognition, they must believe in the system's reliability (Ngugi et al., 2011). These elements of trust are critical across various contexts, such as the relationships between Information Systems (IS) professionals and their clients. Mutual trust can reduce perceived risk, enhance the perceived usefulness of the technology, and strengthen positive behavioral intentions (KUMAR, 1996; Kumar et al., 2023; Yang et al., 2015). Therefore, trust beliefs have a positive impact on behavioral intentions.

Risk beliefs

Risk beliefs (RB) pertain to the anticipation that disclosing personal information to a company may involve substantial risks of potential loss. (Gefen et al., 2003; Malhotra et al., 2004). These beliefs encompass users' concerns about potential losses associated with sharing personal data with online companies. (Harborth & Pape, 2020). Specifically, risk beliefs involve the perceived likelihood of negative outcomes when sharing personal information on social media platforms, including concerns about potential data breaches, uncertainty regarding how the data will be utilized, and unforeseen issues that might arise from sharing personal details. (Koohang et al., 2018). The trust-risk framework and Extended Privacy Calculus Model suggest that when risks are present, trust becomes crucial in shaping individuals' decisions regarding trust or risk-taking behavior (Malhotra et al., 2004). As information technology use increases, so does the perceived privacy risk associated with disclosing personal information. Although privacy notices can help mitigate this risk perception (Milne & Culnan, 2004), effective safeguards are still lacking. (Malhotra et al., 2004). E-commerce studies have examined risk as a precursor to transaction intentions but often focus on economic loss rather than the specific risk of losing personal information (Jarvenpaa et al., 2000; Pavlou, 2003; Pavlou & Gefen, 2004). Our study focuses on risk beliefs related to facial recognition technology, specifically the perceived risk of opportunistic behavior involving personal information misuse (Budnitz, 1998; Rindfleisch, 1997). The Pew Internet & American Life Project (Fox, 2000) found that 84% of users were concerned about unknown entities accessing their personal information. This concern leads to hesitancy in sharing personal information, aligning with expectancy theory's explanation that individuals are motivated to avoid negative outcomes.(Dinev & Hart, 2006; Lee, 2009). Therefore, risk beliefs hurt behavioral intentions.

Habit

Habit (HT) is often understood as the degree to which individuals engage in behaviors automatically due to learned patterns, with some equating habit to a form of automatic response (Venkatesh et al., 2012). A habit can be described as a tendency to perform a behavior or thought pattern that has been previously learned or adopted and is prompted by a specific stimulus or situation (Fleetwood, 2021; Hodgson, 2017). Limayem et al. (2007) employed surveys and perception-based approaches to assess habits and discovered that these habits directly influence technology usage. Their findings revealed that the effect of habits on technology use surpasses that of behavioral intentions and also moderates the relationship between behavioral intentions and technology usage (Limayem et al., 2007; Venkatesh et al., 2012). Habits are sequences of actions or thoughts, either physical or mental, that are triggered by internal or external cues and can be carried out without continuous conscious attention once initiated (Smith & Graybiel, 2016). Facial recognition is widely used in China. In residential areas, facial recognition is required to enter and exit buildings, and in supermarkets, facial recognition is used

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for payment. Habit in the UTAUT2 model is a key variable, referring to the automated behavior patterns that individuals develop during the use of technology. In TAM3, habit is included as an additional variable. TAM3 suggests that habit can influence perceived ease of use and perceived usefulness, and ultimately affect technology acceptance (Venkatesh & Bala, 2008).In college, students have established good habits of facial recognition from the collection of facial information before enrollment to entering and exiting dormitories, class attendance, book borrowing, and canteen consumption. These habits will positively affect behavioral intentions.

Social Influence

Social Influence (SI) in the UTAUT model is considered one of the key factors influencing technology acceptance. It refers to the extent to which users perceive that important others (such as family, friends, colleagues, etc.) support or encourage them to use a particular technology. This is akin to the "Subjective Norms" in TAM2. Social influence (SI) refers to changes in an individual's beliefs, behaviors, or attitudes resulting from external pressures, which may be either perceived or actual. (Guadagno & Cialdini, 2010). It encompasses two primary areas: compliance, which focuses on shifts in behavior, and persuasion, which deals with changes in attitudes and beliefs. (Guadagno & Cialdini, 2010; McDonald & Crandall, 2015). Abrams & Hogg, 1990). defines social influence as "any modification in a person's intellectual activities, emotions, or actions induced by interactions with others, whether they be individuals, groups, institutions, or society at large" (Abrams & Hogg, 1990). Social influence is a crucial factor in media use. (Fulk et al., 1990). In the context of technology adoption, the Social Influence Model (SIM) integrates social influence as a precursor to technology adoption. (Koohang et al., 2018; Venkatesh et al., 2012). Research in technology acceptance has identified social influence factors—particularly subjective norms—alongside utility factors like perceived usefulness and ease of use as key drivers influencing an individual's intention to adopt new technologies. (Song & Kim, 2006; Venkatesh et al., 2003). As facial recognition technology becomes increasingly prevalent, the behavior of schools, teachers, and peers will likely alter students' views on and acceptance of these systems.

Perceived Ease of Use

Perceived ease of use (PEU) refers to "the extent to which a product can be used by specific users to achieve specified goals with effectiveness, efficiency, and satisfaction in a particular context of use" (Davis, 1989). It reflects the user's belief that using a system will reduce the effort required. (Cheng et al., 2022). PEU also encompasses how easily users can learn to operate the system, as systems that are easy to master are perceived to have higher PEU. Factors such as response time and system stability further contribute to this perception. (Unal & Uzun, 2021; Venkatesh & Bala, 2008). User-friendly technology overcomes barriers, while complex interfaces can lead to negative attitudes toward its use. (Hossain et al., 2021). In the case of face recognition systems, the use of high-definition cameras and auxiliary systems, without requiring additional equipment, enhances perceived ease of use. This simplicity in system operation positively impacts users' behavioral intention to adopt the technology. In the Technology Acceptance Model (TAM), PEU influences perceived usefulness (PU), and both factors collectively impact technology adoption decisions. (Dokhanian et al., 2022; Venkatesh & Bala, 2008). The quality of an information system (IS) is often reflected in its PEU, adoption rates, and availability, highlighting the critical role that ease of use plays in system effectiveness. (Dokhanian et al., 2022). Moreover, PEU positively affects PU, shaping users' attitudes and intentions toward adopting the technology.

Perceived Usefulness

Perceived usefulness (PU) refers to an individual's belief that the use of a system will enhance their performance (Cheng, 2022). It reflects the extent to which users perceive that adopting new technology will increase their efficiency and productivity with minimal effort (Khlaif et al., 2022). PU represents

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users' perceptions of the practical benefits derived from using information technology (Bhattacherjee, 2001). In the context of information systems, PU generally indicates how effectively a system helps individuals perform tasks more efficiently (Zubir & Abdul Latip, 2023). Furthermore, PU is a critical factor in influencing continued usage intentions Bhattacherjee et al., 2008; Venkatesh & Bala, 2008), as it enhances productivity, facilitates learning, extends working hours, and increases the utilization of information systems (Cheng et al., 2022). As a core component of the Technology Acceptance Model (TAM), PU plays a pivotal role in technology adoption. Users are more inclined to adopt technologies they perceive as beneficial, and PU is a predictor of both user attitudes and intentions toward technology use. According to TAM, PU is a primary determinant of users' intentions to adopt technology (Hu & Zhang, 2016; Venkatesh & Bala, 2008). Research on TAM has consistently highlighted the importance of PU, particularly when users recognize the value of an information system or online platform (Kim & Lee, 2014). In the context of smart campus face recognition systems, PU is demonstrated through students' ability to swiftly obtain identity recognition and system access, eliminating the need to carry multiple authentication devices or remember passwords for various information systems. This perceived ease of use highlights the system's value and exerts a significant positive influence on behavioral intentions to adopt information systems.

Behavioral Intention

Behavioral intention (BI) is commonly defined as an individual's readiness, inclination, or potential to engage in a specific behavior or action. (Sutenchan & Hareebin, 2024). For example, Song and Kim (2006) describe BI as a measure of the likelihood of participating in a particular activity. (Song & Kim, 2006). Similarly, Wu and Wang (2005) highlight BI as the probability or inclination of a user to participate in online activities.(J.-H. Wu & Wang, 2005). Hwang and Choi (2019) further define BI as the likelihood of engaging in behaviors such as making a repurchase or sharing recommendations via word-of-mouth. (Hwang & Choi, 2019). According to Davis (1989), BI refers to the degree to which an individual plans to engage in a specific behavior. (Davis, 1989). The TAM posits that external factors influencing BI are entirely mediated by the individual's perceptions of usefulness and ease of use.(Yi & Hwang, 2003). This model emphasizes the role of perceived ease of use and perceived usefulness in shaping BI, which are seen as critical determinants of an individual's intention to use a technology. Kaur and Arora (2023) expand on this by identifying additional factors that positively influence BI, including performance expectations, effort expectancy, hedonic motivation, price value, and trust. (Siribowonphitak, 2023). These findings are consistent with the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies similar predictors of BI. Alqudah et al. (2023) add to this discussion by noting that perceived benefit and social influence, alongside performance expectations, effort expectancy, hedonic motivation, and price value, also play a crucial role in shaping BI. (Alqudah et al., 2023). In both the TAM and UTAUT models, BI is influenced by perceived ease of use, perceived usefulness, social influence (or social norms), and habitual behaviors, all of which have a positive impact on an individual's intention to adopt or engage with a particular technology.

Conceptual Framework

This conceptual framework is developed through comprehensive research, building on prior academic achievements while incorporating practical application scenarios and research methodologies. It is grounded in three fundamental theories. The first is the Technology Acceptance Model 3 (TAM3) by Venkatesh and Bala (2008), which evolved from earlier versions (TAM1 and TAM2). This model deepens the understanding of how external factors influence users' cognitive processes during various stages of technology adoption, aiming to explain the factors that shape users' intentions to embrace new technologies. The second theory is the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003), designed to streamline and integrate multiple existing technology acceptance models to offer a more comprehensive explanation and prediction of users' adoption and usage

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behaviors. The third theory is the Extended Privacy Calculus Model (EPCM) from Dinev and Hart (2006), which builds on the Privacy Calculus Model originally introduced by Smith, Milberg, and Burke. EPCM expands the framework by adding variables that explore the balance between privacy risks and perceived benefits, providing insights into users' decision-making in privacy-related contexts. In addition, the framework incorporates elements from three well-established theoretical models. The first, developed by Agarwal and Karahanna (2000), introduced key variables like Perceived Usefulness (PU), and Perceived Ease of Use (PEU). The second model, presented by Malhotra et al. (2004), included dimensions such as Trust Belief (TB), and Risk Belief (RB)). The third model, introduced by Venkatesh et al. (2012), emphasized variables such as Social Influence (SC), Habit (HT), and Behavioral Intention (BI).

In this research, the conceptual framework consists of seven interconnected variables: PU reflects how much students believe that facial recognition systems can enhance their learning or daily efficiency and experiences. A high level of PU indicates that students find the technology beneficial. PEU measures how difficult students think it is to use the facial recognition system. If the system is user-friendly and requires little effort to learn, students will experience higher PEU, which in turn increases their willingness to adopt the technology. SI pertains to the extent to which students are impacted by external social factors, such as peers, teachers, or institutional policies, in their use of facial recognition systems. Positive feedback or recommendations from others can encourage students to engage with the system. HT describes how much students have incorporated the use of facial recognition technology into their routine, where it becomes a natural part of their academic or personal life. RB refers to students' concerns about potential risks associated with facial recognition systems, such as privacy breaches or data misuse. Increased RB may lower students' willingness to use the system. TB gauges the confidence students place in the system and related entities, focusing on whether they trust the facial recognition system to be secure, reliable, and protective of their privacy. BI refers to the student's intention to either continue using or begin using the facial recognition system in the future. BI results from the combined influence of the aforementioned factors and directly influences actual use. The independent variables analyzed in this study include PEU, HT, SI, and TB, while RB and PU serve as mediating variables, and BI is the dependent variable. The research examines eight distinct relationships among these variables and formulates eight corresponding hypotheses, aiming to identify the underlying factors that shape students' intentions to use facial recognition systems.

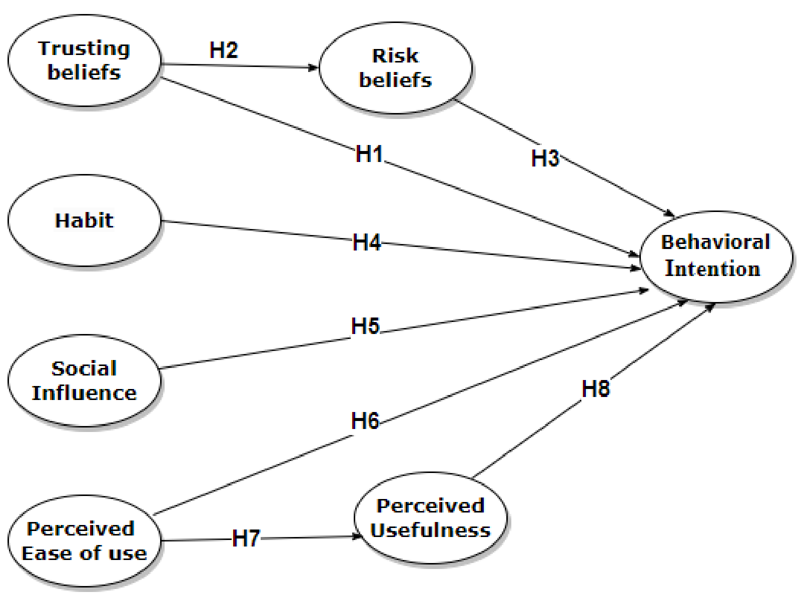

Figure 1 Conceptual Framework

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Hypotheses

H1: Trusting beliefs will have a positive effect on behavioral intention.
H2: Trusting beliefs will hurt risk beliefs.
H3: Risk beliefs will hurt behavioral intention.
H4: Habit will have a positive effect on behavioral intention.
H5: Social influence will have a positive effect on behavioral intention.
H6: Perceived ease of use will have a positive effect on behavioral intention.
H7: Perceived ease of use will have a positive effect on perceived usefulness.
H8: Perceived usefulness will have a positive effect on behavioral intention.

Methodology

Research Design

To achieve the research objectives, this study adopted a quantitative approach by collecting data through an online questionnaire survey. (Wright, 2005). Online surveys are generally regarded as an effective method for gathering a wide range of information from participants. (Van Selm & Jankowski, 2006), including demographic details such as gender, age, educational background, and employment status, as well as personal opinions related to the research topic (Balaban et al., 2013; Wilding & Drees,1973). Participants could complete the questionnaire at any time and from any location, while the system efficiently collected the data.

Xihua University, a multidisciplinary institution, was selected for this study. To ensure the generalizability of the survey, experts recommended including participants from four different academic departments. The content validity of the questionnaire was assessed using the Item-Objective Congruence (IOC) index, and a pre-test with 30 participants was conducted. The reliability of the variables and their items was measured using Cronbach's Alpha via Jamovi software. The results showed that Cronbach's Alpha for each variable exceeded 0.8, and the items for all variables had Cronbach's Alpha values above 0.7, indicating that both validity and reliability tests were passed.

The questionnaire consisted of three main sections: screening questions, measurement of variables, and demographic information. First, validated screening questions were used to classify participants based on specific criteria, such as the university and discipline of students using facial recognition systems. Then, demographic questions gathered basic information, including gender, age, academic level, usage frequency, and usage environment. Finally, each variable was evaluated using a five-point Likert scale (Likert, 1932).

Research Population and Sample

The target population for this study includes students from four distinct colleges at Xihua University: the College of Science (covering disciplines in the sciences), the College of Computer Science (focusing on engineering disciplines), the College of Literature and Journalism (encompassing literature disciplines), and the College of Arts (specializing in the arts). These colleges represent a range of academic fields.

The study involved a total of 2,557 students to determine an appropriate sample size to yield reliable and valid results. Utilizing relevant theoretical frameworks and considering the number of variables and measurement items, the prior sample size calculator for structural equation modeling indicated a minimum sample size of 425. This calculation ensures that the sample is sufficiently large to capture the diversity and complexity of the target population.

The final sample selection process was rigorously conducted to include only those students who met specific eligibility criteria. A quota-based selection method was subsequently applied to ensure that the sample accurately represented various disciplines and demographic groups within the population.

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Ultimately, 500 students were selected to participate, surpassing the initially calculated sample size. This larger sample enhances the robustness of the study results and ensures higher reliability.

Table 1 Sample Units and Sample Size

Four College	Judgmental Size Total=2,557	Proportional Sample Size Total = 500
College of Science	562	110
College of Literature and Journalism	963	189
College of Computer Science	725	141
College of Fine Arts	307	60
Total	2,557	500

Note: Authored by the creator

Data Analysis

After completing the content validity and internal consistency reliability analysis, the questionnaire was distributed to all undergraduate students across the four target colleges. Students filled out the questionnaire online under the guidance of their college counselors. Before data analysis, several data cleaning procedures were performed, including handling missing values, detecting outliers, and standardizing the data. Subsequently, JAMOVI and AMOS software were employed for data analysis.

Confirmatory factor analysis (CFA) was conducted to evaluate the indicators of the measurement model. This analysis involved constructing the theoretical model to determine the relationships between variables and the factor structure while assessing the model fit indices. The factor loadings, t-values, composite reliability (CR), average variance extracted (AVE), CFI, TLI, and RMSEA all met the relevant standards. Following the CFA, structural equation modeling (SEM) was utilized to test the hypothesized relationships. The path coefficients were significant, and the model fit indices adhered to the standards found in the literature. The model was validated, and both the specific, indirect, and overall effects among the latent variables were examined. This approach allowed for a comprehensive evaluation of the data and facilitated drawing meaningful conclusions regarding the factors influencing students' behavioral intentions towards facial recognition systems.

Results

Demographic Information

Table 2 provides a comprehensive overview of the demographic characteristics of the 500 participants. The sample was predominantly male, making up 60.80%, while females comprised 39.20%. In terms of age, 80.00% of the participants were between 18 and 21 years old, 19.60% were aged 22 to 24, and only 0.40% were over 25. The grade distribution included 21.00% freshmen, 39.60% sophomores, 21.00% juniors, and 18.40% seniors. Regarding the frequency of use, 97.80% of respondents reported using facial recognition systems more than seven times per week. The dormitory setting was the most common usage scenario, with a utilization rate of 99%, followed by the school gate scenario, which had a usage rate of 97%.

Table 2 Demographic Profile

Demographic and Behavior Data (N=500)		Frequency	Percentage
Gender	Male	304	60.80%
	Female	196	39.20%
Age	18-21	400	80.00%
	22-24	98	19.60%
	Above 25	2	0.40%

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Demographic and Behavior Data (N=500)		Frequency	Percentage
Grade	Freshman	105	21.00%
	Sophomore	198	39.60%
	Junior	105	21.00%
	Senior	92	18.40%
Weekly frequency	0	0	0.00%
	1-3 times	1	0.20%
	4-7 times	10	2.00%
	8-14 times	325	65.00%
	Above 15	164	32.80%
Usage scenarios	Classroom	196	39.20%
	Dormitory	495	99.00%
	School gate	485	97.00%
	Library	364	72.80%
	others	30	6.00%

Note: Authored by the creator

Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was performed to evaluate if the relationships between observed and latent variables in the measurement model corresponded to the data collected (Brown, 2015). According to Ainur (2017), the Goodness-of-Fit (GoF) index assesses how well the model aligns with the data. The factor loadings, along with the acceptable values for each observed variable, demonstrated a strong alignment with the proposed research framework (Hair et al., 2006). As detailed in Table 3, the metrics for chi-square to degrees of freedom ratio (CMIN/DF), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Comparative Fit Index (CFI), Normed Fit Index (NFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA) all fell within the acceptable ranges. These GoF indicators confirm that the CFA analysis conducted in this study was appropriate.

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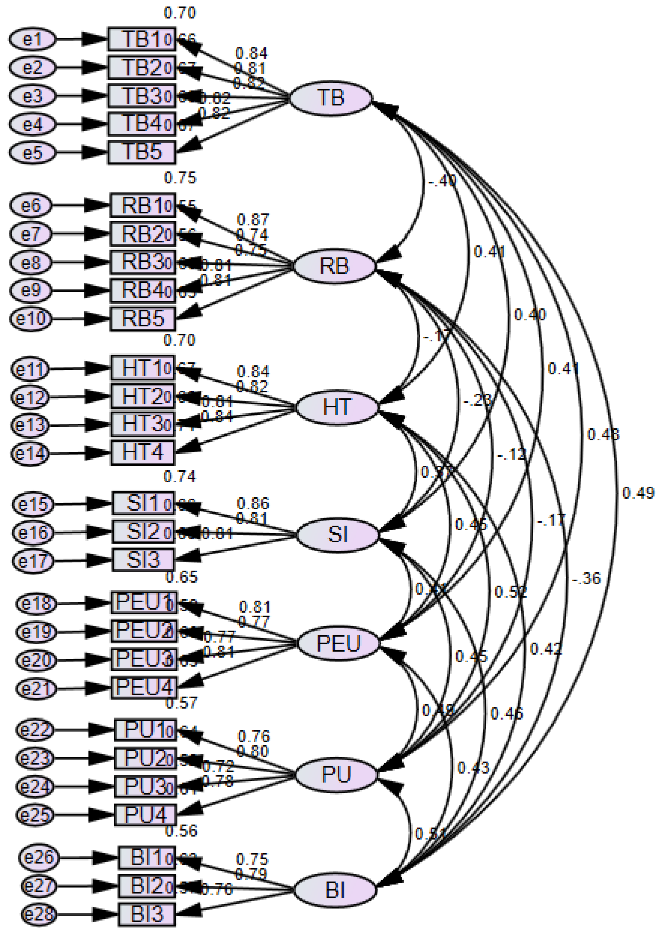

Figure 2 Measurement Model

Note: Authored by the creator

According to Figure 2, the measurement model demonstrates that all SEVEN constructs—Perceived Usefulness (PU), Perceived Ease of Use (PEU), Risk Belief (RB), Trust Belief (TB), Habit (HT), Social Influence (SC), and Behavioral Intention (BI)—were evaluated through Exploratory Factor Analysis (EFA). The study did not exclude any items from the instrument, as their regression weights exceeded the minimum acceptable threshold of 0.60. To further assess the validity of the measurement model, Confirmatory Factor Analysis (CFA) was conducted. The model fit was evaluated against established fit indices including χ^2/df, Goodness-of-Fit Index (GFI), Root Mean Square Error of Approximation (RMSEA), Residual Mean Square (RMR), Normed Fit Index (NFI), Comparative Fit Index (CFI), Incremental Fit Index (IFI), and Tucker-Lewis Index (TLI). The results indicated that the model's fit was satisfactory, with values as follows: CMIN/DF = 1.382, GFI = 0.941, AGFI = 0.927, NFI = 0.982, CFI = 0.946, TLI = 0.982, and RMSEA = 0.028. These results show that all indices are well above the conventional thresholds for acceptable fit. The Goodness of Fit is shown in Table 3.

Table 3 Goodness of Fit for Confirmatory Factor Analysis

Index	Criterion	Source	Practical Values
CMIN/DF	< 3.00	Hair et al. (2006)	1.382
GFI	> 0.85	Sica & Ghisi (2007)	0.941
AGFI	> 0.80	Sica & Ghisi (2007)	0.927

Index	Criterion	Source	Practical Values
CFI	> 0.90	Hair et al. (2006)	0.946
NFI	> 0.90	Hair et al. (2006)	0.982
TLI	> 0.90	Hair et al. (2006)	0.984
RMSEA	< 0.08	Pedroso et al. (2016)	0.028

Note: Authored by the creator

Confirmatory Factor Analysis (CFA) was employed to assess the reliability of the constructs. According to Hair et al. (2010), construct validity refers to the extent to which a set of observed variables accurately represents the theoretical latent variables. In addition to evaluating construct validity, they examined both convergent and discriminant validity. The results confirmed the inclusion of 28 items. Consistent with Bagozzi and Yi (1964), no items were removed as the standardized item loadings all exceeded 0.5. The factor loadings ranged from 0.720 to 0.867, all surpassing the 0.50 threshold, which indicates high reliability. Furthermore, the instrument's reliability, consistency, and validity were assessed. Hair et al. (2014) reported that the composite reliability (CR) values were above 0.70, ranging from 0.811 to 0.911. The average variance extracted (AVE) was greater than 0.50, with values ranging from 0.584 to 0.687, demonstrating strong reliability. Cronbach's alpha coefficients also exceeded 0.80, ranging from 0.811 to 0.911, which indicates high reliability. Table 4 illustrates that all the achieved and recommended measures meet the criteria for convergent validity (CR > 0.70 and AVE > 0.50).

Table 4 Confirmatory Factor Analysis Result, Composite Reliability (CR), and Average Variance Extracted (AVE)

Latent Variables	Source of Questionnaire (Measurement Indicator)	Items Amount	Cronbach's Alpha >0.70	Factors Loading >0.50	CR >0.70	AVE >0.50
TB	(Malhotra et al., 2004)	5	0.911	0.814-0.837	0.911	0.673
RB	(Malhotra et al., 2004))	5	0.896	0.741-0.867	0.896	0.634
HT	(Venkatesh et al., 2012)	4	0.897	0.811-0.843	0.897	0.687
SI	(Venkatesh et al., 2012)	3	0.867	0.809-0.860	0.867	0.685
PEU	(Agarwal & Karahanna, 2000)	4	0.868	0.771-0.808	0.869	0.624
PU	(Agarwal & Karahanna, 2000)	4	0.849	0.72-0.797	0.849	0.584
BI	(Venkatesh et al., 2012)	3	0.811	0.75-0.794	0.811	0.588

Note: Authored by the creator

The discriminant validity was established as the square root of the Average Variance Extracted (AVE) for each construct was greater than the corresponding inter-construct correlation estimates. Discriminant validity is confirmed when the square root of the AVE for each construct exceeds the correlation coefficients between related constructs (Fornell & Larcker, 1981). As illustrated in Table 5, all coefficients between any pair of latent variables are below 0.80. Additionally, the square roots of all AVE values are higher than the inter-construct correlations, thus affirming the discriminant validity of the measurement model. Therefore, the constructs were tested for reliability and validity, which also demonstrated a significant level.

Table 5 Discriminant Validity

	TB	RB	HT	SI	PEU	PU	BI
TB	**0.820**						
RB	-0.364	**0.796**					
HT	0.370	-0.156	**0.829**				

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	TB	RB	HT	SI	PEU	PU	BI
SI	0.353	-0.205	0.322	**0.828**			
PEU	0.363	-0.101	0.398	0.355	**0.790**		
PU	0.416	-0.150	0.456	0.379	0.425	**0.764**	
BI	0.419	-0.308	0.355	0.381	0.355	0.416	**0.767**

Note: The diagonally listed value is the AVE square roots of the variables
Note: Authored by the creator

Structural Equation Model (SEM)

Structural Equation Modeling (SEM) is a statistical method utilized to explore the relationships between variables by analyzing their covariance matrix (Zhang, 2015). The GoF indices for the SEM are shown in Table 6. The statistical results are as follows: CMIN/DF = 2.397, GFI = 0.886, AGFI = 0.864, NFI = 0.903, CFI = 0.941, TLI = 0.934, and RMSEA = 0.053, all of which are within acceptable limits. Thus, the GoF for the SEM was confirmed.

Table 6 Goodness of Fit for Structural Equation Modeling

Index	Criterion	Source	Before Adjust Values	After Adjust Values
CMIN/DF	< 3.00	Hair et al. (2006)	2.566	2.397
GFI	> 0.85	Doll et al (1994)	0.879	0.886
AGFI	> 0.80	Sica & Ghisi (2007)	0.857	0.864
CFI	> 0.90	Hair et al. (2006)	0.933	0.941
NFI	> 0.90	Hair et al. (2006)	**0.895**	0.903
TLI	> 0.90	Hair et al. (2006)	0.926	0.934
RMSEA	< 0.08	Pedroso et al. (2016)	0.056	0.053

Note: Authored by the creator

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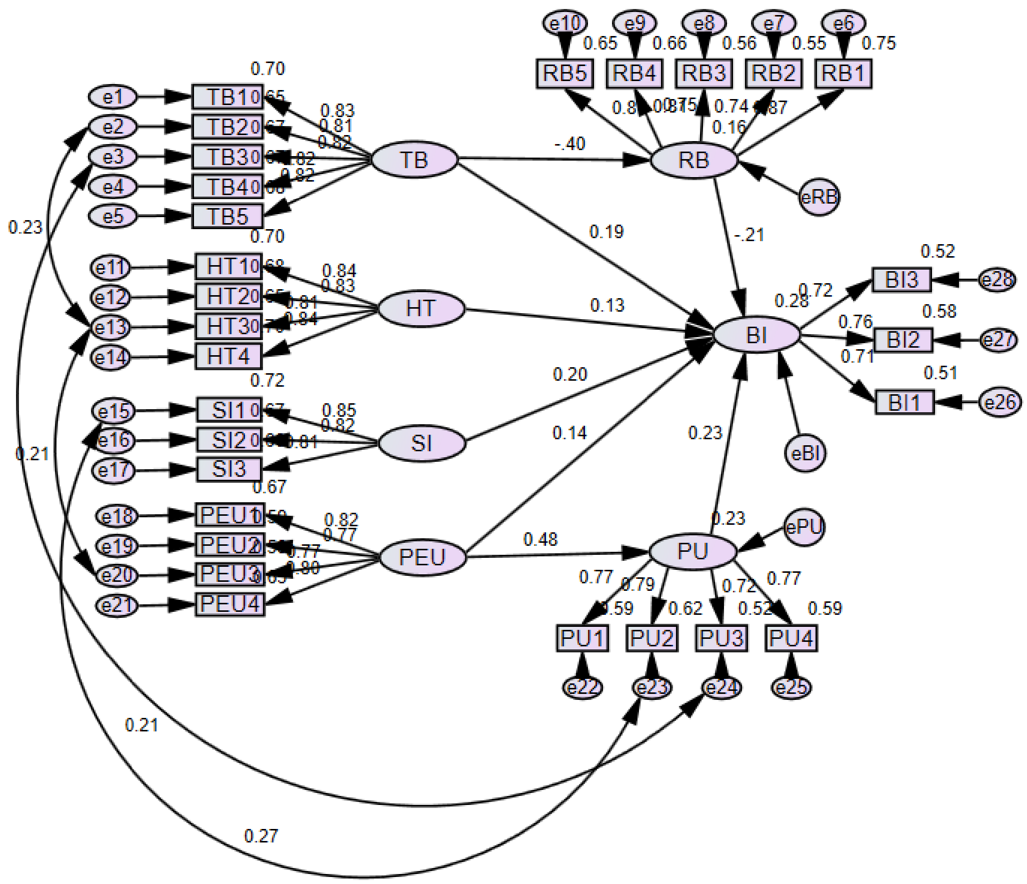

Figure 3 Structural Model Before Adjustment
Note: Authored by the creator

Discussion

According to the results summarized in Table 7, all eight hypotheses tested are supported. Among them, H1, H5, H7, and H8 are all highly significant positive effects, and H2 and H3 are all highly significant negative effects. The direct effect of TB on BI is the most significant, with a standardized path coefficient (β) of 0.279 and a t-value of 3.601***, supporting H1. The second is the effect of PEU on BI, with a β of 0.252 and a t-value of 0.018*, supporting H6. Next is PU with a β of 0.234 and a t-value of 3.875***. RB has a β of -0.208 and a t-value of -3.823***, SI has a β of 0.205 and a t-value of 4.071***, and HT has a β of 0.134 and a t-value of 2.751**. Furthermore, according to the TAM3 framework, PEU has the strongest impact on PU, with a β of 0.483 and a t value of 9.090***, supporting H7 and making it the most influential factor in this quantitative investigation. TB has the second-highest impact on RB, with a β of -0.402 and a t value of -8.306***.

Table 7 Hypothesis Result of the Structural Equation Modeling

Hypothesis	Paths			Standardized Path Coefficient(β)	S.E.	T-Value	Test Result
H1	BI	←	TB	0.279	0.042	3.601***	Supported
H2	RB	←	TB	-0.402	0.048	-8.306***	Supported
H3	BI	←	RB	-0.208	0.043	-3.823***	Supported

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Hypothesis	Paths			Standardized Path Coefficient(β)	S.E.	T-Value	Test Result
H4	BI	←	HT	0.134	0.036	2.751**	Supported
H5	BI	←	SI	0.205	0.039	4.071***	Supported
H6	BI	←	PEU	0.252	0.049	0.018*	Supported
H7	PU	←	PEU	0.483	0.054	9.090***	Supported
H8	BI	←	PU	0.234	0.05	3.875***	Supported

Note: *** p<0.001, ** p<0.01, * p<0.05
Note: Authored by the creator

According to the results of Table 7, the researchers suggest the following expansion:

H1: The hypothesis suggesting that trusting beliefs have a positive influence on behavioral intention (BI) is supported by the findings, showing a standardized path coefficient (β) of 0.279 and a t-value of 3.601***. This result is consistent with previous studies that highlight the crucial role of trust in the adoption of technology. For instance, McKnight et al. (2002) demonstrated that trust plays a pivotal role in fostering users' willingness to adopt new technologies. They argue that when users perceive the technology as reliable and secure, their confidence increases, leading to stronger intentions to engage with the system. Additionally, Gefen et al. (2003) emphasized that trust has a significant impact on BI in e-commerce settings. Their findings indicate that trust lowers psychological barriers, making users with stronger trusting beliefs more likely to use digital technologies. Therefore, the results of this study align with McKnight et al. (2002) and Gefen et al. (2003), confirming the importance of trust in shaping behavioral intentions. (Gefen et al., 2003; McKnight et al., 2002).

H2: The results show that trusting beliefs (TB) negatively impact risk beliefs (RB), with a β value of -0.402 and a highly significant t-value of -8.306***. This inverse relationship is supported by prior research, such as Pavlou (2003), who asserted that trust decreases perceived risks in online transactions. When users trust a system, their concerns about potential risks diminish, which increases the likelihood of adoption. Similarly, Mayer et al. (1995) proposed that trust reduces uncertainty and risk in interactions or transactions, promoting a positive attitude toward technology use. Both Pavlou (2003) and Mayer et al. (1995) highlight how trust can mitigate fears of negative outcomes, which aligns with this study's findings that trusting beliefs reduce risk perceptions.(Mayer et al., 1995; Pavlou, 2003)

H3: The analysis confirms that risk beliefs (RB) negatively affect BI, with a β value of -0.208 and a t-value of -3.823***. This result supports the hypothesis and aligns with research by Featherman and Pavlou (2003), who pointed out that risk perceptions deter users from embracing new technologies. Their study demonstrated that users who perceive greater risks are less likely to engage with online platforms due to concerns about security and privacy. Additionally, Okumu et al. (2008) found that perceived risks are a major barrier to adopting new technologies, particularly in e-commerce and digital services. Both studies confirm the negative impact of risk beliefs on BI, reinforcing the importance of minimizing perceived risks to encourage technology adoption. (Pavlou, 2003)

H4: The hypothesis that habit positively influences BI is confirmed, with a β value of 0.134 and a t-value of 2.751**. This result aligns with research conducted by Limayem et al. (2007), which found that habitual behavior is a key predictor of technology use. They noted that users who regularly engage with a system are more likely to continue doing so due to automatic behaviors, which strengthens their intention to use the system. Moreover, Venkatesh et al. (2012) expanded on this in their Unified Theory of Acceptance and Use of Technology (UTAUT2), emphasizing that habit plays a significant role in technology usage across both voluntary and mandatory contexts. These findings highlight how user familiarity with a system bolsters their intention to continue using it, supporting the idea that habit shapes behavioral intentions.(Limayem et al., 2007; Venkatesh et al., 2012; Venkatesh & Bala, 2008)

H5: The results indicate that social influence (SI) significantly and positively affects BI, with a β value of 0.205 and a t-value of 4.071***. This aligns with Venkatesh et al.'s (2003) Unified Theory of

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Acceptance and Use of Technology (UTAUT), which suggests that social influence—such as peer, colleague, or supervisor opinions—plays a critical role in forming BI, especially in the early stages of technology adoption. Additionally, Ajzen's (1991) Theory of Planned Behavior (TPB) underscores how social norms influence individuals' intentions to adopt new behaviors. Both Venkatesh et al. (2003) and Ajzen (1991) provide strong evidence that social influence is a key factor in determining BI, as individuals are often influenced by the expectations of those around them(Venkatesh et al., 2003).

H6: The results confirm that perceived ease of use (PEU) positively affects BI, with a β value of 0.252 and a t-value of 0.018*. This relationship is well-documented by Davis (1989) in the Technology Acceptance Model (TAM), which asserts that ease of use is a fundamental driver of technology acceptance. Users are more inclined to adopt a system when it simplifies their tasks and minimizes effort. Venkatesh and Davis (2000) expanded on this, noting that perceived ease of use is a critical predictor of intention, particularly when users assess new technologies. These findings corroborate broader research, affirming that ease of use is essential in influencing users' willingness to adopt technologies. (Davis, 1989; Venkatesh et al., 2003).

H7: PEU has the most substantial effect on perceived usefulness (PU), with a β value of 0.483 and a highly significant t-value of 9.090***, confirming the hypothesis. Davis (1989) also found that PEU directly influences PU, suggesting that when users perceive a system as easy to use, they are more likely to see it as beneficial for their tasks. Gefen and Straub (2000) further emphasized that ease of use positively shapes perceptions of usefulness in online environments. Both studies provide solid evidence for the positive relationship between PEU and PU, supporting the notion that a user-friendly system increases the perceived utility of the technology. (Davis, 1989; Gefen et al., 2003).

H8: PU positively influences BI, with a β value of 0.234 and a t-value of 3.875***, supporting the hypothesis. Davis (1989) found that PU is a key factor in determining BI, as users are more inclined to adopt a system they view as beneficial. Venkatesh and Bala (2008) reinforced this in their extension of TAM, arguing that PU is a critical factor in shaping BI, particularly when it comes to technology adoption. Both studies validate the positive link between PU and BI, emphasizing the importance of perceived benefits in driving users' technology adoption decisions. (Davis, 1989; Venkatesh & Bala, 2008).

This research investigated four independent variables, two mediating variables, and one dependent variable, as demonstrated in the path diagram in Figure 4.

The dependent variable, Behavioral Intention, has an R^2 value of 0.280, indicating that 28% of its variance is explained by the combined influence of the independent and mediating variables. Both Risk Beliefs and Perceived Usefulness serve as mediators, impacting Behavioral Intention with coefficients of -0.208*** and 0.234***, respectively. Additionally, the four latent variables—Trusting Beliefs, Habit, Social Influence, and Perceived Ease of Use—exert significant direct effects on Behavioral Intention, with coefficients of 0.195***, 0.134**, 0.205***, and 0.139***, respectively. Furthermore, Trusting Beliefs and Perceived Ease of Use exhibit significant indirect effects on Behavioral Intention, with coefficients of 0.084*** and 0.113***, respectively. Risk Beliefs has an R^2 value of 0.162, meaning that Trusting Beliefs explains 16.2% of its variance, with a direct effect coefficient of -0.402***. Perceived Usefulness, with an R^2 value of 0.233, shows that Perceived Ease of Use explains 23.3% of its variance, with a direct effect coefficient of 0.483***.

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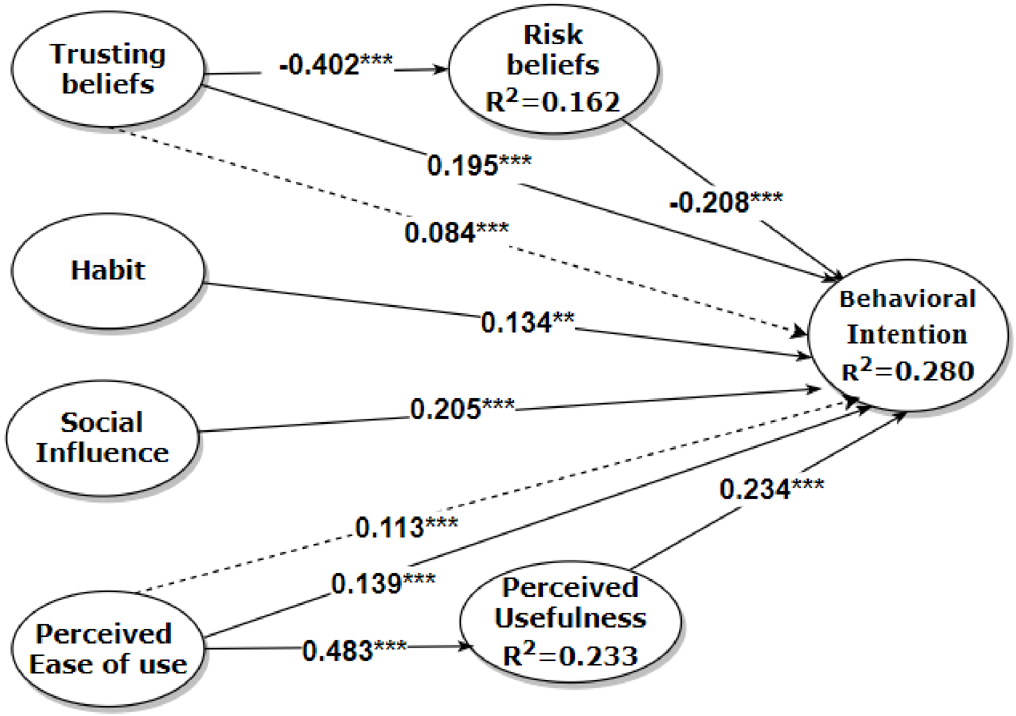

Figure 4 Path Diagram Analysis
Note: *** p<0.001, ** p<0.01, * p<0.05
Note: Authored by the creator

Conclusions

This study examined the primary factors affecting students' intention to use facial recognition systems within a smart campus setting. A conceptual framework was established with eight hypotheses to investigate the interactions between Trusting Beliefs (TB), Risk Beliefs (RB), Habit (HT), Social Influence (SI), Perceived Ease of Use (PEU), Perceived Usefulness (PU), and Behavioral Intention (BI). Data was collected using a questionnaire distributed to 500 students who possess high information technology literacy. Confirmatory Factor Analysis (CFA) was conducted to assess the reliability and validity of the conceptual framework. Additionally, Structural Equation Modeling (SEM) was utilized to identify key factors influencing satisfaction, with all proposed hypotheses being confirmed.

The results reveal that trusting beliefs are pivotal in shaping students' willingness to use the facial recognition system. Greater trust in the system is associated with a higher intention to use it. Risk beliefs and habitual usage also significantly affect behavioral intention. Specifically, students who have high trust in the system tend to perceive fewer risks, which enhances their intention to use it. Furthermore, habitual use of the system influences students' behavioral intentions. Social influence and perceived ease of use are also critical determinants of students' intention to use the system. Peer pressure and the system's usability have a substantial impact on this intention. Finally, perceived usefulness has a direct positive effect on behavioral intention, indicating that students are more inclined to use the system if they find it beneficial.

Table 8 Hypothesis Result of the Structural Equation Modeling

Hypothesis	Standardized Path Coefficient(β)	S.E.	T-Value	Result
H1	0.279	0.042	3.601***	Supported

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Hypothesis	Standardized Path Coefficient(β)	S.E.	T-Value	Result
H2	-0.402	0.048	-8.306***	Supported
H3	-0.208	0.043	-3.823***	Supported
H4	0.134	0.036	2.751**	Supported
H5	0.205	0.039	4.071***	Supported
H6	0.252	0.049	0.018*	Supported
H7	0.483	0.054	9.090***	Supported
H8	0.234	0.05	3.875***	Supported

Recommendation

This study identifies several key factors influencing students' willingness to adopt facial recognition systems within the smart campus environment at Xihua University. To enhance adoption rates and improve user experience, the following recommendations are proposed:

Enhance Trust Beliefs (H1 and H2): To bolster trust, universities should implement robust security measures, including strong encryption methods such as Advanced Encryption Standard (AES) and multi-factor authentication. Regular privacy impact assessments should be conducted to identify and mitigate potential risks associated with facial recognition technology. Additionally, fostering a culture of trust involves engaging various stakeholders—faculty, staff, administrators, and parents—in privacy education programs and communicating the technical safeguards implemented to protect personal data.

Address Risk Beliefs (H3): Effective communication about security measures is crucial. Universities should provide comprehensive information regarding data protection practices and legal guidelines. Developing a clear communication strategy that outlines data collection, storage, and protection practices is essential. Employ multiple communication channels and conduct interactive sessions to address privacy concerns and ensure transparency.

Promote Habit Formation (H4): To facilitate the adoption of facial recognition technology, universities should introduce students to these systems through orientation and training sessions. Integrating technology into routine campus activities, such as automated check-ins and attendance tracking, can encourage habitual use.

Leverage Social Influence (H5): Encourage senior students and influential campus figures to share their positive experiences with the facial recognition system. Their endorsements can create a favorable perception and drive broader acceptance among the student body.

Emphasize Perceived Ease of Use (H6 and H7): Ensure that the facial recognition system features an intuitive and user-friendly interface. Provide detailed user manuals and technical support to assist users. Regular updates to the technology should be made to keep pace with advancements, and user feedback should be utilized to identify areas for improvement.

Highlight Perceived Usefulness (H8): Clearly articulate the benefits of the facial recognition system, such as enhanced campus security, streamlined access processes, and increased overall efficiency. Utilize case studies and real-life examples to demonstrate the tangible advantages of the system. Additionally, explore opportunities to integrate facial recognition technology with other campus systems, such as learning management systems and student information systems, to enhance functionality and create a seamless user experience.

By implementing these recommendations, universities can improve the adoption and satisfaction associated with facial recognition systems in smart campus environments. Engaging a broad range of stakeholders, addressing both immediate and long-term needs, and ensuring transparent communication will contribute to a more effective and user-centered implementation of this technology.

Limitations and Further Exploration

This study is subject to several limitations that could impact the generalizability of its results. First,

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the study's sample limitations include its focus on a specific student population at Xihua University, which may not fully represent the broader student body or other educational settings. Xihua University, located in Chengdu, China, has a distinct cultural, technological, and educational environment that might differ significantly from other institutions. This localized context may influence the generalizability of the results. For instance, cultural attitudes towards privacy and technology adoption can vary widely, potentially affecting how students at Xihua University perceive and accept facial recognition systems compared to students in different regions or educational contexts. Second, the study relies on self-reported data, which may be subject to social desirability bias or inaccuracies in self-assessment. Participants might overstate their acceptance or underreport their concerns due to the desire to present themselves favorably. Additionally, the cross-sectional design of the study restricts the ability to infer causal relationships between variables. While the study identifies correlations between factors, it does not account for changes in perceptions over time or causal dynamics. Additionally, the framework used only includes seven variables, potentially omitting other relevant factors.

Future research should focus on three key areas. First, consider a wider sample and contextual diversity: Future research should aim to include more diverse samples from different educational settings, including vocational schools, private institutions, and universities in different geographic regions. This approach will help determine whether the factors that influence behavioral intentions for facial recognition systems are consistent across contexts or if there are significant differences. Second, conduct longitudinal research: Incorporating a longitudinal design can provide insight into how students' perceptions and behavioral intentions evolve. As students become more familiar with facial recognition technology, tracking changes in trust, perceived usefulness, and other factors will provide more insight into long-term impacts and potential shifts in user attitudes. Track students' technology adoption behaviors and intentions throughout their learning cycle from enrollment to graduation. In addition, add other variables and expand the conceptual framework: Future research should consider other variables that may influence behavioral intentions, such as the role of personal data management habits, ethical considerations, and campus culture. Exploring these factors can provide a more comprehensive understanding of the broader impact of deploying biometric technology in educational settings. Enhance understanding of user acceptance and understand how various factors interact to shape students' behavioral intentions for biometric technology.

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