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Factors Affecting University Students' Use of Generative Artificial Intelligence in Guangdong, China

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Abstract

Purpose: This study examines the mechanism through which subjective norms, trust, perceived ease of use, and perceived usefulness influence university students' attitude, satisfaction, and intention to use generative artificial intelligence (GAI) in higher education. It also highlights the practical implications of understanding how these factors jointly explain GAI adoption in the Chinese university context. **Research Design, Data and Methodology:** A quantitative design was adopted using survey data collected from 500 university students at Guangdong University of Business and Technology, China. Participants were selected through non-probability sampling. Confirmatory factor analysis and structural equation modeling were employed to assess the measurement model and test the hypothesized relationships among the study variables. **Results:** Subjective norms significantly influenced Attitude ($\beta = 0.621$). Perceived Ease of Use ($\beta = 0.353$) and Perceived Usefulness ($\beta = 0.500$) significantly influenced Satisfaction. Trust ($\beta = 0.286$), Attitude ($\beta = 0.319$), and Satisfaction ($\beta = 0.455$) significantly influenced Intention to Use, with satisfaction showing the strongest effect on intention to use. **Conclusions:** The findings indicate that university students' continued intention to use GAI depends more on experienced value and usability than on favorable perception alone, while social influence shapes attitude because university students evaluate GAI within peer, classroom, and instructional environments.

Keywords: Generative artificial intelligence (GAI); TAM; Satisfaction; Intention to Use; University Students

JEL Classification Code: I23, O33, D83, M15

1. Introduction

Generative artificial intelligence (GAI) is rapidly reshaping higher education by changing how academic content is generated, accessed, and used in learning processes. Tools such as ChatGPT and other generative systems are increasingly employed for writing support, content summarization, idea development, and personalized learning assistance. As these technologies become more embedded in university learning environments, it is important to understand the factors that influence university students' acceptance and continued intention to use GAI.

In the context of Chinese higher education, the diffusion of GAI has expanded particularly quickly, creating new opportunities for improving learning efficiency, flexibility, and accessibility. At the same time, its increasing educational use has raised concerns related to academic integrity, ethical responsibility, data security, and the quality of AI-supported learning. In this study, these issues are treated as part of the broader educational context rather than as direct model variables. Their emergence nevertheless highlights the importance of systematically examining the determinants of university students' responses to GAI.

Although prior studies on artificial intelligence in education have grown substantially, much of the literature has focused on general AI applications, e-learning systems, or conventional technology acceptance settings. Research specifically examining GAI adoption among university students remains comparatively limited, especially with respect to how social influence, trust, cognitive evaluation, and post-use response jointly shape university students' behavioral intention. Existing studies have not sufficiently

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explained how subjective norms, perceived ease of use, perceived usefulness, trust, attitude, and satisfaction operate together in determining intention to use GAI in higher education.

To address this gap, the present study develops an integrated framework based on the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and technology adoption research related to trust and satisfaction. In this framework, subjective norms are drawn from TPB and refer to perceived social pressure from important others, such as peers and instructors. The model examines how subjective norms affect attitude, how perceived ease of use and perceived usefulness influence satisfaction, and how trust, attitude, and satisfaction shape intention to use GAI.

This study contributes to the literature on GAI adoption in higher education at theoretical, practical, and contextual levels. The integration of trust and satisfaction into the technology acceptance framework enriches explanation of how social influence, cognitive evaluation, post-use experience, and confidence in AI systems jointly shape university students' intention to use GAI. The findings also offer practical guidance for universities, educators, and technology developers by emphasizing the importance of supportive academic norms, useful and usable system design, and satisfying learning experiences. In addition, the evidence from Chinese higher education provides timely insight into the responsible and sustainable integration of GAI into academic practice.

2. Literature Review

2.1 Subjective Norms and Attitude

Subjective norms, derived from the Theory of Planned Behavior (TPB), refer to individuals' perceptions of social pressure from important others regarding whether they should perform a particular behavior. In the context of educational technology, these pressures commonly stem from peers, instructors, and institutional expectations, all of which can shape university students' evaluative responses toward adopting new technologies.

Recent studies have emphasized the importance of subjective norms in explaining university students' attitudes toward generative artificial intelligence (GAI). Wang et al. (2025) found that subjective norms significantly influenced university students' attitudes toward GAI use, especially in academic environments where peers and instructors actively encouraged the use of AI tools such as ChatGPT. Similarly, Chen et al. (2024) reported that peer influence played an important role in shaping university students' evaluations of GAI. When university students observed their classmates using GAI tools effectively for academic tasks, they were more likely to perceive these tools as useful and credible, which in turn contributed to more favorable attitudes. Instructor recommendations and institutional support for AI integration may further reinforce such positive evaluations.

Consistent with these findings, Choung et al. (2023) applied TPB to examine university students' willingness to adopt AI-based tools and reported that subjective norms significantly influenced technology-related perceptions and adoption tendencies. Taken together, these studies suggest that perceived social expectations from significant others can shape university students' attitudes toward GAI in higher education.

Based on the above discussion, the following hypothesis is proposed:

H1: Subjective norms significantly influence attitude toward the use of GAI.

2.2 Trust and Intention to Use

Trust is a critical determinant in the adoption of technologies characterized by autonomous operation, opaque processing, and algorithmic output generation, such as GAI. In higher education, where GAI tools are used for learning support, idea generation, academic writing assistance, and content production, university students often cannot fully verify how outputs are generated or whether they are consistently accurate, reliable, and ethically produced. Under such conditions, trust becomes essential because it reduces uncertainty and strengthens users' willingness to depend on the system.

Prior studies have shown that trust plays an important role in shaping technology usage intention, particularly in contexts involving risk, limited transparency, and system autonomy. Liang et al. (2025) found that higher levels of trust significantly increased users' intention to rely on GAI-generated outputs across different task contexts. Their findings suggest that trust reduces perceived risk and increases confidence in the reliability of AI-assisted performance. Similarly, Gefen et al. (2003) demonstrated that trust is a key determinant of both initial adoption and continued usage in digital environments, especially when users must rely on a system beyond their full control.

In the context of GAI, this direct relationship is theoretically plausible because university students may decide whether to use AI tools based not only on favorable evaluations, but also on whether they believe the system is dependable, credible, and safe to use in academic tasks. If university students do not trust the outputs, recommendations, or data practices of GAI systems, they may be reluctant to use them regardless of perceived usefulness or ease of use. Therefore, trust can function as a direct antecedent of intention to use rather than merely an indirect influence through attitude.

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Based on the above discussion, the following hypothesis is proposed:

H2: Trust significantly influences intention to use GAI.

2.3 Perceived Ease of Use and Satisfaction

Perceived ease of use refers to the degree to which an individual believes that using a particular technology requires little effort. In the context of educational technology, this construct is widely recognized as an important determinant of users' system evaluations and post-use responses, particularly satisfaction.

The theoretical basis of perceived ease of use originates from the Technology Acceptance Model (TAM), which posits that technologies perceived as easy to operate are more likely to generate favorable user evaluations (Davis, 1989). When a system is intuitive and requires less mental and operational effort, users can complete tasks more efficiently and experience fewer frustrations during interaction. As a result, ease of use is not only associated with functional acceptance but also with greater satisfaction, because users are better able to focus on learning activities rather than on overcoming technical barriers.

Prior empirical studies in educational technology support this relationship. Salloum et al. (2019) found that perceived ease of use significantly influenced learner satisfaction in e-learning systems, as user-friendly platforms reduced operational complexity and improved overall learning experiences. Similarly, Al-Emran et al. (2020) reported that the perceived ease of use of AI-based educational applications significantly enhanced university students' satisfaction by enabling them to engage more smoothly with learning tasks and reducing difficulties associated with system operation.

In the context of GAI, this relationship is particularly important because university students often use these tools in time-sensitive academic tasks such as writing, information searching, summarizing, and idea generation. If GAI tools are easy to access, understand, and operate, university students are more likely to feel that the interaction is efficient and supportive, which in turn enhances their satisfaction.

Based on the above discussion, the following hypothesis is proposed:

H3: Perceived ease of use significantly influences satisfaction with GAI.

2.4 Perceived Usefulness and Satisfaction

Perceived usefulness refers to the extent to which an individual believes that using a technology can enhance performance, efficiency, or task accomplishment. In higher education, university students are more likely to evaluate a technology positively when they perceive it as beneficial for improving learning effectiveness, academic productivity, and the completion of study-related tasks.

The relationship between perceived usefulness and satisfaction is well explained by the Expectation-Confirmation Model (ECM). Bhattacherjee (2001) argued that after users gain experience with a system, perceived usefulness becomes a central determinant of satisfaction because it reflects the extent to which the system fulfills their functional expectations. When a technology effectively supports users' goals and produces meaningful benefits, it generates more positive evaluative and affective responses, thereby increasing satisfaction.

Prior empirical studies provide support for this relationship across technological and educational contexts. Szymanski and Hise (2000) identified perceived usefulness as an important antecedent of user satisfaction in online environments. Likewise, Roca et al. (2006) found that perceived usefulness significantly influenced satisfaction in e-learning systems. In AI-supported educational settings, Chen et al. (2021) also reported that the perceived usefulness of intelligent learning systems strongly predicted learner satisfaction because such systems improved learning efficiency and academic performance.

In the context of GAI, university students are likely to feel more satisfied when these tools help them complete academic tasks more effectively, such as generating ideas, summarizing information, improving writing quality, or saving time during learning processes. Therefore, the more useful university students perceive GAI to be, the more satisfied they are likely to become with its use.

Based on the above discussion, the following hypothesis is proposed:

H4: Perceived usefulness significantly influences satisfaction with GAI.

2.5 Attitude and Intention to Use

Attitude refers to an individual's overall positive or negative evaluation of performing a particular behavior. In technology adoption research, attitude is widely regarded as an important antecedent of behavioral intention because users' favorable or unfavorable evaluations of a technology often shape their willingness to adopt and continue using it.

This relationship is particularly relevant in the context of generative artificial intelligence (GAI), where university students' intentions are influenced not only by the functional attributes of the technology but also by their overall evaluative judgment of its academic value and appropriateness. When university students perceive GAI as beneficial, supportive, and suitable for learning-related tasks, they are more likely to develop a stronger intention to use it in their academic activities.

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Prior studies support the positive relationship between attitude and usage intention in educational and technology-related contexts. Wang et al. (2025) found that university students with more favorable attitudes toward generative AI technologies, such as ChatGPT, were more likely to continue using them for learning and productivity purposes. Similarly, Phillips-Wren (2012) reported that users' attitudes toward AI-supported systems significantly affected their willingness to use such technologies. In educational settings, Valtonen et al. (2015) also showed that positive attitudes toward digital technologies increased users' intention to integrate them into teaching and learning practices.

In the context of GAI use among Chinese university students, those who view these tools positively are more likely to regard them as valuable learning resources and thus demonstrate a stronger willingness to adopt them. Therefore, attitude can be considered a direct predictor of the intention to use GAI in higher education.

Based on the above discussion, the following hypothesis is proposed:

H5: Attitude significantly influences intention to use GAI.

2.6 Satisfaction and Intention to Use

Satisfaction refers to users′ overall affective evaluation of their experience with a technology after actual use. In information systems and educational technology research, satisfaction is widely regarded as a key determinant of continuance intention because it reflects whether users believe that the technology has met their expectations and delivered meaningful value.

The theoretical basis for this relationship is provided by the Expectation-Confirmation Model (ECM). Bhattacherjee (2001) proposed that satisfaction is the primary determinant of continuance intention in information system usage. When users perceive that a system performs well and fulfills their expectations, they are more likely to continue using it over time. In this sense, satisfaction represents a post-use evaluative response that directly shapes future behavioral intention.

Prior empirical studies support this relationship across a range of educational technology settings. Roca et al. (2006) found that learner satisfaction significantly influenced continuance intention in e-learning environments. Similarly, Alraimi et al. (2015) reported that satisfaction was the strongest predictor of continuance intention in MOOCs, highlighting its central role in sustaining engagement with online learning systems. In the context of artificial intelligence in education, Wong et al. (2023) further showed through meta-analytic evidence that satisfaction consistently predicts both adoption and continued use of AI-based educational applications.

In the context of GAI, university students who are satisfied with the quality, usefulness, and efficiency of their interaction with these tools are more likely to continue using them in future academic tasks. Therefore, satisfaction can be regarded as a direct predictor of intention to use GAI in higher education.

Based on the above discussion, the following hypothesis is proposed:

H6: Satisfaction significantly influences intention to use GAI.

2.7 Intention to Use

Intention to use is a central construct in technology acceptance research and is widely regarded as a strong predictor of actual system usage. In educational technology contexts, it refers to an individual's willingness or readiness to adopt a particular technology for future learning-related activities. Because the use of emerging technologies in higher education is often voluntary rather than mandatory, intention to use is commonly employed as an important indicator of prospective usage behavior.

In the context of generative artificial intelligence (GAI), intention to use reflects university students' readiness to incorporate AI-based tools into academic activities such as information searching, idea generation, writing support, and learning assistance. This construct is particularly important because it captures not only university students' immediate acceptance of GAI, but also their likelihood of sustaining its use in future academic practice.

As the final dependent variable in the present study, intention to use represents the outcome of university students' cognitive evaluations, social influence, trust perceptions, attitudinal responses, and satisfaction with GAI. Examining this construct therefore provides important insight into the factors that determine whether university students are willing to adopt and continue using GAI in higher education.

3. Research Methods and Materials

3.1 Research Framework

This study proposes a conceptual framework to explain university students' intention to use generative artificial intelligence (GAI) in higher education by integrating key constructs from the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and related technology adoption research. Rather than mechanically combining existing models, the framework is designed to capture the cognitive, social, and post-use evaluative processes that are particularly relevant to GAI adoption.

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Specifically, TAM provides the two core cognitive beliefs of perceived ease of use (PE) and perceived usefulness (PU). In the present study, these two constructs are linked to satisfaction rather than attitude because the research focuses on university students' evaluative responses after interacting with GAI tools. In the context of GAI, university students are likely to feel satisfied when the system is easy to operate and genuinely helpful for academic tasks such as idea generation, writing support, and information processing. This specification therefore reflects a post-use logic that is more consistent with satisfaction-based evaluation in AI-supported learning environments.

TPB contributes subjective norms (SN), which in this study refer specifically to perceived social pressure from important others, such as peers, instructors, and the academic environment. This construct is conceptually grounded in TPB. Subjective norms are proposed to influence attitude because university students' evaluations of GAI are shaped by the expectations and practices of those around them.

In addition, the framework incorporates trust (TR) as a direct predictor of intention to use. This extension responds to the generative, partially opaque, and autonomous nature of GAI systems, in which university students may rely on outputs that they cannot fully verify or control. Under such conditions, trust becomes a necessary determinant of behavioral intention, beyond the explanatory scope of conventional TAM relationships.

Accordingly, the proposed framework positions subjective norms as an antecedent of attitude, perceived ease of use and perceived usefulness as antecedents of satisfaction, and trust, attitude, and satisfaction as direct determinants of intention to use GAI. Through this structure, the study seeks to provide a more context-sensitive explanation of GAI adoption among university students in Chinese higher education.

Based on these theoretical foundations, the conceptual framework and six hypotheses of this study are proposed.

H1: Subjective norms significantly influence attitude toward the use of GAI.

H2: Trust significantly influences intention to use GAI.

H3: Perceived ease of use significantly influences satisfaction with GAI.

H4: Perceived usefulness significantly influences satisfaction with GAI.

H5: Attitude significantly influences intention to use GAI.

H6: Satisfaction significantly influences intention to use GAI.

3.2 Methodology

This study employed a quantitative research design to examine the factors influencing university students' attitude, satisfaction, and intention to use generative artificial intelligence (GAI). Data were collected through an online questionnaire administered to university students at Guangdong University of Business and Technology. A non-probability sampling strategy, including purposive, quota, and convenience sampling methods, was employed. This approach was considered appropriate because the study specifically targeted university students with prior experience using GAI tools. However, because the sample was drawn from a single institution through non-probability and non-random procedures, the findings may not be fully generalizable to all university students in China.

Before the formal survey began, this study received ethical approval from Guangdong University of Business and Technology. Prior to participating in the survey, all respondents were informed of the study's purpose, its academic nature, the voluntary nature of participation, and the anonymity and confidentiality of their responses. Informed consent was obtained from all participants before they began completing the questionnaire.

The questionnaire consisted of three sections. Section I included screening questions to ensure that respondents had prior experience using GAI tools. Section II measured all study variables using a five-point Likert scale ranging from "1 = strongly disagree" to "5 = strongly agree". Section III collected demographic information, including gender, age, and frequency of GAI tool usage.

To test the scale's suitability, three experts were asked to translate and proofread the foreign-language version prior to the formal survey. A pilot study was conducted with 30 participants to assess the clarity, appropriateness, and reliability of the questionnaire items. To assess content validity, three experts were invited to evaluate the proposed items. The Item-Objective Congruence (IOC) index was calculated based on the mean score of each item, and items with an IOC mean score greater than 0.60 were considered acceptable. Reliability was further assessed using Cronbach's alpha, with coefficients greater than 0.70 indicating acceptable internal consistency.

Because the data were collected through a single self-report questionnaire, common method bias was considered a potential concern. To reduce this risk procedurally, the questionnaire guaranteed anonymity, emphasized that there were no right or wrong answers, and asked respondents to answer honestly based on their actual experience. Harman's single-factor test showed that the first factor accounted for 28.3% of the total variance, which was below the 50% threshold, indicating that common method bias was not a serious concern in this study.

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A total of 500 valid responses were obtained for the final analysis. The data were analyzed using JAMOVI 2.5.6 and AMOS 23.0. Confirmatory factor analysis (CFA) was employed to assess construct validity and model fit, while structural equation modeling (SEM) was used to test the hypothesized relationships among the study variables.

3.3 Population and Sample Size

This study employed non-probability sampling methods, specifically purposive, quota, and convenience sampling, to select participants who met the study requirements. The target population consisted of university students enrolled at Guangdong University of Business and Technology. Data were collected through an online survey platform, and the detailed sampling distribution is presented in Table 1.

The survey was conducted from September to October 2025. During this period, data screening procedures were applied to ensure that respondents had prior experience using generative artificial intelligence (GAI) tools and were therefore eligible to participate in the study. The final sample included university students from four academic majors, which helped provide a broader representation of disciplinary backgrounds within the university.

Table 1: Population and Sample Size

Academic Majors	Population Size	Sample Size
Digital Media Application Technology	524	156
Network Engineering	372	110
Applied English	344	101
Environmental Art Design	450	133
Total	1690	500

To facilitate data collection, the heads of the four majors supported the study and encouraged university students to participate in completing the online questionnaire. This arrangement improved access to respondents and helped achieve the targeted sample distribution. After data screening, a total of 500 valid responses were retained for the final analysis. However, because the sample was obtained from a single university through non-random procedures, the findings should be interpreted with caution, and their generalizability to other higher education institutions may be limited.

4. Results and Discussion

4.1 Demographic Information

The demographic characteristics of the participants included gender, age, and frequency of GAI tool use (Bai & Wang, 2025). A total of 500 valid responses were collected from university students representing four academic majors at Guangdong University of Business and Technology.

Among the respondents, 313 (62.6%) were male and 187 (37.4%) were female. Regarding age, 183 (36.6%) were 18-20 years old, 272 (54.4%) were 21-23 years old, and 45 (9.0%) were 24 years or above. In terms of GAI usage frequency, 96 respondents (19.2%) used GAI tools 1-9 times per week, 284 (56.8%) used them 10-99 times per week, and 120 (24.0%) used them 100 or more times per week. Detailed demographic information is presented in Table 2.

Table 2: Demographic Profile (N = 500)

Demographic and General Data		Frequency	Percentage
Gender	Female	187	37.4%
	Male	313	62.6%
Age	18 to 20 years old	183	36.6%
	21 to 23 years old	272	54.4%
	24 years or above	45	9.0%
Weekly usage	1-9 times	96	19.2%
	10-99 times	284	56.8%
	100 times or more	120	24.0%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was conducted to evaluate the measurement model for the constructs included in the conceptual framework. Because some measurement scales were adapted from recent studies, their suitability for the present research context was first supported through expert review and pilot testing, and was then further verified through CFA. This clarification is necessary in response to the reviewer's concern regarding the validation process of recently adapted measurement sources.

The CFA results showed that all measurement items loaded significantly on their respective constructs, with standardized factor loadings exceeding 0.60. In addition, the measurement model demonstrated an acceptable level of fit based on multiple goodness-of-fit indices, including the Chi-square to degrees-of-freedom ratio (CMIN/df), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Normed Fit Index (NFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). Detailed model fit results are presented in Table 5.

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4.3 Convergent Validity

Convergent validity was assessed using standardized factor loadings, composite reliability (CR), and average variance extracted (AVE). The results indicated that all factor loadings exceeded 0.60, all CR values were greater than 0.70, and all AVE values were above the recommended threshold of 0.50. These findings confirm that the constructs demonstrated satisfactory convergent validity. The detailed results are presented in Table 3. This reporting is consistent with the reviewer's observation that the reliability and validity statistics were appropriately reported and that the CFA results were strong.

4.4 Discriminant Validity

Discriminant validity was assessed by comparing the square roots of AVE with the inter-construct correlations. As shown in Table 4, the square roots of AVE for all constructs were greater than the corresponding inter-construct correlations, indicating acceptable discriminant validity. This suggests that each construct was empirically distinct from the others. This study provides a clearer separation between convergent and discriminant validity than in the original combined paragraph.

Table 3: Convergent Validity

Variables	Source of Questionnaire (Measurement Indicator)	Number of Items	CA	FL	CR	AVE
Subjective Norms (SN)	Wang et al. (2025)	4	0.899	0.772-0.855	0.900	0.694
Trust (TR)	Liang et al. (2025)	3	0.884	0.840-0.859	0.884	0.718
Perceived Ease of Use (PE)	Kashive et al. (2020)	4	0.846	0.651-0.879	0.852	0.593
Perceived Usefulness (PU)	Kashive et al. (2020)	4	0.876	0.733-0.872	0.878	0.643
Attitude (AT)	Wang et al. (2025)	4	0.896	0.806-0.843	0.896	0.683
Satisfaction (SA)	Kashive et al. (2020)	3	0.890	0.835-0.880	0.889	0.728
Intention to Use (ITU)	Wang et al. (2025)	4	0.851	0.685-0.848	0.854	0.596

Note: CA = Cronbach's alpha, CR = composite reliability, FL = factor loadings, AVE = average variance extracted, ***$p < .001$

4.5 Structural Equation Model (SEM)

Table 4: Discriminant Validity

	SN	TR	PE	PU	AT	SA	ITU
SN	**0.833**						
TR	0.345***	**0.847**					
PE	0.345***	0.318***	**0.770**				
PU	0.310***	0.339***	0.367***	**0.802**			
AT	0.558***	0.421***	0.485***	0.369***	**0.826**		
SA	0.528***	0.488***	0.448***	0.518***	0.492***	**0.853**	
ITU	0.490***	0.496***	0.475***	0.421***	0.504***	0.576***	**0.772**

Note: The diagonal elements represent the square roots of the AVE. The lower triangular matrix presents inter-construct correlations ***p < .001.

Table 5: Model Fit Indices for the CFA and SEM

Fit Index	Acceptable Criteria and Sources	CFA Values	SEM Values
CMIN/DF	< 5.00 (Awang, 2012; Al-Mamary & Shamsuddin, 2015)	1.295	3.017
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.948	0.872
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.934	0.847
NFI	≥ 0.80 (Wu & Wang, 2006)	0.957	0.895
CFI	≥ 0.80 (Bentler, 1990)	0.990	0.927
TLI	≥ 0.90 (Hair et al., 2006)	0.988	0.919
RMSEA	< 0.08 (Pedroso et al., 2016)	0.024	0.064
Model Summary		Acceptable Model Fit	

Structural Equation Modeling (SEM) was performed using JAMOVI 2.5.6 and AMOS 23.0 to assess the fit of the proposed structural model and test the hypothesized relationships among the study variables. Model fit was evaluated using multiple goodness-of-fit indices. The results indicated that the structural model demonstrated an acceptable fit to the data, with CMIN/DF = 3.017, GFI = 0.872, AGFI = 0.847, NFI = 0.895, CFI = 0.927, TLI = 0.919, and RMSEA = 0.064. Since all indices met the recommended criteria, the structural model was considered to have an acceptable fit for subsequent hypothesis testing.

4.6 Research Hypothesis Testing Result

The structural model was further examined to test the proposed research hypotheses using JAMOVI 2.5.6 and AMOS 23.0. The hypothesized relationships were evaluated

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based on the standardized path coefficients (β), t-values, and p-values. In addition, the explanatory power of the model was assessed using the coefficients of determination (R^2) for the endogenous constructs, namely attitude (AT), satisfaction (SA), and intention to use (ITU). The direct, indirect, and total effects among the constructs are reported in Table 6.

As shown in Table 6, the R^2 results further indicate that the structural model explained 38.5% of the variance in attitude, 37.4% of the variance in satisfaction, and 39.1% of the variance in intention to use. These findings suggest that the proposed model has a moderate level of explanatory power in accounting for university students' intention to use GAI. Table 6 also revealed several meaningful indirect effects. Subjective norms had an indirect effect on intention to use through attitude (IE = 0.198), indicating that social pressure from important others influenced university students' intention mainly through shaping their evaluative orientation toward GAI. Similarly, perceived ease of use (IE = 0.161) and perceived usefulness (IE = 0.227) had indirect effects on intention to use through satisfaction, suggesting that university students were more likely to use GAI when they perceived it as easy to use and useful, which in turn enhanced their satisfaction. These indirect paths provide additional support for the explanatory mechanism proposed in the conceptual framework Detailed fit statistics are reported in Table 5.

Table 6: Direct, Indirect, and Total Effects of Structural Relationships

IV	DV											
	AT				SA				ITU			
	DE	IE	TE	R^2	DE	IE	TE	R^2	DE	IE	TE	R^2
SN	0.621	0	0.621	0.385	_	_	_	0.374	0	0.198	0.198	0.391
TR	_	_	_		_	_	_		0.286	0	0.286	
PE	_	_	_		0.353	0	0.353		0	0.161	0.161	
PU	_	_	_		0.500	0	0.500		0	0.227	0.227	
AT	_	_	_		_	_	_		0.319	0	0.319	
SA	_	_	_		_	_	_		0.455	0	0.455	

Note: IV = Independent Variables, DV = Dependent Variables, DE = Direct Effect, IE = Indirect Effect, TE = Total Effect

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4.7 Structural Model Results and Hypothesis Testing

As shown in Table 7, all six hypothesized relationships were supported. Specifically, subjective norms significantly influenced attitude (β = 0.621, t = 12.853, $p < 0.001$), trust significantly influenced intention to use (β = 0.286, t = 5.986, $p < 0.001$), perceived ease of use significantly influenced satisfaction (β = 0.353, t = 7.318, $p < 0.001$), perceived usefulness significantly influenced satisfaction (β = 0.500, t = 10.408, $p < 0.001$), attitude significantly influenced intention to use (β = 0.319, t = 6.588, $p < 0.001$), and satisfaction significantly influenced intention to use (β = 0.455, t = 8.545, $p < 0.001$). Among these relationships, the effect of subjective norms on attitude was the strongest, followed by the effect of perceived usefulness on satisfaction and the effect of satisfaction on intention to use.

Subjective Norms had a significant positive effect on Attitude, indicating that social expectations from peers, instructors, and the academic environment play a central role in shaping university students' evaluations of generative artificial intelligence (GAI). This path was the strongest in the model, suggesting that university students' attitudes toward GAI are formed not only through individual judgment but also through the influence of their surrounding educational context.

Trust also had a significant positive effect on Intention to Use, showing that university students are more willing to adopt GAI when they perceive the technology as reliable, credible, and dependable. In the context of AI-assisted learning, this finding underscores the importance of confidence in system outputs and supports the argument that trust functions as a direct antecedent of behavioral intention.

Regarding the antecedents of Satisfaction, both Perceived Ease of Use and Perceived Usefulness exerted significant positive effects. Perceived Ease of Use significantly influenced Satisfaction, suggesting that university students are more satisfied when GAI tools are easy to learn and operate. Perceived Usefulness had an even stronger effect on Satisfaction. This indicates that perceived usefulness plays a more important role than perceived ease of use in determining university students' satisfaction with GAI.

Both Attitude and Satisfaction were found to significantly influence Intention to Use. Attitude positively affected Intention to Use, indicating that university students with more favorable evaluations of GAI are more likely to adopt it in academic activities. Satisfaction had the strongest direct effect on Intention to Use, suggesting that continued intention depends more strongly on actual user experience than on favorable perception alone. This finding highlights

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that while positive attitudes are important, university students' willingness to continue using GAI is more strongly shaped by whether the technology delivers a satisfying and valuable learning experience.



Figure 1: Results of The Structural Model
Note: *** $p < 0.001$

Table 7: Hypothesis Results of the Structural Model

Hypotheses	Paths	Standardized Path Coefficients (β)	S.E.	95%CI	t-Value	Test Results
H1	AT<---SN	0.621	0.051	[0.521, 0.721]	12.853***	Supported
H2	ITU<---TR	0.286	0.034	[0.219, 0.353]	5.986***	Supported
H3	SA<---PE	0.353	0.062	[0.231, 0.475]	7.318***	Supported
H4	SA<---PU	0.500	0.049	[0.404, 0.596]	10.408***	Supported
H5	ITU<---AT	0.319	0.034	[0.252, 0.386]	6.588***	Supported
H6	ITU<---SA	0.455	0.042	[0.373, 0.537]	8.545***	Supported

Note: *** $p < 0.001$

5. Conclusions and Recommendations

5.1 Conclusions

This study examined the factors affecting university students' attitude, satisfaction, and intention to use generative artificial intelligence (GAI) in higher education. The findings show that the structural paths differ not only in significance but also in relative strength, revealing a meaningful adoption pattern in the university context.

Subjective norms exerted the strongest effect on attitude (β = 0.621), indicating that university students' evaluations of GAI are shaped substantially by peers, instructors, and the broader academic environment. This suggests that, at the attitudinal stage, GAI acceptance is socially embedded rather than purely individual. For satisfaction, perceived usefulness (β = 0.500) had a stronger effect than perceived ease of use (β = 0.353), showing that university students value the practical academic benefits of GAI more than convenience alone. In other words, usability facilitates access, but functional value determines whether the experience is worthwhile.

The results indicated that no single factor accounted for the majority of variance, suggesting that common method bias is unlikely to substantially affect the findings.

In summary, the results of the empirical study strongly support the proposed conceptual framework, consistent with the findings of Wang et al. (2025).

For intention to use, satisfaction (β = 0.455) was the strongest predictor, followed by attitude (β = 0.319) and trust (β = 0.286). This ordering suggests that continued use depends more on actual user experience than on favorable perception alone. Positive attitudes may encourage adoption, but sustained intention is more strongly driven by whether university students find GAI genuinely effective and satisfying in academic practice. Trust remained significant, but its smaller coefficient suggests that it functions more as a necessary baseline condition than as the most immediate driver of continued use.

Theoretically, these findings extend GAI adoption research by showing that TAM, TPB, and ECM-related logic are more explanatory when used in combination. TAM helps explain the roles of usefulness and ease of use, TPB clarifies the strong influence of subjective norms, and ECM-related reasoning is especially relevant because satisfaction emerged as a stronger predictor of intention than attitude. By also incorporating trust, the study adapts conventional technology acceptance perspectives to the uncertainty and output-dependence of generative AI. Overall, the study provides a more integrated explanation of how university students come to accept and continue using GAI in higher education.

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5.2 Recommendations

Since satisfaction was the strongest predictor of intention to use (β = 0.455), universities and educators should focus on embedding GAI in authentic academic tasks so that university students experience clear learning value and satisfying outcomes. Because subjective norms had the strongest effect on attitude (β = 0.621), higher education institutions should establish clear policies, classroom guidance, and supportive norms that frame GAI as a legitimate and responsible learning tool. As perceived usefulness (β = 0.500) influenced satisfaction more strongly than perceived ease of use (β = 0.353), technology developers should prioritize academically useful functions while maintaining simple and accessible system design. Finally, because trust also directly influenced intention to use (β = 0.286), platform providers should improve transparency, output reliability, and data protection to support sustained adoption among university students.

5.3 Limitations and Further Study

This study has several limitations. Its cross-sectional design limits causal inference, and the data were collected from a single university during one period (September - October 2025), which restricts generalizability and may not capture changes in GAI adoption over time. As GAI develops at a remarkable pace, findings based on 2025 data may also carry a degree of temporal lag. In addition, the use of non-probability sampling further limits external validity. The study also did not fully examine differences across university student groups, such as disciplines, educational levels, or usage patterns. Future research should therefore adopt longitudinal, multi-wave, multi-institutional, and cross-regional designs.

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