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A Study on the Determinants of Generative AI Adoption among University Students: The Roles of Disciplinary Differences and Cognitive Readiness

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Abstract

Generative Artificial Intelligence (AI) is rapidly transforming higher education, yet existing Unified Theory of Acceptance and Use of Technology (UTAUT)-based studies have largely focused on general technology acceptance factors while paying limited attention to disciplinary differences and AI understanding. Addressing this gap, this study investigates university students' intention to use generative AI by incorporating academic major and AI understanding into the UTAUT framework. Survey data were collected from 224 students across diverse majors. The study examines the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on intention to use generative AI. Results show that performance expectancy, social influence, and facilitating conditions significantly affect intention, while effort expectancy does not. The effects are stronger among students in language, business, and education fields. Additionally, students with higher levels of AI understanding report stronger intentions to use generative AI.

요 약

생성형 인공지능(AI)은 고등교육을 빠르게 변화시키고 있으나, 기존 통합기술수용이론 기반 연구들은 주로 일반적인 기술수용 요인에 초점을 두어 전공 차이와 인공지능 이해도의 영향을 충분히 반영하지 못하였다. 이러한 한계를 보완하기 위해 본 연구는 전공 계열과 인공지능 이해도를 통합적으로 고려하여 대학생의 생성형 AI 이용의도에 영향을 미치는 요인을 규명한다. 다양한 전공의 대학생 224명을 대상으로 성과기대, 노력기대, 사회적 영향, 촉진조건의 영향을 분석하였다. 분석 결과, 성과기대, 사회적 영향, 촉진조건은 이용의도에 유의한 영향을 미쳤으나 노력기대는 그렇지 않았다. 이러한 영향은 어문, 경상, 교육 계열에서 더 강하게 나타났다. 또한 인공지능 이해도가 높을수록 이용의도가 높게 나타났다.

Keywords

AI understanding, generative AI, higher education, intention to use, social influence, technology acceptance

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Ⅰ. Introduction

Generative Artificial Intelligence (AI) has rapidly emerged as a transformative technology capable of producing human-like text, images, and code. It is fundamentally reshaping how individuals interact with information and knowledge systems. Recent advances in large language models and generative architectures have accelerated the diffusion of generative AI across diverse domains, including education, healthcare, creative industries, and professional work environments [1]-[5]. In higher education in particular, generative AI tools such as text-generation systems are increasingly used for learning support, idea generation, writing assistance, and problem solving, raising both opportunities and concerns for students, educators, and institutions [6][7].

Despite the growing presence of generative AI in academic settings, students' willingness to adopt and continuously use these tools remains uneven. Some students actively integrate generative AI into their learning routines. Others remain hesitant because of ethical concerns, uncertainty about appropriate use, or limited understanding of how such technologies function [8][9]. These mixed responses suggest that the adoption of generative AI cannot be explained solely by technological availability. Instead, students' perceptions, social environments, and institutional contexts play a critical role in shaping intention to use generative AI. Understanding these factors is therefore essential for promoting effective, responsible, and equitable integration of generative AI in higher education.

Technology adoption research has long emphasized the importance of users' cognitive and social evaluations in shaping acceptance of new technologies. The Unified Theory of Acceptance and Use of Technology is one of the most influential frameworks in technology adoption research. It explains intention formation and use behavior through key determinants such as performance expectancy, effort expectancy, social influence, and facilitating conditions [10][11]. This framework has been widely applied in educational technology contexts, including e-learning systems, mobile learning, and intelligent tutoring systems, demonstrating robust explanatory power [12]-[14]. However, generative AI differs from earlier educational technologies in that it performs complex cognitive tasks traditionally associated with human expertise, which may alter how students evaluate its usefulness, ease of use, and legitimacy.

Recent studies on generative AI adoption have begun to explore these dynamics, highlighting the continued relevance of perceived usefulness and social influence while reporting mixed findings regarding effort expectancy [15][16]. As university students increasingly possess high levels of digital fluency, ease of use may no longer function as a decisive adoption factor. Instead, perceived performance gains and normative acceptance within academic communities may exert stronger influence. This shift suggests the need to re-examine established adoption models in the specific context of generative AI.

In addition, existing research has paid limited attention to heterogeneity among student groups. Academic major represents a salient contextual factor that reflects disciplinary cultures, epistemological orientations, and task structures [17][18]. Students in language, business, or education fields may perceive generative AI as directly aligned with writing, communication, and pedagogical tasks, whereas students in engineering or medical fields may evaluate such tools through different criteria. Yet, few empirical studies have explicitly tested whether disciplinary background moderates the effects of core adoption determinants. Addressing this gap can enrich technology acceptance theory by incorporating academic context as a meaningful source of variation.

Another underexplored dimension is AI understanding, which refers to individuals' conceptual knowledge of AI capabilities, limitations, and social implications [19]. Emerging research on AI literacy suggests that greater understanding reduces uncertainty, enhances perceived control, and supports more informed engagement with AI technologies [8][20]. However, prior studies often treat AI understanding as a general antecedent or background characteristic, rather than examining whether intention to use generative AI differs systematically across levels of understanding. Investigating this issue is particularly important in educational settings, where AI literacy is increasingly viewed as a foundational competency.

Recent empirical studies have reported increasing adoption of generative AI in higher education while highlighting substantial variation across learning contexts and disciplinary backgrounds. For example, generative AI has been shown to support learning efficiency, creativity, and academic performance, although concerns regarding appropriate use and educational implications remain prevalent [6][7][9]. Furthermore, recent reviews suggest that adoption patterns are shaped not only by technology-related perceptions but also by contextual factors such as academic discipline and AI literacy [20]. Despite these developments, empirical evidence examining the combined roles of disciplinary context and AI understanding remains limited, particularly in the context of Korean university students.

Against this backdrop, the present study aims to examine university students' intention to use generative AI by integrating UTAUT variables with academic major and AI understanding. This study uses survey data from students enrolled in two-year, three-year, and four-year universities in South Korea. It examines the main effects of performance expectancy, effort expectancy, social influence, and facilitating conditions. It also investigates differences across academic major groups and levels of AI understanding. By doing so, this research seeks to extend technology acceptance theory to the emerging context of generative AI and provide evidence-based insights for scholars and practitioners navigating the evolving landscape of AI-enabled education.

Unlike prior UTAUT-based studies that primarily focus on the direct effects of technology acceptance factors, this study extends the existing literature in three important ways. First, it examines generative AI, a technology that performs complex cognitive tasks rather than merely supporting information access or communication. Second, it investigates whether the relationships between UTAUT variables and intention differ across academic disciplines, thereby incorporating disciplinary context into technology acceptance research. Third, it considers AI understanding as a cognitive readiness factor and examines whether intention to use generative AI varies according to different levels of AI understanding. These extensions provide a more comprehensive explanation of generative AI adoption in higher education and address limitations of prior technology acceptance studies.

Ⅱ. Theoretical Foundation and Research Model

This study is grounded in the Unified Theory of Acceptance and Use of Technology, which integrates cognitive, social, and contextual determinants to explain individuals' technology adoption decisions [10]. Drawing on expectancy-based theories and the Technology Acceptance Model, the framework emphasizes users' performance- and effort-related evaluations as key cognitive mechanisms shaping technology appraisal [21]. Social influence theory further explains how normative pressures and reference groups legitimize emerging technologies, particularly in learning environments [22]. Facilitating conditions extend this perspective by incorporating institutional and infrastructural support as enabling contexts for use behavior [23]. To account for heterogeneity among users, the model incorporates academic major as a contextual factor reflecting disciplinary cultures and task demands [17]. It also includes AI understanding as an individual capability that shapes how students interpret generative technologies [19]. Together, these elements form a coherent, theory-driven framework explaining intention formation toward generative AI.

2.1 Performance expectancy

Performance expectancy refers to the degree to which an individual believes that using a particular technology will help improve task performance [10]. In the context of emerging digital technologies, perceived performance gains have consistently been identified as a central cognitive driver shaping users' technology-related evaluations and motivations [21]. Prior studies on AI-based systems suggest that when users recognize clear benefits such as improved efficiency, accuracy, or learning outcomes, they are more likely to develop favorable perceptions toward adoption [2]. Recent empirical research on generative AI in educational and professional settings further indicates that expectations regarding productivity and learning enhancement play a decisive role in shaping usage decisions [15][16]. Accordingly, this study proposes the following hypothesis.

H1. Performance expectancy is positively related to the intention to use generative AI.

2.2 Effort expectancy

Effort expectancy refers to the degree to which an individual perceives that using a technology requires minimal effort and is easy to learn and operate [10]. In technology adoption research, perceived ease of use has long been recognized as a critical cognitive evaluation shaping users' willingness to engage with new systems, particularly during early stages of adoption [21]. Prior studies show that technologies perceived as intuitive and user-friendly reduce cognitive burden and uncertainty, thereby lowering psychological resistance to adoption [11]. Recent research on AI-based and intelligent systems further suggests that when users believe they can quickly understand and apply such tools, they are more inclined to consider them as viable options for regular use [16][24]. Therefore, the following hypothesis is proposed.

H2. Effort expectancy is positively related to the intention to use generative AI.

2.3 Social influence

Social influence refers to the extent to which an individual perceives that important others believe a particular technology should be used [10]. Within social and behavioral theories, individuals often rely on normative cues from peers, instructors, or reference groups when forming evaluations of unfamiliar or emerging technologies [22]. Prior research in information systems consistently demonstrates that social pressure and peer endorsement play a meaningful role in shaping technology-related beliefs, particularly in collective or learning-oriented environments [11]. Recent studies on AI and digital learning tools further indicate that recommendations and usage norms within one's social context can legitimize technology use and reduce perceived risk [25][26]. Based on these arguments, the following hypothesis is developed.

H3. Social influence is positively related to the intention to use generative AI.

2.4 Facilitating conditions

Facilitating conditions refer to the degree to which an individual believes that organizational and technical resources exist to support the use of a technology [10]. In information systems research, access to adequate infrastructure, guidance, and technical support has been identified as a crucial contextual factor shaping users' confidence in engaging with new technologies [23]. Prior empirical studies indicate that when users perceive sufficient institutional support and compatibility with existing systems, uncertainty and perceived barriers to use are substantially reduced [11]. Recent research on AI-enabled learning environments similarly highlights that availability of resources and support mechanisms strengthens users' readiness to adopt advanced digital tools [27]. Accordingly, the following hypothesis is suggested.

H4. Facilitating conditions are positively related to the intention to use generative AI.

2.5 Major

Major refers to an individual's academic field of study, which reflects distinct disciplinary cultures, learning goals, and cognitive orientations toward technology use [17]. Prior research suggests that students from different majors develop heterogeneous perceptions of technology value and relevance based on disciplinary norms and task requirements [18]. Learners in engineering, business, or science-related majors may emphasize performance outcomes and functional utility. In contrast, students in humanities or social sciences may be more sensitive to social norms and contextual support [28]. Differences in curricular exposure and pedagogical practices further shape how students interpret ease of use and availability of resources when engaging with digital tools [29]. Recent studies on AI and learning technologies also indicate that disciplinary background conditions the salience of main factors in shaping adoption decisions [28][30]. Based on this theoretical reasoning, the present study puts forward the following hypothesis.

Following prior research on disciplinary cultures and knowledge structures [17][18], the present study grouped language, business, and education majors into one category and natural science, engineering, and medical majors into another. The former disciplines are generally characterized by communication-intensive, interpretive, and human-centered learning activities, where generative AI can directly support writing, content creation, and knowledge articulation. In contrast, the latter disciplines are more strongly oriented toward analytical, technical, and scientific problem-solving tasks. This classification was adopted to examine whether the relationships between UTAUT variables and intention to use generative AI differ across disciplinary contexts that involve distinct learning practices and technology-use expectations. Therefore, the following hypothesis is proposed.

H5. The relationships between the UTAUT variables and intention to use generative AI differ across academic major groups.

2.6 AI understanding

AI understanding refers to an individual's level of knowledge, familiarity, and conceptual comprehension of how AI systems function and are applied [19]. Prior research indicates that higher levels of AI-related knowledge enhance individuals' confidence, reduce uncertainty, and improve their ability to critically evaluate AI-driven tools [9][31]. Studies in educational and information systems contexts suggest that users with greater AI literacy are more capable of recognizing potential benefits and limitations, which shapes differentiated adoption patterns [8]. Variations in AI understanding lead to heterogeneous responses toward generative AI technologies across user groups. Taken together, the following hypothesis is formulated.

H6. There are significant differences in the intention to use generative AI according to levels of AI understanding.

III. Methodology

3.1 Instrument

Table 1. List of constructs and items

Construct	Item	Description	Source
Performance expectancy	PFM1	Using generative AI will be useful for my learning.	Venkatesh, Thong [11]
	PFM2	The use of generative AI will improve the efficiency of my learning.	
	PFM3	Generative AI will be useful to me.	
	PFM4	Using generative AI will enable me to complete my tasks more quickly.	
Effort expectancy	EFT1	I think generative AI is generally easy to use.	Venkatesh, Thong [11]
	EFT2	I think learning how to use generative AI is generally easy.	
	EFT3	Learning using generative AI will be easier than traditional learning methods.	
	EFT4	I think I can adapt to generative AI quickly.	
Social influence	SCL1	If I do not use generative AI, I will fall behind others in learning.	Venkatesh, Thong [11]
	SCL2	If I do not use generative AI, I will feel socially isolated.	
Facilitating conditions	FCL1	I have the knowledge necessary to use generative AI.	Venkatesh, Thong [11]
	FCL2	I have the resources necessary to use generative AI.	
	FCL3	I can use generative AI without help from others.	
Behavioral intention	BHV1	I will recommend using generative AI for learning to others.	Venkatesh, Thong [11]
	BHV2	I will actively use generative AI for learning in the future.	
	BHV3	I think using generative AI for learning will be beneficial.	
	BHV4	I think generative AI for learning is necessary for me.	
AI understanding	AIU1	I understand the basic concepts and characteristics of AI.	Kim and Son [32]
	AIU2	I understand the usefulness, risks, and limitations of AI.	
	AIU3	The development of AI technology will dramatically change human social life in the future.	
	AIU4	I understand the factors influencing the social acceptance of AI (e.g., government support, institutional improvement, public education, and expansion of application areas).	

The measurement instrument was developed based on constructs and items adapted from previously validated studies to ensure conceptual clarity and measurement reliability. All constructs included in the research model were operationalized using multi-item scales drawn from established literature. These constructs included performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and AI understanding, as summarized in Table 1 [11][32]. Each item was measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), which is widely used in technology adoption research to capture respondents' perceptual evaluations.

The questionnaire was structured into three parts. The first section collected demographic information, including gender, age, academic year, and major. The second section measured users' perceptions of the main theoretical constructs related to generative AI adoption. The third section focused on respondents' generative AI usage patterns, including the type of generative AI tools most frequently used and their intention to continue using such tools for learning purposes.

To establish content validity, the initial questionnaire was reviewed through a pre-test involving experts from academia and industry with experience in AI and educational technology. Based on their feedback, minor wording revisions were made to improve item clarity and contextual relevance. In addition, a pilot test was conducted with voluntary participants from related academic fields to assess item comprehensibility and survey flow. The pilot results indicated no major issues, supporting the suitability of the instrument for full-scale data collection.

3.2 Sample

This study employed a survey-based research design, which is appropriate for examining individual perceptions, intentions, and behavioral tendencies toward emerging technologies [11][21]. Surveys are particularly suitable in early diffusion stages of technological innovation, as they enable efficient collection of perceptual data from a broad population. The target population consisted of students enrolled in two-year, three-year, and four-year universities across South Korea.

A purposive sampling technique was applied to ensure relevance to the research objectives. Respondents were first asked whether they had prior experience using generative AI. Only those who answered yes were allowed to complete the questionnaire. Purposive sampling was considered appropriate because the primary objective of this study was to examine perceptions and intentions among actual users of generative AI rather than the general student population. Since meaningful evaluation of performance expectancy, effort expectancy, social influence, and facilitating conditions requires prior experience with generative AI, respondents without such experience were excluded. In addition, students from two-year, three-year, and four-year institutions were included to capture a broader range of educational backgrounds and learning environments. This approach ensured that participants could provide informed evaluations based on actual usage experience. Data were collected through an online survey administered via Naver Form, which facilitated broad geographic coverage and respondent accessibility.

Prior to participation, respondents were informed of the purpose of the study and assured that their participation was voluntary and anonymous. No personally identifiable information was collected. Data collection was conducted over a four-month period from April to July 2024. After data collection, responses were screened to remove incomplete questionnaires, patterned responses, and cases indicating no experience with generative AI. Following this data preprocessing procedure, the final dataset was deemed appropriate for subsequent statistical analysis.

Table 2 summarizes the demographic characteristics of the respondents. The sample consists of 224 university students, with females accounting for a larger proportion than males. Most respondents are between 18 and 25 years old, reflecting the typical age range of undergraduate students. Lecture-based classes are the most common instructional format, followed by presentation- and project-based learning. Fourth-year students and those in advanced stages of study represent the largest academic year group. In terms of major, business and engineering students constitute the largest proportions, followed by humanities and social sciences, indicating a diverse academic background among participants. It should be noted that female respondents accounted for a larger proportion of the sample (66.1%) than male respondents (33.9%).

Table 2. Demographic features of respondents

Category	Group	Frequency	%
Gender	Male	76	33.9
	Female	148	66.1
	Total	224	100.0
Age	18 - 25	192	85.7
	26 - 29	31	13.8
	30 or above	1	0.4
	Total	224	100.0
Class format	Lecture-based	88	39.3
	Presentation/discussion-based	53	23.7
	Project-based	45	20.1
	Laboratory/practice-based	38	17.0
	Total	224	100.0
Academic year	First year (four-year program)	24	10.7
	Second year (four-year program)	33	14.7
	Third year (four-year program)	53	23.7
	Fourth year or above	85	37.9
	First year (two-/three-year program)	1	0.4
	Second year (two-/three-year program)	3	1.3
	Third year (two-/three-year program)	3	1.3
	Graduation postponed/on leave	22	9.8
	Total	224	100.0
Major	Humanities and social sciences	44	19.6
	Business and economics	65	29.0
	Education	19	8.5
	Engineering	65	29.0
	Natural sciences	16	7.1
	Medical, pharmaceutical, and health sciences	15	6.7
	Total	224	100.0

Although this distribution reflects the composition of the collected sample, it may influence the generalizability of the findings if gender-related differences in perceptions of generative AI exist. Therefore, the results should be interpreted with caution and future studies are encouraged to employ more balanced sampling strategies to enhance representativeness.

To explore group differences according to AI understanding, respondents were classified into low-, medium-, and high-understanding groups using cluster analysis. The resulting cluster centers reflected distinct levels of AI understanding and were used as the basis for subsequent ANOVA.

Ⅳ. Research Results

4.1 Reliability and validity

The reliability and validity of the measurement model were assessed using internal consistency analysis and exploratory factor analysis (Table 3). Internal consistency was examined using Cronbach's alpha, with all constructs exceeding the recommended threshold of 0.70, indicating satisfactory reliability [33]. Specifically, performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention demonstrated strong internal consistency, suggesting that the items within each construct consistently captured the intended concept.

Construct validity was evaluated through exploratory factor analysis. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.897, exceeding the recommended minimum value of 0.60, while Bartlett's test of sphericity was statistically significant, confirming the suitability of the data for factor analysis [34]. The rotated component matrix revealed clear factor loadings, with all items loading strongly on their respective constructs and minimal cross-loadings on other factors. Factor loadings generally exceeded 0.60, supporting convergent validity, while the distinct loading patterns across components indicate satisfactory discriminant validity [35].

Table 3. Factor analysis and reliability

Construct	Item	Cronbach's α	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Performance expectancy	PFM1	0.824	0.291	0.759	0.119	0.181	0.008
	PFM2		0.304	0.727	0.141	−0.036	0.102
	PFM3		0.183	0.733	0.18	0.244	0.069
	PFM4		0.177	0.72	0.312	0.046	0.056
Effort expectancy	EFT1	0.817	0.137	0.252	0.746	0.272	−0.023
	EFT2		0.147	0.015	0.719	0.375	0.156
	EFT3		0.347	0.347	0.61	0.102	0.104
	EFT4		0.083	0.286	0.755	0.178	−0.004
Social influence	SCL1	0.772	0.215	0.187	−0.016	0.146	0.847
	SCL2		0.091	−0.012	0.125	0.028	0.906
Facilitating conditions	FCL1	0.768	0.078	0.061	0.421	0.673	0.13
	FCL2		0.239	0.093	0.164	0.79	0.147
	FCL3		0.109	0.192	0.238	0.772	−0.044
Intention to use	ITU1	0.859	0.767	0.169	0.214	0.146	0.091
	ITU2		0.844	0.172	0.11	0.119	0.09
	ITU3		0.721	0.295	0.089	0.129	0.083
	ITU4		0.75	0.319	0.127	0.106	0.171

To further assess convergent validity, Composite Reliability (CR) and Average Variance Extracted (AVE) were examined. The results showed that the composite reliability values ranged from 0.866 to 0.904, exceeding the recommended threshold of 0.70. In addition, the AVE values ranged from 0.644 to 0.808, all above the recommended cutoff value of 0.50. These findings indicate satisfactory internal consistency and convergent validity of the measurement model. Together with the exploratory factor analysis and cross-loading results, the measurement model demonstrates acceptable reliability and construct validity for subsequent hypothesis testing.

Cross-loadings were generally lower than the corresponding primary loadings, indicating acceptable discriminant validity among the constructs. The Kaiser-Meyer-Olkin value was 0.897, and Bartlett’s test of sphericity was significant ($p < .001$), confirming the appropriateness of the data for factor analysis. The rotated component matrix revealed that all items loaded strongly on their intended constructs, with most factor loadings exceeding 0.60. Taken together, these results demonstrate satisfactory reliability and construct validity of the measurement model, supporting its suitability for subsequent hypothesis testing.

4.2 Main effects of UTAUT variables on intention to use generative AI (H1–H4)

The regression analysis shows that performance expectancy (β = 0.401, $p < 0.001$), social influence (β = 0.218, $p < 0.001$), and facilitating conditions (β = 0.146, p = .046) have significant positive effects on the intention to use generative AI, supporting H1, H3, and H4. In contrast, effort expectancy is not significant (β = 0.029, p = .708), leading to the rejection of H2. The overall model explains a substantial proportion of variance in intention (R^2 = 0.399; adjusted R^2 = 0.388), indicating good explanatory power (Table 4).

Table 4. Regression results

H	Predictor	Outcome	β	t	p	Result
H1	PFM	ITU	.401	6.158	< .001	Supported
H2	EFT	ITU	.029	.375	.708	Not supported
H3	SCL	ITU	.218	3.655	< .001	Supported
H4	FCL	ITU	.146	2.011	.046	Supported

4.3 Group differences of academic major (H5)

To examine group differences across disciplinary contexts, students were classified into two major groups: language, business, and education majors, and natural science, engineering, and medical majors. This classification was based on prior research distinguishing communication-oriented disciplines from analytically oriented disciplines [17][18]. Group-specific regression equations were then estimated and compared (Table 5). The analysis reveals that the effects of the four antecedents on intention to use generative AI vary depending on students' academic disciplines. In particular, the moderating effects are more pronounced among students majoring in language, business, and education-related fields than among those in natural science, engineering, and medical-related fields.

Table 5. Group-specific regression equations

Major group	Performance expectancy	Effort expectancy	Social influence	Facilitating conditions
Language/ business/ education	y = 0.628x + 1.143	y = 0.439x + 1.884	y = 0.395x + 2.197	y = 0.482x + 1.807
Natural science/ engineering/ medical	y = 0.525x + 1.397	y = 0.376x + 1.906	y = 0.381x + 2.099	y = 0.267x + 2.248

The group-specific regression equations suggest possible differences across academic major groups. However, because formal interaction tests were not conducted, the findings should be interpreted as exploratory evidence of group-level differences rather than definitive moderation effects.

4.4 Group differences by AI understanding (H6)

To test whether intention to use generative AI differs according to levels of AI understanding, respondents were classified into three groups (low, medium, and high) using cluster analysis based on AI understanding scores. The three-cluster solution was adopted because it provided a meaningful segmentation of respondents according to their relative levels of AI understanding. A one-way ANOVA was subsequently conducted to examine differences in intention to use generative AI across the three groups. A one-way ANOVA was then conducted using intention to use generative AI as the dependent variable. The results indicate that intention to use generative AI varies significantly across the three AI understanding groups. Specifically, the high-level AI understanding group shows the highest standardized intention score. The medium-level group follows, while the low-level group shows the lowest score (Table 6). This pattern suggests that greater understanding of AI is associated with a stronger inclination to adopt generative AI. Overall, the ANOVA results provide empirical support for H6, confirming that differences in AI understanding correspond to meaningful differences in intention to use generative AI.

Table 6. ANOVA result

Source	Sum of squares	df	F	p
Between groups	7.393	2	10.815	0.000
Within groups	75.538	221		
Total	82.931	223		

Ⅴ. Discussion

The findings indicate that performance expectancy plays a meaningful role in shaping students' intention to use generative AI. This result suggests that students are more inclined to adopt generative AI when they perceive it as enhancing learning effectiveness, productivity, or task completion. This aligns with prior technology adoption studies emphasizing perceived performance benefits as a primary cognitive driver in educational technology use [10][21]. This finding is also consistent with recent Korean studies demonstrating that generative AI can enhance learning support, content generation, and educational effectiveness when students perceive clear functional benefits [3][4]. In the context of generative AI, this result implies that students view such tools less as experimental technologies and more as functional learning aids. From an interpretive perspective, generative AI appears to be evaluated through a pragmatic lens, where tangible learning outcomes outweigh novelty. This finding reinforces the importance of demonstrating concrete academic value when integrating generative AI into higher education environments.

Effort expectancy, however, does not exhibit a significant influence on the intention to use generative AI. This finding contrasts with early-stage technology adoption literature that emphasizes ease of use as a critical determinant [21]. Similar non-significant results have been reported in recent studies on advanced digital tools, where users already possess sufficient baseline digital competence [11]. A plausible interpretation is that contemporary university students perceive generative AI as inherently easy to use due to prior exposure to intuitive digital platforms. Consequently, ease of use may no longer function as a differentiating factor in adoption decisions. Instead, effort expectancy may have reached a threshold level, beyond which its influence diminishes. This suggests a maturation effect in technology adoption contexts involving digitally fluent user groups.

Social influence is found to significantly affect the intention to use generative AI, highlighting the role of peer norms and social validation in adoption decisions. This result is consistent with studies emphasizing normative pressure in educational and collaborative settings [11][22]. In learning environments, students often look to classmates, instructors, or broader academic discourse to evaluate the legitimacy of new technologies. The result implies that generative AI use is socially constructed as an acceptable and even desirable learning practice. From a broader perspective, this finding suggests that informal diffusion through peer interaction may be as influential as formal institutional policies. Encouraging visible and responsible use of generative AI within academic communities may therefore accelerate its acceptance.

Facilitating conditions also show a significant relationship with intention to use generative AI, underscoring the importance of supportive infrastructure and resources. This finding aligns with prior research highlighting institutional support, access to tools, and technical readiness as enabling factors for technology use [11][23]. In the case of generative AI, availability of access, guidance, and compatible learning systems appears to reduce uncertainty and psychological barriers. A key inference is that even highly capable students may hesitate to adopt generative AI if supportive conditions are insufficient. This emphasizes that successful integration of generative AI in education depends not only on individual perceptions but also on the broader learning ecosystem that sustains continuous and confident use.

The comparison of group-specific regression equations suggests possible differences across academic major groups in the relationships between UTAUT antecedents and intention to use generative AI. Across all four predictors, the language, business, and education group exhibits steeper regression slopes, suggesting that changes in perceived performance benefits, social influence, and facilitating conditions translate more strongly into intention formation. In contrast, the natural science, engineering, and medical group shows relatively flatter slopes, indicating weaker sensitivity to these factors. This pattern implies that students in applied and communication-oriented disciplines are more responsive to contextual and perceptual evaluations of generative AI, whereas students in technically oriented fields may rely more on intrinsic task requirements than on perceptual drivers.

The ANOVA results demonstrate that intention to use generative AI differs meaningfully across levels of AI understanding, highlighting the role of cognitive preparedness in technology adoption. Students with higher AI understanding exhibit stronger adoption intentions, suggesting that familiarity with AI concepts reduces uncertainty and enables more informed evaluations of generative tools. This pattern aligns with prior research indicating that AI literacy enhances confidence and perceived control when engaging with intelligent systems [8][19]. Recent empirical evidence also suggests that students with stronger AI-related knowledge and experience are more likely to perceive generative AI as a useful learning resource and to engage with it more actively [9]. From an interpretive standpoint, students who better understand AI are likely to anticipate realistic benefits and limitations, which fosters purposeful rather than hesitant adoption. Conversely, lower understanding may amplify ambiguity and risk perceptions, dampening intention. These findings underscore the importance of foundational AI education as a prerequisite for sustainable and responsible integration of generative AI in academic contexts.

Ⅵ. Conclusion

This study contributes to the literature by extending traditional UTAUT research to the emerging context of generative AI in higher education. Unlike previous studies that mainly examined the direct effects of technology acceptance factors, this research incorporates disciplinary differences and AI understanding to explain heterogeneity in students' adoption intentions. By doing so, the study moves beyond the assumption that technology acceptance mechanisms operate uniformly across all users.

First, while prior studies applying TAM or UTAUT have consistently highlighted performance expectancy and effort expectancy as core drivers of adoption, most have treated these relationships as stable and universal across user groups [10][21]. This study demonstrates that performance expectancy remains a robust predictor of intention to use generative AI, whereas effort expectancy does not exert a meaningful influence. This finding challenges early-stage adoption assumptions and suggests a theoretical shift in digitally mature contexts, where usability is taken for granted rather than actively evaluated [11]. Second, this study advances theory by empirically identifying academic major as a contextual moderator shaping the salience of UTAUT antecedents. Previous research has acknowledged disciplinary differences conceptually, but has rarely tested moderation effects using group-specific regression comparisons. By showing that students in language-, business-, and education-related majors are more responsive to performance, social influence, and facilitating conditions, this study reveals how disciplinary cultures condition technology evaluation processes. This insight extends UTAUT by embedding it within an academic context characterized by heterogeneous epistemic norms [17]. Third, the study highlights AI understanding as a differentiating cognitive capability rather than a background trait. Unlike prior studies that treated AI literacy as an antecedent or control variable, this research demonstrates that intention to use generative AI varies significantly across levels of AI understanding. This finding complements emerging AI literacy research by linking conceptual understanding to adoption readiness [8][19]. Collectively, these contributions suggest that future technology adoption models should move beyond uniform effects and incorporate disciplinary and cognitive heterogeneity to better explain generative AI use in education.

This study offers several practical implications for stakeholders seeking to integrate generative AI into higher education settings. For higher education institutions, the strong role of performance expectancy suggests that generative AI initiatives should emphasize demonstrable academic benefits rather than technical novelty. Universities can achieve this by embedding generative AI into authentic learning tasks, such as literature review support, coding assistance, or case-based problem solving, where students can clearly observe performance gains. Merely providing access to AI tools without instructional framing is unlikely to maximize adoption. For service providers and platform developers, the findings highlight the limited importance of ease of use for digitally fluent students. Instead of focusing exclusively on interface simplification, developers should prioritize features that directly enhance learning outcomes, such as citation support, feedback explainability, or domain-specific prompts. In addition, the significant role of facilitating conditions underscores the need for reliable access, institutional licenses, and clear usage guidelines. Technical instability or ambiguous policies may discourage adoption even among motivated users. The moderating role of academic major further suggests that a one-size-fits-all implementation strategy may be ineffective. Universities should consider discipline-sensitive approaches, such as tailored workshops for humanities and education students that emphasize writing and pedagogy, and different use cases for science or engineering students that align with analytical tasks. Finally, the ANOVA results point to the importance of strengthening students' AI understanding. Introductory AI literacy modules, focusing on capabilities, limitations, and ethical considerations, can reduce uncertainty and promote more confident engagement. For students, this implies that developing conceptual understanding of AI is not optional but instrumental for effective and responsible use.

Despite its contributions, this study has limitations that open avenues for future research. First, intention to use generative AI was examined at a single point in time, which limits insight into how perceptions evolve with prolonged use or institutional normalization. Longitudinal designs could capture shifts from exploratory to routinized use. Second, the study treated generative AI as a general category, although students may evaluate tools differently depending on task type or disciplinary alignment. Future research could compare writing-oriented, analytical, and creative AI applications. Third, moderation effects were examined using group comparisons, but future studies could employ mixed-method approaches to uncover why disciplinary differences emerge. Qualitative interviews may reveal deeper cognitive or cultural mechanisms underlying adoption decisions. Furthermore, the sample contained a higher proportion of female respondents, which may limit the generalizability of the findings to the broader university student population.

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