Disciplinary Differences in University Students' AI Adoption: A Technology Acceptance Model Approach

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***Abstract*—This study investigates university students' acceptance and use of Artificial Intelligence (AI) technologies, drawing on the Technology Acceptance Model (TAM) as the guiding framework. This study collected pre- and post-semester survey data from 108 university students representing diverse academic majors. Four TAM constructs—Actual Use, Attitudes toward AI, Perceived Usefulness (PU), and Perceived Ease of Use (PEOU)—were measured through a validated survey instrument. Paired-samples t-tests revealed no statistically significant changes in university students' perceptions across the semester, despite small numerical increases in Actual Use and PEOU. One-way Analysis of Variance (ANOVA) results indicated that disciplinary differences played a notable role in shaping perceptions of AI usefulness. Significant differences emerged in the expectations and usefulness dimensions of PU, with Science, Technology, Engineering, and Mathematics (STEM) students reporting higher PU than humanities and social science majors. These findings suggest that university students' academic backgrounds influence their expectations and evaluations of AI. The study underscores the importance of designing AI-integrated curricula that account for interdisciplinary differences in AI literacy.**

***Keywords*—Artificial Intelligence (AI), AI literacy, Technology Acceptance Model (TAM), university students, disciplinary differences, academic majors**

I. Introduction

The rapid advancement of Artificial Intelligence (AI) has reshaped contemporary educational practices, with particularly consequential implications for education. A wide range of AI-driven applications—such as conversational agents, automated translation tools, and adaptive learning systems—now support personalized instruction, foster greater learner autonomy, and facilitate engagement in diverse learning environments [1, 2]. Among these tools, large language model–based systems like ChatGPT constitute a notable advancement, providing learners with real-time interaction and feedback tailored to their learning needs. Such affordances enable a shift from traditional, standardized instruction to more flexible, learner-centered approaches.

In South Korea, governmental initiatives—including the Ministry of Education's AI Digital Textbook (AIDT) project—reflect a strong national commitment to integrating advanced technologies into formal education [3]. These efforts are expected to accelerate the adoption of AI-based tools in classrooms, among both faculty and students, further expanding opportunities for personalized and self-directed language learning [4]. Yet the mere presence of AI technology does not guarantee meaningful learning. Effective integration requires alignment between the affordances of AI tools and university students' pedagogical goals, technological readiness, and attitudes toward innovation.

While earlier scholarship contrasts generational groups—such as Gen Z and older generations—in their adoption of emerging technologies [5, 6], fewer studies have examined differences across academic disciplines within the same generation of learners. University students in Science, Technology, Engineering, and Mathematics (STEM) fields could be more accustomed to experimenting with AI tools, treating them as natural extensions of their academic environment [7, 8]. Conversely, students majoring in the humanities or social sciences may approach AI with greater caution, adopting these tools more selectively or for limited purposes.

Despite the growing visibility of AI in higher education, empirical research on how disciplinary backgrounds shape university students' perceptions and uses of AI for learning remains limited. This gap is particularly significant because students' academic fields can influence their AI literacy, learning strategies, and motivational orientations—factors that collectively shape the trajectory of AI integration in higher education. Without such insights, institutional attempts to incorporate AI into programs may be misaligned with learners' actual needs.

Recent research on the adoption of Generative Artificial Intelligence (GenAI) in higher education has increasingly emphasized the importance of students' lived experiences, instructional framing, and institutional context. For instance, Chan and Hu [9] foreground students' voices by documenting how perceived benefits, challenges, and ethical concerns surrounding GenAI are shaped by classroom practices and instructors' guidance rather than by access to technology alone. Such findings suggest that students' engagement with GenAI cannot be fully understood without considering how AI is pedagogically framed within specific learning environments.

In addition, emerging scholarship has highlighted the role of faculty AI literacy as a structural determinant of students' AI adoption. Bian *et al.* [10] argue that disparities in AI use across disciplines are rooted in uneven faculty preparedness and curricular integration, rather than in differences in students' willingness or capacity to engage with AI. These perspectives collectively point to the need for discipline-sensitive analyses that situate student adoption within broader institutional and curricular contexts.

Rather than treating students as a homogeneous group of technology users, this study examines how perceived usefulness, ease of use, attitudes, and actual AI use may vary

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across students' academic majors within a shared curricular setting. Specifically, this study responds to recent calls for more contextually grounded analyses of AI adoption in higher education. By integrating a pre–post survey design within an AI-focused general education course, this study further contributes to distinguishing stable perceptions from short-term instructional effects. As such, the findings offer empirical insights not only into whether students accept AI but also into how disciplinary orientation shapes the perceived educational value of AI beyond initial exposure.

II. Theoretical Background

A. Technology Acceptance Model (TAM)

The adoption of new technologies in educational settings is primarily shaped by how users perceive and accept them. The Technology Acceptance Model (TAM), first proposed by Davis [11], remains one of the most influential frameworks for explaining the cognitive and behavioral processes underlying technology adoption. TAM suggests that an individual's Behavioral Intention (BI) to use a technology—and ultimately their Actual Use (AU)—is driven primarily by two core beliefs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU refers to the belief that a particular technology will improve one's performance, while PEOU concerns the degree to which the technology is seen as straightforward and effort-free.

A central premise of TAM is that PEOU positively influences PU; technologies that feel intuitive or simple to operate are more likely to be viewed as beneficial. Together, PU and PEOU shape users' attitudes toward the technology, which, in turn, influence BI and eventual adoption behavior. In English as a Foreign Language (EFL) education, learners' willingness to adopt AI tools is not determined solely by their instructional value—such as automated feedback, adaptive learning, or increased engagement—but also by the perceived simplicity of integrating these tools into everyday learning without substantial technical expertise. External variables, including institutional support, teachers' digital competence, and pedagogical orientations, further mediate these perceptions and ultimately guide learners' acceptance and continued Use of AI.

While the TAM has been widely applied to examine technology adoption, its recent extensions to GenAI contexts warrant particular attention. Strzelecki [12] demonstrates that TAM remains a robust explanatory framework for understanding students' acceptance of ChatGPT in higher education, while also highlighting the need to interpret PU and ease of use in relation to pedagogical norms and academic expectations. Building on this line of research, this study adopts TAM not as a static or universal model, but as a context-sensitive framework through which disciplinary differences, instructional practices, and institutional signaling shape students' AI acceptance. In this respect, the study aligns with contemporary TAM-based GenAI research while extending it by foregrounding disciplinary variation within a shared educational setting.

B. Perceived Usefulness and Perceived Ease of Use in AI Adoption

Within the TAM framework, PU and PEOU serve as pivotal determinants of educators' decisions to incorporate AI into their instructional practices. Davis [11] conceptualized PU as the belief that a technology enhances job performance, whereas PEOU reflects the belief that using the technology requires minimal effort. Applied to education, these constructs correspond to teachers' judgments about whether AI meaningfully supports learning objectives and whether it can be implemented without creating additional instructional or administrative burdens.

Accumulating evidence suggests that PU is often a stronger predictor of technology adoption than PEOU. For instance, Zhang *et al*. [13] demonstrated that pre-service teachers' perceptions of AI's pedagogical value were more influential in shaping their adoption intentions than ease of use. However, ease of use still played a secondary but essential role. This pattern highlights the need for professional development that foregrounds the instructional benefits of AI rather than focusing solely on operational simplicity.

Ethical considerations also weigh heavily in the adoption of AI. Issues involving privacy, data security, and the safeguarding of human interaction have become increasingly salient as AI usage expands. GenAI models depend on vast training datasets, prompting questions about how personal information is collected, stored, and used [14]. Without transparent and secure data governance, trust in AI systems may erode. Additionally, concerns about academic integrity—particularly regarding plagiarism, authorship, and the veracity of AI-generated content—have prompted calls for clear institutional guidelines.

On a practical level, educators frequently note that adopting AI can increase, rather than reduce, their workload. While AI is often promoted as a labor-saving innovation, its implementation may require continuous monitoring, verification of AI-generated materials, and efforts to ensure that outputs align with pedagogical goals [15]. In many cases, teachers are responsible for ensuring ethical compliance and contextualizing AI's outputs for instruction [16]. These realities underscore the importance of sustained technical support, teacher training, and institutional leadership to ensure that AI adoption in education is both feasible and sustainable.

C. The Role of GenAI in Higher Education

AI represents a significant leap beyond earlier forms of educational technology, mainly because of its capacity to create new content rather than merely classify or analyze existing data. Whereas discriminative AI identifies patterns within datasets, generative AI produces original text, interactive dialogue, and contextually appropriate responses [17, 18]. AI tools such as ChatGPT enable real-time, dynamic interaction, allowing learners to engage in extended communication.

Although AI adoption research has contrasted generational groups—emphasizing, for example, Generation Z's intuitive engagement with digital tools relative to older generations—far fewer studies have examined how disciplinary background influences the acceptance and Use of AI within the same generation of learners in higher education. Students in STEM-related majors often encounter AI regularly and may view it as a natural extension of their academic and professional trajectories. Students in the humanities or social sciences, however, may use AI more selectively, relying on it for specific tasks such as translation or writing support rather than as a comprehensive learning tool [19, 20].

D. Research Gaps and the Present Study

Despite growing enthusiasm for the educational potential of GenAI, empirical research specifically on AI adoption in higher education remains scarce. This absence is notable given the growing importance of AI literacy and the likelihood that university students' academic majors shape their exposure to and perceptions of AI technologies [21, 22].

By identifying differences in acceptance patterns and recognizing the challenges faced by students across majors, this research seeks to inform pedagogical decision-making, curriculum design, and institutional policy to promote the effective integration of AI into university-level programs. Accordingly, the study addresses the following research questions:

RQ1. How do university students from different academic majors differ in their adoption and Use of AI technologies for learning?

RQ2. How do university students' attitudes toward AI integration in learning vary across academic majors?

RQ3. What differences exist across majors in university students' perceptions of the usefulness of AI technologies for learning?

RQ4. How do perceptions of ease of use differ among university students from various academic majors regarding AI-based tools in learning?

III. METHOD

A. The Course Structure

Introduction to Artificial Intelligence is a foundational general education course designed to cultivate essential AI literacy in the era of the Fourth Industrial Revolution. It aims to build students' conceptual understanding of AI while enabling them to integrate AI creatively within their disciplinary contexts, with overarching goals that include critical technological comprehension, ethical awareness, interdisciplinary thinking, and collaborative problem-solving.

Conceptually, the course introduces the intellectual foundations and operational mechanisms of contemporary AI systems. Students examine the historical development of AI, differentiate between narrow and general intelligence, and learn core machine learning paradigms (supervised, unsupervised, and reinforcement learning), supported by real-world examples that illustrate how these approaches function in everyday digital environments.

This foundation is coupled with attention to AI's capabilities and limitations to promote responsible decision-making. The course further emphasizes interdisciplinary application and practical engagement with generative AI. Students explore how AI can be applied across fields such as the humanities, social sciences, engineering, and the arts, and gain hands-on experience with large language models, focusing on effective prompting, critical evaluation of outputs, and risk reduction, such as hallucinations. Pedagogically, the course adopts team-based and problem-based learning to support active knowledge construction through collaborative inquiry and iterative feedback.

B. Study Participants

The study employed a class-based convenience sampling approach. All participants were enrolled in the same mandatory *Introduction to Artificial Intelligence* course, and both the pre- and post-surveys were administered during scheduled course periods. Only responses from students who completed both surveys were included in the final dataset to ensure matched comparisons.

A total of 120 students initially completed the survey. To ensure data quality and comparability, only respondents who completed both the pre- and post-surveys were included in the final analysis, resulting in 108 matched cases. The demographic composition of the sample was relatively balanced, with 42.6% identifying as male and 57.4% as female. In terms of academic standing, the dataset was predominantly composed of first-year students (83.3%), with smaller proportions of sophomores (3.7%), juniors (9.3%), and seniors (3.7%). Participants represented a broad range of academic fields. Most were enrolled in the non-declared majors (60.2%), followed by business-related majors (17.6%) and STEM disciplines (12.0%). Students from the humanities and social sciences were present but formed a tiny minority, each accounting for less than 2% of the sample. Table 1 shows demographic data of survey participants.

Table 1. Demographic of survey participants

Category		Frequency (N = 108)	Percentage (%)
Gender	Male	46	42.6
	Female	62	57.4
Grades	Freshmen	90	83.3
	Sophomores	4	3.7
	Juniors	10	9.3
	Seniors	4	3.7
Majors	Humanities	2	1.9
	Non-declared majors	65	60.2
	Social Sciences	2	1.9
	Business-related majors	19	17.6
	STEM majors	13	12.0
	College of Natural Sciences	3	2.8
	Glocal Advanced Institute of Science & Technology (GAST)	4	3.7
AI education (courses) previously	Yes	66	61.1
	No	42	38.9
Type of AI Learning	K-12 Software (SW) education	36	33.3
	University courses	27	25
	non-credit/extra-curricular courses	3	2.8
	None	42	38.9
Type of coding education	Unplugged Education	3	2.8
	Block coding	31	28.7
	Text-based coding	32	29.6
	None	42	38.9
Willingness to receive AI-related education in the future	Yes	84	77.8
	No	24	22.2

Students' backgrounds in AI education also varied. A majority (61.1%) had completed at least one AI-related course, most commonly K–12 software or coding education (33.3%) or university-level AI coursework (25.0%). However, 38.9% reported no prior exposure to AI-related learning. A similar pattern emerged in coding experience: 28.7% had experience with block coding, 29.6% with text-based coding, and 38.9% had never received any coding instruction. Finally, a substantial proportion of students (77.8%) indicated that they were willing to pursue additional AI-related education in the future. This intense interest highlights the growing recognition among university learners that AI literacy is becoming an essential component of both academic success and future career readiness.

It should be noted that the distribution of study participants across academic majors was uneven. While university students from non-declared majors and STEM-related fields constituted the majority of the sample, several disciplinary groups, the humanities, social sciences, and natural sciences, were represented by fewer than five respondents each. As a result, comparisons involving these groups should be interpreted as exploratory rather than confirmatory.

C. Survey Instruments

The primary instrument for data collection was a survey developed to assess four core constructs of the Technology Acceptance Model (TAM): (1) Actual Use of AI Technology (Actual AI Use), (2) Attitudes Toward Using AI Technology, (3) Perceived Usefulness (PU), and (4) Perceived Ease of Use (PEOU). The survey instrument was adapted from established TAM literature, primarily Venkatesh and Bala [23], and underwent content review by two researchers with expertise in educational technology to ensure clarity and contextual appropriateness. Although the attitudes subscale consisted of only two items and yielded a relatively lower Cronbach's α (0.625), this value is considered acceptable for exploratory research using short scales. Nevertheless, the findings related to attitudes toward AI should be interpreted with caution, and future studies are encouraged to employ expanded item sets or complementary qualitative measures to enhance construct validity.

Reliability testing indicated that all subscales demonstrated acceptable internal consistency, with Cronbach's α values ranging from 0.625 to 0.883. The overall reliability of the whole instrument was 0.878, indicating strong internal consistency across the survey. PU was examined using six items that evaluated learners' beliefs about AI's ability to support individualized learning, enhance higher-order thinking through task- and project-based activities, and deliver adaptive feedback and instructional materials tailored to student needs. Perceived Ease of Use (PEOU) was assessed using four items that measured self-reported proficiency with AI tools and the perceived effort required to incorporate these technologies at different stages of the instructional process. Table 2 shows the reliability of TAM-Based AI Technology Acceptance.

Table 2. Composition and reliability of measurement tools

Category	Question	Cronbach's α
Actual AI Use	1, 2, 3, 4	0.693
Attitudes toward Using AI Technology	5, 6	0.625
PU of AI Technology-Expectations	7, 8, 9	0.869
PU of AI Technology-Usefulness	10, 11, 12	0.853
Perceived Ease of Use of AI Technology	13, 14, 15	0.883
Total	1–15	0.878

D. Data Collection and Analysis

The survey was administered online through Google Forms and was presented in Korean to ensure clarity and accessibility for all participants. Prior to completing the survey, respondents were provided with detailed information about the study's purpose and their rights as participants, after which they provided informed consent. The final instrument included 24 items alongside one open-ended question designed to elicit more nuanced reflections on AI use and perceptions.

For the analytical phase, descriptive statistics were first computed to summarize participants' demographic profiles and to capture general trends in their responses. To evaluate changes occurring over the course of the semester, paired-samples t-tests were conducted using matched pre- and post-survey data. Additionally, one-way Analysis of Variance (ANOVA) tests were employed to determine whether perceptions of AI differed significantly across students' academic majors. All statistical procedures were performed using SPSS, following conventional guidelines for educational and social science research.

IV. Results

A series of paired-samples t-tests was conducted to determine whether university students' understanding and perceptions of AI technology changed over the course of the semester. As summarized in Table 3, none of the four TAM constructs showed statistically significant differences between the pre-test and post-test. Students' Actual AI use increased slightly from the pre-test ($M = 3.178$, $SD = 0.741$) to the post-test ($M = 3.299$, $SD = 0.741$); however, this difference was not statistically significant, $t(107) = -1.228$, $p > 0.05$. Attitudes toward using AI remained similarly stable, with pre-test scores ($M = 3.056$, $SD = 0.731$) and post-test scores ($M = 3.111$, $SD = 0.728$) showing no significant change, $t(107) = -0.600$, $p > 0.05$.

With respect to PU, neither the expectations component nor the usefulness component exhibited meaningful variation over time. Expectations were comparable between the pre-test ($M = 3.849$, $SD = 0.771$) and post-test ($M = 3.806$, $SD = 0.700$), $t(107) = 0.419$, $p > 0.05$. Similarly, the usefulness subscale showed no significant change from the pre-test ($M = 3.704$, $SD = 0.683$) to the post-test ($M = 3.762$, $SD = 0.712$), $t(107) = 0.596$, $p > 0.05$. Perceived ease of use displayed a slight numerical increase from pre-test ($M = 3.481$, $SD = 0.825$) to post-test ($M = 3.623$, $SD = 0.713$), but this difference did not reach statistical significance, $t(107) = 1.314$, $p > 0.05$.

Table 3. Comparison of the understanding of AI technology

Category	Pre-Post	M	SD	*t*	*p*
Actual Use of AI Technology	Pre-test	3.178	0.741	−1.228	0.222
	Post-test	3.299	0.741		
Attitudes toward Using AI Technology	Pre-test	3.056	0.731	−0.600	0.550
	Post-test	3.111	0.728		
PU of AI Technology-Expectations	Pre-test	3.849	0.771	0.419	0.676
	Post-test	3.806	0.700		
PU of AI Technology-Usefulness	Pre-test	3.704	0.683	−0.596	0.553
	Post-test	3.762	0.712		
Perceived Ease of Use of AI Technology	Pre-test	3.481	0.825	−1.314	0.192
	Post-test	3.623	0.713		

To examine potential disciplinary differences, a one-way ANOVA was conducted on each TAM construct. For Actual

AI use, mean scores varied across the seven academic discipline groups. College of Natural Sciences students reported the highest mean (M = 3.75, SD = 0.177), whereas Social Sciences students reported the lowest (M = 2.38, SD = 1.125). Despite these differences, the overall model was not statistically significant, F = 0.937, p > 0.05 (Table 4).

Table 4. Comparison of the actual AI Use across academic majors

Category	Major	M	SD	F	p	Scheffe
Actual AI Use	Humanities (a)	3.63	0.625	0.937	0.472	-
	Non-declared majors (b)	3.25	0.096			
	Social Sciences (c)	2.38	1.125			
	Business-related majors (d)	3.39	0.161			
	STEM majors (e)	3.42	0.144			
	College of Natural Sciences (f)	3.75	0.177			
	Glocal Advanced Institute of Science & Technology(GAST) (g)	3.25	0.071			

In terms of attitudes toward using AI technology, Social Sciences students recorded the highest mean score (M = 3.50, SD = 0.707), and GAST students the lowest (M = 2.63, SD = 1.088). Nevertheless, the one-way ANOVA indicated no significant differences among academic majors, F = 0.898, p > 0.05 (Table 5).

Table 5. Comparison of the attitudes toward using AI technology

Category	Major	M	SD	F	p	Scheffe
Attitudes toward Using AI Technology	Humanities (a)	3.00	1.41	0.898	0.500	-
	Non-declared majors (b)	3.10	0.692			
	Social Sciences (c)	3.50	0.707			
	Business-related majors (d)	3.13	0.642			
	STEM majors (e)	3.08	0.838			
	College of Natural Sciences (f)	3.83	0.764			
	Glocal Advanced Institute of Science & Technology (GAST) (g)	2.63	1.088			

A different pattern emerged for PU. As shown in Table 6, expectations of AI usefulness varied considerably across groups, ranging from 3.17 (Social Sciences) to 4.58 (GAST). The ANOVA revealed a statistically significant difference, F = 2.625, p < 0.05. Scheffe post hoc tests identified a significant difference between Non-declared majors students (M = 3.65, SD = 0.726) and College of Natural Sciences students (M = 4.00, SD = 0.000), indicating that students in science-focused fields held notably higher expectations regarding AI's usefulness. No other pairwise comparisons reached significance.

Table 6. Comparison of PU—Expectations across academic majors

Category	Major	M	SD	F	p	Scheffe
PU of AI Technology-Expectations	Humanities (a)	3.83	0.236	2.625	0.021*	$b<f$
	Non-declared majors (b)	3.65	0.726			
	Social Sciences (c)	3.17	0.236			
	Business-related majors (d)	4.11	0.545			
	STEM majors (e)	3.97	0.548			
	College of Natural Sciences (f)	4.00	0.000			
	Glocal Advanced Institute of Science & Technology (GAST) (g)	4.58	0.833			

*: Statistical Significance

A similar trend was observed for the usefulness component of PU (Table 7). Mean scores ranged from 3.50 (Social Sciences) to 4.25 (GAST). The overall ANOVA was significant, F = 2.305, p < 0.05. Scheffe tests again indicated a significant difference between Non-declared majors students (M = 3.58, SD = 0.731) and College of Natural Sciences students (M = 4.00, SD = 0.000).

Although one-way ANOVA revealed statistically significant differences in PU across academic majors, the robustness of these findings is constrained by the small and uneven group sizes. In particular, some groups exhibited minimal variance due to a small number of participants, potentially inflating mean differences. Accordingly, these results are reported as indicative patterns rather than conclusive evidence of disciplinary effects.

Table 7. Comparison of PU—Usefulness across academic majors

Category	Major	M	SD	F	p	Scheffe
PU of AI Technology-Usefulness	Humanities (a)	3.83	0.236	2.305	0.040*	$b<f$
	Non-declared majors (b)	3.58	0.731			
	Social Sciences (c)	3.50	0.707			
	Business-related majors (d)	4.16	0.463			
	STEM majors (e)	3.90	0.671			
	College of Natural Sciences (f)	4.00	0.000			
	Glocal Advanced Institute of Science & Technology (GAST) (g)	4.25	1.101			

*: Statistical Significance

Finally, perceived ease of use showed minor differences among groups, ranging from 3.50 (Non-declared majors) to 4.00 (Humanities and Natural Sciences). However, these variations were not statistically significant, F = 1.073, p > 0.05 (Table 8).

Table 8. Comparison of perceived ease of use across academic majors

Category	Major	M	SD	F	P	Scheffe
Perceived Ease of Use of AI Technology	Humanities (a)	4.00	0.000	1.073	0.383	-
	Non-declared majors (b)	3.50	0.649			
	Social Sciences (c)	4.00	0.000			
	Business-related majors (d)	3.86	0.548			
	STEM majors (e)	3.64	0.907			
	College of Natural Sciences (f)	4.00	0.000			
	Glocal Advanced Institute of Science & Technology (GAST) (g)	3.83	1.732			

In addition to the quantitative survey items, an open-ended question was included to capture students' reflections on their experiences with AI use during the course. Although a complete qualitative analysis was beyond the scope of this study, a brief thematic review of the responses revealed several recurring patterns that help contextualize the quantitative findings.

First, many students described AI as "already familiar" or "something I use when needed", suggesting that pre-existing habits may have limited observable growth in usage over time. For example, one student noted, "I was already using ChatGPT for basic tasks, so the course did not really change how often I use it".

Second, several respondents emphasized uncertainty about how AI could be meaningfully applied within their specific academic disciplines. This theme was particularly evident among students from non-STEM or non-declared majors, who reported difficulty identifying discipline-relevant applications beyond general writing support or information searching. One student commented, "I know AI is useful, but I am not sure how it fits into my major yet".

Finally, some students expressed cautious or selective attitudes toward AI use, citing concerns about overreliance, academic integrity, or the appropriateness of AI-generated outputs for graded assignments. These reflections suggest that stable attitudes and usage patterns may reflect deliberate, critical engagement with AI rather than disengagement or resistance. Taken together, these findings support the quantitative findings by illustrating why pre–post changes were limited and by highlighting how disciplinary relevance and prior familiarity shape students' AI adoption behaviors.

V. Discussion

This study investigated university students' acceptance and use of AI technologies through the lens of the Technology Acceptance Model (TAM). Regarding RQ1, the results indicated that students' actual AI use for learning did not differ meaningfully across academic majors, despite minor mean-level differences. This pattern suggests that GenAI tools may now function as a widely shared learning resource across disciplines, potentially because their interfaces and workflows are sufficiently intuitive to lower entry barriers for most learners. In this respect, the findings diverge from prior studies that STEM students tend to use AI tools more frequently or with greater confidence than students in the humanities or social sciences [24, 25]. A plausible explanation is that the diffusion of GenAI has reduced adoption disparities commonly associated with earlier educational technologies. That relatively high Perceived Ease of Use (PEOU) across groups may have minimized discipline-linked barriers to using AI for everyday academic purposes, consistent with core TAM assumptions.

Regarding RQ2, students' attitudes toward integrating AI into learning were also relatively uniform across majors. While some groups reported slightly more positive attitudes than others, the overall pattern did not support a clear disciplinary divide in attitudinal orientation. This finding contrasts with studies suggesting stronger positivity among STEM students. Yet, it aligns with work that emphasizes that GenAI has become normalized in everyday digital environments and is increasingly perceived as broadly applicable to routine academic tasks such as drafting, revising, summarizing, and clarifying content across fields [19]. Taken together, the RQ1 and RQ2 results imply that disciplinary background may not strongly differentiate between students who adopt AI at a basic level and those who hold generally favorable views toward AI use; instead, the more consequential differences appear to emerge in how students evaluate AI's academic value.

The most pronounced disciplinary pattern was identified in RQ3, which examined PU. Students' perceptions of AI's usefulness varied by major, with learners in more STEM-oriented or natural-science–aligned contexts tending to report higher PU than students in less STEM-centered or non-declared pathways. This result corroborates earlier findings that STEM students often perceive greater academic benefits from AI tools [3, 10] because their disciplinary training and learning routines more frequently involve computational reasoning, structured problem-solving, and data-oriented tasks, making AI's affordances immediately relevant. Importantly, the present findings also reinforce TAM's central claim that PU is a primary driver of technology acceptance and sustained engagement [9]. In other words, the findings suggest that disciplinary differences are expressed less in students' ability to use AI and more in whether AI is perceived as meaningfully advantageous for accomplishing discipline-relevant learning goals.

The results for RQ4 further clarify this point. Perceived ease of use did not differ significantly across majors, suggesting that learners generally found AI tools accessible and manageable regardless of disciplinary background. This result aligns with the broader literature characterizing contemporary GenAI applications as user-friendly and requiring minimal technical expertise [8, 17], as well as research suggesting that university students' baseline digital fluency supports comfort with interactive technologies [6, 20]. The overall absence of statistically meaningful pre–post change across TAM-related constructs should be interpreted as stability rather than inconsequence.

Given that many participants reported prior exposure to AI-related learning experiences, students may have entered the course with already established perceptions, producing a ceiling effect that constrained measurable change over one semester. This interpretation is also consistent with evidence that improvements in PEOU and related perceptions are more likely when courses provide explicit, hands-on AI training and guided practice, which may not have been sufficiently intensive in the present context [21, 22].

From a theoretical standpoint, these findings extend TAM-based explanations of AI acceptance by demonstrating that disciplinary variation is concentrated primarily in PU rather than PEOU. While TAM accounts for acceptance through perceived usefulness and perceived ease of use [9], the present results indicate that ease-of-use perceptions may have reached a relatively uniform threshold across majors due to the accessibility of modern GenAI tools, thereby shifting the explanatory burden to perceived value.

At the same time, interpreting disciplinary differences in PU purely as differences in individual preference risks overlooking the structural and instructional conditions that shape perceived value. The algorithmic gap (algorithmic divide) perspective provides an essential interpretive lens here, suggesting that unequal patterns of AI engagement arise not only from access to tools but also from disparities in institutional signaling, curriculum integration, and faculty preparedness [25].

In STEM fields, AI is often legitimized through curricula that explicitly incorporate automation, modeling, and data analytics, and faculty members may be more prepared to integrate AI meaningfully into coursework and assessment, thereby reinforcing students' perceptions that AI is professionally and pedagogically valuable [25]. In contrast, where AI integration is less clearly aligned with disciplinary practices or where instructional guidance remains ambiguous, students may perceive fewer compelling reasons to use AI, lowering PU even when ease of use is comparable. This interpretation is compatible with student-centered research showing that instructor framing and course norms substantially shape learners' perceptions of GenAI's legitimacy, purpose, and boundaries [24].

Accordingly, the present findings suggest that disciplinary variation in PU reflects not only what students know about AI, but also what their educational environments implicitly authorize and reward them to do with it. These theoretical insights carry direct practical implications for curriculum design. Because disciplinary differences were most evident in PU, institutions should avoid uniform, generic AI implementation and instead adopt discipline-responsive approaches that explicitly connect AI use to each field's learning objectives, task structures, and evaluative standards.

For STEM-related majors, AI-integrated instruction may emphasize data-driven reasoning, computational problem-solving, simulation, and verification-oriented practices, such as AI-assisted coding and debugging, accompanied by structured evaluation of accuracy and limitations. For humanities disciplines, AI can be positioned as a cognitive partner for idea generation and language refinement, while maintaining human-led critical interpretation and revision through tasks such as comparative argument construction and evidence-based synthesis.

For social sciences, AI integration can support methodological and analytical work (e.g., survey design, visualization, scenario analysis) while foregrounding contextual reasoning and evaluative judgment. For non-declared or interdisciplinary students, scaffolded sequences that begin with foundational AI literacy and progress toward exploratory, interest-aligned projects may help learners develop discipline-relevant value pathways over time. Across all disciplines, strengthening PU requires making the pedagogical relevance of AI visible through authentic tasks and assessment criteria that reward critical oversight rather than superficial tool use.

VI. Conclusion

This study investigated university students' acceptance of generative AI with particular attention to whether perceptions differ by disciplinary background. The analysis focused on core acceptance constructs and examined both cross-sectional disciplinary patterns and pre–post changes over the study period. The primary finding is that PU varied significantly across academic majors, suggesting that disciplinary orientations and learning needs shape students' judgments of AI's value.

By contrast, no significant changes were observed between the pre-test and post-test measures, suggesting that overall perceptions remained stable rather than shifting meaningfully over time. Building on these results, the study concludes that disciplinary background is a key determinant of AI acceptance, primarily through its association with PU. In other words, differences in how students evaluate AI are better explained by whether they see it as beneficial for discipline-relevant learning and performance than by general attitudes alone. At the same time, the results indicate that Perceived Ease of Use (PEOU) did not differ by discipline, suggesting that usability is experienced similarly across majors. This pattern suggests that acceptance gaps are less likely to be driven by interface difficulty and more likely by how clearly AI aligns with disciplinary tasks, norms, and outcomes.

Practically, these findings support discipline-responsive AI-integrated curriculum design rather than uniform implementation. Institutions should align AI activities, examples, and assessments with the authentic practices and learning objectives of each field, and provide instructor support to design AI-enhanced tasks that make disciplinary relevance explicit. Such alignment is likely to strengthen PU within each discipline and promote more meaningful, sustained engagement with generative AI in higher education.

Several limitations should be acknowledged. First, the sample showed an uneven distribution across academic majors, with a large proportion from non-declared majors and minimal representation from the humanities, social sciences, and natural sciences. This imbalance constrained the statistical power of between-group comparisons and limited the generalizability of the findings. In particular, results about underrepresented disciplines should be regarded as preliminary.

Second, although a one-way ANOVA was employed to explore disciplinary differences, small subsample sizes may violate the assumptions of normality and homogeneity of variance. As such, the reported significant differences—especially in PU—should be interpreted with caution. Future research should aim to recruit more diverse and balanced samples across disciplines and institutions, and consider alternative analytical strategies, such as broader disciplinary clustering, to enhance robustness.

Lastly, although the TAM-based instrument demonstrated acceptable overall internal consistency, the Attitudes toward Using AI Technology subscale was measured with only two items and consequently showed comparatively lower reliability; therefore, future research should expand this attitude subscale by adding a broader set of theoretically grounded items to capture better the multidimensional nature of learners' evaluative responses toward AI and to improve internal consistency beyond what is feasible with a two-item measure.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Yong-Jik Lee prepared the first draft of the paper and

conducted the analysis, and Hyun-Cheol Choi reviewed and revised the paper. All authors had approved the final version.

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