Perception and Acceptance of Generative AI Tools in Software Engineering Education

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Abstract

Generative AI (GenAI) tools are increasingly embedded in software engineering education, yet students' perceptions and adoption patterns remain underexplored in emerging contexts. This study employs a mixed-method design to examine software engineering undergraduates' perceptions of GenAI using core Technology Acceptance Model (TAM) constructs—Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude (ATT), and Behavioral Intention (BI)—and to assess whether BI differs across academic-year groups. A survey of 190 students was analyzed using descriptive statistics, reliability tests, and one-way ANOVA with Tukey HSD. To clarify quantitative trends, eight semi-structured interviews were thematically analyzed. Results indicate moderately positive perceptions across TAM and a statistically significant difference in BI across academic years, with fourth-year students showing stronger intention. Qualitative insights explain developmental contrasts in GenAI use across cohorts.

CCS Concepts

• **Social and professional topics** → **Software engineering education**; • **Human-centered computing** → **Empirical studies in HCI**; • **Applied computing** → *Education.*

Keywords

Artificial Intelligence, Technology Acceptance Model, Behavioral Intention, Software Engineering, Higher Education

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1 Introduction

Generative artificial intelligence (GenAI) tools such as ChatGPT, GitHub Copilot, and Amazon CodeWhisperer have rapidly reshaped higher education. In software engineering education, these tools support code generation, peer-review assistance, and example-based learning, thereby enhancing students' engagement in programming tasks [11]. However, many learners adopt GenAI without fully recognizing its limitations, ethical implications, or potential impacts on deeper learning outcomes [2].

Although research on GenAI in education is rapidly expanding, discipline-specific and context-sensitive evidence on students' perceptions and acceptance remains limited [1]. Empirical research from emerging higher education contexts, particularly Vietnam, is still scarce, constraining a nuanced understanding of how students perceive and adopt GenAI in software engineering classrooms.

Accordingly, this study examines software engineering students' perceptions of and acceptance toward GenAI tools using the Technology Acceptance Model (TAM), which explains how perceived usefulness and perceived ease of use shape attitudes and behavioral intention toward technology adoption.

Empirical research from emerging higher education contexts, particularly Vietnam and Southeast Asia, remains limited. Vietnam represents a rapidly developing digital education environment characterized by expanding software engineering programs, growing adoption of generative AI tools, and increasing collaboration between universities and the technology industry. These contextual characteristics make it important to understand how students in Vietnamese universities perceive and adopt generative AI technologies.

The study addresses the following research questions:

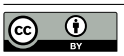
- **RQ1:** How do software engineering students perceive generative AI tools in terms of Perceived Usefulness, Perceived Ease of Use, Attitude, and Behavioral Intention?
- **RQ2:** Does Behavioral Intention to use generative AI differ across academic-year groups?

2 Literature Review

2.1 Generative AI in Software Engineering Education

Generative AI (GenAI) tools such as ChatGPT, GitHub Copilot, and Gemini have rapidly diffused into higher education and become embedded in students' learning workflows. Studies show that students use GenAI for brainstorming, writing support, and personalized feedback, while also expressing concerns about accuracy, ethics, and overreliance [4, 8]. In computing and engineering education, adoption is particularly intensive, with frequent use for debugging and code explanation alongside concerns about reliability and transparency [7, 9].

In software engineering contexts, GenAI tools function as intelligent coding assistants supporting code completion, debugging suggestions, and documentation generation. Powered by large language models trained on extensive programming datasets, these



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systems can generate syntactically correct code fragments and provide contextual explanations during development workflows [7, 9, 11].

2.2 Institutional Influences and Technology Acceptance Perspective

From an institutional perspective, educators recognize GenAI's potential to improve feedback and assessment but remain concerned about plagiarism and reduced independent learning [10]. Research also highlights tensions between students and instructors regarding ethical risks and institutional regulation of GenAI use [3]. Trust in AI-generated outputs has therefore emerged as an important factor influencing students' willingness to rely on these tools [15].

Most empirical research on GenAI adoption in higher education applies the Technology Acceptance Model (TAM), which proposes that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) influence Attitude toward Using Technology (ATT) and Behavioral Intention (BI) [5, 14]. In Asian contexts, TAM has often been extended with TPB or UTAUT, showing that PU, PEOU, and social factors significantly predict students' intentions to use tools such as ChatGPT in academic settings [6, 12]. However, empirical evidence from emerging higher education contexts remains limited. Vietnam represents a rapidly developing digital education environment characterized by expanding software engineering programs, increasing adoption of GenAI tools, and growing collaboration between universities and the technology industry. These contextual conditions make it important to examine how Vietnamese university students perceive and adopt generative AI technologies. Accordingly, this study adopts the core TAM framework as a parsimonious model to guide construct selection (PU, PEOU, ATT, BI).

2.3 Research Gap: Academic-Year Differences in GenAI Acceptance

Few studies explicitly compare GenAI acceptance across academic-year groups within computing-related disciplines, as most prior surveys aggregate participants or treat academic year as a control variable [3, 13, 15]. Academic experience may shape how students integrate GenAI into learning: senior students engaged in capstone projects, internships, and career preparation may value GenAI for debugging, documentation, and workflow efficiency [9], whereas junior students may experience greater uncertainty regarding appropriate and ethical use [10]. Empirical evidence on how TAM constructs vary across academic years therefore remains limited.

Accordingly, this study applies TAM to examine software engineering students' acceptance of GenAI across academic years at a Vietnamese university and employs one-way ANOVA to test differences in Behavioral Intention.

- **H1:** Students will report moderately positive levels of PU, PEOU, ATT, and BI toward GenAI tools.
- **H2:** Behavioral Intention (BI) toward GenAI tools will differ significantly across academic-year levels.

3 Methodology

3.1 Theoretical Framework

This study applies the Technology Acceptance Model (TAM) proposed by Davis [5]to examine software engineering students' perceptions and acceptance of generative AI tools such as ChatGPT and GitHub Copilot. According to TAM, perceived usefulness (PU) and perceived ease of use (PEOU) influence users' attitudes toward a technology, which subsequently shape behavioral intention (BI) to adopt the technology in learning contexts.

3.2 Research Design and Participants

The study aims to identify patterns in key TAM constructs and examine whether students' academic year is associated with differences in acceptance levels. A mixed-method design was employed, combining a descriptive quantitative survey with follow-up qualitative interviews for explanatory purposes. Using convenience sampling, data were collected from 190 undergraduate software engineering students at a private university in Vietnam.

3.3 Research Instrument

Data were collected using a structured questionnaire adapted from the original TAM instrument developed by Davis [5]. The questionnaire consisted of 16 items measuring four constructs: perceived usefulness (PU), perceived ease of use (PEOU), attitude toward using technology (ATT), and behavioral intention (BI). All items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

3.4 Data Analysis

The collected responses were analyzed using SPSS version 25. Descriptive statistics, including means and standard deviations, were used to summarize students' perceptions of generative AI tools. The internal consistency of each construct was assessed using Cronbach's alpha, with all values exceeding the recommended threshold of 0.70 (PU = 0.780; PEOU = 0.735; ATT = 0.806; BI = 0.807).

To examine differences across academic-year groups, a one-way ANOVA was conducted. No inferential models such as regression or structural equation modeling were estimated, as TAM was employed primarily to guide construct selection and descriptive interpretation rather than to test a full causal model.

3.5 Qualitative Interviews

To complement the quantitative findings, eight semi-structured interviews were conducted, with two participants from each academic year. Interviews were conducted in Vietnamese and audio-recorded with participants' consent. Each interview lasted approximately 20–30 minutes. The interview transcripts were analyzed using inductive thematic coding by two researchers to identify patterns related to perceived usefulness, perceived ease of use, attitude, and behavioral intention across academic years. These qualitative insights were used to explain and contextualize the quantitative patterns observed in the survey results.

4 Findings and Discussion

4.1 Sample Characteristics

Table 1 presents the sample characteristics of the 190 respondents.

Table 1: Sample Characteristics

Variable	Category	Frequency
Gender	Male	76
	Female	94
	Other	20
Academic year	First year	54
	Second year	46
	Third year	45
	Fourth year	45
Coding experience	< 1 year	120
	1–2 years	67
	≥ 3 years	3

The sample included 190 students with a relatively balanced distribution across academic years. Most respondents reported low to moderate coding experience, while the gender distribution was also relatively balanced.

4.2 Mean and Standard Deviation

Descriptive statistics indicated moderately positive perceptions across all TAM constructs, with mean scores ranging from 3.36 to 3.68 and standard deviations ranging approximately from 1.1 to 1.2.

4.3 Reliability Analysis

Table 2 summarizes the descriptive statistics and reliability of the study constructs.

Table 2: Descriptive Statistics and Reliability of Constructs

Construct	Mean	SD	α
PU	3.51–3.57	1.15–1.21	0.780
PEOU	3.36–3.59	1.07–1.15	0.735
ATT	3.45–3.68	1.11–1.22	0.806
BI	3.42–3.63	1.10–1.18	0.807

Mean scores ranged from 3.36 to 3.68, indicating moderately positive perceptions. Standard deviations suggest moderate response dispersion. All constructs demonstrated acceptable internal consistency, with Cronbach's alpha values exceeding the recommended threshold of 0.70.

4.4 One-way ANOVA

Table 3 reports the one-way ANOVA results for Behavioral Intention across academic-year groups.

The one-way ANOVA indicates a statistically significant difference in Behavioral Intention across the four academic-year groups, $F(3, 186) = 5.710$, $p = .001$. The effect size was $\eta^2 = 0.084$, indicating a medium effect.

Table 3: One-Way ANOVA Results for Behavioral Intention

Source	SS	df	MS	F	η^2
Between Groups	13.025	3	4.342	5.710	0.084
Within Groups	141.440	186	0.760		
Total	154.466	189			

4.5 Mean Behavioral Intention

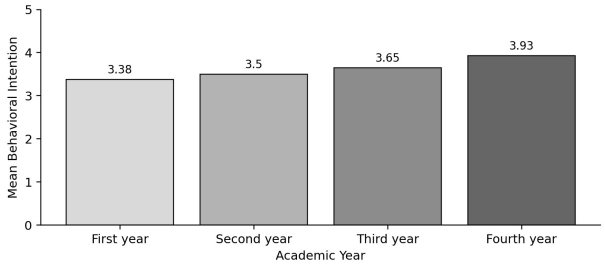

Figure 1: Mean Behavioral Intention toward Generative AI across Academic Years

Figure 1 illustrates the mean Behavioral Intention scores across academic years. Descriptively, Behavioral Intention increased steadily from the first year (M = 3.38) to the fourth year (M = 3.93).

4.6 Qualitative Results

4.6.1 Perceived Usefulness. Qualitative findings reveal a clear contrast in Perceived Usefulness between early- and late-year students. First-year students perceived Generative AI as moderately useful, mainly for basic troubleshooting, whereas fourth-year students emphasized its strong value in supporting complex academic tasks.

> *"I mainly ask small questions like syntax or why the code is wrong. It helps me understand things faster, but for practical assignments, the answers often do not match what I need."*
>
> *Participant 2, Question 1*

4.6.2 Perceived Ease of Use. The qualitative data indicate a developmental shift in Perceived Ease of Use across academic years. Second-year students viewed Generative AI as generally manageable but requiring repeated prompt adjustments, whereas fourth-year students described it as intuitive and easy to control.

> *"It is fairly easy to use, but I often need to rephrase my prompts several times to get the answer I want."*
>
> *Participant 3, Question 2*

4.6.3 Attitude Toward Using Technology. Students' attitudes toward using Generative AI showed a clear progression over time. First-year students expressed interest alongside uncertainty, whereas fourth-year students demonstrated confident and proactive acceptance of the technology.

> *"I think it is interesting, but I am worried I might not be using it correctly compared to others."*
>
> *Participant 1, Question 3*

> *"Using AI saves time, improves my work quality, and helps me approach problems more effectively."*
> *Participant 7, Question 3*

4.6.4 Behavioral Intention. Interview data reveal a marked contrast in students' future intentions to use Generative AI. Second-year students expressed cautious and conditional intentions, while fourth-year students reported strong and consistent intentions to continue using the technology.

> *"I plan to keep using GenAI regularly because it boosts my productivity and helps me focus on higher-level problem-solving."*
> *Participant 8, Question 4*

5 Discussion

With respect to H2, the findings show that Behavioral Intention (BI) toward generative AI differs significantly across academic-year groups. The one-way ANOVA, supported by a non-significant Levene's test ($p = 0.433$), justified the use of Tukey's HSD and indicated that fourth-year students reported significantly higher BI than first- and second-year students (Mean Difference = 0.554, $p = 0.010$; 0.705, $p = 0.001$). Although the effect size was moderate ($\eta^2 = 0.084$), the results suggest meaningful differences in GenAI acceptance across academic levels. Qualitative findings further indicate that senior students use GenAI more strategically for debugging, documentation, rapid prototyping, and advanced coursework, while junior students mainly rely on it for basic troubleshooting and remain more concerned about accuracy and hallucinations. This pattern may reflect differences in task complexity and evaluative skills, as fourth-year students are more often involved in capstone projects, internships, and advanced technical modules [4, 10]. It also aligns with prior research showing that senior engineering students increasingly use GenAI for coding and problem-solving activities [7, 9]. Regarding H1, students reported moderately positive levels of Perceived Usefulness, Perceived Ease of Use, Attitude toward Using Technology, and Behavioral Intention, suggesting that GenAI is generally perceived as useful and accessible within the TAM framework, with acceptance strengthening as academic experience increases.

6 Conclusion

Software engineering students generally perceived generative AI as useful and moderately easy to use, forming positive attitudes toward adoption. Behavioral Intention was strongest among fourth-year students, reflecting closer alignment between GenAI capabilities and advanced academic tasks. These findings suggest that early-stage instructional guidance and AI-literacy support may help reduce acceptance gaps across academic years and promote more effective and responsible GenAI use.

7 Limitations and Future Research

This study is limited by its focus on a single academic discipline and a cross-sectional design, which restrict generalizability and prevent examination of changes in acceptance over time. Another limitation concerns potential disparities in access to advanced generative AI tools. Students in emerging economies may rely primarily on free or limited versions of AI systems, while industry environments often employ premium tools with more advanced capabilities. Such differences in feature availability may influence perceived usefulness and future adoption intentions. Future research should employ longitudinal or experimental designs, include multiple disciplines or institutional contexts, and extend the analytical framework beyond TAM (e.g., TAM2 or UTAUT) to capture social and contextual influences. Additionally, future studies should incorporate behavioral or outcome-based measures to assess the actual effectiveness of generative AI in supporting learning and skill development.

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