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Utilization of Artificial Intelligence Tools in Engineering Education among HEIs in Eastern Visayas, Philippines

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Abstract. This study investigates the ways in which engineering faculty members and students in Eastern Visayas, Philippines, adopt and use artificial intelligence (AI) tools, assistants, and generative applications within teaching and learning. Using a quantitative descriptive–correlational design with purposive sampling, we surveyed 44 faculty members and 391 students across EVSU, SSU, ESSU, and BiPSU (formerly NIT/NSU) and analyzed responses using descriptive statistics, correlation tests, and group comparisons. Findings show broadly similar overall adoption rates between faculty members and students (no significant difference), but highlight role-specific patterns: faculty members more often use AI for grading automation, classroom management, and content verification, while students use AI more for computer-aided design, simulation, and creative outputs. Results revealed generally similar adoption rates between faculty members and students, with ChatGPT being the most widely used generative AI tool (Faculty: 94.1%; Students: 91.6%) and academic writing support being the most common purpose (Faculty: 67.6%; Students: 79.8%). Shared concerns include data privacy/security, ethical use, and usability/complexity. The study contributes: (1) a regional evidence base for AI adoption in engineering education; (2) an integrated TAM–IDT framework operationalized for HEI decision-making; and (3) role-specific implications for training, governance, and curriculum. We recommend institution-wide governance on responsible AI use, targeted capacity-building for faculty and students, and AI-literacy embedded in engineering curricula.

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1. Introduction

Artificial intelligence (AI) is no longer a distant technological promise but an embedded feature of modern life, influencing industries, economies, and everyday decision-making. In the education sector, AI technologies are increasingly transforming teaching and learning processes, offering the potential to revolutionize instructional design, assessment, and student engagement (Holmes et al., 2021; Zawacki-Richter et al., 2019). In higher education, the rise of AI aligns with the Fourth Industrial Revolution's emphasis on digital transformation, data-driven decision-making, and adaptive learning environments (Schwab, 2017).

For higher education institutions (HEIs) in the Philippines, especially those offering engineering programs, the integration of AI into curricula is both an opportunity and a necessity. AI tools—ranging from generative language models to simulation software—can facilitate personalized learning pathways, automate routine academic tasks, and enhance complex simulations in technical disciplines (Alshahrani & Ward, 2023; Lensing & Haertel, 2020). In particular, engineering education stands to benefit from AI-driven solutions that support modeling, prototyping, predictive analytics, and interactive problem-solving (Nuñez & Lantada, 2020).

Globally, universities are experimenting with AI to support intelligent tutoring systems, predictive analytics for student success, and AI-assisted research. However, these advancements raise concerns regarding data privacy, ethical use, potential job displacement, and the readiness of faculty members to adapt to AI-enhanced pedagogy (Kasneci et al., 2023; UNESCO, 2023). In developing contexts, including the Philippines, AI adoption in education is constrained by disparities in infrastructure, uneven access to high-speed internet, gaps in faculty training, and varying levels of student digital literacy (Boholano, 2017; Popenici & Kerr, 2017).

In the Philippine higher education landscape, early AI integration efforts have been concentrated on computing and information technology programs, with less focus on systematic adoption in engineering education (CHED, 2021). Nevertheless, engineering disciplines demand the very competencies—problem-solving, systems thinking, and innovation—that AI can enhance (Johri, 2020). Without structured integration, graduates may face a skills mismatch, limiting their competitiveness in global and AI-influenced industries. Despite its clear potential to enhance modelling, prototyping, and simulation, adoption in engineering programs remains uneven across institutions and infrastructures (Zawacki-Richter et al., 2019; Holmes et al., 2021; Dwivedi et al., 2023; CHED, 2021; Johri, 2020).

Empirical evidence on AI adoption in engineering education in Eastern Visayas remains limited, particularly with regard to comparative insights between faculty members and students, and theory-led explanations of adoption patterns. In response to these evolving educational demands, this study investigates the current level of AI usage among HEIs in Eastern Visayas, Philippines, focusing on its integration within engineering education.

The study aims to answer the following research questions (RQs):
RQ1: What is the profile of study respondents?
RQ2: What is the frequency and purpose of AI use among engineering faculty and students?
RQ3: Do adoption rates differ significantly between groups across tool categories (AI tools, assistants, generative AI)?
RQ4: How do constructs from the Technology Acceptance Model (TAM) (perceived usefulness, perceived ease of use) and Innovation Diffusion Theory (IDT) (compatibility, complexity, observability) relate to adoption in this context?
RQ5: What concerns and implementation enables shape sustainable use?

Answers to these RQs can provide a foundational understanding of AI adoption in engineering education; thus, this study aims to contribute to the development of responsive and innovative educational frameworks that enhance both teaching and learning outcomes in the Philippines.

2. Methodology

2.1 Theoretical Framework

This study adopts an integrated TAM–IDT framework. In TAM, perceived usefulness (PU) and perceived ease of use (PEOU) shape behavioral intention and use; IDT adds compatibility (COMP), complexity (COMPLX), and observability (OBS) to explain diffusion in educational settings. As illustrated in Figure 1, the conceptual model links these constructs to role-specific adoption (faculty vs. students) and informs targeted interventions (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Rogers, 2003).

TAM and IDT highlight specific levers—perceived usefulness and ease (TAM) alongside compatibility, complexity, and observability (IDT)—that predict uptake and meaningful use. This study addresses these gaps by providing region-specific evidence and aligning interpretations explicitly with TAM–IDT constructs (Celik et al., 2022; OECD, 2023; UNESCO, 2023); theoretical lenses commonly include TAM and IDT (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Rogers, 2003; King & He, 2006; Venkatesh & Bala, 2008).

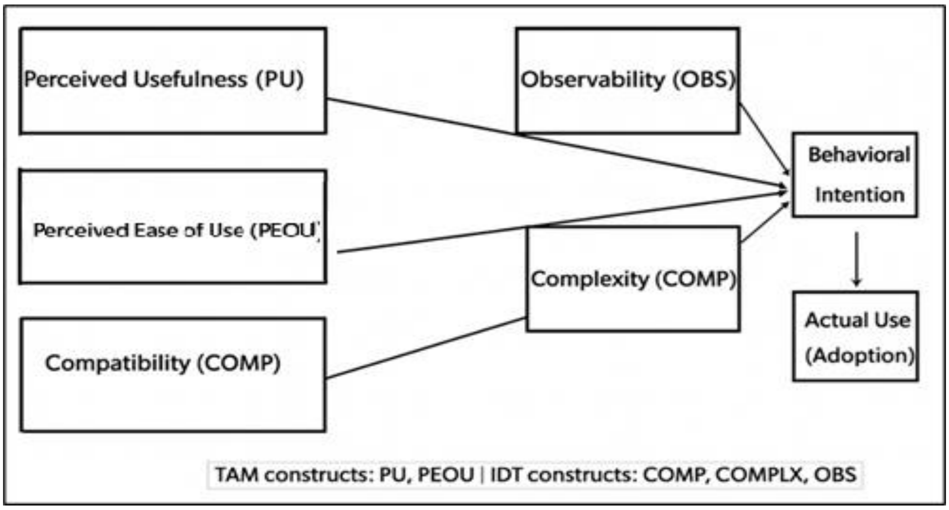

Figure 1: Integrated TAM–IDT Conceptual Framework

2.2 Research Design

Because of its suitability for examining patterns of technology adoption and identifying relationships between variables in educational contexts, this study adopted a quantitative descriptive–correlational research design as its methodological approach. The descriptive component was employed to generate a comprehensive profile of the respondents and to document the extent, frequency, and purposes of artificial intelligence (AI) tool utilization in engineering education. This included quantifying the use of specific AI applications, such as generative AI platforms, intelligent tutoring systems, grading automation tools, and simulation software, across both faculty members and student populations.

The selection of this design is consistent with methodological recommendations for technology adoption studies, in which descriptive–correlational approaches enable researchers to both depict current practices and test theoretically grounded relationships without manipulating study variables (Bhandari, 2022; Peck et al., 2008). This approach allows for capturing a snapshot of current AI usage patterns while simultaneously testing hypotheses related to TAM and IDT, which are the theoretical frameworks underpinning this research.

2.3 Study Site and Respondents

The study was conducted in Eastern Visayas, Philippines (Figure 2), across four HEIs with engineering programs: EVSU, SSU, NSU, and ESSU. Respondents included 44 faculty members and 391 students, selected through purposive sampling.

2.4 Instrumentation

Data for this study were collected using a structured online survey questionnaire developed through Google Forms® (Google LLC, Mountain View, CA). The instrument was designed to capture both quantitative and qualitative data on the usage of artificial intelligence (AI) tools in engineering education among both faculty members and students from selected higher education institutions (HEIs) in Eastern Visayas, Philippines.

The questionnaire comprised three main sections: (a) Respondent Profile, which gathered demographic and professional details; (b) AI Usage in Engineering Education, focusing on the extent, frequency, and purposes of AI tool usage and including a five-point Likert scale on which respondents were asked to rate their usage frequency (1 = Never utilized, 5 = Frequently utilized); and (c) Open-ended Questions, which elicited qualitative insights regarding the challenges, opportunities, and recommendations for AI integration in engineering curricula. Open-text responses were included to provide contextual depth beyond numeric ratings.

To ensure content validity, the questionnaire underwent expert evaluation by a panel of engineering educators who assessed the item clarity, relevance, and coverage of the constructs being measured. The Scale Content Validity Index (S-CVI/Ave) was computed at 0.92, indicating strong agreement in terms of the instrument's relevance and comprehensiveness (Shi et al., 2012). Face validity was confirmed through peer review by colleagues with advanced degrees, who evaluated the grammar, syntax, and readability to ensure unambiguous interpretation (Stangor, 2014).

Reliability testing was conducted via a test–retest procedure over a two-week period with a pilot group of faculty members and students, following established practices for educational survey instruments (Miller et al., 2013; Nasab et al., 2015). The resulting correlation coefficient indicated moderate to high stability, confirming the instrument's ability to yield consistent results over repeated iterations.

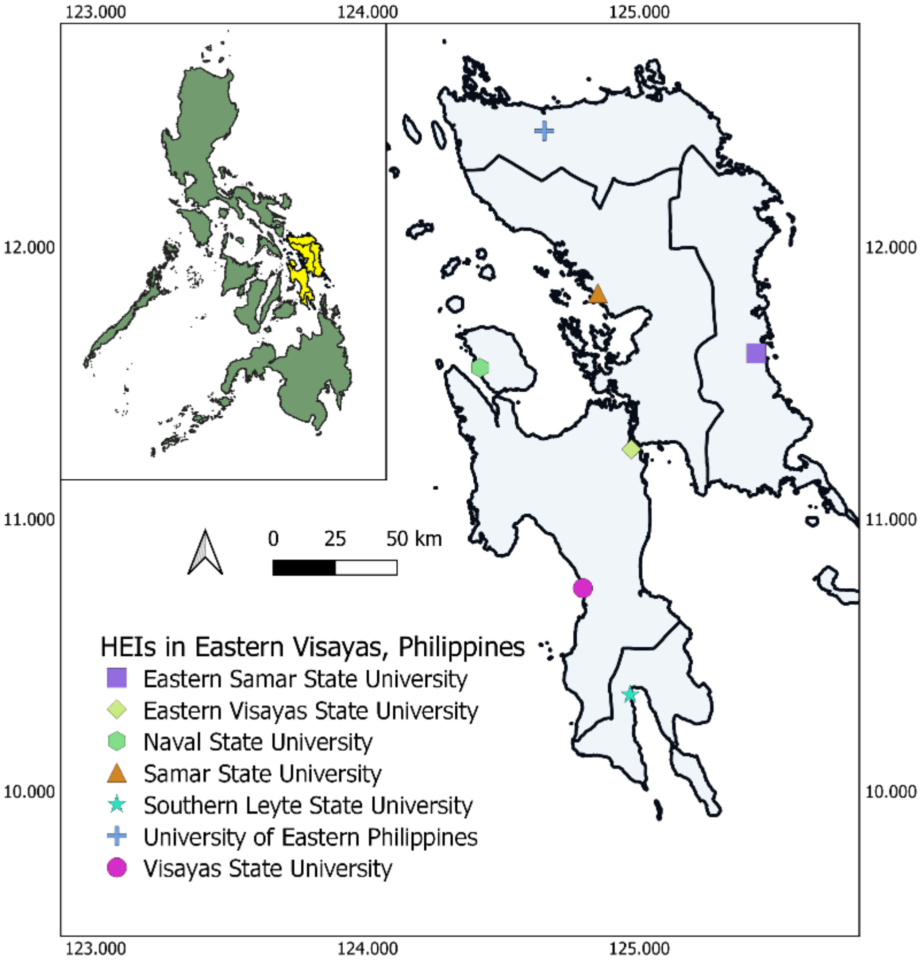

Figure 2: Location of the HEIs in Eastern Visayas, Philippines, which participated in the survey: EVSU (n=148), ESSU (n=32), SSU(n=22), and NSU (n=189)

2.5 Data Gathering

In order to maximize reach and facilitate participation across geographically dispersed institutions, the survey was disseminated online. Official requests for participation were sent to faculty coordinators and department heads of the participating HEIs—Eastern Visayas State University (EVSU), Samar State University (SSU), Eastern Samar State University (ESSU), and Biliran Province State University (NSU)—explaining the purpose of the study and inviting eligible respondents to participate voluntarily.

The recruitment process involved: (a) Sending introductory emails to institutional representatives, containing the study background, objectives, ethical considerations, and the survey link; (b) Distributing two separate Google Form links—one tailored for faculty members and another for students—to ensure the relevance of the questions to each respondent group; (c) Providing informed consent statements at the beginning of the survey, outlining data confidentiality, participation being voluntary, and the respondents' option to withdraw at any stage without penalty, in accordance with ethical research guidelines (Creswell &

Creswell, 2018). The survey period spanned four weeks, allowing adequate time for participants to respond while minimizing recall bias.

2.6 Data Analysis

Microsoft Excel was used to conduct descriptive and correlation analyses. Descriptive statistics were generated to summarize patterns of usage, while t-tests were applied to compare responses between faculty and students. Correlation analysis explored relationships consistent with the TAM–IDT framework. Qualitative responses were thematically coded to contextualize quantitative patterns, particularly in relation to privacy, ethics and usability. Likert-scale scores (Table 1) were interpreted using a standardized frequency classification (Bhandari, 2022).

Table 1: The Likert-scale ratings of AI usage were interpreted using a standardized usage frequency classification (Bhandari, 2022)

Score	Interpretation	Usage Frequency (%)
5	Frequently utilized	100% usage
4	Often utilized	75% usage
3	Sometimes utilized	50% usage
2	Rarely utilized	25% usage
1	Never utilized	0% usage

3. Results, Discussion, and Findings

3.1 Respondents' Profile

Table 2 presents the demographic and institutional profile of the faculty and student respondents. Among the faculty respondents (N = 44), more than half were affiliated with Biliran Province State University (NSU) (54.5%), followed by Eastern Visayas State University (EVSU) (11.4%), Samar State University (SSU) (9.1%), and Eastern Samar State University (ESSU) (6.8%). In terms of age, the largest group was comprised of those over 50 years old (27.3%), with other notable age clusters being 40–49 years (18.2%) and 30–39 years (15.9%). Gender distribution indicated a slight predominance of females (45.5%) over males (31.8%), with the remainder not specifying gender.

For the student respondents (N = 391), the majority were enrolled in the Bachelor of Science in Civil Engineering (BSCE) program (84.7%), followed by Bachelor of Science in Computer Engineering (BSCompt.E) (4.3%), Bachelor of Science in Electrical Engineering (BSEE) (5.1%), and Bachelor of Science in Mechanical Engineering (BSME) (5.9%). Institutionally, nearly half of the students came from NSU (48.3%), while EVSU accounted for 37.9%, ESSU for 8.2%, and SSU for 5.6%. The largest age group was 20 years old (56.3%), followed by 19 years (25.3%), less than 20 years (11.8%), and 18 years (6.6%). Gender distribution was male-dominated (61.9% male; 37.3% female; 0.8% not specified).

The distribution reflects that NSU was the most represented institution for both faculty members and students, suggesting stronger participation or accessibility in this HEI. Faculty respondents tended to be more senior in age, reflecting experience and possibly longer exposure to traditional teaching methods. On the other hand, students were predominantly young and male, which is consistent with the typical demographic patterns in engineering programs in the region. This composition provides a useful context for interpreting subsequent findings on AI tool usage, as institutional affiliation, age, and gender may influence access to technology, openness to innovation, and frequency of AI adoption in academic activities.

Table 2: Profile of Faculty and Student Respondents

	Variable	Category	n	%
Faculty (N = 44)	**HEI**	NSU	24	54.5
		EVSU	5	11.4
		SSU	4	9.1
		ESSU	3	6.8
	Age	> 50 years	12	27.3
		40–49	8	18.2
		30–39	7	15.9
		< 50	4	9.1
		20–29	3	6.8
	Gender	Male	14	31.8
		Female	20	45.5
Students (N = 391)	**Course**	BSCE	331	84.7
		BSCompt.E	17	4.3
		BSEE	20	5.1
		BSME	23	5.9
	HEI	NSU	189	48.3
		EVSU	148	37.9
		SSU	22	5.6
		ESSU	32	8.2
	Age	20 years	220	56.3
		19 years	99	25.3
		18 years	26	6.6
		< 20 years	46	11.8
	Gender	Male	242	61.9
		Female	146	37.3
		NA	3	0.8

3.2 Frequency and Purpose of AI Use

The analysis compared the AI usage rates of both faculty members and students across three primary categories: general AI tools, AI assistants, and generative AI (Table 3). Percentages were derived from survey responses, and a paired-samples t-test was conducted to determine whether differences between groups were statistically significant.

Faculty members reported an average usage rate of 25.03%, closely mirroring the 25.00% observed for students (Table 3, Figure 4). This near parity suggests that both groups have incorporated AI tools—such as grammar checkers, data analysis applications, and research aids—into their academic workflows at similar levels. Faculty members often integrate these tools for course preparation, grading, and research purposes (Alshahrani & Ward, 2023), whereas students primarily use them for assignments, studying, and content creation (Zawacki-Richter et al., 2019).

AI assistants (e.g. ChatGPT, Microsoft Copilot) showed usage rates of 19.98% for faculty members and 20.02% for students. Typically, faculty members employ such assistants for lesson planning, summarizing literature, and drafting academic materials (Holmes et al., 2021), while students use them for clarifying concepts, generating ideas, and aiding in problem-solving (Kasneci et al., 2023).
Generative AI tools (e.g. DALL·E, Midjourney, GPT-based text generators) were reported as having 25.00% usage among faculty members and 24.80% among students. Faculty applications often involve creating educational visuals, simulations, or prompts for case-based learning (Smutny & Schreiberova, 2020). Students apply generative AI primarily for creative outputs in projects and assignments.

Table 3: Frequency of AI Usage among Faculty (n=34) and Student Respondents (n=391)

Category	**Response**	**Faculty** (n & %)		**Students** (n & %)	
Use of AI tools	Sometimes (50% usage)	14	41.2	202	53.0
	Often (75% usage)	11	32.4	98	25.7
	Rarely (25% usage)	7	20.6	65	17.1
	Frequently (100% usage)	2	5.9	16	4.2
Use of AI assistants	Sometimes (50% usage)	13	38.2	185	48.6
	Rarely (25% usage)	10	29.4	94	24.7
	Often (75% usage)	8	23.5	80	21
	Never (0% usage)	2	5.9	10	2.6
	Missing/No response	1	2.9	12	3.2
Use of Generative AI	Sometimes (50% usage)	16	47.1	192	50.4
	Often (75% usage)	9	26.5	97	25.5
	Rarely (25% usage)	8	23.5	74	19.4
	Frequently (100% usage)	1	2.9	15	3.9

Both faculty members (67.6%) and students (79.8%) reported using AI tools most frequently for academic writing support, consistent with literature highlighting AI's role in improving text quality and structure (Kasneci et al., 2023; Zawacki-Richter et al., 2019) (Figure 3). Research and data analysis ranked second, with faculty members (58.8%) slightly ahead of students (53.3%), while AI use for designing and simulation was more common among students (41.2%) than faculty members (23.5%), reflecting engineering curriculum demands (Holmes et al., 2021).

Faculty members reported higher AI use for classroom management (47.1% vs. 21.3%) and automating grading and assessments (23.5% vs. 6.0%), tasks aligned with teaching responsibilities (Alshahrani & Ward, 2023). Although overall differences were not statistically significant, patterns reveal role-specific tendencies; faculty members favor administrative and evaluative applications, while students lean toward creative, design, and learning support uses, underscoring the need for targeted AI literacy training for each group.

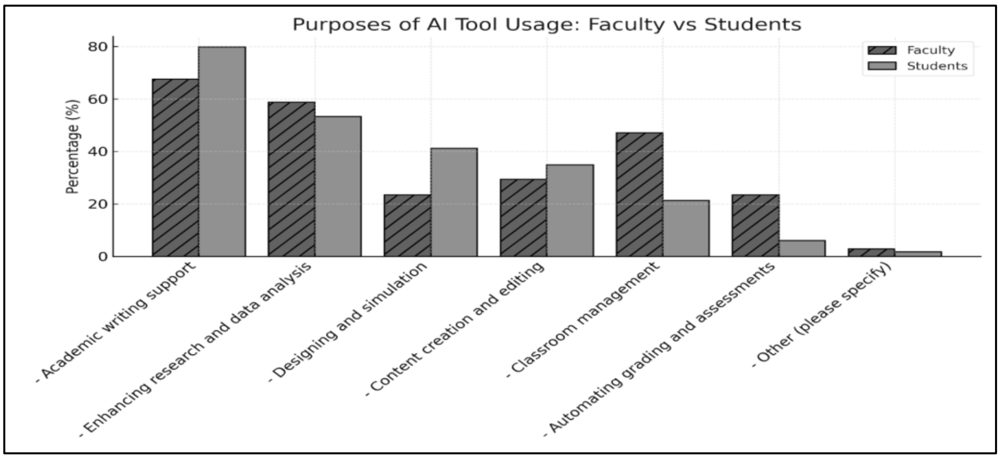

Figure 3: Faculty and Student Purposes in using Artificial Intelligence Tools

3.3 Adoption Rate Across AI Tool Categories

Across both faculty and students, generative AI tools and grading automation platforms emerged as the most widely used categories. Faculty members reported 70.6% usage of grading automation tools and 67.6% use of generative AI, while students showed comparable adoption for generative AI (68.0%) but lower use of grading tools (52.8%), reflecting the faculty's primary responsibility for assessment tasks (Alshahrani & Ward, 2023). However, students demonstrated higher engagement with computer-aided software (57.7% vs. 47.1%), consistent with coursework in technical and design-intensive disciplines, while plagiarism detection software was used at similar rates by both groups (≈38%).

With regard to AI assistants, Google Assistant dominated across groups (faculty: 73.5%; students: 83.5%), followed by Microsoft Copilot, which saw notably higher use among faculty members (29.4% vs. 10.0%), likely due to its integration with productivity software for lesson planning and documentation. Students showed greater adoption of mobile-friendly assistants such as Siri and DataBot, suggesting convenience-oriented usage. When examining specific generative AI applications, ChatGPT overwhelmingly led adoption (faculty: 94.1%; students: 91.6%), underscoring its versatility for both teaching and learning tasks (Kasneci et al., 2023). Faculty members reported a higher use of Claude (26.5% vs. 1.8%) and Turnitin (14.7% vs. 7.3%), aligning with a greater need for content evaluation and originality checks, while students were more likely to use Adobe Photoshop (22.6% vs. 8.8%) and Microsoft Power Apps (22.3% vs. 20.6%) for creative and project-based outputs. While statistical tests indicated no significant overall differences in adoption rates, the data reveal distinct role-driven preferences. Faculty members lean toward tools for grading, content verification, and productivity, while students favor applications that support technical coursework, creative design, and rapid information retrieval. These findings highlight the need for targeted AI integration strategies in HEIs, with training and resource allocation aligned to the functional requirements of both educators and learners.

Table 4: AI Tools, Assistants, and Generative AI Used by Students and Faculty

AI Tools	Faculty (n)	Student (n)	Faculty (%)	Student (%)
- Grading Automation Tools (e.g. Google Classroom, Alma Gradebook)	24	201	70.6	52.8
- Generative AI Tools (e.g. Midjourney, DALL·E, ChatGPT)	23	259	67.6	68
- Chatbots and Virtual Assistants	18	172	52.9	45.1
- Computer-Aided Software (e.g. AutoCAD, MathCAD)	16	220	47.1	57.7
- Plagiarism Detection Software	13	147	38.2	38.6
- Virtual Reality Tools (e.g. 3D simulations, virtual field trips)	2	33	5.9	8.7
AI Assistants				
Google Assistant	25	318	73.5	83.5
Microsoft Copilot	10	38	29.4	10
Siri	4	71	11.8	18.6
AI scheduling	3	16	8.8	4.2
Bixby	2	8	5.9	2.1
Cortana	1	9	2.9	2.4
DataBot Personal Assistant	1	42	2.9	11
AI Generative				
ChatGPT	32	349	94.1	91.6
Claude	9	7	26.5	1.8
Microsoft Power Apps	7	85	20.6	22.3
Turnitin	5	28	14.7	7.3
Adobe Photoshop	3	86	8.8	22.6
Midjourney	2	3	5.9	0.8
DALL·E	2	4	5.9	1
Wondershare Filmora	2	22	5.9	5.8
Bard	2	18	5.9	4.7
Beautiful.ai	1	1	2.9	0.3
Tome	1	1	2.9	0.3
Anyword	1	11	2.9	2.9

3.4 TAM-IDT Effect on Usage: Student vs Faculty

A paired-samples t-test comparing faculty and student usage percentages across all AI tool categories revealed no significant difference in overall adoption rates, $t(9) = 0.035$, $p = .973$. This statistical similarity indicates that both groups exhibit comparable levels of engagement with AI technologies, likely reflecting shared institutional exposure to digital infrastructure, common access to widely available tools, and parallel opportunities for AI integration in academic contexts (Kasneci et al., 2023; UNESCO, 2023).

While the frequency of use is statistically similar between the two groups of respondents, functional purposes and contexts differ markedly. Faculty members predominantly leverage AI for instructional and administrative functions, such as grading automation (70.6%), classroom management (47.1%), and content verification using tools such as Turnitin and Claude. Their adoption patterns reflect strong perceived usefulness in terms of efficiency, accuracy, and compatibility with teaching workflows (Alshahrani & Ward, 2023; Holmes et al., 2021). In contrast, students employ AI primarily for design, simulation, and content creation, including computer-aided software (57.7%) and generative AI tools for project outputs (68.0%), aligning perceived usefulness with creative affordances and learning enhancement (Zawacki-Richter et al., 2019; Kasneci et al., 2023).

Applying the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003) clarifies these adoption patterns. Both groups demonstrate positive perceptions of perceived usefulness (PU) and perceived ease of use (PEOU) as central drivers. For faculty members, PU centers on improving their pedagogical efficiency through grading and assessment automation. From students' perspective, PU relates to enhancing learning performance and supporting simulation and design work. PEOU is similarly evident in the widespread use of user-friendly platforms such as ChatGPT and Google Assistant.

The Innovation Diffusion Theory (IDT) framework (Rogers, 2003) adds explanatory depth through compatibility (COMP), complexity (COMPLX), and observability (OBS) constructs. For faculty members, compatibility with existing teaching practices and administrative systems facilitates adoption, particularly for productivity tools such as Microsoft Copilot. On the other hand, observability—seeing the clear benefits of AI in task performance—drives student uptake of generative AI tools (e.g. ChatGPT), whose utility is widely demonstrated in academic settings (Kasneci et al., 2023; Dwivedi et al., 2023).

However, perceived complexity remains a constraining factor, especially for advanced or less intuitive tools, potentially limiting more sophisticated integration without structured capacity-building (Celik et al., 2022; Popenici & Kerr, 2017). Taken together, these findings illustrate that adoption patterns converge quantitatively but diverge qualitatively. Both faculty members and students perceive AI as being useful and increasingly easy to use, but their role-based utility perceptions differ. Faculty members prioritize tools that align with teaching and administrative functions, while students emphasize applications that support learning, creativity, and technical skill development. This reinforces the explanatory power of the integrated TAM–IDT model, which reveals the ways in which perceived usefulness, ease of use, compatibility, complexity, and observability collectively shape adoption behaviors in role-specific ways (Davis, 1989; Venkatesh & Davis, 2000; Rogers, 2003).

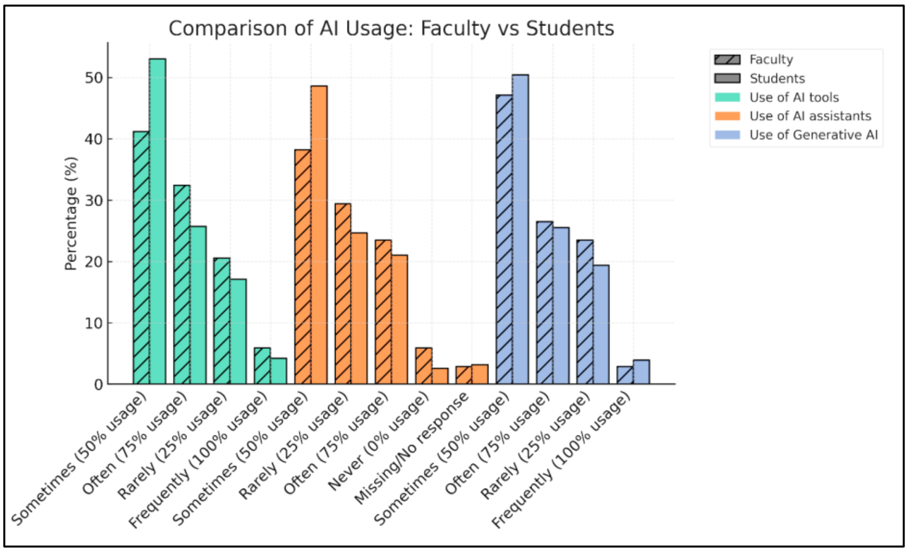

Figure 4: Faculty and Student Frequency of Usage of Artificial Intelligence Tools

3.5 Concerns Relating to AI Integration

The foremost concerns of the respondents relating to AI integration are as follows: (1) Data privacy/security (Faculty 64.7%, Students 55.4%); (2) Ethical concerns (Faculty 55.9%, Students 44.4%); and (3) Complexity/usability (Students 42.0%, Faculty 35.3%). The findings reveal no significant overall difference ($p > .05$). Both faculty members and students expressed parallel concern profiles regarding the integration of AI into engineering education. Data privacy and security concerns constituted the most frequently cited issue (faculty: 64.7%; students: 55.4%), reflecting apprehensions regarding the ways in which personal and academic data might be collected, stored, and potentially misused by AI-driven platforms. This aligns with the global discourse emphasizing the need for robust data protection and transparency in educational AI systems (UNESCO, 2023).

Ethical concerns ranked second (faculty: 55.9%; students: 44.4%), encompassing issues such as academic integrity, bias in AI-generated content, and the risk of over-reliance on algorithmic outputs. These findings are consistent with prior studies that highlight the necessity of embedding ethical AI literacy in higher education curricula (Kasneci et al., 2023; Selwyn, 2019). Concerns relating to complexity and usability were slightly more pronounced among students (42.0%) than faculty members (35.3%), suggesting that learners may encounter greater difficulty navigating AI tools without sufficient onboarding or training. Meanwhile, job displacement (faculty: 29.4%; students: 33.3%) and AI replacing teachers (faculty: 23.5%; students: 26.8%) were mid-tier concerns, reflecting moderate apprehension about AI's long-term impact on the academic labor landscape.

Interestingly, statistical analysis revealed no significant differences in concern rates between the two groups, suggesting that both faculty members and students share similar apprehensions, albeit from different vantage points—with faculty members focusing on the implications of AI for pedagogy and professional roles, and students more concerned with the learning experience and skill relevance. These findings underscore the importance of institutional policies and training programs that address ethical use, promote transparency, ensure data protection, and provide practical guidance on integrating AI into teaching and learning without undermining human roles in education.

Overall, the findings indicate parallel AI adoption rates between faculty members and students, suggesting shared institutional exposure and similar access to infrastructure. However, functional roles shape tool preferences; faculty members lean toward grading, assessment, and classroom management tools, while students focus on design, simulation, and creative content.

4. Conclusion

This study provides region-specific evidence on AI adoption in engineering education across four HEIs in Eastern Visayas. Overall adoption levels are comparable between faculty members and students, but purposes diverge; educators primarily leverage AI for grading, content verification, and course management, whereas students rely on AI for design, simulation, and creative tasks. These role-specific patterns align with an integrated TAM–IDT framework, whereby perceived usefulness, ease, and compatibility encourage uptake, while complexity and limited observability temper deeper integration. Shared concerns—especially regarding privacy, ethics, and usability—highlight the need for institutional governance and capacity-building (Dwivedi et al., 2023).

The implications of these findings are threefold. First, governance policies should codify responsible use, data protection, and academic integrity expectations for generative AI. Second, capacity-building must be role-specific; faculty training should emphasize pedagogical integration and assessment workflows, while student programs should focus on the design/simulation and critical appraisal of AI outputs. Third, embedding AI literacy into engineering curricula can cultivate the competencies required in AI-infused industries while fostering ethical practice (UNESCO, 2023; OECD, 2023).

Limitations of this study include the purposive sampling technique applied as well as the reliance on self-reporting by respondents. Future research should examine construct-level associations (e.g. SEM), compare disciplines and campuses, and evaluate the learning outcomes from targeted interventions. With balanced governance, training, and curricular integration, AI can augment—rather than replace—human expertise in engineering education.

In conclusion, AI adoption in Eastern Visayas HEIs is at a promising yet formative stage. While enthusiasm and practical engagement are evident among both educators and learners, the sustainability of AI integration will ultimately depend on institutional readiness to address ethical, technical, and pedagogical challenges. By coupling infrastructure provision with targeted training, governance, and curricular integration, HEIs can ensure that AI becomes a catalyst for innovation, critical thinking, and skill development, preparing both faculty members and students for the demands of an increasingly AI-driven engineering profession.

5. Recommendations

To ensure that AI adoption in engineering education is both sustainable and ethically responsible, higher education institutions (HEIs) in Eastern Visayas should implement a multi-pronged strategy, grounded in role-specific capacity building, governance, and curricular innovation. The following recommendations are proposed:

(a) Develop role-specific AI capacity-building programs. For faculty members, this can be done through training and should emphasize the pedagogical integration of AI, advanced use of grading automation, plagiarism detection, data analytics, and ethical evaluation of AI outputs. This will strengthen teaching efficiency while safeguarding academic integrity (Alshahrani & Ward, 2023; Holmes et al., 2021). For students, programs should focus on AI-supported research, computer-aided design, simulation tools, and creative problem-solving applications that are relevant to engineering practice.

Practical workshops on evaluating AI-generated content will also help to develop critical thinking skills (Zawacki-Richter et al., 2019). HEIs should establish clear policies on AI use, addressing data privacy, transparency, accountability, and bias mitigation. These policies should align with international standards, such as UNESCO's Guidance for Generative AI in Education and Research (2023). Policies must define acceptable use cases, outline procedures for verifying AI outputs, and integrate safeguards against over-reliance on AI in both instruction and assessment (Kasneci et al., 2023).

(b) Enhance accessibility and technical support systems for all. Given that usability challenges are more pronounced among students, institutions should invest in user-friendly AI platforms, onboarding modules, and help-desk or peer-mentoring systems (Holmes et al., 2021). This includes periodic technology audits to ensure equitable access to high-speed internet, compatible devices, and licensed AI applications across campuses.

(c) Integrate AI literacy into engineering curricula. AI literacy should be embedded in engineering programs to equip learners with the necessary skills to critically assess AI outputs, understand algorithmic limitations, and apply AI ethically in professional practice (Johri, 2020; Zawacki-Richter et al., 2019). Curricular integration should also address the societal impacts of AI, including potential job displacement, ethical dilemmas, and sustainability concerns.

(d) Promote faculty–student collaborative AI projects. Encouraging joint projects in which faculty members and students co-develop AI-driven solutions for engineering problems can foster innovation as well as a mutual understanding of AI's capabilities and limitations (Nuñez & Lantada, 2020). These projects should be documented and disseminated within and beyond the institution to create a knowledge base of best practices in AI integration.

By implementing these recommendations, HEIs can move from ad-hoc AI adoption to structured, ethical, and innovation-driven integration. This will ensure that AI serves as a tool to enhance—not replace—human expertise, cultivating engineering graduates who are both technologically proficient and ethically grounded.

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Informed Consent and Data Availability Statement
Informed consent was obtained from all subjects involved in the study.
Data is not publicly available, though may be made available on request from the author.

Authors' Contributions
Wenceslao C. Perante, Felisa Gomba, Vinyl H. Oquino, and Mark Kevin T. Cidro conceptualized the study; Wilferd A. Perante and Glenda M. Barquin assisted with data gathering. All authors were involved in the data analysis and writing of the manuscript.

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