

Generational Differences in the Academic Integration of Artificial Intelligence in Higher Education

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Abstract– *The accelerated integration of artificial intelligence (AI) in higher education is reshaping academic practices, particularly within engineering and technology-oriented environments. Despite this transformation, empirical evidence regarding generational differences in the academic adoption of AI remains limited. This study examined generational patterns in the academic integration of AI among 301 university students, assessing three dimensions: academic use of AI, trust in AI systems, and ethical awareness. Using a validated three-dimensional instrument (CFI = .974; RMSEA = .051), results indicated moderate levels of academic use ($M = 2.92$), slightly higher levels of trust ($M = 3.05$), and comparatively lower levels of ethical awareness ($M = 2.73$). Pearson correlations revealed significant positive associations among all dimensions ($p < .001$). No statistically significant differences were found by gender. However, Welch's ANOVA showed a significant age effect on academic AI use ($F = 7.02$, $p < .001$), with participants aged 43 years or older reporting significantly lower utilization. No generational differences were observed in trust or ethical awareness. These findings suggest that generational disparities in AI integration are primarily behavioral rather than attitudinal, posing important implications for university AI governance, curriculum design, and the implementation of differentiated training strategies within digitally transforming educational ecosystems.*

Keywords– Artificial intelligence; Higher education; Generational differences; Academic integration; AI governance; Digital transformation.

INTRODUCTION

The integration of artificial intelligence (AI) in higher education has substantially transformed teaching and learning processes. AI-driven tools enhance personalized learning, optimize educational outcomes, and streamline administrative functions [1]. They also automate repetitive tasks, facilitate early academic interventions, and support learning experiences tailored to individual student needs [2]. Machine learning-based platforms have enabled adaptive learning systems capable of dynamically adjusting content and pedagogical strategies to maximize academic performance [3].

AI technologies—including natural language processing and machine learning—further support the comprehension of complex concepts and provide individualized academic assistance, particularly in scientific and technical disciplines [4]. In fields such as engineering and computer science, generative AI tools have been progressively incorporated into curricula, with high levels of awareness and utilization among students [5]. Additionally, generative AI has demonstrated specific benefits for neurodivergent students by offering

personalized and multimodal support that enhances writing skills, time management, and academic self-efficacy [6].

Despite these benefits, the rapid expansion of AI in university contexts has raised significant concerns. Risks to academic integrity have been highlighted, particularly regarding overreliance on generative tools and the ease with which AI can produce content that may facilitate plagiarism [7], [8]. Questions about fairness in automated assessment systems and the potential for algorithmic bias have also intensified debates about responsible AI use in academia. These challenges underscore the importance of developing AI literacy among both faculty and students, supported by continuous training initiatives and clear institutional governance frameworks [7].

Trust in AI systems represents a central determinant of academic adoption. Research indicates that performance expectancy and perceived usefulness significantly shape trust, both functionally and in anthropomorphic dimensions [9]. Transparency, explainability, reliability, and technical efficiency are critical in strengthening trust [10]. However, ethical concerns and privacy considerations may undermine trust if not adequately addressed through responsible design and institutional safeguards [11]. Cultural context and social norms further influence trust formation, highlighting the need for sociocultural sensitive AI implementation strategies [10].

Importantly, technology adoption in higher education is not uniform. The literature consistently documents generational differences in digital appropriation. Younger cohorts tend to demonstrate greater familiarity with interactive environments and emerging digital tools, whereas older students often exhibit lower levels of adoption in certain technological domains. Variables such as cognitive flexibility, prior exposure, and technological habit formation contribute significantly to this variability [12].

Recent studies have identified generational distinctions specifically related to generative AI. For instance, Generation Z students often display high awareness of generative tools, though not necessarily greater trust or sustained practical integration. Older cohorts, in contrast, present more heterogeneous usage patterns and, in some cases, heightened ethical sensitivity [13]. Differences have also been observed in the academic application of generative tools for tasks such as grammar correction, idea development, and scientific writing [14]. In contexts characterized by infrastructural limitations, generational effects appear moderated by structural conditions and collaborative dynamics among faculty of different age

groups [15]. Additionally, disparities between undergraduate and graduate students have been reported in terms of confidence and willingness to integrate AI into learning processes [16].

Access to technological infrastructure further conditions adoption patterns. Large-scale national initiatives, such as the Digital India Program, demonstrate that improved access significantly enhances technology uptake, particularly among younger and more educated populations in underserved regions [17]. These findings suggest that AI adoption is shaped not only by individual attitudes but also by structural and contextual determinants.

Overall, existing research indicates that academic AI integration is influenced by a constellation of factors, including perceived usefulness, performance expectations, transparency, ethical considerations, cultural norms, technological access, and generational characteristics. Nevertheless, there remains a need for empirical evidence that simultaneously examines behavioral (use), cognitive (trust), and normative (ethical awareness) dimensions from a generational perspective within the general university population.

Against this backdrop, the present study investigates generational differences in the academic integration of artificial intelligence in higher education, analyzing academic AI use, trust in AI systems, and associated ethical awareness. By jointly examining these dimensions, the study seeks to provide empirical evidence regarding potential generational gaps in behavioral adoption and to inform university governance and institutional strategies for responsible and inclusive technological integration.

MATERIALS AND METHODS

Design and Context

A quantitative, cross-sectional, and non-experimental study was conducted in Honduras between September and December 2025. Data collection was carried out through a self-administered online questionnaire, implemented via Google Forms.

Participants and Sampling

The sample consisted of 301 university students. Non-probability voluntary sampling was used. The questionnaire link was distributed through multiple channels, including institutional social networks, university email, classroom dissemination, QR codes, and instant messaging applications such as WhatsApp. In addition, collaborating students participated in the dissemination of the instrument.

The inclusion criteria were being an active university student and being 18 years or older. Incomplete, duplicate, extremely low response time, or inconsistent response pattern answers were excluded.

The characterization variables collected were age, categorized into five groups (18–22, 23–32, 33–37, 38–42, and

43 years or older), and gender. These variables served as grouping factors for subsequent comparative analyses. Given the non-probability convenience sampling approach, the distribution of participants across age groups may not reflect the actual composition of the university population, which constitutes a limitation for the generalizability of generational comparisons.

Instrument

The study used a structured questionnaire to assess central dimensions of artificial intelligence (AI) literacy in university students. The items were answered on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree).

To examine the internal structure of the instrument, an exploratory factor analysis was performed using the minimum residual extraction method with oblique rotation (oblimin), followed by a confirmatory factor analysis to evaluate the plausibility of the obtained model. The analyses supported a structure of three correlated factors, conceptually consistent with the literature on AI and higher education.

The confirmatory model presented an adequate fit (CFI = 0.974; TLI = 0.961; RMSEA = 0.051; IC 90%: 0.024–0.075). All standardized factor loadings were statistically significant ($p < .001$) and of moderate to high magnitude.

The instrument consisted of three dimensions: trust in AI systems, which evaluates the perception of accuracy and decision-making capacity of AI (3 items; loadings between 0.684 and 0.912); ethical awareness about AI, which addresses aspects of bias, regulation, privacy, and transparency (4 items; loadings between 0.602 and 0.858); and academic use of AI, which measures the instrumental use of AI tools in academic activities (2 items; loadings of 0.769 and 0.859). Internal consistency was assessed for each dimension using Cronbach's Alpha (α) and McDonald's Omega (ω). Both coefficients indicated adequate reliability across the three dimensions, supporting the use of the instrument for analytical purposes in this context. The complete list of items is presented in Appendix A.

Procedure and Ethical Considerations

The questionnaire included an informed consent at the beginning, which explained the purpose of the study, the voluntary nature of participation, and the confidentiality of the information provided. The study received approval from an institutional ethics committee.

Statistical analysis

Statistical analyzes were performed using Jamovi software. Descriptive statistics were calculated, including means, standard deviations, and 95% confidence intervals. Pearson correlations were used to examine the associations between the dimensions. Differences by gender were analyzed using t-tests for independent samples, applying Welch's correction when the assumption of homogeneity of variances was violated. Differences between age groups were evaluated using Welch's ANOVA and, when necessary, post hoc comparisons were

performed using the Games–Howell procedure. The assumptions of normality and homogeneity of variances were previously verified. The exploratory factor analysis was conducted on an independent subsample, and the confirmatory factor analysis was performed on a separate subsample, following the standard practice of not using the same observations for both procedures.

RESULTS

The sample consisted of 301 university students, with no missing data in the analyzed dimensions. Three composite variables were calculated corresponding to academic use of AI, trust in AI systems, and ethical awareness of AI.

Overall level of use, trust, and ethical awareness

Regarding the academic use of artificial intelligence, students reported a moderate level ($M = 2.92$; $SD = 0.99$; 95% CI [2.80, 3.03]) on a 1-to-5 scale. The median score of 3.00 indicates that AI tools are integrated into academic activities at an intermediate level within the sample (see Table 1).

Trust in AI systems yielded a slightly higher mean ($M = 3.05$; $SD = 0.95$; 95% CI [2.95, 3.16]), with a median of 3.00. This finding suggests that students generally hold a moderately favorable perception of the capability, reliability, and performance of AI systems.

In contrast, ethical awareness regarding AI showed a comparatively lower mean ($M = 2.73$; $SD = 0.87$; 95% CI [2.63, 2.83]), with a median of 2.75. Relative to the other dimensions, this result indicates that concerns related to bias, regulation, privacy, and transparency are present but less strongly developed, reflecting a moderate-to-low level of critical ethical reflection within the analyzed sample.

TABLE 1
DESCRIPTIVE STATISTICS OF AI LITERACY DIMENSIONS

	AI USE	AI TRUST	AI ETHICS
N	301	301	301
Missing	0	0	0
Mean	2.92	3.05	2.73
95% CI mean lower bound	2.80	2.95	2.63
95% CI mean upper bound	3.03	3.16	2.83
Median	3.00	3.00	2.75
Standard deviation	0.992	0.952	0.869
Skewness	0.219	0.244	0.476
Std. error skewness	0.140	0.140	0.140
Kurtosis	-0.0677	-0.332	0.434
Std. error kurtosis	0.280	0.280	0.280

Note. AI_Use = Academic AI Use; AI_Trust = Trust in AI Systems; AI_Ethics = Ethical Awareness of AI. Values are based on $N = 301$ participants. Scores were computed as mean composite values on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Ninety-five percent confidence intervals were estimated assuming a t -distribution with $N - 1$ degrees of freedom.

Table 1 displays the mean scores and 95% confidence intervals for the three AI literacy dimensions. The pattern shows trust in AI systems scoring highest ($M = 3.05$), followed by academic AI use ($M = 2.92$), with ethical awareness registering the lowest mean ($M = 2.73$). This ordering suggests that students' functional and attitudinal engagement with AI precedes the development of critical normative reflection on its implications.

Association Between AI Literacy Dimensions

Bivariate Pearson correlations were calculated to examine the relationship between academic use of AI (AI_Use), trust in AI systems (AI_Trust), and ethical awareness regarding AI (AI_Ethics). The results are presented in Table 2.

A positive and statistically significant correlation was observed between academic use of AI and trust in AI systems ($r = .396$, $df = 299$, 95% CI [.296, .487], $p < .001$).

Similarly, academic use of AI showed a positive and significant correlation with ethical awareness regarding AI ($r = .310$, $df = 299$, 95% CI [.204, .409], $p < .001$).

Finally, trust in AI systems demonstrated a positive and significant correlation with ethical awareness regarding AI ($r = .461$, $df = 299$, 95% CI [.367, .545], $p < .001$).

Overall, the three dimensions exhibited statistically significant associations ranging from small to moderate in magnitude.

TABLE 2
PEARSON CORRELATIONS AMONG AI LITERACY DIMENSIONS

		AI_US E	AI_TRUST	AI_ETHICS
AI_USE	Pearson's r	—		
	df	—		
	p-value	—		
	95% CI Upper	—		
	95% CI Lower	—		
AI_TRUST	Pearson's r	0.396	—	
	df	299	—	
	p-value	<.001	—	
	95% CI Upper	0.487	—	
	95% CI Lower	0.296	—	
AI_ETHICS	Pearson's r	0.310	0.461	—
	df	299	299	—
	p-value	<.001	<.001	—
	95% CI Upper	0.409	0.545	—
	95% CI Lower	0.204	0.367	—

Note. AI_Use = Academic AI Use; AI_Trust = Trust in AI Systems; AI_Ethics = Ethical Awareness of AI. Values correspond to Pearson's r coefficients. Degrees of freedom (df) = 299. All reported correlations were statistically significant at $p < .001$. Ninety-five percent confidence intervals (CI) are presented in brackets.

Gender Differences

Independent samples t-tests were conducted to examine potential gender differences in academic use of AI, trust in AI systems, and ethical awareness regarding AI. Due to the significance of Levene's test, adjusted results for unequal variances were considered when appropriate.

No statistically significant differences were observed in academic use of AI ($t(275) = 1.034$, $p = .302$, $d = 0.12$), trust in AI systems ($t(275) = -1.237$, $p = .217$, $d = -0.15$), or ethical awareness regarding AI ($t(275) = 0.155$, $p = .877$, $d = 0.02$).

Effect sizes were trivial across all three dimensions, indicating that mean scores were comparable between the groups analyzed (see Table 3).

TABLE 3
INDEPENDENT SAMPLES T-TESTS COMPARING AI LITERACY
DIMENSIONS BY GENDER

		Statistic	df	p		Effect Size
AI_USE	Student's t	1.034 ^a	275	0.302	Cohen's d	0.1243
AI_TRUST	Student's t	-1.237	275	0.217	Cohen's d	-0.1487
AI_ETHICS	Student's t	0.155	275	0.877	Cohen's d	0.0186

Note. AI_Use = Academic AI Use; AI_Trust = Trust in AI Systems; AI_Ethics = Ethical Awareness of AI. Cohen's d is reported as the measure of effect size. Degrees of freedom (df) = 275. Levene's test for equality of variances was significant ($p < .05$), indicating violation of the homogeneity of variance assumption; therefore, results should be interpreted considering unequal variances. None of the comparisons reached statistical significance ($p > .05$).

Age Group Differences

A one-way analysis of variance (ANOVA) was conducted to examine differences in AI literacy dimensions across age groups (Table 4). The results indicated statistically significant differences only in academic use of AI ($F(4, 53.0) = 7.02$, $p < .001$). No significant differences were observed in trust in AI systems ($F(4, 51.2) = 1.33$, $p = .271$) or ethical awareness regarding AI ($F(4, 51.0) = 1.47$, $p = .225$).

TABLE 4
ONE-WAY ANOVA EXAMINING DIFFERENCES IN AI LITERACY
DIMENSIONS BY AGE GROUP

Dimension	F	df1	df2	p
AI_Use	7.02	4	53.0	< .001
AI_Trust	1.33	4	51.2	.271
AI_Ethics	1.47	4	51.0	.225

Note. AI_Use = Academic AI Use; AI_Trust = Trust in AI Systems; AI_Ethics = Ethical Awareness of AI. Age was categorized into five groups (18–22, 23–32, 33–37, 38–42, 43 or older). Welch's ANOVA results are

reported. Homogeneity of variances assumptions were met (Levene's test $p > .05$ for all dimensions). Post hoc comparisons (Games–Howell) indicated significant differences only for AI_Use, specifically between the 43+ group and all other age groups.

Post hoc comparisons using the Games–Howell test revealed that the group aged 43 years or older scored significantly lower in academic use of AI compared to the 18–22 years group ($p = .001$), 23–32 years ($p = .002$), 33–37 years ($p = .001$), and 38–42 years ($p = .021$). No significant differences were identified among the remaining age groups.

These results reveal a pattern directly relevant to the study's central question: the generational gap in AI literacy is not uniformly distributed across all dimensions but concentrates specifically in behavioral adoption. The significant age effect on academic AI use—driven entirely by the oldest cohort—stands in clear contrast with the absence of significant differences in trust and ethical awareness across age groups. This dissociation indicates that older participants hold equivalent attitudes toward AI and equivalent levels of ethical sensitivity yet engage with AI tools in academic contexts at substantially lower rates. Table 2 presents the mean academic AI use scores across age groups, illustrating the pronounced gap of the 43 years or older cohort relative to all other groups.

DISCUSSION

The present study examined generational differences in the academic integration of artificial intelligence within a general university population. The results reveal a clear pattern: the age-related gap is primarily reflected in instrumental use of AI, rather than in attitudes or ethical evaluations. This finding emerges in a context where AI is already embedded in educational transformation, enhancing personalized learning, optimizing academic outcomes, and supporting administrative functions [1], [2].

First, the overall level of academic AI use was moderate, confirming that artificial intelligence is already part of the university experience, though not yet fully consolidated. This result aligns with studies documenting the growing integration of generative tools into curricula—particularly in technical fields such as engineering and computer science [3]—as well as their use in academic tasks such as writing, idea generation, and linguistic revision [4]. Trust in AI systems showed slightly higher levels, while ethical awareness displayed comparatively lower scores. This pattern suggests that functional adoption of AI may be advancing more rapidly than critical reflection on its normative implications, consistent with recent concerns regarding academic integrity and responsible use of generative tools [5], [6].

However, the most relevant finding of the study is the significant difference in academic AI use among participants aged 43 years or older. While younger groups did not show substantial differences among themselves, the oldest group reported significantly lower use of AI tools in academic activities. This result is consistent with prior evidence

indicating that age influences the adoption of new technologies, particularly when digital familiarity and cognitive flexibility are required [7]. Recent studies have also identified generational differences in familiarity with and application of generative AI tools, showing distinct patterns across cohorts such as Generation Z, Millennials, and older generations [8].

Notably, this gap did not extend to trust or ethical awareness. In other words, older students neither expressed lower trust nor reduced ethical sensitivity; they simply reported lower usage. This suggests that the identified gap is primarily behavioral rather than attitudinal. The literature on trust in AI indicates that factors such as perceived usefulness, performance expectancy, and system transparency significantly shape trust formation [9], [10]. However, in the present study, trust did not vary significantly by age, reinforcing the interpretation that lower adoption among older groups may stem from differences in exposure, technological habits, or contextual usage rather than negative system perceptions.

From an institutional perspective, this pattern may be interpreted as a difference in technological adaptation rather than conceptual resistance. In contexts marked by infrastructure limitations or access gaps, technological adoption is often conditioned by structural and contextual factors [11], as well as intergenerational dynamics within educational environments [12]. Consequently, strategies for AI integration in higher education should not focus exclusively on modifying perceptions or attitudes, but rather on facilitating processes of practical appropriation and providing differentiated support according to age profiles.

The absence of gender differences further reinforces the idea that academic AI integration in this sample is not segmented by traditional digital divide variables. This suggests that the generational dimension may represent a more salient factor than gender in the academic adoption of AI-based technologies, particularly when considering patterns of instrumental use.

From the perspective of engineering and technology education, these findings provide empirical evidence supporting the need to design differentiated training strategies and AI literacy development programs [5]. The literature highlights that transparency, explainability, and ethical practices strengthen trust in AI systems [13]; however, this study indicates that relatively homogeneous trust does not guarantee equitable practical integration. Therefore, institutions must complement ethical governance initiatives with programs aimed at reducing behavioral gaps in effective academic AI use.

These findings are particularly significant for engineering education, where AI tools are increasingly embedded in design processes, system modeling, simulation environments, and data-driven decision-making workflows. In such contexts, uneven behavioral adoption across age groups may translate into asymmetries in technical proficiency, innovation capacity,

and readiness for AI-augmented professional practice. Ensuring equitable and practical engagement with AI technologies is therefore not only a matter of academic integration, but also of preparing future engineers and technologists to operate responsibly, effectively, and competitively in AI-intensive industries.

Overall, the results indicate that the academic integration of artificial intelligence in higher education is not a homogeneous process. Beyond general acceptance or favorable attitudes toward AI, generational differences persist in patterns of effective use. These behavioral gaps present strategic challenges for university AI governance, curriculum design aligned with digital transformation, and the development of inclusive educational ecosystems capable of supporting diverse learner profiles. Addressing these disparities is essential to ensure that institutional AI initiatives promote both technological advancement and equitable participation in the evolving landscape of technology-driven education.

CONCLUSIONS

The study provides empirical evidence that the academic integration of artificial intelligence in higher education is not determined solely by levels of acceptance or trust, but rather by differentiated patterns of use associated with age. The identified gap is predominantly behavioral, suggesting that digital transformation in universities requires interventions more focused on practical engagement than on attitudinal change.

These findings have implications for the design of institutional AI policies, particularly in engineering and technology education contexts, where the effective use of intelligent tools may influence academic productivity and the development of advanced digital competencies. University AI governance should therefore consider not only ethical and regulatory frameworks but also differentiated support strategies aimed at reducing asymmetries in technological appropriation.

Future research should examine how these behavioral differences affect academic outcomes, performance in complex tasks, and professional competency development, thereby consolidating a research agenda on generational AI adoption in higher education.

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