

Relationship between Generative AI Usage and Academic Performance among Undergraduate and Graduate Students in Kenyan Universities

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Abstract

This study examined the relationship between Generative Artificial Intelligence (GenAI) usage and academic performance among undergraduate and graduate students in Kenyan universities, with particular emphasis on differences between the two groups. A quantitative cross-sectional survey design was employed, collecting data from 458 students across diverse academic disciplines. Data were analysed using descriptive statistics, exploratory and confirmatory factor analyses, and structural equation modelling (SEM). The findings revealed moderate-to-high levels of GenAI usage (mean scores: 3.55–4.07), while academic performance indicators recorded consistently high ratings ($M = 3.98\text{--}4.17$). SEM results showed that GenAI usage positively and significantly associated with academic performance among both undergraduate ($\beta = 0.278$, $p < 0.05$) and graduate students ($\beta = 0.403$, $p < 0.001$), with a stronger effect observed among graduate students. Multi-group SEM confirmed a significant difference in the relationship between GenAI usage and academic performance across the two groups ($p = 0.036$), indicating that academic level moderates this relationship. The findings suggest that graduate students derive greater academic benefits from GenAI, likely due to higher levels of research competence and self-regulated learning. The study concludes that GenAI can enhance academic performance when used as a cognitive support tool rather than a substitute for independent learning. These findings provide empirical evidence to inform institutional policies, pedagogical strategies, and responsible AI integration in higher education.

Keywords: *Generative AI, Academic Performance, Undergraduate, Graduate, Higher Education*

1.0 Introduction

The rapid advancement of digital technologies has transformed teaching, learning, and research in higher education. Among the most significant innovations is Generative Artificial Intelligence (GenAI), which includes conversational AI, intelligent tutoring systems, and automated writing assistants capable of generating text, code, images, and other content. Since the release of ChatGPT in 2022, GenAI has been rapidly adopted across universities, reshaping how students access information, conduct research, complete assignments, and engage with learning (Dwivedi et al., 2023). While this technology offers considerable opportunities to enhance education, it also raises concerns regarding academic integrity, ethical use, and responsible AI governance.

Generative AI use in higher education ranges from AI-assisted to AI-generated use. AI-assisted use supports learning through editing, proofreading, brainstorming, outlining, and draft development while students remain the primary authors. In contrast, AI-generated use involves GenAI producing substantial or complete assignments with minimal student input, raising concerns about academic integrity and cognitive engagement. Researchers should distinguish these forms when examining their relationship with academic outcomes.

Generative AI supports academic writing, literature reviews, problem-solving, programming, and personalized learning by providing context-specific responses and immediate feedback. Evidence suggests that these capabilities improve learning efficiency, academic engagement, and higher-order thinking. For example, a recent meta-analysis found that GenAI significantly enhances university students' learning outcomes and academic achievement (Liu et al., 2025). However, its educational impact remains contested. Although many studies report positive effects, others argue that excessive reliance on AI may reduce critical thinking, independent learning, and academic integrity

(Baidoo-Anu & Ansah, 2023). These contrasting findings suggest that the educational value of GenAI depends largely on how students use the technology.

The effectiveness of GenAI may also differ across academic levels because undergraduate and graduate students vary in academic maturity, research competencies, and self-regulated learning (Kasneci et al., 2023). Despite increasing adoption of AI technologies in African universities, comparative evidence on their educational effects remains limited, particularly in Kenya. This study addresses this gap by examining the influence of GenAI usage on the academic performance of undergraduate and graduate students and determining whether academic level moderates this relationship.

Statement of the Problem

The rapid adoption of GenAI has transformed teaching and learning in higher education by supporting academic writing, research, problem-solving, and information retrieval. Studies indicate that GenAI can enhance learning efficiency, personalized learning, and academic performance (Dwivedi et al., 2023; Kasneci et al., 2023). However, its educational impact remains inconclusive, as excessive reliance on AI may weaken critical thinking, independent learning, and academic integrity (Baidoo-Anu & Ansah, 2023; Cotton et al., 2024). These mixed findings suggest that the educational value of GenAI depends on how students use the technology.

The influence of GenAI may also vary across academic levels because undergraduate and graduate students differ in academic maturity, research competencies, and self-regulated learning. Despite these differences, comparative empirical evidence remains limited, particularly in developing countries. In Kenya, universities are rapidly adopting digital technologies, yet little is known about whether GenAI affects academic performance differently among undergraduate and graduate students. This study addresses this gap by examining the relationship between GenAI usage and academic performance across the two groups, providing evidence to inform

institutional policies and pedagogical strategies for the effective integration of AI in higher education.

General Objective

To examine the influence of GenAI usage on the academic performance of undergraduate and graduate students in Kenyan universities and determine whether this influence differs between the two groups.

Theoretical Framework

This study is anchored on the Technology Acceptance Model (TAM) and Constructivist Learning Theory, which explain the adoption of GenAI and its relationship with academic performance. TAM posits that technology adoption is driven by perceived usefulness and perceived ease of use (Davis, 1989). Accordingly, students are more likely to adopt GenAI when they perceive it as improving learning efficiency, academic productivity, and performance (Dwivedi et al., 2023).

“This study examined the relationship between GenAI usage and the academic performance of undergraduate and graduate students”

Constructivist Learning Theory emphasizes that meaningful learning occurs through active knowledge construction, critical reflection, and interaction with learning resources (Piaget, 1972; Vygotsky, 1978). While GenAI can enhance inquiry, feedback, and problem-solving, excessive reliance on AI-generated content may reduce critical thinking through cognitive offloading (Chan & Hu, 2023; Gerlich, 2025). Together, these theories suggest that the educational benefits of GenAI depend on its effective use. This study therefore examines whether GenAI usage positively influences academic performance and whether

this relationship differs between undergraduate and graduate students.

The study tested the following hypotheses:

H1: GenAI usage has a positive and statistically significant relationship on the academic performance of undergraduate students in Kenyan universities.

H2: GenAI usage has a positive and statistically significant relationship on the academic performance of graduate students in Kenyan universities.

H3: The influence of GenAI usage on academic performance differs significantly between undergraduate and graduate students in Kenyan universities

2.0 Materials and Methods

This study employed a quantitative cross-sectional survey design involving 458 undergraduate and graduate students from Kenyan universities. Data were collected using a structured questionnaire measuring GenAI usage, TAM constructs, academic performance, and demographic characteristics on a five-point Likert scale. Content validity was established through expert review, while reliability and construct validity were assessed using Cronbach's alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and confirmatory factor analysis (CFA).

Data were analysed using descriptive statistics, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and structural equation modelling (SEM) to test the hypothesized relationships. Academic performance was self-reported because institutional confidentiality limited access to official records. Validated scales and statistical diagnostics mitigated bias.

Institutional permissions were secured from participating universities. Written informed consent was obtained from all participants, and confidentiality was maintained throughout. The study did not account for contextual factors, including internet reliability, digital infrastructure, and institutional policies on

GenAI use, which may moderate the relationship between GenAI use and academic performance. Future studies should incorporate these contextual variables to improve the generalizability and contextual relevance of the findings.

3.0 Results and Discussion

Demographic Characteristics

Table 1 summarizes the demographic characteristics of the 458 respondents. Females constituted 58.08% of the sample, while males accounted for 41.92%. Most participants were undergraduate students (66.81%), followed by master's students (31.22%), with doctoral students representing only 1.97%. The majority (75.88%) were aged between 17 and 27 years,

reflecting a predominantly Generation Z population. Respondents also reported high levels of digital engagement, with 73.74% using the internet for more than four hours daily, indicating substantial exposure to digital technologies, including GenAI. Participants were drawn from diverse academic disciplines, notably Accounting and Finance (16.59%), Technology (12.88%), International Relations (12.23%), MScII (11.35%), and Psychology (11.14%), enhancing the representativeness and generalizability of the findings across academic fields. Master's and doctoral students were analysed as a single graduate group because doctoral respondents represented only 1.97% of the sample, limiting the feasibility of separate statistical analysis.

Table 1

Demographics

Variable		Frequency (n)	Percentage (%)
Gender	Male	192	41.92
	Female	266	58.08
Education	Bachelor's	306	66.81
	Master's	143	31.22
	DBA/PhD	9	1.97
Age	17 - 21 yrs	154	33.77
	22 - 27 years	192	42.11
	28 - 35 yrs	65	14.25
	More than 35 yrs	45	9.87
Daily internet use	1 - 4 hrs	120	26.26
	4 - 8 hrs	219	47.92
	More than 8 hrs	118	25.82
Program	MBA	48	10.48
	MIS	39	8.52
	MSCII	52	11.35
	IR	56	12.23
	others	27	5.90
	Technology	59	12.88
	Pyschology	51	11.14
	IBA	41	8.95
	Account/finance	76	16.59
	Doctorate	9	1.97

GenAI Usage Perceptions

Table 2 presents respondents' perceptions and usage of GenAI. Overall, the findings indicate moderate-to-high levels of GenAI adoption, with mean scores ranging from 3.07 to 4.07. Most indicators (GAI1–GAI5 and GAI7)

recorded mean values above 3.50, reflecting favourable perceptions and widespread acceptance of GenAI for academic purposes. GAI3 recorded the highest mean ($M = 4.07$, $SD = 1.05$), followed by GAI1 ($M = 3.88$) and GAI7 ($M = 3.83$), indicating strong

endorsement of these aspects of GenAI. Conversely, GAI6 recorded the lowest mean ($M = 3.07$, $SD = 1.42$), suggesting more divergent views, possibly reflecting concerns about overreliance or other negative consequences of AI use. Negative skewness values (-0.127 to -1.235) indicate that responses were concentrated toward

agreement, while kurtosis values (-1.261 to 1.158) were within acceptable limits, confirming approximate normality. Overall, the results suggest that university students generally perceive GenAI positively and report substantial levels of usage, although concerns regarding some aspects of AI adoption remain.

Table 2
Perception of GAI use

Generative Artificial Intelligence	SD (%)	D (%)	N (%)	A (%)	SA (%)	Mean	Std. Deviation	Skewness	Kurtosis
GAI1	4.0	4.2	23.7	36.3	31.9	3.88	1.034	-0.854	0.445
GAI2	5.1	7.7	25.9	35.4	25.9	3.69	1.092	-0.668	-0.076
GAI3	4.2	4.2	13.9	35.8	41.8	4.07	1.050	-1.235	1.158
GAI4	6.0	9.1	24.6	31.2	29.2	3.69	1.159	-0.646	-0.332
GAI5	6.4	10.8	29.4	28.1	25.2	3.55	1.165	-0.456	-0.544
GAI6	20.8	14.4	22.6	21.9	20.4	3.07	1.417	-0.127	-1.261
GAI7	5.1	6.0	21.5	36.1	31.4	3.83	1.095	-0.865	0.241

Note: SD = Strongly Disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly Agree

Academic Performance Perceptions

Table 3 summarizes the descriptive statistics for academic performance. Overall, respondents reported high levels of association on academic performance, with 77.6%–85.4% agreeing or strongly agreeing with the statements. Mean scores ranged from 3.98 to 4.17, indicating consistently positive evaluations. AP2, AP4, and AP5 recorded the highest mean scores, while AP1 had the lowest but still reflected general agreement. Low standard deviations (0.84–0.90) indicate strong consensus among respondents. Negative skewness and acceptable kurtosis values

suggest that responses were concentrated toward the higher end of the scale and satisfied normality assumptions, supporting the suitability of the data for structural equation modelling.

The cross-sectional design does not permit determination of causal direction. Consequently, the positive association observed may reflect reverse causality, whereby academically stronger students are more likely to adopt and use GenAI effectively. Longitudinal studies are recommended to examine temporal ordering.

Table 3
Descriptive statistics for Academic Performance

Academic Performance	SD (%)	D (%)	N (%)	A (%)	SA (%)	Mean	Std. Deviation	Skewness	Kurtosis
AP1	1.8	4.6	13.9	53.3	26.3	3.98	0.865	-1.050	1.538
AP2	1.8	2.7	10.2	49.3	36.1	4.15	0.840	-1.285	2.448
AP3	1.8	2.4	17.7	39.4	38.7	4.11	0.900	-1.002	1.066
AP4	1.5	4.0	12.6	40.0	41.8	4.17	0.904	-1.165	1.342
AP5	1.5	2.9	14.8	38.5	42.3	4.17	0.893	-1.110	1.257

Note: SD = Strongly Disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly Agree

Exploratory Factor Analysis

Table 4 presents the exploratory factor analysis (EFA) results, which identified two distinct

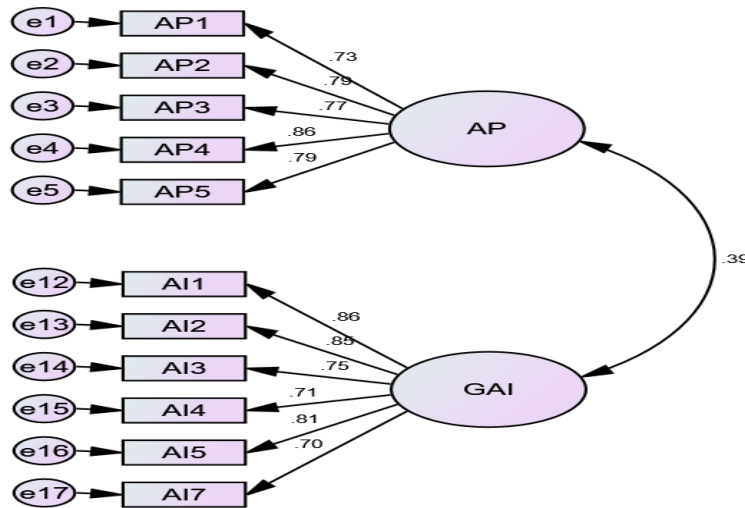
factors representing GenAI and Academic Performance (AP). GenAI indicators loaded strongly on their construct (0.710–0.896), with GAI2 and GAI5 exhibiting the highest

loadings. Academic Performance indicators also demonstrated strong loadings (0.778–0.881), led by AP4, AP5, and AP3. All factor loadings exceeded the recommended threshold of 0.50, and no significant cross-loadings were observed, confirming convergent and

discriminant validity. These findings demonstrate that the measurement items reliably capture the two latent constructs and support their suitability for confirmatory factor analysis and structural equation modelling.

Figure 1

Confirmatory Factor analysis of GAI and Academic Performance



Confirmatory Factor Analysis

The confirmatory factor analysis (CFA) results for the measurement model demonstrated that standardized factor loadings ranged from 0.73 to 0.86 for Academic Performance and 0.70 to 0.86 for GenAI, exceeding the recommended threshold of 0.70. AP4 ($\beta = 0.86$) and GAI1 ($\beta = 0.86$) were the strongest

indicators of their respective constructs. The CFA also revealed a moderate positive correlation between GenAI usage and Academic Performance ($r = 0.39$), suggesting that greater GenAI use is associated with improved academic performance. Overall, the measurement model demonstrated satisfactory reliability and construct validity.

Table 5

Model fit indices for the measurement model

Model measures	CMIN/DF	RMSEA	GFI	CFI	NFI	TLI
Model score	2.788	0.045	0.93	0.96	0.94	0.949

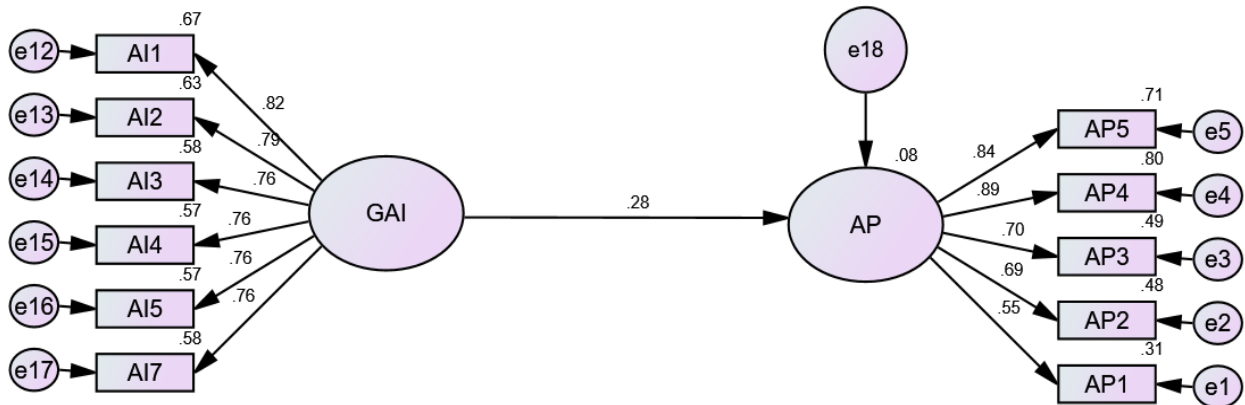
All fit indices satisfied the recommended SEM criteria, indicating a good fit between the model and the observed data. The chi-square to degrees of freedom ratio ($\chi^2/df = 2.788$) was below the recommended threshold of 3.0, while the Root Mean Square Error of Approximation (RMSEA = 0.045) indicated excellent model fit. The Goodness-of-Fit Index (GFI = 0.93), Comparative Fit Index (CFI = 0.96), Normed Fit Index (NFI = 0.94), and Tucker–Lewis Index (TLI = 0.949) all exceeded the recommended benchmark of 0.90.

Undergraduate SEM Results

The structural equation model (SEM) examining the relationship between GenAI usage and Academic Performance among undergraduate students revealed a positive and statistically significant association ($\beta = 0.278$, $t = 2.873$, $p = 0.004$). Standardized factor loadings for the GenAI indicators ranged from 0.76 to 0.82, indicating strong indicator reliability

Figure 2

Undergraduate SEM GAI VERSUS Academic Performance (AP)



Similarly, the Academic Performance construct was measured by five indicators with loadings ranging from 0.55 to 0.89. AP4 ($\beta = 0.89$) and AP5 ($\beta = 0.84$) were

the strongest indicators, while AP1 ($\beta = 0.55$) remained above the minimum acceptable threshold. These findings support the convergent validity and reliability of the measurement model and confirm Hypothesis 1 (H1).

Table 6

Model Fit Indices for Undergraduate SEM

Model Measures	CMIN/DF	RMSEA	GFI	CFI	NFI	TLI
Model Score	2.371	0.055	0.922	0.959	0.932	0.959

Table 7

Path Analysis for Undergraduate GenAI vs Academic Performance

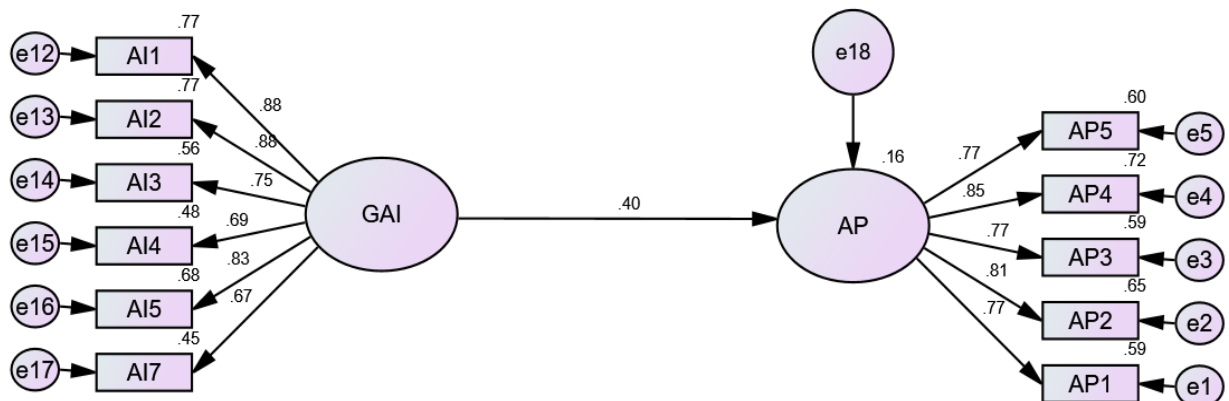
Hypothesis	B-value	T-value	P-value	Decision
H1: GenAI $\rightarrow$ AP	0.278	2.873	0.004	Supported

These findings provide empirical evidence that GenAI is a significant predictor of academic performance among undergraduate students,

highlighting its potential association with learning outcomes when effectively integrated into higher education.

Figure 3

Graduate SEM GAI vs AP



Graduate SEM Results

The structural equation model examining the relationship between GenAI usage and Academic Performance among graduate students demonstrated satisfactory psychometric properties, with GenAI indicator loadings ranging from 0.67 to 0.88 and Academic Performance loadings ranging from 0.77 to 0.85, all exceeding the recommended threshold of 0.50. AI1 and AI2 (0.88) and AP4 (0.85) were the strongest indicators of their respective constructs.

The SEM results showed a positive relationship between GenAI usage and Academic Performance among graduate students ($\beta = 0.403$, $t = 6.396$, $p < 0.001$), indicating that greater use of GenAI is associated with improved academic outcomes. The model explained 16% of the variance in academic performance ($R^2 = 0.16$), demonstrating moderate explanatory power. These findings confirm Hypothesis 2 (H2).

Table 8

Path Analysis for Graduate GenAI vs Academic Performance

Hypothesis	B-value	T-value	P-value	Decision
H1: GenAI $\rightarrow$ AP	0.403	6.396	0.000	Supported

The relatively large standardized coefficient suggests that graduate students derive substantial academic benefits from GenAI, likely due to its support for research, scholarly writing, and complex analytical tasks. These findings are consistent with previous research showing that AI-assisted learning technologies enhance higher-order learning, research productivity, and academic achievement when integrated appropriately into higher education environments.

relationship between GenAI usage and academic performance among undergraduate and graduate students. The structural invariance test was significant (CMIN = 19.352, $df = 10$, $p = 0.036$), indicating that constraining the structural paths across the two groups significantly reduced model fit. Small changes in the incremental fit indices (NFI = 0.006, IFI = 0.007, RFI = -0.002, and TLI = -0.002) further support the presence of structural differences between the groups. Consequently, Hypothesis 3 (H3) was supported, confirming that the influence of GenAI on academic performance differs significantly by academic level.

Multi-Group Comparison

Table 9 presents the multi-group structural equation modelling results comparing the

Table 9

SEM Model Comparison (Graduate vs Undergraduate)

Model	DF	CMIN	P	NFI Delta-1	IFI Delta-2	RFI rho-1	TLI rho2	Decision
Structural Weights	10	19.352	0.036	0.006	0.007	-0.002	-0.002	Significant

The findings suggest that graduate students derive greater academic benefits from GenAI than undergraduate students, highlighting the need for level-specific strategies to support effective AI integration in higher education. This finding aligns with previous studies showing that GenAI is associated with learning efficiency, academic achievement, and higher-order thinking when integrated effectively into

higher education (Anyanwu et al., 2024; Chen & Cheung, 2025). Similarly, Wang and Fan (2025) reported a large positive effect of ChatGPT on students' learning performance, while Fan et al. (2025) found that AI-supported learning significantly improved students' academic performance and cognitive skills.

However, these findings should be interpreted alongside emerging evidence highlighting the

potential risks of excessive AI dependence. Studies indicate that overreliance on GenAI may reduce deep learning, critical thinking, and long-term knowledge retention, leading to lower academic performance (Fan et al., 2025; Weeks et al., 2025). These contrasting findings suggest that the educational value of GenAI depends on how it is used. When employed as a cognitive support tool that complements rather than replaces independent learning, GenAI can substantially enhance academic performance. Consequently, universities should promote responsible and pedagogically guided use of GenAI to maximize its educational benefits while minimizing the risks associated with cognitive offloading and excessive dependence.

Although this study found a positive association between GenAI use and academic performance, the literature also identifies potential risks, including cognitive offloading, reduced critical thinking, overreliance on AI-generated content, and academic dishonesty. These concerns suggest that GenAI should be used to support rather than replace students' cognitive engagement. Accordingly, its educational value depends on responsible and ethical use alongside institutional guidance that promotes academic integrity and independent learning (Roy & Jony, 2026).

4.0 Conclusion

This study examined the relationship between GenAI usage and the academic performance of undergraduate and graduate students in Kenyan universities. The findings demonstrate that GenAI positively and significantly associated with academic performance in both groups, with a stronger effect observed among graduate students. These results suggest that GenAI can enhance learning, research, and problem-solving when used to support, rather than replace, students' cognitive engagement. However, excessive reliance on AI may undermine critical thinking and independent learning, highlighting the importance of responsible use. Universities should therefore develop evidence-based policies, AI literacy initiatives, and pedagogical strategies that

promote the ethical and effective integration of GenAI while minimizing the risks of overdependence. Overall, this study contributes empirical evidence demonstrating the potential of GenAI to enhance academic performance and support digital transformation in higher education.

5.0 Recommendations

Implications for Practice

Universities should establish governance frameworks that promote the ethical, transparent, and responsible use of GenAI, with clear guidelines on academic integrity, AI disclosure, assessment, privacy, and intellectual property. Institutions should integrate GenAI into teaching and assessment as a tool that supports inquiry, creativity, problem-solving, and research while preserving students' critical thinking and independent learning. Faculty development programmes should strengthen AI literacy and pedagogical competencies to facilitate effective AI integration, while curricula should incorporate AI literacy and digital skills to prepare graduates for AI-enabled workplaces.

Theoretical Implications

The study extends the Technology Acceptance Model (TAM) by demonstrating that technology acceptance translates into improved academic performance and that academic level moderates this relationship, with graduate students deriving greater benefits than undergraduates. These findings provide evidence to inform institutional AI strategies, curriculum redesign, and investment in digital learning infrastructure.

Recommendations for Further Research

Future research should employ longitudinal and mixed-methods approaches to examine the long-term effects of GenAI on critical thinking, self-regulated learning, academic integrity, and graduate employability across diverse educational contexts. Studies should also incorporate objective measures of academic performance alongside self-reported data to enhance validity and reliability. Additionally,

research should examine contextual factors such as internet reliability, digital infrastructure, and institutional policies that

may moderate the relationship between GenAI use and academic performance.

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