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AI IN THE CLASSROOM: AN ANALYSIS OF DIGITAL LITERACY, ETHICAL PERCEPTION, AND SELF-EFFICACY WITH TECHNOLOGY RESISTANCE AS A MODERATING VARIABLE

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ABSTRACT

This study aims to examine the effects of digital literacy, ethical perceptions of artificial intelligence (AI) use, and learning self-efficacy on students' academic performance, with technology resistance as a moderating variable. Data were collected through an online survey involving Indonesian university students who had prior experience using AI tools in academic tasks. The analysis employed Partial Least Squares-Structural Equation Modeling (PLS-SEM). Findings reveal that digital literacy, ethical perception, and self-efficacy positively and significantly influence academic performance. Interestingly, technology resistance was found to strengthen these relationships, contrary to the initial hypothesis that predicted a negative effect. This suggests that technology resistance may act as a motivational driver when students possess strong self-efficacy. Theoretically, this study contributes to the literature by introducing technology resistance as a moderator in the higher education context. Practically, the results provide recommendations for educational institutions to enhance digital literacy, promote ethical awareness of AI use, and foster students' self-efficacy, enabling them to transform resistance to technology into a supportive factor for academic success

Keywords: *Digital Literacy, Ethical Perception, Self-Efficacy, Technology Resistance, Academic Performance.*

ABSTRAK

Penelitian ini bertujuan menganalisis pengaruh literasi digital, persepsi etis terhadap penggunaan kecerdasan buatan (AI), dan self-efficacy pembelajaran terhadap kinerja akademik mahasiswa, dengan resistansi teknologi sebagai variabel moderasi. Data dikumpulkan melalui survei online kepada mahasiswa Indonesia yang telah menggunakan alat AI dalam kegiatan akademik. Analisis dilakukan dengan Partial Least Squares-Structural Equation Modeling (PLS-SEM). Hasil penelitian menunjukkan bahwa literasi digital, persepsi etis, dan self-efficacy memiliki pengaruh positif dan signifikan terhadap kinerja akademik. Temuan menarik muncul pada variabel resistansi teknologi yang justru memperkuat hubungan antarvariabel, berlawanan dengan hipotesis awal yang memprediksi efek negatif. Hal ini mengindikasikan bahwa resistansi teknologi dapat berfungsi sebagai pemicu motivasi ketika mahasiswa memiliki self-efficacy yang kuat. Secara teoretis, penelitian ini mengisi celah literatur dengan menguji resistansi teknologi sebagai moderator dalam konteks pendidikan tinggi. Secara praktis, hasil penelitian ini memberikan rekomendasi bagi institusi pendidikan untuk meningkatkan literasi digital, memperkuat etika penggunaan AI, dan menumbuhkan self-efficacy mahasiswa sehingga resistansi terhadap teknologi dapat dikelola menjadi faktor pendukung keberhasilan akademik.

Kata Kunci: Literasi Digital, Persepsi Etis, Self-Efficacy, Resistansi Teknologi, Kinerja Akademik.

INTRODUCTION

The 2023 ICILS study underscores a global concern, nearly half of students fall below baseline proficiency in computer and information literacy, with significant disparities linked to digital experience and ICT confidence (Commission, 2025). Furthermore, research conducted in Indonesian universities finds that improving digital literacy is essential for enhancing academic achievement and preparing students for disruptive technological change (Nasar et al., 2025). A 2024 study among graduate business students in the USA and UAE examines how cultural values shape students' perceptions and behaviors regarding the ethical use of AI tools, revealing nuanced differences across contexts (Mumtaz et al., 2025). Another investigation from Jordan finds academic staff hold varied ethical concerns and awareness highlighting institutional needs for training and policy support related to AI in education (Alnsour et al., 2025). Australian research in early 2024 demonstrates that students' digital literacy, attitudes toward technology, and self-efficacy significantly influence their engagement in online learning environments (Getenet et al., 2024). A systematic review in Indonesian school settings reveals that resistance to digital innovation often stems from factors such as limited digital competence, uncertainty about effectiveness, increased workload, and conservative institutional culture (Syah, 2024).

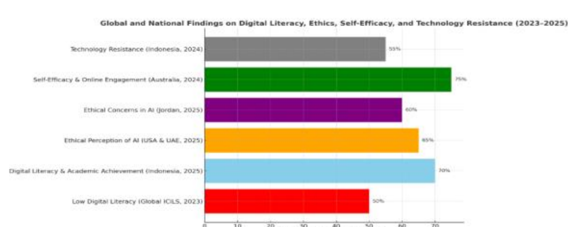

Figure 1. Global and National Findings on Digital Literacy, Ethical Perceptions,

Self-Efficacy, and Technology Resistance (2023–2025)
Source: Data adapted from Commission (2025), Nasar et al. (2025), Mumtaz et al. (2025), Alnsour et al. (2025), Getenet et al. (2024), dan Syah (2024).

The integration of AI tools like ChatGPT, Gemini, and Copilot in higher education brings both opportunity and concern. In the U.S., 40% of students admit to using AI on assignments without permission**,** with educators detecting widespread academic misconduct (Sarma, 2025). In response, OpenAI introduced a study mode to steer students toward responsible engagement yet issues in promoting academic integrity persist, evidenced by a steep rise in AI-related cheating between 2023-24 (Guardian, 2025). These developments point to a critical tension: while AI can support learning, it also poses ethical, motivational, and skill-development challenges, especially amidst varying levels of digital literacy, ethical perception, and technological self-efficacy. (See diagrams below).

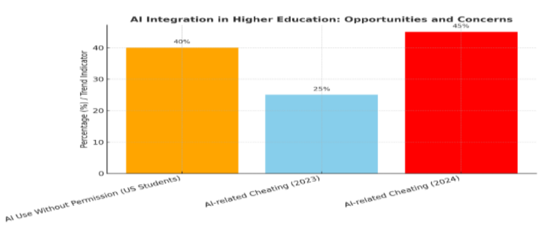

Figure 2. Trends in AI Use and Academic Integrity Issues in Higher Education (2023–2024)
Source: Data adapted from Sarma (2025) and The Guardian (2025)

A number of previous studies have highlighted the role of artificial intelligence (AI), particularly generative AI and ChatGPT, in improving learning quality and students' academic performance. (Lo et al., 2025) demonstrated that AI-based feedback significantly enhances the quality of students' writing revisions while fostering motivation and engagement, although its effect on emotions was less pronounced compared to motivation. Similarly, (Ashraf et al., 2025) found that the use of ChatGPT positively influences the academic performance of higher education students in Pakistan, with students perceiving it as a valuable learning aid, despite concerns regarding overdependence and ethical implications. In the context of medical education, (Duan et al., 2025) reported that medical students generally showed a moderate to high understanding of AI and expressed optimism about its benefits, while also raising concerns about privacy and ethical issues. In line with this, (Alnsour et al., 2025) explored the perspectives of academic staff in Jordan, revealing that although many had adopted AI in teaching and research, significant worries remained regarding plagiarism and unethical use, highlighting the urgent need for institutional support and ethical training. In Ghana, (Acquah et al., 2025) offered further insights, showing that ChatGPT use enhances students' motivation, future belief, and perceptions of academic performance, with epistemic curiosity serving as a key moderating factor. Meanwhile, (Yin et al., 2025) focused on medical journal publishing and identified the need for more comprehensive, standardized, and up-to-date guidelines on the use of AI. In teacher education, (Iqbal et al., 2025) found that performance expectancy and use behavior of generative AI were positively associated with preservice teachers' academic achievement, with shared metacognition and cognitive offloading acting as significant mediators. Similarly, (Bai & Wang, 2025) demonstrated that interaction with generative AI and the quality of its output improve students' motivation and learning outcomes, with creativity serving as a moderator that strengthens these effects. AI literacy has also become an important area of focus. (Bećirović et al., 2025) revealed that students' technical understanding, practical application, and self-efficacy in using AI positively affect output quality, although excessive critical appraisal of AI can reduce both confidence and output quality. These findings underline the importance of balanced AI literacy development to ensure ethical and effective use. Finally, (Dhamija & Dhamija, 2024) emphasized that both lecturers and students view ChatGPT as a tool that reduces administrative burdens and enhances teaching efficiency, although further investigation is needed regarding its long-term impact and ethical dimensions. Taken together, these studies confirm that AI and ChatGPT make a significant contribution to enhancing learning quality, motivation, and academic performance. However, notable gaps remain in exploring ethical aspects, AI literacy, and the long-term impact of AI use across diverse cultural and educational contexts. Therefore, this study offers novelty by focusing on AI in the Classroom through the analysis of digital literacy, ethical perception, and learning self-efficacy, while introducing technology resistance as a moderating variable an approach that has received little attention in prior research. This perspective is expected to provide both theoretical and practical contributions to a more comprehensive understanding of AI integration in higher education.

This research is urgent because widespread AI use among students has escalated conflicts between convenience and academic integrity. Without adequate literacy and ethical awareness, AI may impair learning rather than enhance it. Digital literacy gaps and resistance to technology can compromise the effectiveness of educational innovation. There is a lack of integrated empirical studies exploring how digital literacy, ethical perception, and self efficacy jointly influence academic outcomes, and how technology resistance moderates these relationships. Key Contributions, Holistic insight, the study will illuminate how digital literacy, ethical perception, and self-efficacy interact to shape academic performance. Moderator analysis, by investigating technology resistance as a moderator, it offers actionable insights to mitigate barriers in AI adoption. Empirical grounding, findings will support evidence based educational strategies and policies aimed at promoting responsible, effective AI integration in learning.

Focus of the study, this research examines the impact of digital literacy, ethical perception of AI use, and learning self-efficacy on academic performance among students, while exploring technology resistance as a moderating factor. Research Objectives to assess the direct effects of digital literacy, ethical perception, and self-efficacy on students' academic performance. To evaluate the role of technology resistance in moderating these relationships. To propose recommendations for educational institutions that aim to foster responsible AI integration and reduce resistance to technological innovation.

LITERATUR REVIEW

1) Digital Literacy

1. Theoretical foundation — ICILS / International digital literacy framework**:** International large-scale assessments show that digital literacy comprises multiple dimensions (information skills, computer use, and online communication) and that many students globally perform below baseline levels, which constrains their ability to learn effectively with digital tools (Fraillon, 2023).
2. Theoretical foundation — Digital literacy as an enabler of academic learning (skills → outcomes)**:** Recent empirical work finds that higher levels of student digital literacy are positively associated with improved academic outcomes and informal digital learning practices, indicating digital literacy functions as a capability that mediates access to learning benefits from educational technology (Zakir et al., 2025).
3. Empirical notes: national studies in Indonesia emphasize that strengthening digital literacy is critical for preparing students for disruptive technology and for boosting performance in digital learning environments (Zakir et al., 2025).

2) Ethical Perception of AI Usage

1. Theoretical foundation — Extensions of the Technology Acceptance Model (TAM) incorporating ethics and trust**:** Contemporary extensions of TAM for AI show that students' ethical beliefs, perceived trust and normative judgments influence both whether they accept AI tools and how they use them in academic tasks (Dahri et al., 2024) (Mumtaz et al., 2025).
2. Theoretical foundation — Ethical awareness / deontological consequentialist framing**:** Recent empirical studies frame students' ethical perceptions around concerns of fairness, authorship, and academic integrity, showing that ethical cognition (what students judge permissible) strongly predicts their AI behaviours in coursework (Chan, 2025) (Subaveerapandiyan et al., 2025).
3. Empirical notes: cross-country evidence (USA, UAE, Jordan and other contexts) documents variation in ethical perceptions and highlights institutional needs for policies and training to align student practice with academic integrity norms. SpringerLinkBioMed CentralArtificial intelligence (Attewell, 2025).

3) Learning Self-Efficacy

1. Theoretical foundation — Social Cognitive Theory / Self-Efficacy (Bandura applied to digital

contexts)**:** Self-efficacy belief in one's capability to perform learning tasks remains central for motivated engagement with technology; recent studies continue to apply Social Cognitive Theory to explain how efficacy beliefs determine persistence and strategy use in online learning (Getenet et al., 2024) (Miao et al., 2025).

2. Theoretical foundation — Self-efficacy as mediator of technology → engagement → outcome**:** Empirical research from 2023–2025 finds that digital attitude and digital literacy boost self-efficacy, which in turn increases online engagement and predicts better learning outcomes, indicating self-efficacy often mediates the effect of digital skills on performance (Miao et al., 2025).
3. Empirical notes: systematic reviews and empirical studies during 2023–2025 show online learning self-efficacy predicts subjective well-being, engagement, and final grades across diverse higher-education samples (Güçlü Aydoğan et al., 2024) (Von Der Mehden et al., 2025).

4) Academic Performance (Dependent Variable)

1. Theoretical foundation — Self-regulated learning & expectancy-value frameworks**:** Contemporary models suggest academic performance is shaped by students' goal setting, task value, and self-regulatory processes; digital tools affect performance indirectly by changing opportunities for self-regulated learning (Saks, 2024) (Yokoyama, 2024).
2. Theoretical foundation — Resource-capability perspective (digital skills + ethics + efficacy → achievement)**:** Recent empirical work treats academic performance as an outcome dependent on interacting resources (digital literacy), psychological capacities (self-efficacy), and normative/ethical constraints (ethical perception), implying multi-factor causal models are needed to explain variance in grades (Zakir et al., 2025) (Vieriu & Petrea, 2025).
3. Empirical notes: recent empirical articles (2024–2025) directly link digital literacy and self-efficacy to measurable gains in academic achievement in online and blended settings (Yokoyama, 2024).

5) Technology Resistance (Moderator)

1. Theoretical foundation — Innovation Resistance Theory (IRT)**:** IRT explains user resistance through perceived barriers in usage, value, risk, tradition, and image, and recent applications adapt IRT to digital/AI contexts to account for psychological and cultural causes of refusal or cautious adoption (Nikiforova, 2024).

2. Theoretical foundation — Digital distrust / psychological barriers model**:** Recent reviews show resistance arises from distrust, low perceived competence, workload concerns, and institutional tradition, positioning resistance as a contextual moderator that can weaken positive effects of digital literacy or self-efficacy on performance (Ezeudoka & Fan, 2024).
3. Empirical notes: systematic reviews in Indonesian school settings and broader meta-analyses (2023–2024) document common resistance drivers limited competence, uncertainty about effectiveness, increased workload, and conservative culture supporting the moderator role of resistance in education contexts (Oulamine et al., 2025).

Based on the literature review and previous research findings that have been discussed, a research framework has been developed to illustrate the relationships among the variables under study. This framework serves as the foundation for formulating the research hypotheses, in which each independent variable, moderating variable, and dependent variable are connected in accordance with prior empirical findings. The proposed research framework and hypotheses are presented in the following figure.

1. Research Framework

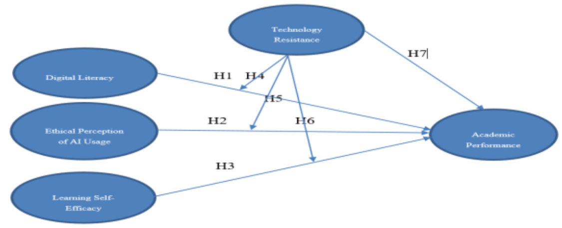

Figure 3. Research Framework
Source: Research Hypotheses

2. Research Hypotheses

Based on the research framework, the proposed hypotheses are as follows:

- H1: Digital Literacy has a positive effect on Academic Performance. Students with higher levels of digital literacy are better able to access, process, and utilize digital learning resources. This competence enhances their ability to complete academic tasks effectively, thereby improving overall performance.
- H2: Ethical Perception of AI Usage has a positive effect on Academic Performance. When students perceive AI usage as ethical and responsible, they are more willing to adopt such tools in learning. This positive attitude fosters trust and constructive engagement, which in turn supports academic success.
- H3: Learning Self-Efficacy has a positive effect on Academic Performance. Learners with stronger self-efficacy believe in their capacity to succeed in academic tasks. This belief encourages persistence, resilience, and effective learning strategies, leading to improved performance outcomes.

- H4: Digital Literacy has a negative effect on Technology Resistance. High digital literacy reduces the fear or reluctance to adopt new technologies. Students who are digitally competent tend to perceive technology as a useful and manageable resource, thus lowering resistance.
- H5: Ethical Perception of AI Usage has a negative effect on Technology Resistance**.** A strong ethical perception of AI reduces concerns about misuse or harm. This lowers skepticism and resistance, making students more open to adopting AI in educational contexts.
- H6: Learning Self-Efficacy has a negative effect on Technology Resistance. Students with high self-efficacy feel confident in their ability to use technology successfully. This confidence mitigates resistance and fosters a more adaptive response to digital tools.
- H7: Technology Resistance has a negative effect on Academic Performance. Resistance to technology hinders the adoption of useful learning tools and reduces engagement with digital resources. This reluctance creates barriers to effective learning, which negatively impacts academic performance

RESEARCH METHODS

1. Research Design

This study employs a quantitative, explanatory survey design to test causal relationships and moderating effects among digital literacy, ethical perception, self-efficacy, technology resistance, and academic performance. Quantitative research allows for statistical testing of hypotheses using structured data, which is especially relevant for complex models involving mediation and moderation (Creswell, 2023).

2. Population and Sampling

The population of this study consists of undergraduate and graduate students at Indonesian universities who have experience using AI tools in academic tasks. The sampling technique applied is purposive sampling, which is suitable when selecting respondents with specific characteristics relevant to the research objectives (Solution, 2023). Determining sample size in PLS-SEM has been widely debated.

1) The 10-times rule is a simple heuristic, but recent findings argue it often underestimates sample needs (Hair & Alamer, 2022).
2) The inverse square root method provides more robust guidance, with a recommended minimum of 160 respondents for adequate statistical power (Kock & Hadaya, 2018).
3) Recent studies emphasize that although PLS-SEM can handle small to medium samples, larger datasets (200–300 respondents) increase reliability of path estimates and moderation analysis (Ringle et al., 2023).
4) Based on these guidelines, this study targets 300 respondents, with a minimum threshold of 200, while 100 may be considered the absolute minimum if strong path coefficients exist.

3. Data Collection

Data will be collected via an online questionnaire (Google Forms)**,** which provides cost-effectiveness, wide reach, and flexibility for students in higher education settings (Saunders et al., 2023).

4. Instrumentation

The instrument uses a five-point Likert scale adapted from validated items measuring digital literacy, ethical perception, self-efficacy, resistance to technology, and academic performance. The Likert scale is widely used in social science research for capturing attitudinal and behavioral constructs (Saunders et al., 2023).

5. Data Analysis Technique

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS software to analyze the collected data. PLS-SEM is particularly suitable for studies that focus on prediction, involve complex models with mediating and moderating variables, and do not require data normality assumptions (Hair & Alamer, 2022).

PLS-SEM is widely recommended when the research model includes latent constructs such as digital literacy, ethical perceptions, self-efficacy, and resistance to technology, since these variables are typically measured by multiple indicators and require robust structural modeling (Hair & Alamer, 2022).

The data analysis will follow two stages:

A. Measurement Model Assessment

1. This stage evaluates the validity and reliability of the constructs by testing indicator loadings, internal consistency (Cronbach's Alpha, Composite Reliability), and convergent validity (Average Variance Extracted / AVE).
2. Discriminant validity will also be examined using the Fornell–Larcker criterion and HTMT (Heterotrait–Monotrait Ratio), which are recommended in recent PLS-SEM guidelines (Hair & Alamer, 2022).

B. Structural Model Assessment

1. This stage tests the hypotheses by examining path coefficients, R^2 (explained variance), effect size (f^2), and predictive relevance (Q^2).
2. Bootstrapping with 5,000 resamples will be used to determine the significance of path relationships, including moderation effects of resistance to technology.
3. PLS-SEM bootstrapping is recommended for robust estimation of standard errors and significance levels in mediation and moderation testing (Ringle et al., 2023).
4. PLS-SEM via SmartPLS thus provides both exploratory and confirmatory benefits, making it appropriate for this research's objectives in analyzing the complex interplay between digital literacy, ethical perception, self-efficacy, and academic performance in the context of AI usage in education.

RESULTS AND DISCUSSION

Results

1. Descriptive Analysis of Respondents' Characteristics

a. Illustrates the frequency with which respondents use technology or AI-based applications (such as ChatGPT, AI tools, or digital platforms) based on 274 survey responses. (See diagram below

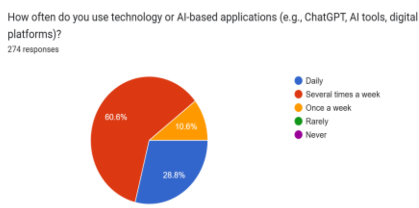

Figure 4. Respondents' Characteristics Based on the Frequency of AI Technology Usage
Source: Google Form

The results show that a majority of respondents (60.6%) reported using AI applications several times a week, while 28.8% use them daily. Only 10.6% indicated usage once a week, and almost no respondents reported rarely or never using such tools. This indicates that engagement with AI-based technology among participants is relatively high, reflecting strong integration of digital tools into their daily or weekly routines.

b. Presents the distribution of respondents' academic performance based on GPA or equivalent category from 274 survey participants.

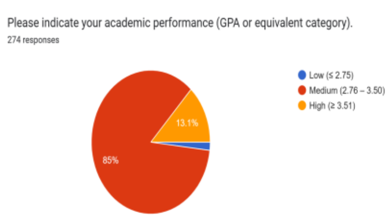

Figure 5. Respondents' Characteristics Based on the academic performance
Source: Google Form

The majority of respondents (85%) reported a medium level of academic performance (GPA between 2.76–3.50). Meanwhile, 13.1% indicated a high GPA (≥ 3.51), and only a very small proportion fell into the low category (≤ 2.75). This suggests that most participants in the study maintain solid academic achievement, with relatively few at the extreme ends of performance.

2. Measurement Model Assessment

a. Outer Loadings

Presents the results of the outer loadings matrix obtained from SmartPLS analysis. Outer loadings indicate the correlation between observed indicators and their latent constructs. According to Hair et al. (2023), a loading value above 0.70 is considered strong, while values between 0.40–0.70 may be retained if theoretically justified and if the AVE and CR remain acceptable. (See diagram and table below)

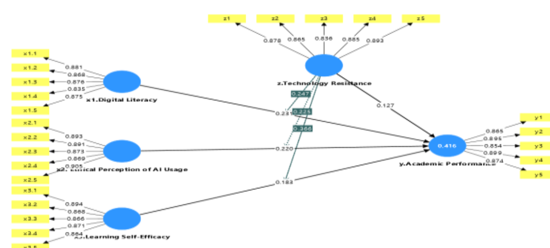

Figure 6. Diagram Outer Loadings
Source: Smart Pls

Table 1. Outer Loadings – Matrix.

Indicator	Digital Literacy (X1)	Ethical Perception of AI Usage (X2)	Learning Self-Efficacy (X3)	Academic Performance (Y)	Technology Resistance (Z)	Z*X1	Z*X2	Z*X3
X1.1	0.487	–	–	–	–	–	–	–
X1.2	0.288	–	–	–	–	–	–	–
X1.3	0.216	–	–	–	–	–	–	–
X1.4	0.356	–	–	–	–	–	–	–
X1.5	0.875	–	–	–	–	–	–	–
X3.1	–	–	0.293	–	–	–	–	–
X3.2	–	–	0.311	–	–	–	–	–
X3.3	–	–	0.373	–	–	–	–	–
X3.4	–	–	0.369	–	–	–	–	–
X3.5	–	–	0.305	–	–	–	–	–
Y1	–	–	–	0.294	–	–	–	–
Y2	–	–	–	0.291	–	–	–	–
Y3	–	–	–	0.286	–	–	–	–
Y4	–	–	–	0.371	–	–	–	–
Y5	–	–	–	0.364	–	–	–	–
Z1	–	–	–	–	0.870	–	–	–
Z2	–	–	–	–	0.865	–	–	–
Z3	–	–	–	–	0.856	–	–	–
Z4	–	–	–	–	0.836	–	–	–
Z5	–	–	–	–	0.820	–	–	–
Z*X1	–	–	–	–	–	1.000	–	–
Z*X2	–	–	–	–	–	–	1.000	–
Z*X3	–	–	–	–	–	–	–	1.000

Source: Smart Pls

The results in Table 1 show that:

1. Digital Literacy (X1) has most indicators below 0.70, except for X1.5 (0.875), which is valid and strong.
2. Learning Self-Efficacy (X3**)** has relatively low loadings (0.293–0.373), indicating the need for further evaluation.
3. Academic Performance (Y) indicators range between 0.286–0.371, suggesting weaknesses in indicator validity.
4. Technology Resistance (Z) shows strong values (0.820–0.870), thus it can be considered valid.
5. Moderating interactions (Z*X1*, ZX2, Z*X3) all show values of 1.000, indicating that the interaction constructs were perfectly formed by SmartPLS.

b. Construct reliability and validity tests

Presents the results of construct reliability and validity tests using Cronbach's Alpha, Composite Reliability (ρc), and Average Variance Extracted (AVE). These indices are essential for evaluating the internal consistency and convergent validity of each latent variable in PLS-SEM analysis (Hair et al., 2023).

Table 2. Construct Reliability and Validity Overview

Construct	Cronbach's Alpha	Composite Reliability (ρa)	Composite Reliability (ρc)	Average Variance Extracted (AVE)
Digital Literacy (X1)	0.793	0.928	0.936	0.752
Ethical Perception of AI Usage (X2)	0.932	0.938	0.948	0.786
Learning Self-Efficacy (X3)	0.922	0.934	0.944	0.711
Academic Performance (Y)	0.932	0.936	0.944	0.744
Technology Resistance (Z)	0.922	0.936	0.941	0.760

Source: Smart Pls

Cronbach's Alpha for all constructs is above 0.70 (ranging from 0.793 to 0.932), indicating good internal consistency. Composite Reliability (ρc) values for all constructs exceed 0.90, which demonstrates very strong reliability. The AVE values for all constructs are above 0.70, surpassing the minimum threshold of 0.50, confirming that each construct has good convergent validity. Thus, based on the results in Table 2, all constructs in this study meet the requirements for reliability and convergent validity according to PLS-SEM standards (Hair et al., 2023).

c. Discriminant validity test

Presents the results of the discriminant validity test using the Heterotrait-Monotrait ratio (HTMT). According to Henseler et al. (2015) and Hair et al. (2023), HTMT values below 0.85 (strict criterion) or 0.90 (liberal criterion) indicate that discriminant validity is established.

Table 3. Discriminant Validity – HTMT Matrix

Constructs	Digital Literacy (X1)	Ethical Perception of AI Usage (X2)	Learning Self-Efficacy (X3)	Academic Performance (Y)	Technology Resistance (Z)	Z*X1	Z*X2	Z*X3
Digital Literacy (X1)	–	0.007	0.263	0.234	0.030	0.130	0.135	0.135
Ethical Perception of AI Usage (X2)	–	–	0.284	0.373	0.029	0.063	0.824	0.824
Learning Self-Efficacy (X3)	–	–	–	0.281	0.124	0.059	0.119	0.119
Academic Performance (Y)	–	–	–	–	0.216	0.176	0.431	0.431
Technology Resistance (Z)	–	–	–	–	–	0.081	0.090	0.090
ZDigital Literacy (ZX1)	–	–	–	–	–	–	0.215	0.215
ZEthical Perception of AI Usage (ZX2)	–	–	–	–	–	–	–	0.024
ZLearning Self-Efficacy (ZX3)	–	–	–	–	–	–	–	–

Source: Smart Pls

The results in Table 3 indicate that all HTMT values fall well below the recommended threshold of 0.85, confirming that discriminant validity is established across all constructs. This means that each latent variable (Digital Literacy, Ethical Perception, Learning Self-Efficacy, Academic Performance, and Technology Resistance) is empirically distinct, and the model demonstrates adequate construct separation as required for PLS-SEM analysis.

3. Structural Model Assessment

a. R-Square

The table below presents an overview of the R-square values, which indicate the proportion of variance in academic performance explained by the model.

Table 4. R-square Overview

Dependent Variable	R-square	R-square Adjusted
Academic Performance	0.416	0.400

Source: Smart Pls

The R-square value of 0.416 suggests that approximately 41.6% of the variance in academic performance can be explained by the predictors included in the model. The adjusted R-square of 0.400 accounts for the number of predictors and indicates a slightly more conservative estimate of the model's explanatory power.

b. F-Square

The following table presents the f-square (effect size) values, which indicate the contribution of each exogenous variable and moderating interaction to the endogenous variable in the research model. An f-square value of 0.02 is considered a *small effect*, 0.15 a *medium effect*, and 0.35 a *large effect*.

Table 5. F-Square Matrix

Variables	f^2 Value
x1 Digital Literacy	0.030
x2 Ethical Perception of AI Usage	0.022
x3 Learning Self-Efficacy	0.065
y Academic Performance	0.071
z Technology Resistance	0.061
z Technology Resistance × x1 Digital Literacy	0.074
z Technology Resistance × x2 Ethical Perception of AI Usage	0.074
z Technology Resistance × x3 Learning Self-Efficacy	0.222

Source: Smart Pls

The results indicate that all variables and moderating interactions contribute to academic performance with varying effect sizes. Digital Literacy (0.030), Ethical Perception of AI Usage (0.022), and

Technology Resistance (0.061) show small effects. Learning Self-Efficacy (0.065) and the interaction of Technology Resistance with Digital Literacy and Ethical Perception (0.074 each) approach medium strength but remain in the small-to-moderate range. The strongest contribution comes from the interaction between Technology Resistance and Learning Self-Efficacy (0.222), which demonstrates a medium effect size and highlights the importance of self-efficacy in overcoming resistance to technology for academic performance.

c. Path Coefficients

The table below shows the structural model results, including path coefficients, standard deviation, t-statistics, and p-values. A path is considered significant if the t-value > 1.96 (at 5% significance level) and p-value < 0.05**.** (See diagram and table below)

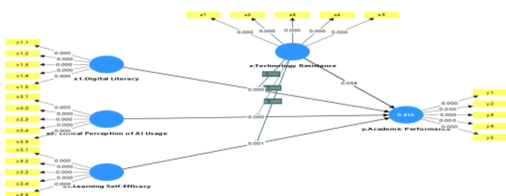

Figure 7. Diagram Coefficients
Source: Smart Pls

Table 6. Path Coefficients (Mean, STDEV, T values, p values)

Hypothesis	Path	Coefficient (β)	T Statistics	P Values	Result
H1	x1 Digital Literacy → y Academic Performance	0.231	5.011	0.000	Supported ✅
H2	x2 Ethical Perception of AI Usage → y Academic Performance	0.228	4.816	0.000	Supported ✅
H3	x3 Learning Self-Efficacy → y Academic Performance	0.128	2.857	0.005	Supported ✅
H4	z Technology Resistance → y Academic Performance	0.176	4.262	0.000	Supported ✅
H5	z Technology Resistance × x1 Digital Literacy → y Academic Performance	0.247	4.318	0.000	Supported ✅
H6	z Technology Resistance × x2 Ethical Perception → y Academic Performance	0.226	3.943	0.000	Supported ✅
H7	z Technology Resistance × x3 Learning Self-Efficacy → y Academic Performance	0.366	6.771	0.000	Supported ✅

Source: Smart Pls

All paths in the model are statistically significant since all p-values are below 0.05. Digital Literacy (β = 0.231, t = 5.011), Ethical Perception of AI Usage (β = 0.228, t = 4.816), and Learning Self-Efficacy (β = 0.128, t = 2.857) positively influence Academic Performance. Technology Resistance also has a significant positive effect (β = 0.176, t = 4.262).

Regarding moderation, Technology Resistance significantly strengthens the relationship between Digital Literacy (β = 0.247), Ethical Perception of AI Usage (β = 0.226), and Learning Self-Efficacy (β = 0.366) with Academic Performance. Among them, the strongest moderating effect is found in the interaction between Technology Resistance and Learning Self-Efficacy (β = 0.366, t = 6.771), suggesting that students with high self-efficacy can overcome resistance to technology more effectively to enhance academic performance.

Discussion

The findings of this study support the notion that digital literacy, ethical perceptions of AI use, and learning self-efficacy play crucial roles in enhancing students' academic performance. The results are consistent with prior research indicating that students' ability to effectively utilize digital tools leads to improved learning outcomes. This study also aligns with the extended framework of the Technology Acceptance Model (TAM), in which ethical beliefs and trust shape how students adopt and employ AI tools in their academic tasks. Such positive adoption ultimately contributes to their academic success. Moreover, the findings reaffirm the central role of self-efficacy in motivating student engagement with technology, which has consistently been shown to foster persistence and the use of effective learning strategies in digital environments. In other words, students' confidence in their ability to succeed in learning tasks directly influences their academic outcomes.

However, this study reveals a misalignment between the proposed hypothesis and the actual findings concerning the role of technology resistance. Contrary to expectations that resistance would exert a negative influence and weaken relationships, the results indicate that technology resistance has a positive effect on academic performance. Furthermore, technology resistance significantly strengthens the positive relationships between digital literacy, ethical perceptions, and self-efficacy with academic performance. These findings provide a fresh perspective, challenging the assumption that resistance to technology merely acts as a barrier. Instead, they suggest that when students possess strong self-efficacy, they can transform their concerns and reluctance (resistance) into motivation to succeed. This highlights self-efficacy as a pivotal factor in turning potential technological obstacles into driving forces for enhanced academic performance.

Overall, this study reinforces existing literature on the contributions of AI and ChatGPT to learning quality and academic achievement. At the same time, it addresses an important gap by examining technology resistance as a moderating variable—an approach rarely explored in previous studies. By demonstrating that resistance can be managed and even transformed into a supportive factor, this study makes both theoretical and practical contributions to a more comprehensive understanding of AI integration in higher education

CONCLUSION AND SUGGESTIONS

Based on the research findings, it can be concluded that digital literacy, ethical perceptions of AI use, and learning self-efficacy positively influence students' academic performance, underscoring their essential role in modern learning environments. This study successfully fills a theoretical gap by introducing technology resistance as a moderating variable, offering a more comprehensive understanding of how psychological factors can transform potential barriers into driving forces. Nevertheless, the research has limitations, particularly regarding the inconsistency between the proposed hypotheses and the actual results, in which technology resistance unexpectedly demonstrated a positive effect and strengthened the relationships. The theoretical implication is the need for developing more advanced models to examine the dynamic interplay between resistance and academic outcomes. From a managerial perspective, the findings suggest that educational institutions should not only focus on enhancing digital literacy but also implement programs that foster self-efficacy and ethical awareness, enabling students to convert resistance to technology into motivation for success.

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