

The Effect of Generative AI Dependency on Academic Integrity among Postgraduate Students at KPPIM

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Abstracts

The increasing integration of Generative AI (Gen-AI) tools in higher education has transformed students' learning processes, offering benefits such as enhanced productivity, idea generation, and writing assistance. However, concerns are growing over students' dependency on these tools and its impact on cognitive development and academic integrity. This study investigates how postgraduate students at KPPIM, Universiti Teknologi MARA (UiTM), transition from using Gen-AI as an academic aid to developing a dependency that may undermine critical thinking, problem-solving, and ethical decision-making. Guided by the Technology Acceptance Model (TAM), this study adopts a quantitative research approach to analyze the relationship between students' perceptions of Gen-AI (Perceived Usefulness and Perceived Ease of Use), their dependency behaviors, and their ability to uphold academic integrity. Data will be collected through structured surveys, using validated instruments such as the Dependence on Artificial Intelligence (DAI) Scale and the Academic Integrity Scale (AIS). Regression analysis will be employed to examine the influence of AI dependency on students' ethical academic practices. The findings of this study are expected to provide valuable insights into the ethical implications of AI usage in education. By identifying the factors contributing to Gen-AI dependency and its effects on academic integrity, this research will support the development of institutional policies, ethical guidelines, and AI literacy programs to promote responsible AI use in higher education. Ultimately, the study aims to contribute to the broader discourse on balancing AI's benefits with the need for academic integrity and independent learning.

Keywords: Generative Artificial Intelligence, Dependency, Acceptance

Introduction

The rapid advancement of Generative Artificial Intelligence (Gen-AI) has significantly transformed teaching and learning in higher education. Tools such as ChatGPT and

Grammarly are increasingly used by students to support academic tasks including idea generation, writing, and information processing. While these technologies offer benefits such as efficiency and accessibility, their widespread use has raised concerns regarding students' overreliance on AI and the potential impact on academic integrity.

The Technology Acceptance Model (TAM) explains students' adoption of AI tools through perceived usefulness and perceived ease of use (Davis, 1989). When students perceive Gen-AI as helpful and easy to use, they are more likely to integrate it into their academic work. However, frequent use may lead to dependency, which could reduce independent thinking and critical engagement. Academic integrity, which emphasizes honesty, originality, and ethical behavior, is a core value in higher education and is closely linked to the development of critical thinking and problem-solving skills (Mahajan & Singh, 2017).

Recent studies have raised concerns that excessive reliance on AI tools may encourage superficial learning and unethical practices such as plagiarism and overdependence on automated content (Husna, 2020; Nguyen et al., 2024). Morales-García et al. (2024) further reported that increasing AI dependency among university students may weaken cognitive engagement, motivation, and self-regulation. Despite these concerns, existing research has largely focused on AI adoption and performance outcomes, with limited attention given to how AI dependency affects students' academic integrity.

This gap highlights the need for empirical investigation, particularly in postgraduate education where higher levels of academic responsibility and ethical awareness are expected. Understanding whether Gen-AI dependency undermines or coexists with academic integrity is essential for guiding institutional policies and promoting responsible AI use.

Therefore, this study aims to examine the effect of Generative AI dependency on academic integrity among postgraduate students at Universiti Teknologi MARA (UiTM). Specifically, it investigates the extent of students' dependency on Gen-AI tools and its relationship with their ability to uphold academic integrity. The findings of this study are expected to contribute to the growing literature on AI in education and provide practical insights for educators and policymakers in promoting ethical and responsible AI usage.

Research Aims and Objectives

This research specifically aims to explore the effect of Gen-AI tools on students' academic integrity by examining how dependency on these tools weaken the development of their cognitive skills, which in turn effect on their ability to uphold academic integrity. The key research objectives (ROs) are outlined as below:

1. RO 1: To identify the factors that contribute to students' dependency on Gen-AI tools for academic tasks.
2. RO 2: To investigate the presence of Gen-AI dependency among students.
3. RO 3: To examine the relationship between Gen-AI dependency and students' ability to uphold academic integrity.

Literature Review

The literature review in Figure 1 examines existing studies on the integration of generative artificial intelligence (Gen-AI) in education, with particular emphasis on its adoption, limitations, and associated risks. Guided by the Technology Acceptance Model (TAM), prior research highlights factors influencing students' acceptance and use of Gen-AI tools, while also drawing attention to emerging concerns related to AI dependency, including reduced independent thinking, creativity, and problem-solving abilities. The literature further underscores significant academic integrity challenges, such as plagiarism, misinformation, and unethical academic practices. Collectively, these studies reveal both the potential benefits and critical concerns surrounding Gen-AI in higher education. However, notable gaps remain, particularly regarding the long-term effects of Gen-AI dependency on students' ethical decision-making, thereby justifying the need for further empirical investigation in this area.

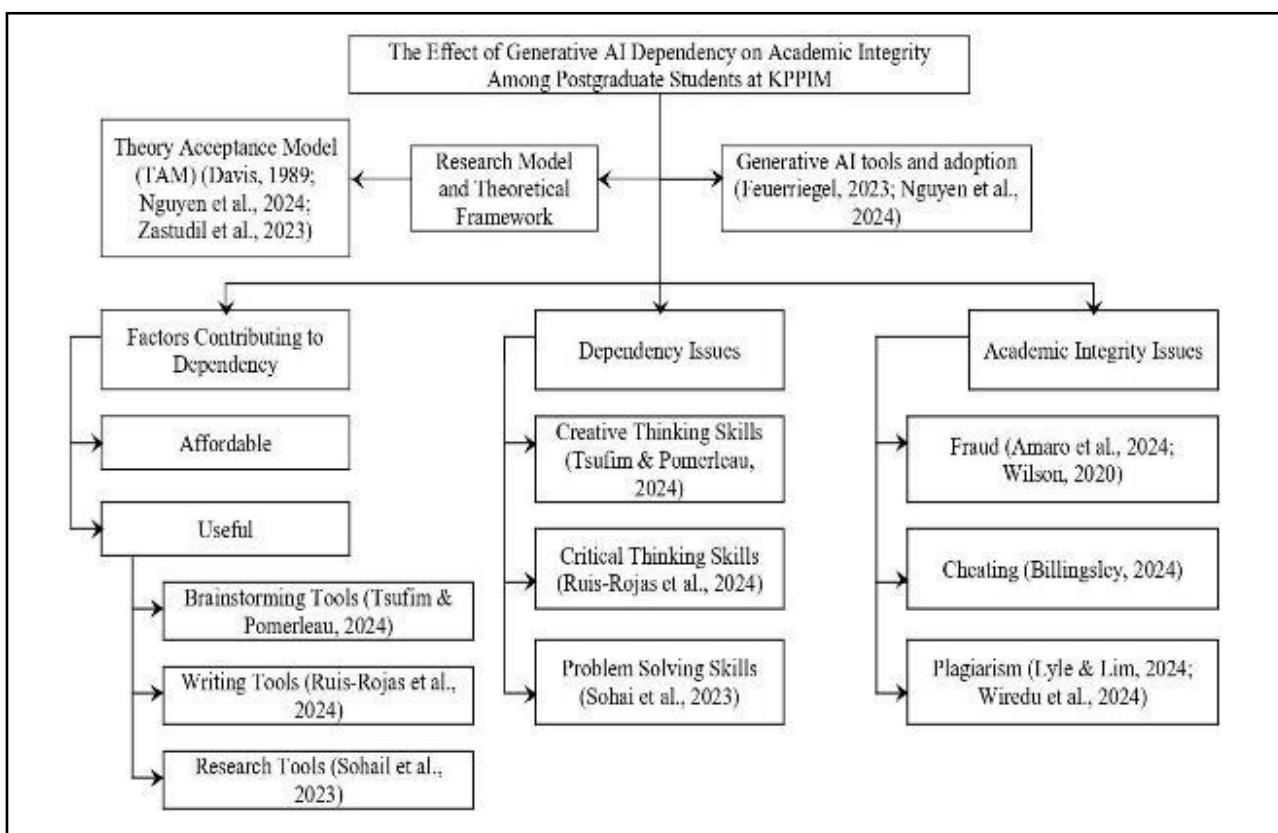


Figure 1. The Literature Map

Methodology

This research will utilize the quantitative research design, which allows for the systematic collection and analysis of numerical data. This design is particularly effective for examining the relationship between the dependency behavior on using Gen-AI tools and academic integrity among students. The cross-sectional approach will remain in place, enabling the collection of data from a diverse sample of postgraduate students at the KPPIM UiTM.

The target population will consist of postgraduate students enrolled at KPPIM. This encompasses a wide range of disciplines and backgrounds, providing a rich dataset for analysis. The methodology will involve the development of a structured questionnaire that

captures students' dependency on using Gen-AI and their academic integrity when using AI for their academic task. The questionnaire will be administered online, ensuring accessibility and convenience for respondents. This methodology aims to gather data that reflects if there are signs of Gen-AI dependency among students and link with their academic integrity if any. Overall, these phases collectively lay the groundwork for a research study that seeks to contribute valuable insights into the intersection of technology and academic integrity in higher education.

Data Collection

In this research, the survey instruments play a crucial role in exploring the relationship between KPPIM postgraduate students' attitudes toward academic dishonesty as facilitated by Gen-AI tools. To achieve this, an online quantitative questionnaire has been developed, drawing inspiration from established research methodologies to ensure its validity and reliability. The questionnaire will be hosted on the user-friendly Google Forms platform, which is well-suited for the target demographic of postgraduate students. This platform not only allows for easy access and navigation but also enhances the overall user experience, encouraging higher response rates. The design of the questionnaire incorporates Likert scale questions, with two sections to adapt the scale to measure students' dependency level and academic integrity in the context of Gen-AI usage.

Data Analysis

In this phase, the focus will be on the analysis of the collected data, which is crucial for deriving meaningful insights related to the research questions. This phase will involve several key steps to ensure a thorough examination of the data. Initially, the collected data will be cleaned and organized to facilitate accurate analysis.

Descriptive Analysis

Descriptive analysis will summarize the data, providing an overview of the demographic information and usage patterns. The demographic statistics will provide an overview of the respondents. While descriptive analysis will help to identify the usage patterns that can potentially give an overview of the presence of Gen-AI dependency amongst the respondents.

Regression Analysis

Following the descriptive analysis, regression analysis will be used to test the hypotheses proposed in this study (H1-H3). This analysis aims to examine the relationship between students' PEOU and PU, Attitudes towards using Gen-AI, Gen-AI dependency, and Academic Integrity. Multiple regression will be conducted to determine:

1. whether PEOU and PU significantly predict students' attitudes towards Gen-AI.
2. whether attitudes significantly predict Gen-AI dependency.
3. whether Gen-AI dependency significantly predicts academic integrity.

This statistical method was chosen to evaluate the strength and direction of the relationship between these key variables on the proposed research model.

Results and Findings

This phase presents the findings of the data analysis conducted to achieve the research objectives.

Descriptive Analysis

This section presents an overview of the sample characteristics and the general distribution of responses in the study. It includes an analysis of the respondents' demographic profile and descriptive statistics for both individual questionnaire items and original constructs. The purpose of this section is to provide a clear summary of the data before conducting inferential analyses.

Demographic Profile for Respondents

Demographic analysis provides a basic description of the population involved in a study. In this research, demographic data were collected from postgraduate students at the KPPIM (currently known as Faculty of Computer and Mathematical Science). Demographic analysis provides a basic description of the population involved in a study which include gender, age group, and current level of study.

In terms of gender, most of the respondents were female, with 107 individuals, making up 59% of the total. On the other hand, 73 respondents were male, which is about 41%. This shows that there were more female than male respondents in the sample. Looking at age, the largest group of respondents were between 30 and 39 years old, with 133 people or 74% of the sample. A smaller group, made up of 39 respondents (22%), were aged 18 to 29 years, while the remaining 8 individuals (4%) were aged 40 to 49 years. This suggests that most of the students are in their thirties.

As for their current level of study, the majority of them, 167 respondents (93%), were Master's Degree students and only 13 individuals (7%) were PhD students. These numbers show that most of the respondents were focused on Master's programs. In conclusion, this demographic summary shows that the study mostly involved female Master's students in their thirties. This background helps to better understand the context of the research findings in the next sections.

Descriptive Statistics for Constructs

This phase presents the descriptive analysis of individual items and original constructs measured in the study.

Descriptive Analysis for Individual Items

This section reports the descriptive statistics of the 37 individual items used in the questionnaire. The items were initially grouped under nine conceptual constructs, designed to assess students' dependency on Gen-AI tools and their academic integrity practices. Overall, the item means range from 2.98 to 3.81, indicating a moderate to high level of agreement across most statements. Standard deviations mostly fall within the 1.0 to 1.3 range, suggesting acceptable levels of variation in responses. The lowest mean (2.98) was observed for the item "I worry that AI can perform academic tasks better than I can", while the highest mean (3.81) was recorded for "I take responsibility for the originality of my work, even when AI tools are involved."

Descriptive Analysis of Original Construct

This section presents the descriptive statistics for the key constructs used in this study. The constructs include both AI Dependency and Academic Integrity dimensions. The descriptive results for each construct are shown in Table 1 below.

Table 1

Descriptive Statistics for Original Construct

Construct Label	Description	Mean	SD
VUL_SCORE	Feeling of vulnerability	3.42	1.07
PER_SCORE	Concern about relevance and performance	3.60	0.98
IMG_SCORE	Need to maintain an updated image	3.47	0.97
VLD_SCIRE	Seeking external validation	3.64	0.97
OBS_SCORE	Fear of feeling obsolescence	3.35	0.97
HON_SCORE	Honesty	3.77	1.03
FAI_SCORE	Fairness	3.63	1.04
RES_SCORE	Respect	3.60	1.08
TRU_SCORE	Trust	3.69	1.17
ETH_SCORE	Responsibility	3.44	1.14

As shown in the table, the mean values for all constructs range between 3.35 to 3.77, indicating moderate to moderately high agreement across all constructs. The highest mean was recorded for Honesty (HON_SCORE), $M=3.75$ and $SD=1.03$, showing that most respondents believe in upholding personal understanding and responsibility even when using AI tools. Meanwhile, the lowest mean was for Obsolescence (OBS_SCORE), $M=3.35$ and $SD=0.97$, suggesting that fewer students feel that AI threatens their academic capabilities or learning process.

Reliability Analysis

Reliability analysis was conducted to examine the internal consistency of the measurement items under each construct using Cronbach's Alpha (α). A value of 0.70 or higher is considered acceptable for reliability, while values above 0.80 indicate good internal consistency (Nunnally & Bernstein, 1994). Most construct showed good internal consistency, with α values ranging between 0.82 and 0.89. However, the Trust construct recorded a slightly lower reliability value of 0.67, which is below the acceptable threshold. Since this construct only contain two items, a lower alpha may be expected but should be interpreted with caution. Overall, the results suggest that the majority of the constructs used in this study are reliable and consistent in measuring the intended dimensions of AI Dependency and Academic Integrity.

Exploratory Factor Analysis (EFA)

EFA was conducted to examine the underlying factor structure of the AI Dependency in this study. Although the original construct was adapted from Morales-Garcia et al. (2024), who proposed the five key components, it was necessary to validate whether these conceptual dimensions would be reflected similarly in the current dataset. It was employed to identify the latent factor structure of the AI Dependency items and determine how the items group together in the context of postgraduate students at KPPIM UiTM. This step supports RO2 which is to identify patterns of students' dependency on Gen-AI tools. Before conducting EFA, the data was evaluated to ensure it met the assumptions for factor analysis. This study used Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity. The output showed a KMO coefficient of 0.95, indicating excellent adequacy for factor analysis. On the other hand, Bartlett's Test of Sphericity was significant, ($\chi^2 = 2715.61$, $df = 190$, $p < 0.001$), confirming that the correlation matrix was not an identity matrix and thus appropriate for factor analysis.

Principal Component Analysis with Varimax rotation was applied to the 20 items measuring AI Dependency. The analysis revealed two distinct factors with eigenvalues greater than 1, explaining a combined 63% of the total variance. Factor 1 had an eigen value of 11.42, contributing to 58% of the variance, while Factor 2 had eigenvalue of 1.1 contributing an additional 6%, as presented in Table 2.

Table 2

Extracted Component 1 and 2 of Total Variance Explained

Component	Initial Eigenvalue	Variance (%)	Cumulative (%)
1	11.52	58	58
2	1.10	6	64

The rotated Component Matrix in Table 3 displays how each item loaded onto the two extracted factors. Items with factor loadings of 0.50 or higher were retained for interpretation. The items originally under multiple conceptual dimensions were reorganized into two broader underlying factors, suggesting the presence of overlapping themes across constructs.

Table 3

Rotated Component Matrix

Item Statement	Component 1	Component 2
I feel insecure about completing academic work without access to AI tools.	0.59	0.58
When I cannot use AI tools, I feel helpless or anxious.	0.54	0.61
I feel overwhelmed if I have to complete tasks without AI assistance.	0.54	0.63
I avoid starting academic tasks if I don't have access to AI tools.		0.82
I worry my academic work won't meet expectations without using AI.	0.57	0.55
I rely on AI tools to help me meet deadlines and academic standards.	0.72	

Based on the EFA analysis, two distinct patterns of AI Dependency emerged among the respondents. These factors represent the underlying dimensions of how students psychologically and behaviorally interact with Gen-AI tools in academic tasks. The first factors reflect students' emotional and functional reliance on AI, including confidence, performance concerns, and validation needs. The second factor captures a sense of academic vulnerability and fear of falling behind, particularly in the absence of AI tools. These findings suggest that students' dependency on Gen-AI is not uniform but consists of multiple interrelated tendencies, supporting the aim of RO2 to identify the patterns of students' dependency on Gen-AI tools.

Correlation Analysis

This section presents the Pearson correlation analysis used to examine the relationship between students' AI Dependency and Academic Integrity dimensions. This analysis was conducted to address the RO3 which is to examine the relationship between Gen-AI dependency and students' ability to uphold their academic integrity.

Following the results of EFA, two new components were identified as underlying patterns of AI Dependency. These two factors were computed as new variables, named FACTOR1_SCORE and FACTOR2_SCORE respectively based on the items that loaded significantly onto each other. Factor 1 primarily captured items related to general reliance, validation seeking, and performance support. Factor 2 reflected vulnerability, helplessness and anxiety-related dependency on AI tools. These factors replaced the original conceptual constructs of AI Dependency that was adapted from Morales-Garcia et al. (2024) for this correlation analysis. This is to ensure the actual patterns observed in the dataset is aligned.

Table 4 presents the Pearson correlation coefficients between the computed dependency factors and five academic integrity dimensions that was adapted from Ramdani (2018), which consist of Honesty, Fairness, Respect, Responsibility and Trust.

Table 4

Pearson Correlation Matrix Between AI Dependency Factors and Academic Integrity Dimensions

Variables	FACTOR1_SCORE	FACTOR2_SCORE	HON_SCORE	FAI_SCORE	RES_SCORE	TRU_SCORE	ETH_SCORE
Factor 1	1	0.85**	0.06	0.08	0.14	0.19*	-0.01
Factor 2	0.85**	1	-0.06	0.05	0.05	0.09	-0.02
Honesty	0.06	-0.06	1	0.83**	0.84**	0.76**	0.71**
Fairness	0.08	0.05	0.83**	1	0.88*	0.75*	0.79**
Respect	0.14	0.05	0.84**	0.88**	1	0.82*	0.71**
Trust	0.19*	0.09	0.76**	0.75**	0.82**	1	0.64**
Responsibility	-0.01	-0.02	0.71**	0.79**	0.71**	0.64*	1

Factor 1 and Factor 2 exhibit weak to very weak correlations with the Academic Integrity. Factor 1 showed a positive but weak correlation with Responsibility ($r=0.19$, $p<0.05$), suggesting that students who rely on AI for performance support and validation may still exhibit a moderate sense of responsibility in academic settings. Factor 2 however did not

correlate with any of the Academic Integrity dimensions, indicating that emotional dependency may not have a strong relationship with integrity-related behavior. The correlation between Factor 1 and Factor 2 was strong ($r=0.85$, $p<0.01$) implying that the two forms of dependency often co-occur but still capture distinct emotional and functional aspects of AI dependency.

In contrast, the Academic Integrity dimensions showed a strong intercorrelations with one another. Honesty, Fairness, Respect, Trust and Responsibility all had strong positive correlations (ranging from 0.64 to 0.88, $p<0.01$), confirming they reflect a coherent and unified construct of Academic Integrity consistent with Ramdani (2018). These findings provide insights into the subtle relationship between Gen-AI tool dependency and students' ethical academic behavior. While general use of AI may align slightly with responsible conduct, while emotional reliance appears less associated with how students practice academic integrity.

Regression Analysis

This section presents the multiple linear regression analysis conducted to addresses RO3 which is to examine the relationship between Gen-AI dependency and students' ability to uphold academic integrity. Originally, this research was guided by a research model, linking technology acceptance factor (PEOU and PU) to attitudes, then to dependency, and then to academic integrity. This research model was grounded with the combination of TAM and TPB and extended using validated instruments from Morales-Garcia (2024) and Ramdani (2018), with the assumption it will represent attitudinal dimensions based on PU, motivation, and reliance.

However, upon conducting EFA, the results revealed that the items did not form an attitudinal construct as theorized. Instead, they grouped into two factors representing behavioral and emotional dependency patterns on Gen-AI tools such as validation seeking, performance assurance, helplessness and anxiety. This finding suggests that the instrument captured actual dependency behavior, rather than attitudinal predispositions toward Gen-AI usage. Therefore, constructs related to PEOU, PU and attitude were not represented in final analysis, and the corresponding H1 and H2 were not tested. These conceptual relationships are instead discussed through literature review in Chapter 2. The regression analysis that follows focuses solely on H3, which investigates whether students' Gen-AI dependency significantly predicts their academic integrity.

Normality Test

Before interpreting the results, the normality of residuals was assessed. A histogram of standardized residuals (Figure 2) showed a roughly bell-shaped curve centered around zero, with a SD closed to 1. In addition, the normal P-P plot (Figure 3) showed that most points aligned closely with the diagonal line. These findings suggest that the residuals are approximately normally distributed, and the assumption of normality is reasonably met.

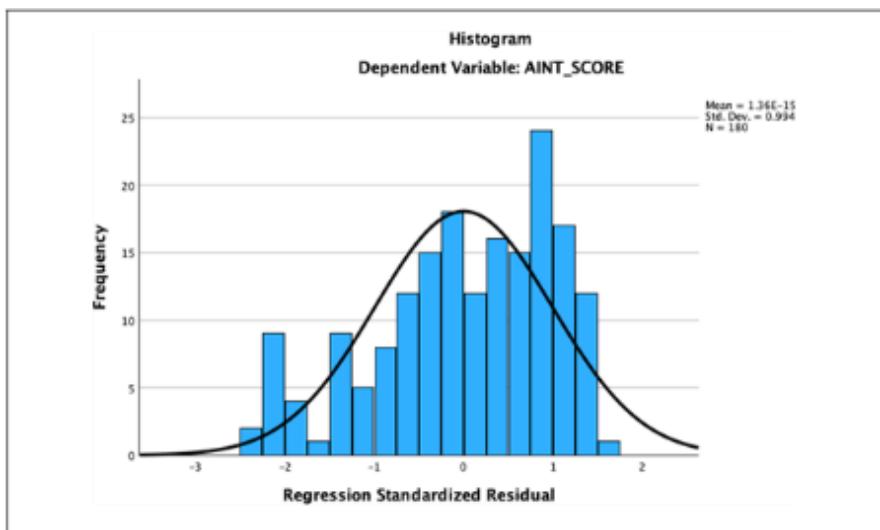


Figure 2. Histogram of Standardized Residual

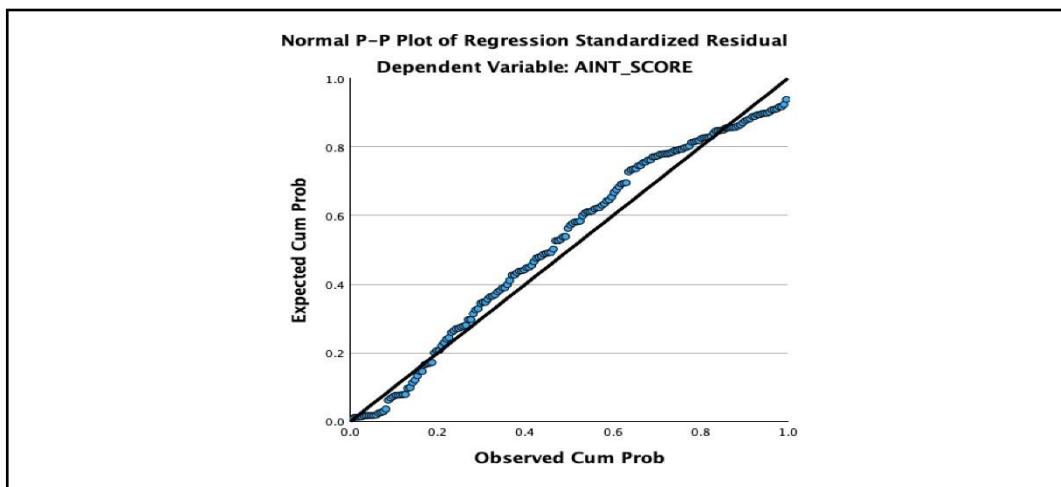


Figure 3. P-P Plot of Regression Standardized Residual

Multiple Linear Regression Result

This sub-section presents the multiple linear regression analysis conducted to address RO3 and test H3.

1. Hypothesis H31: There will be a significant relationship between students' Gen-AI dependency and their ability to uphold academic integrity.
- Hypothesis H30: There will be no significant relationship between students' Gen-AI dependency and their ability to uphold academic integrity.

Factor 1 and Factor 2 that was identified through EFA were used as independent variables. The dependent variable was the AINT_SCORE, computed by averaging five dimensions of academic integrity by Ramdani (2018). Table 5 shows the result of the regression model assessing whether AI Dependency factors predict students' academic integrity. The R^2 value was 0.02 indicating that approximately 2% of the variance in AINT_SCORE can be explained by the combination of FACTOR1_SCORE and FACTOR2_SCORE.

Table 5

Regression Model Summary and ANOVA

Model	R	R ²	Adj. R ²	F	Sig.
1	0.15	0.02	0.01	2.08	0.13

The overall model was not statistically significant, $F(2, 177)=2.08$, $p=0.13$, suggesting that the two factors do not significantly predict academic integrity levels among the students in this study. Despite the low explanatory power, this analysis provides an initial empirical understanding of the relationship between Gen-AI dependency and academic integrity. Further investigation may be needed with additional variables or a larger sample to uncover stronger relationships.

Table 6

Coefficient of Regression Predicting Academic Integrity

Predictor	Unstandardized B	Std. Error	Standardized β	t	Sig. (p)
Constant	3.27	0.30	-	10.93	<0.001
FACTOR1_SCORE	0.30	0.15	0.28	2.01	0.046
FACTOR2_SCORE	-0.22	0.14	-0.21	-1.51	0.134

Table 6 displays the regression coefficients for each of the two factors. The aim was to determine which of the two factors had a significant effect on AINT_SCORE. FACTOR1_SCORE was found to have a positive and significant effect on AINT_SCORE, $\beta=0.28$, $p=0.046$. This means that students who rely on Gen-AI tools for validation and academic support, actually showed a slightly higher AINT_SCORE. Although some may assume this kind of dependency could harm academic integrity, the result suggests that using AI responsibly to support academic performance does not necessarily lead to dishonest behavior. Instead, these students may still be trying to uphold academic standards while getting help from AI tools in ethical way.

FACTOR2_SCORE however was not a significant predictor, where $\beta= -0.21$, $p=0.134$ which means students who reported emotional dependency or helplessness when using AI tools did not show a statistically significant difference in their academic integrity. Although direction of the relationship suggests that higher emotional dependency may be linked to slightly lower academic integrity, this relationship was not strong enough to be considered meaningful in this study.

The findings of this study partially support the H3. Among the two dependency patterns identified through EFA, only Factor 1 showed a statistically significant positive relationship with academic integrity. In contrast, Factor 2 did not significantly predict academic integrity, although the direction of the relationship hinted at a possible negative relationship.

As a conclusion, the quantitative data collected to examine postgraduate students' dependency on Gen-AI tools and its relationship with academic integrity. The EFA revealed two distinct components of AI dependency, which named as Factor 1 (Validation and Academic Support Dependency) and Factor 2 (Emotional Dependency and Helplessness). These were used as predictors in the regression analysis. The regression results showed that Factor 1 had a positive and significant effect on students' academic integrity, indicating that students who use AI tools to support their academic task may still maintain integrity in their academic practices. Factor 2 did not show a significant effect although the negative direction suggests a potential association worth exploring further.

Conclusion

In conclusion, this study has provided meaningful insights into postgraduate students' dependency on Gen-AI tools and how it may affect their academic integrity. The research addressed three main objectives in order to find the relationship between the Gen-AI dependency and academic integrity, either between those two have significant effect or not. The findings suggest that Gen-AI dependency is present among students and that it may contribute to academic dishonesty if left unaddressed. This research adds to the growing discussion on how new technologies are shaping student behavior in higher education. While Gen-AI tools offer convenience and support, this study highlights the importance of using them responsibly. The results may help educators and institutions better understand how to guide students in balancing innovation with ethical learning.

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