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Dependence on Artificial Intelligence as Predicted by Usefulness, Usability and Trust

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Abstract

Dependence on Artificial Intelligence (AI) is a concern in education. The study examines the significance of forecasting AI dependence using usefulness, usability, and trust in AI as predictors. Using a predictive research design, an online survey technique, stratified random sampling to select 231 Senior High School students, and multiple linear regression to analyze the data, the results revealed that AI dependence was strongly (77.5%) and significantly predicted, supporting the Extended Technology Acceptance Model (TAM). The study recommends further exploration of additional factors influencing the remaining variance in AI dependence, conducting qualitative research to better understand students' lived experiences with AI, and strengthening AI literacy programs that promote calibrated trust and critical evaluation of AI outputs in academic use.

Keywords: Dependence on artificial intelligence; usefulness; usability; trust

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1. INTRODUCTION

1.1. The Problem and Its Scope

High dependence on Artificial Intelligence (AI) was a significant concern in the global education sector. Students across countries were turned to AI tools to complete their assignments and generate written outputs, often bypassing critical thinking (Abubakar et al., 2025; Özer et al., 2025). In July 2024, a study conducted by the Digital Education Council gathered information from more than 3,839 students across 16 nations. The study found that 86% of students used AI tools in their academic work. The top four ways they used AI included searching for information (69%), checking grammar (42%), paraphrasing texts (28%), and drafting first drafts of assignments (24%). Although various programs that promote learning through AI helped students be more successful, having students become reliant on any provided AI tool remained an issue (Ahmed, 2024).

In various countries, research highlighted the scale of this phenomenon. In Latin America, studies in Peru reported that university students exhibited dependence on AI tools in their academic activities (Estrada-Araoz et al., 2025). In addition, similar patterns emerged in research from Pakistan, where a high reliance on AI was a strong predictor of decreased memory consolidation, lower critical thinking, and greater algorithmic anchoring among university students (Akhtar et al., 2026). This was also evident in data from the United States, where Schöffer et al. (2025) reported that a significant proportion of US citizens relied on AI-generated decision-making processes, including those with ethical implications. Furthermore, this behavior has prompted considerable debate regarding cognitive engagement among UK students; for instance, Kajan et al (2025) found that most students were concerned about their over-reliance on AI chatbots.

Additionally, the Philippines has implemented the K to 12 system for senior high school students were required to complete a range of academic writing assignments, including essays, critiques, and research papers. A study by Discutido (2025) found that many senior high schools relied heavily on AI writing assistance tools to manage their academic writing workload. Furthermore, news reports illustrated how AI use extended beyond legitimate support. The “Your Thesis Bestie” case, for example, involved a content creator allegedly selling thesis writing packages powered by ChatGPT for around ₱5,000, sparked debate about integrity in higher education (Palad, 2025). In addition, numerous local online marketplaces, for example, RaketPh, sold prompt packs and AI-generated content services marketed to students as a means to assist them in fulfilling their academic writing and research tasks; thus confirming the existence of a large underground economy surrounding AI-generated work.

A broad analysis of the literature showed an increasing reliance on AI by students for academic purposes. While previous studies have focused on general attitudes and frequency of AI use by students (Balabdaoui et al.,2024; Amiri et al., 2024), limited attention was given to how student perceptions of AI usefulness across different academic task types, such as reading, writing, and arithmetic, shaped their dependence on AI tools. Another limitation lay in the lack of examination of trust in AI as a variable linking to actual dependence, despite growing evidence that showed that trust was a major predictor of future technology use (Huynh & Aichner, 2025). This gap in the literature demonstrated the need to investigate these variables simultaneously. Addressing this issue was urgent because excessive reliance on AI may weaken students’ critical thinking, independent learning, and decision-making skills (Gerlich, 2025); thus, this study is pursued. Promoting responsible and balanced use of AI was considered critical for academic success and solving real-world problems.

1.2. Significance of the Study

This study supported SDG 4: Quality Education by addressing students' growing reliance on Artificial Intelligence (AI) and promoting the responsible, balanced, and critical use of AI in academic settings. In the Philippine educational context, the study responded to the increasing integration of AI tools in learning, highlighting the need to strengthen students’ critical thinking, independent learning, and decision-making skills. Findings from this study may assist school leaders in implementing policies and practices that will help students develop appropriate, productive, and ethical use of AI in education. School leaders can help design academic support systems and initiatives to develop AI literacy in their schools. At the same time, teachers can adjust their teaching strategies to foster students' creativity, critical thinking, and independent learning by using AI resources. Students will benefit from developing greater awareness of the benefits of using AI as a supportive resource compared to the risks associated with relying solely on AI for their learning; therefore, students should use AI intentionally as a support to learning and for the development of original ideas rather than as a replacement for effort and original thought. In addition to enhancing student learning through the appropriate and responsible use of AI resources, this study could serve as a useful reference for future researchers investigating AI in education, the acceptance of technology in educational settings, and AI dependence among students and educators.

1.3. Statement of the Problem

This study determined the significance of forecasting Artificial Intelligence dependence using Usefulness, usability, and trust as predictors.

Specifically, it pursued the following objectives:

1. To determine the levels of Usefulness of Artificial Intelligence in academic tasks in terms of writing, reading, and arithmetic; usability of AI tool; trust; and the Artificial Intelligence Dependence in terms of instrumental dependency and relational dependency.
2. To determine if there is a significant correlation between the Usefulness and the Artificial Intelligence dependence, usability of AI tools, trust, and the Artificial Intelligence dependence.
3. To determine the extent to which Usefulness, AI tool usability, and trust, both collectively and individually, predict students' dependence on Artificial Intelligence.

1.4. Null Hypotheses

Based on the statement of the problem, the following null hypotheses:

Ho1. There is no significant relationship between Usefulness and Artificial Intelligence Dependence.

Ho2. There is no significant relationship between the usability of AI tools and the Artificial Intelligence Dependence.

Ho3. There is no significant relationship between trust and the Artificial Intelligence Dependence.

Ho4.The model to predict Usefulness, usability, and trust in AI as predictors is not significant.

1.5. Theoretical Framework

This study was anchored on the Extended Technology Acceptance Model (Extended TAM) developed by Gefen et. al. (2003), which explains that users' behavior toward online systems is driven not only by Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and the trust users place in the system.

In the context of this study, Usefulness referred to Perceived Usefulness (PU) and reflected the extent to which students believe that AI tools enhanced their academic performance and productivity, and helped them accomplish learning tasks more efficiently (Aldraiweesh & Alturki, 2025). Usability referred to Perceived Ease of Use (PEOU) and pertained to how easily and efficiently students could navigate and operate AI systems to accomplish academic tasks (Binyamin, Rutter, & Smith, 2019). Meanwhile, Trust in AI reflects Trust; it reflected students’ confidence that AI systems could provide useful and trustworthy information, assist them effectively in learning activities, and produce outputs that aligned with their academic needs and expectations (Glikson & Woolley, 2020)

Together, these constructs were hypothesized to predict AI Dependence among students, referring to the extent to which learners relied on AI technologies to accomplish academic tasks, generate ideas, solve problems, and support learning activities. The Extended Technology Acceptance Model provided a foundation for this research, which provides evidence that perceived Usefulness, usability, and trustworthiness shaped the extent to which students will depend on artificial intelligence (AI) technologies. Students continued to use and rely on AI technologies for educational purposes when they viewed them as effective, user-friendly, and reliable.

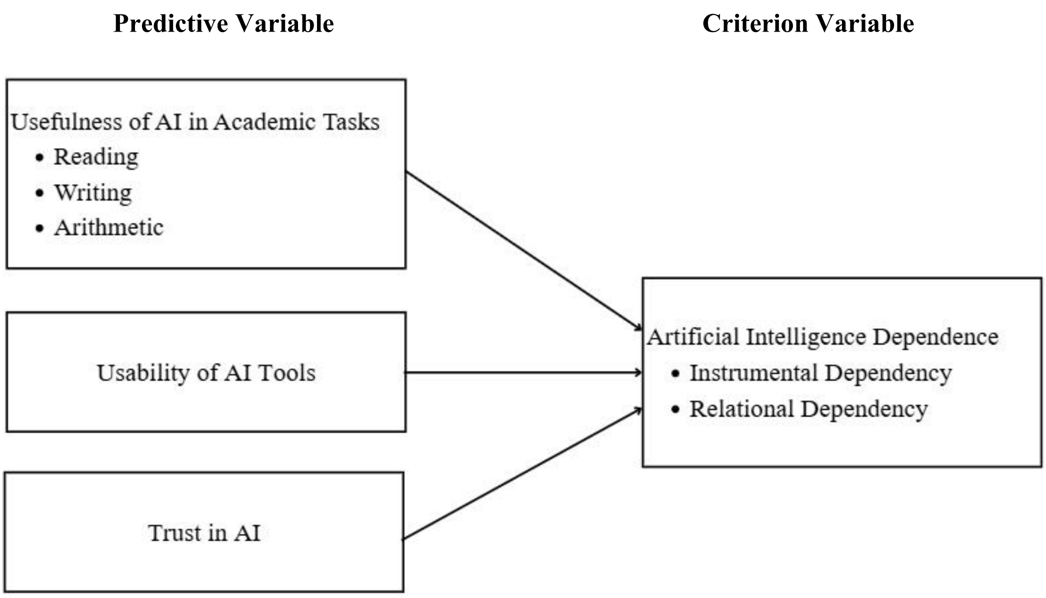

Figure 1: Conceptual Framework of the Study

2. METHODS

2.1. Research Design

This study employed a predictive research design. The focus of the design was to use patterns and relationships of previously recorded data with sufficient statistical modeling to determine the potential outcome of a future or criterion variable based on the identified predictor variables and not to describe past events (Van Witteloostuijn et al., 2022). The predictive design was used when the objective of the study was to determine which variable or variables significantly predicted the outcome and to provide data-driven support for decision-making, particularly in education and behavior-based research that aimed to guide intervention and policy development (Fayda-Kinik, 2025). The advantages of this type of design were that it could help researchers uncover meaningful predictive structures, improve decision-making accuracy, identify risks earlier, and provide forward-looking evidence to assist in developing strategic intervention plans (Almalawi et al., 2024).

2.2. Locale of the Study

This study was conducted at a private educational institution in Poblacion, District, Davao City, Philippines, which was recognized for having excellent tourism, hospitality, and business programs. The institution was selected as the study's location because it provideed a modern learning environment where Artificial Intelligence (AI) tools are increasingly integrated into academic activities such as writing, research, and digital communication. The school's digital infrastructure, accessibility of internet resources, and availability of AI-enabled applications exposed students to diverse AI tools in their daily academic routines.

2.3. Sample and Sampling Technique

The respondents in this study were students of a private educational institution in Poblacion District, Davao City, enrolled for Academic Year 2025–2026, with a total of 573 students (Grade 11: 397; Grade 12: 176). The sample size of 231 respondents was determined using the Rao-Soft sample size calculator, based on Cochran's (1977) formula for a finite population, with a 95% confidence level, a 5% margin of error, and a 50% response rate. This number is deemed sufficient to obtain statistically reliable data.

To ensure representation across all year levels, the study utilized a stratified random sampling technique. The entire population was first divided into strata by Grade 11 and Grade 12, and the 231 respondents were then proportionally allocated to the two strata as follows: 161 from Grade 11 and 70 from Grade 12. Within each stratum, participants were selected randomly from a class list provided by the school using a simple random sampling method to ensure each participant was selected and represented equally across year levels.

2.4. Data Gathering Technique

The study used an online survey to collect data. An online survey is a data-collection methodology in which researchers collect data from participants via questionnaire-based online technologies (Regmi et al., 2017). According to Hooker and De Zúñiga (2017), online surveys were used when researchers desired an efficient, fast, and convenient means of collecting data from respondents who had access to the internet; this was particularly relevant in studies including large numbers of respondents or when researchers had to collect data from a geographically dispersed population.

Specifically, this study utilized four adapted survey questionnaires. The first part, "Usefulness of AI in Academic Tasks," was adapted from Capinding (2024). The adapted questionnaire was validated and reliability-tested using Cronbach's alpha (0.854).

The second part of the instrument measured the usability of AI Tools, adapted from Brooke (1996). The adapted questionnaire was validated and reliability-tested using Cronbach's alpha of 0.827. The third part of the instrument measured Trust in AI, as defined by Lee and See (2023). The adapted questionnaire was validated and reliability-tested using Cronbach's alpha of 0.845. The fourth part of the instrument measured AI Dependence, the study's dependent variable, which is divided into two dimensions: Instrumental Dependency and Relational Dependency. This section was adapted from the LLM-D12 scale developed by Yankouskaya et al. (2025), which is specifically designed to measure behavioral and psychological reliance on Large Language Models. The adapted questionnaire was validated and reliability-tested using Cronbach's alpha (0.885).

2.5. Data Analysis Technique

Three data analysis techniques were used in this study. These are descriptive, correlational, and multiple regression analyses.

The descriptive analysis technique was used to summarize and present data in a clear, organized way, using basic statistical tools. It was applied when the goal was to describe data, identify patterns, and provide an overview of information, such as the mean and standard deviation (Creswell, J. W., & Creswell, J. D., 2018). It was applied when the goal is to describe the levels of Usefulness of Artificial Intelligence (AI) in academic tasks (in terms of writing, reading, and arithmetic), usability of AI, trust in AI, and AI dependence (in terms of instrumental dependency and relational dependency) among Senior High School students, as these measures were appropriate for summarizing central tendency and variability.

Moreover, this study applied correlation analysis to examine the relationships among the variables. It was used to determine the strength and direction of the relationship between two or more variables without implying causation (Privitera, G. J., 2022). One of its key advantages was its simplicity: it was easy to compute and interpret using a single coefficient ranging from −1 to +1, while also enabling researchers to identify meaningful relationships that may have guided further hypothesis testing or more advanced statistical analyses (Hassan, 2024). In particular, the Pearson Product-Moment Correlation Coefficient was used to measure the strength and direction of relationships among the variables (Tomasz, 2011), specifically between Usefulness, AI usability, trust in AI, and AI dependence.

Lastly, multiple linear regression was used to examine the relationship between a continuous dependent variable and two or more independent variables, estimating how each predictor uniquely contributed to the outcome while holding other variables constant (Gabriel et al., 2024). It was typically used in research to explain or predict an outcome variable. It was applied in this study to determine the individual and combined influence of Usefulness, usability, and trust on AI dependence. One of its key advantages was that it allowed researchers to assess the relative importance of each predictor while controlling for the effects of other variables, thereby improving explanatory power and prediction accuracy; it also supported hypothesis testing and model-based decision-making in complex datasets (Margalina et al., 2026).

The following scale was used to interpret the level of variables:

Range	*Descriptive Level*	*Usefulness*	*Usability*	*Trust in AI*	*AI Dependence*
3.26 – 4.00	Very High	Very Strong	Very Strong	Very Positive	Very High
2.51 – 3.25	High	Strong	Strong	Positive	High
1.76 – 2.50	Low	Weak	Weak	Negative	Low
1.00 – 1.75	Very Low	Very Weak	Very Weak	Very Negative	Very Low

For the interpretation of standard deviation, the guidelines of Omda and Sergent (2022) and Scribbr Statistics (2024) were adopted, defining standard deviation as a measure of the consistency of responses around the mean in survey data.

Standard Deviation Range	***Descriptive Interpretation***
Below 0.50	Very Low Variability (High Consistency)
0.51-0.99	Low Variability (Consistent Responses)
1.00-1.49	Moderate Variability (Varied Responses)
1.50 and above	High Variability (Polarized/Inconsistent)

For the interpretation of r-value, the following scheme is used as proposed by Schober et al. (2018; updated in NCBI/StatPearls, 2024.

Computed r	***Descriptive Interpretation***
Between +/- 0.90 to +/- 1.00	Very Strong Correlation
Between +/- 0.70 to +/- 0.89	Strong Correlation
Between +/- 0.40 to +/- 0.69	Moderate Correlation
Between +/- 0.10 to +/- 0.39	Weak Correlation
0.00 to +/- 0.09	No Correlation

In terms of Scale of Beta (β) Coefficient Strength, the following scheme as proposed by Hair et al., 2022; updated 2025 (Updated for modern multivariate modeling and PLS-SEM).

β Value Range	**Predictive Strength**
+/- 0.50 and above	Very strong
+/- 0.30 - +/- 0.49	Strong
+/- 0.20 - +/- 0.29	Moderate
+/- 0.10 - +/- 0.19	Weak
Below +/- 0.10	Very weak/ Negligible

2.6. Ethical Considerations

This research was conducted in accordance with the SMILE (Safety, Minimal Risk, Informed Consent, Learning Benefit, and Ethics) principles and adhered to established ethical research practices to protect the rights and welfare of all individuals who participated in the study. The research procedures used to collect data in this study were intended to minimize any potential physical, psychological, and social risks or harm to individuals, as the only data collection method was a non-invasive survey questionnaire targeting AI dependence. Participants were able to skip questions or withdraw from the study at any time without penalty.

Participation was voluntary, and both students and their parents were fully informed of the study's purpose, procedures, and benefits through informed consent forms, ensuring understanding and voluntary agreement (Babbie, 2016). The study aimed to provide meaningful educational insights into the relationships among AI usefulness, usability, and trust with student AI dependence, which may have informed teaching strategies and promoted responsible AI integration in education.

In this study, confidentiality and anonymity were maintained by not collecting any personally identifiable information and by storing all data in password-protected files accessible only to the researcher. Further, all instruments and related literature used in the study were properly cited to maintain academic integrity and prevent plagiarism (Saunders et al., 2019).

By following the SMILE principles and established ethical guidelines, this study ensured that participants were treated with dignity and respect, no harm or disadvantage was incurred, and the research was conducted with integrity, transparency, and adherence to the ethical principles of autonomy, beneficence, and justice.

3. RESULTS

3.1. Descriptive Results

Table 1 presents the descriptive analysis of Usefulness, Usability, Trust in AI, and AI Dependence, including their respective indicators, means, and standard deviation.

Table 1. Descriptive Analysis Results (n = 231)

Variables	**Mean**	**SD**	**Interpretation**
Usefulness	**2.92**	**0.52**	**High**
Reading	2.99	0.51	High
Writing	2.99	0.57	High
Arithmetic	2.78	0.66	High
Usability of AI Tools	**3.01**	**0.51**	**High**
Trust in AI	**2.77**	**0.61**	**High**
AI Dependence	**2.78**	**0.61**	**High**
Instrumental Dependency	2.74	0.66	High
Relational Dependency	2.82	0.60	High

The table specifically revealed the Usefulness of AI in academic tasks, which obtained a mean of 2.92, which was described as high. This indicated that AI was highly useful for academic tasks; students perceived it as helpful in improving their academic learning. The corresponding standard deviation of 0.52, which was considered low, reflected consistent responses among the students. Among the others, the reading and writing indicator registered the highest mean, indicating that students found AI particularly beneficial for language-related tasks.

Moreover, the results revealed that the usability of AI tools had a mean of 3.01, indicating high usability. This implied that AI tools were highly usable and that students perceived AI-based platforms as user-friendly and easy to navigate. The standard deviation of 0.51, which was considered low, indicated a consistent response among the respondents. Furthermore, trust in AI had a mean of 2.77, indicating high trust. This indicated that trust in AI was positive, reflecting students' belief that AI provides reliable data, although some will do so with reservations. The standard deviation of 0.61, which was considered low, indicated a consistent response among the respondents.

Regarding AI dependence, a mean of 2.78 was obtained, indicating a high level of dependence. This indicates that students' AI dependence was high; they frequently relied on AI tools as a regular support in their studies. The standard deviation of 0.61, which was considered low, indicated a consistent response among the respondents. Both of its indicators obtained a mean described as high. Among its indicators, relational dependency had a slightly higher mean, which was considered high. This indicated that students did not rely solely on AI systems as academic tools but may have also formed relationships based on a preference for AI systems.

The findings demonstrated that students found AI highly useful and usable, and generally trustworthy in supporting their academic tasks, leading to the regular integration of AI tools into their learning activities.

3.2. Correlation Analysis

Table 2 is the correlation table. This section describes the correlation variables that examine relationships among Usefulness, AI Tool Usability, Trust in AI, and AI Dependence among students.

Table 2. Correlation Analysis Results

Variables	AI Dependence			
	r-value	p-value	Decision on HO	Interpretation
Usefulness	0.784	0.000	Reject	Positive, Strong, and Significant Relationship
Usability of AI Tools	0.741	0.000	Reject	Positive, Strong, and Significant Relationship
Trust in AI	0.848	0.000	Reject	Positive, Strong, and Significant Relationship

The correlation between usefulness and AI dependence variables yielded an r-value of 0.738 with a p-value of 0.0000. Since the p-value is less than 0.05, the null hypothesis (Ho1) was rejected, indicating a significant relationship. This strong positive correlation implies that as students perceive AI as more useful for academic tasks, their dependence on it increased. Furthermore, the usability of AI tools and AI dependence variables yielded an r-value of 0.741 (p-value = 0.000). Since the p-value is less than 0.05, the null hypothesis (Ho2) was rejected, indicating a significant relationship. This strong positive correlation implies that AI tools were perceived as user-friendly and that dependence on them increased accordingly. Similarly, trust in AI and AI dependence variables showed an r-value of 0.848 (p-value = 0.000). Since the p-value is less than 0.05, the null hypothesis (Ho3) was rejected, indicating a significant relationship. This strong positive correlation indicates that students' trust in AI outputs and their level of dependence increased in parallel. Among the three variables, trust in AI shows the highest correlation coefficient, indicating that students' confidence in AI's accuracy, reliability, and credibility was a key driver of their dependence on AI.

The study demonstrated that the Usefulness of AI in academic tasks, the usability of AI tools, and trust in AI were all significantly related to AI dependence. While each factor played a crucial role, the strong correlation in trust in AI indicates that students' confidence in AI-generated outputs was the most influential factor in their dependence on AI.

3.3. Regression Analysis

Table 3 is the regression table. This section presents the regression analysis examining the predictive relationships among Usefulness, Usability of AI Tools, Trust, and AI Dependence.

Table 3. Regression Analysis Results

Independent Variables	AI Dependence					
	Estimate	Stand. Estimate	SE	T	p	Interpretation
Intercept	-0.140		0.120	-1.160	0.246	
Usefulness	0.321	0.274	0.062	5.200	0.000	Significant Influence
Usability of AI Tools	0.164	0.138	0.061	2.690	0.008	Significant Influence
Trust in AI	0.539	0.539	0.053	10.190	0.000	Significant Influence
$R= 0.880$, $R^2= 0.775$, Adjusted $R^2=0.772$, $F=260.0$, Sig.=0.000						

Table 3 specifically shows that the model predicting AI dependence using Usefulness, usability, and trust in AI was: AI dependence = -0.140 + 0.321 (U) + 0.164 (UAIT) + 0.539 (TAI). The R2 value of 0.775 indicates that the model very strongly predicted AI dependence, with Usefulness, AI tool usability, and trust in AI as predictors. Furthermore, the corresponding p-value of 0.000, which is less than the 0.05 level of significance, indicates that the null hypothesis was rejected. It indicates that the model's very strong performance was significant. Finally, this implies that for every unit change in any predictor in the model, there was a corresponding change in the AI dependence prediction.

The overall model yielded an adjusted R2 of 0.772, suggesting that approximately 77.2% of the variance in AI Dependence was explained by these three variables combined. The F-value of 260.0 and p-value of 0.000 confirm that the regression was statistically significant.

The findings reveal that the regression model demonstrated a strong, significant ability to predict students' AI dependence, with Usefulness, usability, and trust in AI as predictors. This indicates that these variables collectively played an important role in explaining why students depend on AI tools in their academic activities. The results further suggest that changes in students' perceptions of AI usefulness, usability, and trust were associated with corresponding changes in their level of AI dependence. Among the predictors, trust in AI emerged as the most influential factor, underscoring the importance of students' confidence in AI tools' reliability and accuracy in shaping their dependence on these technologies.

3.4. Summary of Findings

Based on statistical results, it was specifically found that:

1.The Usefulness of AI in academic tasks was significantly and positively correlated with the AI dependence among Senior High school students.
2.The usability of AI tools was significantly and positively correlated with AI dependence among Senior High school students.
3.Trust in AI was significantly and positively correlated with the AI dependence among Senior High school students.
4.The model predicting Usefulness, usability, and trust in AI was significant.

4. DISCUSSIONS

4.1. Usefulness, Usability, Trust, and AI Dependence Correlation

The findings of this study revealed that there was a strong positive correlation among usefulness, usability, and trust in AI with AI dependence. This finding affirmed Limna and Shaengchart (2025), who stated significant positive associations between perceived AI usefulness and AI reliance among Thai university students. Thus, students who viewed AI as functionally useful tended to use it regularly and ultimately became reliant on it because it could provide explanations, assist with writing, and expedite research. Likewise, the current finding supported Gu et al. (2026), who found that students were more likely to use tools and did so on a more frequent basis for academic support when the tools required minimal effort to navigate; therefore, this increased usage will also led to eventual dependence upon these tools over time.

Among all examined variables, the correlation between trust in AI and AI dependence yielded the highest coefficient in the present study, establishing trust as the most powerful associative variable with student AI reliance. This finding supported Alshammari and Al-Mamary (2025), who, in a quantitative study of Saudi Arabian university students, found that trust was the greatest predictor of user behavior when utilizing AI chatbots. Furthermore, this finding was consistent with Zhai et al. (2024), who cautioned that when students trust AI too readily, they began to accept data unquestioningly and, as a result, contributed to an environment in which misinformation was prevalent and critical thinking skills were eroded. Conversely, the current findings of this study were at odds with Kumbo et al. (2025), who found that perceived trust did not significantly correlate with Tanzanian university students' behavior when using AI for mobile learning.

4.2. Usefulness, Usability, Trust, and AI Dependence Regression Analysis

The findings of this study revealed that Usefulness, usability, and trust, both individually and collectively, exerted a significant influence on students' dependence on artificial intelligence, with trust emerging as the strongest predictor. This finding was consistent with Ghimire et al. (2024), who found among engineering students in Indonesia that perceived ease of use, trust, and perceived Usefulness were crucial constructs in understanding AI reliance, as these factors were unique to the characteristics of AI systems and consistently emerged as significant predictors of technology-related behavior in higher education contexts. Furthermore, the current finding supported the study by Gulati et al. (2024), which found that trust was a foundational mechanism shaping users' behaviors. On the contrary, the current finding contradicted Ku et al. (2025), who found that trust was not a statistically significant predictor of AI dependency. Their research indicated that the relationship between trust and AI dependency was inconsistent and weakened when users experienced high workload.

4.3. Conclusions

Based on the findings, it was concluded that forecasting Artificial Intelligence dependence was significant when Usefulness, usability, and trust were used as predictors. The model's strength (77.5%) in forecasting the criterion was very strong. This result supported the Extended Technology Acceptance Model (TAM), which posits that users' behavior toward a digital system was driven by Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and users' trust in the system.

4.4. Recommendations

Based on the conclusion of this study, the following recommendations were proposed.

- The researchers may explore the remaining 22.5% of the variance in student AI dependence by investigating other potential predictors. There was also a pressing need for a qualitative study that could go deeper than survey scores, capturing how students personally experienced, justified, and narrated their reliance on AI in their own words.
- Educational leaders may strengthen AI literacy by emphasizing helping students develop calibrated trust: the ability to critically evaluate AI outputs, recognize their limitations, and verify information before relying on it for academic purposes.

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