

Original Research Article

Factors Influencing the Adoption of Artificial Intelligence Tools and Their Association with Employability Skills among Undergraduate and Postgraduate Student

Dr. Amandeep Singh Manku

Assistant Professor & In-charge, Bachelor of Financial Markets (BFM) Department, Guru Nanak College of Arts, Science and Commerce (Autonomous), Mumbai, Maharashtra, India

Corresponding author E-mail: amandeep.manku@gmail.com

Received: 10 September, 2026 | Accepted: 24 September, 2026 | Published: 12 October, 2026

Abstract:

Artificial Intelligence (AI) tools such as ChatGPT, Gemini, Microsoft Copilot, and Claude have rapidly permeated higher education, fundamentally altering the ways in which students learn, conduct research, and prepare for careers. Despite their widespread availability, the extent to which students adopt these tools varies considerably, influenced by factors such as perceived usefulness, ease of use, AI literacy, trust, and ethical awareness. This study investigates the determinants of AI tool adoption among 300 undergraduate and postgraduate students and examines the association between AI tool adoption and perceived employability skills. Employing a quantitative, survey-based research design with a structured five-point Likert scale questionnaire, data were analysed using multiple linear regression, simple linear regression, and independent samples t-test. The multiple regression model explained 34.1% of the variance in AI adoption ($R^2 = 0.341$, $F(5, 294) = 30.4$, $p < .001$), with AI literacy emerging as the strongest predictor ($\beta = 0.304$, $p < .001$), followed by perceived ease of use ($\beta = 0.269$), trust in AI ($\beta = 0.269$), perceived usefulness ($\beta = 0.263$), and ethical awareness ($\beta = 0.164$). The simple regression demonstrated that AI adoption significantly predicted employability skills ($R^2 = 0.349$, $\beta = 0.591$, $p < .001$). Furthermore, postgraduate students exhibited significantly higher AI adoption levels than undergraduate students, $t(298) = 2.74$, $p = .007$, with

a small effect size (Cohen's $d = 0.334$). These findings underscore the necessity for educational institutions to integrate AI literacy training and responsible AI usage policies into curricula, thereby equipping students with the digital competencies demanded by AI-driven workplaces. The study contributes to the emerging literature on AI adoption in higher education by integrating multiple adoption determinants within a single empirical framework and linking them to employability outcomes.

Keywords: Artificial Intelligence, AI Adoption, AI Literacy, Employability Skills, Higher Education, Technology Acceptance.

1. Introduction

1.1 Background

Artificial Intelligence (AI) has rapidly emerged as one of the most transformative technological forces in higher education in the twenty-first century. The proliferation of generative AI tools, including ChatGPT, Gemini, Microsoft Copilot, and Claude, has introduced unprecedented opportunities for students to enhance their learning experiences, streamline academic workflows, and develop new competencies that are increasingly valued in the contemporary labor market (Kasneji et al., 2023). These tools support a wide array of academic activities, ranging from content creation and literature synthesis to coding assistance and problem-solving, thereby redefining traditional pedagogical approaches and prompting institutions worldwide to reconsider how they prepare students for an AI-augmented workforce.

The integration of AI into educational contexts is not merely a technological shift but represents a fundamental change in the relationship between learners, knowledge, and digital tools. As AI systems become more capable and accessible, the concept of AI literacy, defined as the ability to understand, evaluate, and effectively use AI technologies, has gained prominence as a critical competency for academic success and career readiness (Long & Magerko, 2020). Students who possess higher levels of AI literacy are better equipped to leverage these tools responsibly, distinguish between reliable and inaccurate AI-generated outputs, and apply AI capabilities to complex academic and professional tasks. Consequently, understanding the factors that drive or hinder AI tool adoption among students has become a priority for educators, policymakers, and researchers alike.

The significance of this inquiry is further amplified by the growing emphasis on employability skills in higher education. Employers across industries increasingly seek graduates who can work alongside AI systems, demonstrate digital fluency, and adapt to rapidly evolving technological landscapes (World Economic Forum, 2023). AI competencies, including the ability to prompt AI systems effectively, critically evaluate AI outputs, and integrate AI into workflow processes, are emerging as differentiating factors in graduate employability. This convergence of AI adoption and employability outcomes creates a compelling rationale for empirical research that examines both the determinants of AI tool usage among students and its association with their perceived readiness for the workforce.

1.2 Problem Statement

Although AI tools are widely available and increasingly integrated into academic settings, students differ markedly in their willingness and capacity to adopt them. Prior research in technology acceptance has established that factors such as perceived usefulness and perceived ease of use are significant determinants of technology adoption (Davis,

1989; Venkatesh et al., 2003). However, the unique characteristics of generative AI tools, including their potential for producing inaccurate information (often referred to as hallucination), concerns about academic integrity and plagiarism, and the need for users to develop specific prompting skills, introduce additional dimensions that extend beyond traditional technology acceptance models. Trust in AI-generated information and ethical awareness regarding responsible AI usage may play particularly important roles in shaping adoption behaviors in the educational context (Tlili et al., 2023). Despite the growing body of literature on AI in education, there remains a need for empirical studies that simultaneously examine multiple adoption determinants and their collective association with students' AI tool usage while also examining the relationship between such adoption and perceived employability skills.

1.3 Research Gap

Existing studies in the domain of AI adoption in education have made valuable contributions by examining individual factors in isolation. For instance, some researchers have focused exclusively on perceived usefulness and ease of use (Kazykhankyzy et al. 2026), while others have investigated AI literacy (Ng et al., 2021) or ethical concerns (Shahzad, M. F., Xu, S., & Javed, I., 2024) as standalone predictors. However, fewer studies have adopted an integrated approach that combines multiple determinants, including perceived usefulness, perceived ease of use, AI literacy, trust, and ethical awareness, within a single analytical framework. Moreover, the relationship between AI tool adoption and the development of employability skills among students remains underexplored. This gap is particularly significant given the growing demand for AI-competent graduates and the increasing relevance of AI tool usage in connecting academic learning with workplace readiness. The present study addresses this gap by developing and testing a comprehensive model that links multiple adoption determinants to AI tool usage and, subsequently, to perceived employability skills among undergraduate and postgraduate students.

1.4 Significance of the Study

The findings of this study carry practical implications for multiple stakeholders in the higher education ecosystem. For educational institutions, understanding the relative importance of different adoption determinants can inform the design of targeted interventions, such as AI literacy workshops, user-friendly tool integration, and responsible AI usage policies. For students, the study highlights the potential benefits of AI tool adoption for developing workplace-relevant competencies. For policymakers, the results provide evidence-based insights that can guide the alignment of higher education curricula with national frameworks such as the National Education Policy (NEP) 2020 in India, which emphasizes the integration of emerging technologies into education. By bridging the gap between technology adoption research and employability outcomes, this study contributes to both academic knowledge and practical strategy development in the evolving landscape of AI in higher education.

2. Literature Review

2.1 Perceived Usefulness

Perceived usefulness, defined as the degree to which a person believes that using a particular system would enhance their job performance, is a foundational construct in technology acceptance research (Davis, 1989). In the context of AI tools in higher education, perceived usefulness encompasses students' beliefs about the extent to which AI applications can improve their learning efficiency, academic performance, and research productivity. Studies have consistently demonstrated that when students perceive AI tools as beneficial for their academic tasks, they are more likely to adopt them (Al-Emran & Granić, 2021). For example, AI-powered writing assistants can help students

refine their drafts, while AI-based research tools can accelerate the literature review process by identifying relevant sources and synthesizing key findings.

The relationship between perceived usefulness and AI adoption is particularly salient in educational settings where students face increasing academic pressures and time constraints. Research by Sallam et al. (2023) found that healthcare students who perceived ChatGPT as useful for their studies reported higher adoption rates and more frequent usage patterns. Similarly, Tanvir et al. (2023) demonstrated that perceived usefulness was a significant predictor of students' intentions to use AI tools for academic purposes. These findings align with the broader technology acceptance literature, which consistently identifies perceived usefulness as one of the strongest predictors of technology adoption across diverse user populations and contexts (King & He, 2006). In the present study, perceived usefulness is hypothesized to exert a positive influence on students' adoption of AI tools, reflecting the expectation that students who recognize the academic benefits of AI are more likely to integrate these tools into their learning processes.

2.2 Perceived Ease of Use

Perceived ease of use refers to the degree to which a person believes that using a system would be free from effort (Davis, 1989). This construct is especially relevant for AI tools, as the usability of these tools can significantly influence students' willingness to experiment with and sustain their usage over time. Modern AI platforms such as ChatGPT and Claude feature conversational interfaces that are designed to be intuitive, requiring users to simply type queries in natural language rather than navigating complex software environments. This design philosophy lowers the barrier to entry and encourages adoption even among students with limited technical backgrounds (Yan et al., 2023).

Empirical evidence supports the positive relationship between perceived ease of use and AI tool adoption in educational contexts. Farrokhnia et al. (2023) examined students' interactions with ChatGPT and found that the tool's user-friendly interface was a significant factor in encouraging initial adoption and continued use. Furthermore, the study revealed that students who perceived AI tools as easy to use were more likely to explore advanced features, such as prompt engineering and multi-modal inputs, thereby deepening their engagement with the technology. The concept of perceived ease of use also intersects with the broader notion of digital accessibility, as tools that require minimal technical expertise are more inclusive and can be adopted by a wider range of students regardless of their academic discipline or prior technical knowledge. In the present study, perceived ease of use is expected to be a significant positive predictor of AI tool adoption, consistent with the established theoretical and empirical foundations of the Technology Acceptance Model (TAM).

2.3 AI Literacy

AI literacy is a multidimensional construct that encompasses an individual's understanding of AI capabilities and limitations, the ability to interact effectively with AI systems, and the capacity to critically evaluate AI-generated outputs (Long & Magerko, 2020). As AI tools become increasingly integrated into educational and professional settings, AI literacy has emerged as a crucial competency that enables students to harness the full potential of these technologies while mitigating associated risks such as misinformation and over-reliance. Ng et al. (2021) proposed a framework for AI literacy that includes the ability to recognize AI applications, understand how AI systems work, evaluate AI outputs, and implement AI tools responsibly in various contexts.

The relationship between AI literacy and AI tool adoption is bidirectional and mutually reinforcing. On one hand, students with higher levels of AI literacy are more likely to understand the potential benefits of AI tools and use them effectively, leading to greater adoption. On the other hand, increased usage of AI tools provides students with practical experience that further enhances their AI literacy. Research by Wang et al. (2023) demonstrated that AI literacy significantly predicted students' use of AI tools for learning, with literate students being more adept at crafting effective prompts, interpreting AI responses critically, and integrating AI outputs into their academic work. The importance of AI literacy is further underscored by policy frameworks such as the European Union's AI Literacy Framework (2023), which emphasizes the need for educational institutions to develop students' AI competencies as part of their digital literacy curricula. In this study, AI literacy is hypothesized to be a significant positive predictor of AI tool adoption, reflecting the expectation that students who possess a deeper understanding of AI are more confident and frequent users of AI-powered tools.

2.4 Trust in AI

Trust in AI refers to the confidence that users place in the accuracy, reliability, and appropriateness of AI-generated information and recommendations. In educational contexts, trust is a critical factor because students rely on AI tools for tasks such as generating explanations, solving problems, and producing academic content. However, the inherent limitations of generative AI systems, including their tendency to produce plausible but factually incorrect outputs (known as hallucinations), can undermine user trust and, consequently, adoption (Jakesch et al., 2023). The challenge of establishing appropriate levels of trust, balancing skepticism with openness to AI assistance, is a central concern in the literature on human-AI interaction.

Research has shown that trust in AI is influenced by multiple factors, including the transparency of AI systems, the consistency and accuracy of their outputs, and users' prior experiences with AI technologies (Glikson & Woolley, 2020). In the educational domain, students who have had positive experiences with AI tools and who perceive the outputs as reliable are more likely to develop trust and continue using these tools. Conversely, students who encounter frequent inaccuracies or who lack the skills to verify AI-generated information may develop distrust and reduce their usage. Tlili et al. (2023) found that trust was a significant predictor of students' continued use of generative AI tools, particularly when combined with adequate AI literacy that enabled students to assess the quality of AI outputs. In the present study, trust in AI is hypothesized to positively influence AI tool adoption, reflecting the expectation that students who have greater confidence in AI-generated information are more likely to adopt and sustain their use of AI tools for academic purposes.

2.5 Ethical Awareness

Ethical awareness in the context of AI usage encompasses students' understanding of the ethical implications of using AI tools, including issues related to plagiarism, academic integrity, data privacy, and the responsible use of AI-generated content. As AI tools become more capable of producing human-like text, code, and other academic outputs, concerns about academic dishonesty and the erosion of authentic learning have intensified among educators and institutions (Cotton et al., 2023). Students who are more ethically aware are expected to adopt AI tools in a more measured and responsible manner, using them as aids for learning rather than substitutes for independent thought and original work.

The relationship between ethical awareness and AI adoption is complex and potentially nonlinear. On one hand, high ethical awareness may encourage responsible adoption, as students who understand the boundaries of acceptable AI use are more likely to integrate these tools into their learning processes in ways that align with

institutional policies and academic integrity standards. On the other hand, excessive concern about ethical implications may deter some students from using AI tools altogether, even when such usage would be beneficial for their learning. Studies by Shahzad, M. F., Xu, S., & Javed, I. (2024) and Atlas (2023) have explored the ethical dimensions of AI use in education, highlighting the need for clear guidelines and educational programs that promote responsible AI usage. In the present study, ethical awareness is hypothesized to positively influence AI tool adoption, reflecting the expectation that students who are conscious of ethical considerations are more likely to develop mature and sustainable AI usage patterns that contribute positively to their academic development.

2.6 AI Adoption and Employability Skills

The concept of employability skills, also referred to as soft skills or twenty-first-century skills, encompasses a broad range of competencies that are valued by employers, including problem-solving, critical thinking, creativity, digital literacy, communication, and adaptability. As AI technologies transform the nature of work across industries, the ability to work effectively with AI systems has emerged as an increasingly important employability skill (World Economic Forum, 2023). Students who are proficient in using AI tools for tasks such as data analysis, content generation, and problem-solving may be better prepared for AI-augmented workplaces, where human-AI collaboration is becoming the norm rather than the exception.

Research on the link between AI adoption and employability skills is still in its early stages, but emerging evidence suggests a positive relationship. A study by Baidoo-Anu and Ansah (2023) found that university students who actively used AI tools reported improved research skills, enhanced creativity, and greater confidence in their ability to handle technology-driven tasks in professional settings. Similarly, Mhlana (2023) argued that the integration of AI into education can equip students with the digital competencies and adaptive thinking skills that are essential for thriving in the fourth industrial revolution. The theoretical basis for this relationship can be traced to human capital theory (Becker, 1964) and the concept of digital human capital, which posits that technology-related skills enhance individuals' productive capacity and labor market outcomes. In the present study, AI tool adoption is hypothesized to positively influence students' perceived employability skills, reflecting the expectation that greater engagement with AI tools enhances the competencies that employers seek in graduates.

3. Conceptual Framework and Research Design

3.1 Conceptual Framework

The conceptual framework for this study integrates five independent variables (perceived usefulness, perceived ease of use, AI literacy, trust in AI, and ethical awareness) as determinants of AI tool adoption (the dependent variable), which in turn influences the outcome variable of employability skills. This framework extends the Technology Acceptance Model (TAM) by incorporating additional constructs, namely AI literacy, trust, and ethical awareness, that are particularly relevant to the adoption of generative AI tools in educational settings. The inclusion of employability skills as an outcome variable further extends the model beyond traditional technology acceptance research, which typically focuses on behavioral intention or usage as the ultimate dependent variable.

The independent variables were selected based on a comprehensive review of the literature on technology adoption (Davis, 1989; Venkatesh et al., 2003), AI literacy (Long & Magerko, 2020; Ng et al., 2021), trust in AI (Glikson & Woolley, 2020), and ethical awareness in AI usage (Cotton et al., 2023). The dependent variable, AI tool adoption, captures the extent to which students actively use AI tools for academic purposes. The outcome variable, employability skills, reflects students' perceptions of how AI tool usage enhances their readiness for the workforce.

This multi-variable framework enables a holistic examination of the factors that drive AI adoption and its implications for student career preparedness.

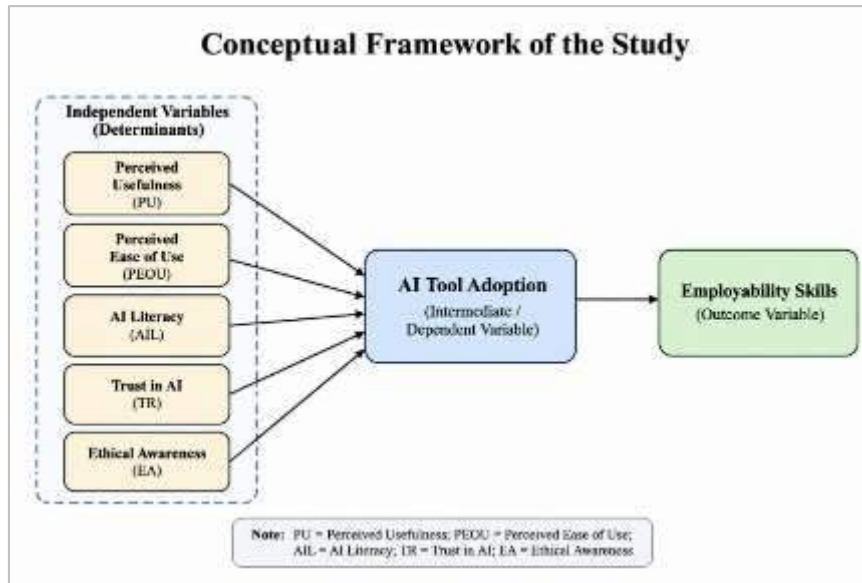


Figure 3-1: Conceptual Framework of the Study

Table 3-1 Classification of Research Variables

Variable Type	Variable
Independent Variable	Perceived Usefulness (PU)
Independent Variable	Perceived Ease of Use (PEOU)
Independent Variable	AI Literacy (AIL)
Independent Variable	Trust in AI (Trust)
Independent Variable	Ethical Awareness (Ethics)
Dependent Variable	Adoption of AI Tools
Outcome Variable	Employability Skills

3.2 Research Objectives

This study pursues three primary research objectives. First, it seeks to examine whether perceived usefulness, perceived ease of use, AI literacy, trust in AI, and ethical awareness significantly predict AI tool adoption. Second, it seeks to examine whether AI tool adoption significantly predicts students' perceived employability skills. Third, it endeavors to compare AI tool adoption between undergraduate and postgraduate students to identify whether academic level constitutes a differentiating factor in AI adoption behavior. These objectives are addressed through a series of hypotheses tested using appropriate statistical techniques.

3.3 Research Hypotheses

Based on the conceptual framework and the review of literature, three hypotheses were formulated. Hypothesis 1 H1: Perceived usefulness, perceived ease of use, AI literacy, trust in AI, and ethical awareness significantly predict AI tool adoption, tested using multiple linear regression. Hypothesis 2 (H2) states that the AI tool adoption significantly predicts students' perceived employability skills, tested using simple linear regression. Hypothesis 3

(H3) asserts that there is a significant difference in AI tool adoption between undergraduate and postgraduate students, tested using independent samples t-test.

Table 3-2 Summary of Research Hypotheses

Hypothesis	Statement	Statistical Test
H1	PU, PEOU, AIL, Trust, and Ethics significantly predict AI Adoption	Multiple Linear Regression
H2	AI Adoption significantly predicts Employability Skills	Simple Linear Regression
H3	Significant difference in AI Adoption between UG and PG students	Independent samples T-Test

3.4 Research Methodology

This study adopted a quantitative research approach with a descriptive and explanatory research design. Primary data were collected from undergraduate (UG) and postgraduate (PG) students using a structured questionnaire administered through Google Forms. Data collection was conducted over a two-month period from June to July 2026. Prior to initiating the survey, ethical approval was obtained from the institutional review board, ensuring adherence to ethical guidelines for research involving human participants. All respondents provided informed consent regarding anonymity, confidentiality, and their right to withdraw. A total of 350 questionnaires were distributed electronically; of the 315 responses received, 15 were rejected due to incomplete data, yielding a final valid sample of 300 respondents (effective response rate: 85.7%). Convenience sampling was employed to recruit participants, supplemented by broad outreach across different faculties and levels of study. The questionnaire comprised nine sections: demographic information (gender, age, level of study, faculty or stream), AI usage patterns, and seven measurement scales corresponding to the study variables, all measured on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The instrument included four items per construct, resulting in a total of 28 scale items plus demographic questions.

Table 3-3 Research Methodology Summary

Item	Description
Research Approach	Quantitative
Research Design	Descriptive and Explanatory
Data Source	Primary (Survey-based)
Population	Undergraduate (UG) and Postgraduate (PG) Students
Sampling Technique	Convenience Sampling
Sample Size	300 (valid responses)
Data Collection Period	June – July 2026
Instrument	Structured Questionnaire (distributed via Google Forms)
Scale	Five-point Likert Scale (1 = Strongly Disagree to 5 = Strongly Agree)
Ethical Approval	Ethical measures: Informed consent, anonymity, and voluntary participation strictly maintained (IRB review not applicable for minimal-risk exploratory survey)
Response Rate	85.7% (350 distributed; 315 received; 15 rejected due to incompleteness)

3.5 Data Analysis Plan

The data analysis was conducted in multiple stages to address each research objective. First, descriptive statistics, including mean, standard deviation, frequency, and percentage, were computed to characterize the sample and the distribution of responses across all study variables. Second, Pearson correlation analysis was performed to examine the bivariate relationships among all variables. Third, multiple linear regression (Model 1) was employed to test H1, with AI adoption as the dependent variable and the five independent variables as predictors. Fourth, simple linear regression (Model 2) was conducted to test H2, with employability skills as the dependent variable and AI adoption as the predictor. Fifth, an independent samples t-test was conducted to test H3 by comparing AI adoption scores between undergraduate and postgraduate students. Although the Shapiro–Wilk test was statistically significant, the near-zero skewness and kurtosis values, together with the sample size, indicated only a minor departure from normality; Levene’s test confirmed homogeneity of variance. Prior to conducting regression analyses, assumption checks were performed, including tests for normality (Shapiro-Wilk, Kolmogorov-Smirnov, Anderson-Darling), homoscedasticity (Breusch-Pagan, Goldfeld-Quandt, Harrison-McCabe), autocorrelation (Durbin-Watson), and multicollinearity (VIF and tolerance statistics). Reliability was assessed using Cronbach’s alpha.

4. Data Analysis and Results

4.1 Demographic Profile of Respondents

The final sample comprised 300 respondents. In terms of gender distribution, 154 respondents (51.30%) were male and 146 respondents (48.70%) were female, indicating a relatively balanced representation. The age distribution showed that the majority of respondents fell within the 20-22 age group (118 respondents, 39.30%), followed by the 17-19 age group (81 respondents, 27.00%), the 23-25 age group (70 respondents, 23.30%), and those above 25 years of age (31 respondents, 10.30%). With respect to the level of study, 199 respondents (66.30%) were undergraduate students and 101 respondents (33.70%) were postgraduate students. This distribution reflects a higher proportion of UG students, which is consistent with the typical demographic composition of higher education institutions.

Table 4-1 Frequency Distribution of Gender

Gender	Count	% of Total
Female	146	48.70%
Male	154	51.30%

Table 4-2 Frequency Distribution of Age Group

Age Group	Count	% of Total
17-19	81	27.00%
20-22	118	39.30%
23-25	70	23.30%
Above 25	31	10.30%

Table 4-3 Frequency Distribution of Level of Study

Level of Study	Count	% of Total
Postgraduate (PG)	101	33.70%
Undergraduate (UG)	199	66.30%

4.2 Descriptive Statistics

Table 4-4 presents the descriptive statistics for all study variables. The mean scores for the independent variables ranged from 3.62 to 3.92, indicating a generally positive disposition toward AI-related constructs among the respondents. Perceived usefulness received the highest mean score ($M = 3.92$, $SD = 0.612$), followed by ethical awareness ($M = 3.90$, $SD = 0.526$) and perceived ease of use ($M = 3.84$, $SD = 0.623$). AI literacy ($M = 3.64$, $SD = 0.693$) and trust in AI ($M = 3.62$, $SD = 0.696$) scored slightly lower, suggesting that while students recognize the utility and ethical dimensions of AI, there is room for improvement in their technical understanding of AI systems and confidence in AI-generated outputs. AI adoption exhibited a mean of 3.86 ($SD = 0.510$), indicating a relatively high level of reported AI tool adoption among the respondents. Employability skills had a mean of 2.75 ($SD = 0.530$), indicating comparatively lower perceived employability outcomes. All variables exhibited acceptable skewness and kurtosis values, with magnitudes below the conventional thresholds of 2.0 and 7.0, respectively, indicating approximate normality of the distributions (Hair et al., 2019).

Table 4-4 Descriptive Statistics of Study Variables (N = 300)

Variable	N	Mean	SD	Skewness	Kurtosis
Perceived Usefulness	300	3.92	0.612	-0.228	-0.238
Perceived Ease of Use	300	3.84	0.623	-0.391	0.073
AI Literacy	300	3.64	0.693	-0.160	-0.251
Trust in AI	300	3.62	0.696	-0.187	-0.033
Ethical Awareness	300	3.90	0.526	-0.086	-0.347
AI Adoption	300	3.86	0.510	-0.067	-0.058
Employability Skills	300	2.75	0.530	0.099	0.200

Table 4-5: Reliability Statistics of Study Constructs

Variable / Construct	No. of Items	Cronbach's α	Acceptance Criterion	Interpretation
Perceived Usefulness	4	0.871	$\alpha \geq 0.70$	Good
Perceived Ease of Use	4	0.875	$\alpha \geq 0.70$	Good
AI Literacy	4	0.894	$\alpha \geq 0.70$	Good
Trust in AI	4	0.889	$\alpha \geq 0.70$	Good
Ethical Awareness	4	0.829	$\alpha \geq 0.70$	Good
AI Adoption	4	0.827	$\alpha \geq 0.70$	Good
Employability Skills	4	0.818	$\alpha \geq 0.70$	Good

Note. α = Cronbach's alpha. An α value ≥ 0.70 indicates acceptable internal consistency.

All seven constructs recorded Cronbach's alpha values between **0.818 and 0.894**, exceeding the accepted threshold of 0.70. Thus, all scales demonstrate **good internal consistency reliability** (Nunnally & Bernstein, 1994; Taber, 2018).

4.3 Correlation Analysis

Table 4-6 presents the Pearson correlation matrix for all study variables. The results indicate that the correlations among the five independent variables were generally weak and non-significant (r ranging from -0.086 to 0.097 , $p > .05$), suggesting limited overlap among the predictors. This indicates that the independent variables represent relatively distinct dimensions and provides preliminary evidence of limited multicollinearity. However, multicollinearity was assessed more directly through the tolerance and Variance Inflation Factor (VIF) statistics

reported in the regression analysis. All five independent variables demonstrated statistically significant positive correlations with AI adoption. AI literacy showed the strongest correlation with AI adoption ($r = 0.309$, $p < .001$), followed by perceived ease of use ($r = 0.297$, $p < .001$), trust in AI ($r = 0.270$, $p < .001$), perceived usefulness ($r = 0.238$, $p < .001$), and ethical awareness ($r = 0.196$, $p < .001$). AI adoption also demonstrated a statistically significant positive correlation with employability skills ($r = 0.591$, $p < .001$), indicating a relatively strong bivariate association between the two variables. In addition, all five independent variables showed significant positive correlations with employability skills, although these associations were weaker than the relationship between AI adoption and employability skills. Overall, the correlation findings provide preliminary evidence supporting the relationships examined in the subsequent regression analyses, while the regression results provide a more appropriate basis for assessing the unique predictive contribution of each independent variable.

Table 4-6 Pearson Correlation Matrix

Variable	1	2	3	4	5	6	7
1. PU	—						
2. PEOU	-0.029	—					
3. AIL	0.020	-0.009	—				
4. Trust	-0.086	0.082	0.001	—			
5. Ethics	0.001	0.097	0.013	0.007	—		
6. AI Adoption	0.238***	0.297***	0.309***	0.270***	0.196***	—	
7. Employability	0.211***	0.209***	0.182**	0.157**	0.198***	0.591***	—

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

4.4 Regression Analysis: Determinants of AI Adoption (H1)

To test Hypothesis 1, a multiple linear regression analysis was conducted with AI adoption as the dependent variable and perceived usefulness, perceived ease of use, AI literacy, trust in AI, and ethical awareness as independent variables. Prior to conducting the regression, several assumption checks were performed. The normality of residuals was confirmed using the Shapiro-Wilk test ($W = 0.993$, $p = 0.189$), the Kolmogorov-Smirnov test ($D = 0.0267$, $p = 0.983$), and the Anderson-Darling test ($A = 0.389$, $p = 0.382$), all of which indicated that the residuals were normally distributed. Homoscedasticity was confirmed through the Breusch-Pagan test (6.7 , $p = 0.244$), the Goldfeld-Quandt test (1.15 , $p = 0.208$), and the Harrison-McCabe test (0.466 , $p = 0.222$). The Durbin-Watson statistic was 2.03 ($p = 0.726$), indicating no significant autocorrelation. Multicollinearity was assessed using the Variance Inflation Factor (VIF), with all values ranging from 1.00 to 1.02 , well below the conventional threshold of 5.0 , and tolerance values ranging from 0.983 to 0.999 , confirming the absence of multicollinearity concerns. Cook's distance values were all below 0.064 , and no Mahalanobis distances exceeded the $p < 0.001$ threshold, indicating the absence of influential outliers.

The overall model was statistically significant, $F(5, 294) = 30.4$, $p < .001$, explaining 34.1% of the variance in AI adoption ($R = 0.584$, $R^2 = 0.341$, Adjusted $R^2 = 0.330$). Table 4-6 presents the regression coefficients for each predictor. All five independent variables emerged as statistically significant predictors of AI adoption. AI literacy was the strongest predictor, with a standardized coefficient of 0.304 ($t = 6.412$, $p < .001$), indicating that for every one-standard-deviation increase in AI literacy, AI adoption increased by 0.304 standard deviations, holding all other variables constant. Perceived ease of use ($\beta = 0.269$, $t = 5.630$, $p < .001$) and trust in AI ($\beta = 0.269$, $t = 5.633$, $p < .001$) were the second and third strongest predictors, respectively, with nearly identical standardized effects.

Perceived usefulness ($\beta = 0.263$, $t = 5.527$, $p < .001$) also made a substantial contribution. Ethical awareness, while statistically significant ($\beta = 0.164$, $t = 3.443$, $p < .001$), had the smallest standardized effect among the five predictors. These results provide strong statistical support for Hypothesis 1, indicating that perceived usefulness, perceived ease of use, AI literacy, trust in AI, and ethical awareness are significant predictors of students' AI tool adoption

Table 4-7 Model 1 Summary: Multiple Regression (DV: AI Adoption)

Model	R	R ²	Adjusted R ²	F	df1	df2	p
1	0.584	0.341	0.330	30.4	5	294	< .001

Note. $N = 300$. Predictors: PU, PEOU, AIL, Trust, Ethics.

Table 4-8 Model 1 Coefficients: Predictors of AI Adoption

Predictor	B	SE	t	p	β	95% CI Lower	95% CI Upper
(Intercept)	0.012	0.326	0.037	.970	—	-0.630	0.655
Perceived Usefulness	0.219	0.040	5.527	< .001	0.263	0.141	0.297
Perceived Ease of Use	0.220	0.039	5.630	< .001	0.269	0.143	0.297
AI Literacy	0.224	0.035	6.412	< .001	0.304	0.155	0.292
Trust in AI	0.197	0.035	5.633	< .001	0.269	0.128	0.265
Ethical Awareness	0.159	0.046	3.443	< .001	0.164	0.068	0.250

Table 4-9 Collinearity Diagnostics (VIF and Tolerance)

Predictor	VIF	Tolerance
Perceived Usefulness	1.01	0.992
Perceived Ease of Use	1.02	0.983
AI Literacy	1.00	0.999
Trust in AI	1.01	0.986
Ethical Awareness	1.01	0.990

4.5 Regression Analysis: AI Adoption and Employability Skills (H2)

To test Hypothesis 2, a simple linear regression was conducted with employability skills as the dependent variable and AI adoption as the sole predictor. The assumption checks for Model 2 were equally satisfactory. Normality of residuals was confirmed by the Shapiro-Wilk test ($W = 0.994$, $p = 0.274$), the Kolmogorov-Smirnov test ($D = 0.0576$, $p = 0.272$), and the Anderson-Darling test ($A = 0.466$, $p = 0.252$). Homoscedasticity was verified through the Breusch-Pagan test (1.17 , $p = 0.280$), the Goldfeld-Quandt test (0.959 , $p = 0.601$), and the Harrison-McCabe test (0.511 , $p = 0.614$). The Durbin-Watson statistic was 2.14 ($p = 0.204$), indicating no significant autocorrelation, and the VIF for the single predictor was 1.00 , confirming the absence of multicollinearity.

The model was statistically significant, $F(1, 298) = 160$, $p < .001$, explaining 34.9% of the variance in employability skills ($R = 0.591$, $R^2 = 0.349$, Adjusted $R^2 = 0.347$). The unstandardized regression coefficient for AI adoption was 0.614 ($SE = 0.0486$, $t = 12.64$, $p < .001$, 95% CI [$0.518, 0.709$]), with a standardized coefficient of 0.591 . This indicates that a one-unit increase in reported AI adoption was associated with a 0.614 -unit higher predicted score for perceived employability skill. The intercept was 0.383 ($SE = 0.189$, $t = 2.02$, $p = 0.044$), which was statistically significant, suggesting a baseline level of perceived employability even in the absence of AI adoption. These results provide strong support for Hypothesis 2, indicating that AI tool adoption is a significant positive

predictor of students' perceived employability skills. The effect size is substantial, with AI adoption alone accounting for approximately 35% of the variance in employability perceptions.

Table 4-10 Model 2 Summary: Simple Regression (DV: Employability Skills)

Model	R	R ²	Adjusted R ²	F	df1	df2	p
2	0.591	0.349	0.347	160	1	298	< .001

Note. N = 300. Predictor: AI Adoption.

Table 4-11 Model 2 Coefficients: AI Adoption Predicting Employability Skills

Predictor	B	SE	t	p	β	95% CI Lower	95% CI Upper
(Intercept)	0.383	0.189	2.02	.044	—	0.011	0.755
AI Adoption	0.614	0.049	12.64	< .001	0.591	0.518	0.709

4.6 Group Comparison: UG vs. PG Students (H3)

To test Hypothesis 3, an independent samples t-test was conducted to examine whether AI adoption differed significantly between undergraduate (UG) and postgraduate (PG) students. Before conducting the t-test, the assumptions of normality and homogeneity of variance were examined. The overall AI adoption scores showed very low skewness (−0.067) and kurtosis (−0.058), indicating an approximately symmetric distribution. Although the Shapiro–Wilk test was statistically significant ($W = 0.962$, $p < .001$), the near-zero skewness and kurtosis values, together with the sample size of 300, suggested that the deviation from normality was minor for the purpose of the independent samples t-test. Levene's test for equality of variances was non-significant ($F = 0.033$, $p = .857$), indicating that the assumption of homogeneity of variance was satisfied.

The independent samples t-test revealed a statistically significant difference in AI adoption between postgraduate and undergraduate students, $t(298) = 2.74$, $p = .007$. Postgraduate students reported a higher mean AI adoption score ($M = 3.98$, $SD = 0.525$) than undergraduate students ($M = 3.81$, $SD = 0.494$). The mean difference was 0.169, with a standard error of 0.0616. The effect size, measured using Cohen's d , was 0.334, indicating a small effect. These findings provide statistical support for H3, indicating that AI adoption scores differ significantly between postgraduate and undergraduate students, with postgraduate students reporting higher levels of AI adoption.

The higher reported AI adoption among postgraduate students may be associated with their greater exposure to research activities, thesis writing, academic projects, and other advanced academic tasks that provide more opportunities for AI tool use. However, given the cross-sectional nature of the study, this finding should be interpreted as a group difference rather than evidence of a causal effect.

Table 4-12: Independent Samples t-Test of AI Adoption by Level of Study

Test	Statistic	df	p	Mean Difference	SE Difference	Effect Size
Student's t	2.74	298	.007	0.169	0.0616	Cohen's $d = 0.334$

Note. PG = Postgraduate; UG = Undergraduate. A statistically significant result is indicated by $p < .05$.

Table 4-13 Group Descriptive for AI Adoption by Level of Study

Group	N	Mean	Median	SD	SE
PG	101	3.98	4.00	0.525	0.0522
UG	199	3.81	4.00	0.494	0.0350

5. Discussion

5.1 Key Findings and Interpretation

The results of this study provide robust empirical evidence for the multi-factor determinants of AI tool adoption among higher education students and the positive relationship between such adoption and perceived employability skills. AI literacy emerged as the strongest predictor of AI tool adoption ($\beta = 0.304$), highlighting the importance of AI-related knowledge and competencies in students' adoption patterns. This finding is consistent with the growing recognition of AI literacy as a foundational competency in the digital age (Long & Magerko, 2020; Ng et al., 2021). Students with greater understanding of AI capabilities, limitations, and effective interaction strategies may be more confident and intentional in their use of AI tools, which is reflected in higher reported levels of AI adoption. The finding has important implications for educational institutions, suggesting that AI literacy initiatives, including workshops on prompt engineering, critical evaluation of AI outputs, and understanding AI system capabilities, may support more effective and responsible use of AI tools among students.

The nearly identical predictive effects of perceived ease of use ($\beta = 0.269$) and trust in AI ($\beta = 0.269$) highlight two complementary dimensions associated with students' AI adoption. The significant relationship between perceived ease of use and AI adoption is consistent with the principles of the Technology Acceptance Model (Davis, 1989) and suggests that user-friendly AI interfaces are associated with greater adoption. Similarly, the significance of trust indicates that students' confidence in the reliability and accuracy of AI-generated information is an important factor associated with their engagement with these tools. These findings suggest that AI tool developers and educational institutions should consider both usability and transparency, including features such as source references and clear indications of potential inaccuracies, when promoting responsible AI use.

Perceived usefulness ($\beta = 0.263$) also emerged as a significant predictor of AI adoption, although its standardized effect was slightly smaller than those of AI literacy, perceived ease of use, and trust. This finding is noteworthy because traditional TAM research often identifies perceived usefulness as an important predictor of technology adoption (King & He, 2006). The present results suggest that, within the context of generative AI tools, ease of use, trust, and AI literacy may be particularly relevant alongside perceived usefulness. Ethical awareness, while the weakest predictor ($\beta = 0.164$), was nevertheless statistically significant, indicating that students with greater awareness of ethical considerations related to AI use also reported higher levels of AI adoption. This association may reflect the role of ethical awareness in supporting more informed and responsible engagement with AI-assisted academic work.

The results indicate a statistically significant positive association between AI tool adoption and students' perceived employability skills. The simple linear regression model was statistically significant, with AI tool adoption significantly predicting perceived employability skills ($\beta = 0.591$, $R^2 = 0.349$, $p < .001$). The model explains approximately 34.9% of the variance in students' perceived employability skills, indicating that differences in AI tool adoption are associated with meaningful differences in perceived employability outcomes. However, given the cross-sectional nature of the study and the use of self-reported data, the findings should be interpreted as evidence

of a significant statistical relationship rather than as proof of a causal effect. In practical terms, students who reported higher levels of AI tool adoption also tended to report higher levels of perceived employability skills, including competencies such as problem-solving, creativity, digital fluency, adaptability, and readiness for AI-enabled workplaces. These findings highlight the potential relevance of responsible and effective AI engagement in supporting students' perceptions of their career preparedness, while further longitudinal research would be required to establish causal relationships.

The independent samples t-test indicated a statistically significant difference in AI adoption scores between postgraduate and undergraduate students, $t(298) = 2.74, p = .007$. Postgraduate students reported a higher mean AI adoption score ($M = 3.98, SD = 0.525$) than undergraduate students ($M = 3.81, SD = 0.494$), with a mean difference of 0.169. The effect size (Cohen's $d = 0.334$) indicates a small effect. These findings provide statistical support for H3 and indicate that postgraduate students reported significantly higher levels of AI adoption than undergraduate students. The higher adoption scores among postgraduate students may be associated with their greater exposure to research activities, thesis writing, academic projects, and other advanced academic tasks that provide opportunities for AI tool use. However, given the cross-sectional nature of the study, this group difference should not be interpreted as evidence of a causal relationship.

5.2 Comparison with Existing Research

The findings of this study are broadly consistent with the existing literature on technology acceptance and AI adoption in education, while also offering several novel insights. The significance of perceived usefulness and ease of use as predictors of AI adoption aligns with the TAM framework and prior empirical studies (Kazykhankyzy et al. 2026; Tanvir et al. , 2023). The prominence of AI literacy as the strongest predictor extends the findings of Wang et al. (2023) and Ng et al. (2021) by demonstrating its relative importance within a multi-predictor framework. The significance of trust in AI is consistent with the findings of Tlili et al. (2023) and Glikson and Woolley (2020), who highlighted the importance of trust in sustaining user engagement with AI systems.

The positive relationship between AI adoption and employability skills contributes to an emerging body of literature that links educational technology usage to career readiness outcomes. While Baidoo-Anu and Ansah (2023) and Mhlanga (2023) have discussed the potential of AI tools to enhance employability, the present study provides quantitative empirical evidence for this relationship using a regression framework. The finding that postgraduate students adopt AI tools more than undergraduates adds to the limited research on demographic differences in AI adoption, an area that warrants further investigation with larger and more diverse samples.

5.3 Limitations

Several limitations of this study should be acknowledged. First, the use of convenience sampling limits the generalizability of the findings to the broader population of higher education students, as the sample may not be representative of all demographic groups, academic disciplines, or geographic regions. Second, the cross-sectional research design precludes causal inferences, as the data were collected at a single point in time and cannot establish the temporal sequencing of variables. Third, the reliance on self-reported measures introduces the possibility of common method bias and social desirability effects, whereby respondents may overstate their AI adoption or perceived employability skills. Fourth, the study was conducted within a limited geographical area, which may affect the applicability of the findings to other educational and cultural contexts. Fifth, the explained variance in Model 1 (34.1%) suggests that approximately 66% of the variance in AI adoption is attributable to factors not

included in the model, such as institutional support, peer influence, subjective norms, and facilitating conditions, which future research could incorporate.

6. Conclusions, Implications, and Future Scope

6.1 Conclusions

This study investigated the factors associated with the adoption of AI tools and the relationship between AI tool adoption and perceived employability skills among 300 undergraduate and postgraduate students. First, perceived usefulness, perceived ease of use, AI literacy, trust in AI, and ethical awareness collectively explained 34.1% of the variance in AI tool adoption, with AI literacy emerging as the strongest predictor. Second, AI tool adoption significantly predicted perceived employability skills, explaining 34.9% of the variance with a substantial standardized effect ($\beta = 0.591$). Third, postgraduate students exhibited significantly higher AI adoption levels compared to undergraduates. These findings contribute to the theoretical understanding of AI adoption in higher education by demonstrating the importance of extending traditional technology acceptance models with AI-specific constructs such as AI literacy, trust, and ethical awareness, and by establishing an empirical link between AI adoption and employability outcomes.

6.2 Practical Implications

The findings carry important practical implications for educational institutions, students, and policymakers. For educational institutions, the prominence of AI literacy as the strongest adoption predictor underscores the need to integrate AI literacy programs into curricula across all disciplines. Such programs should cover not only the technical aspects of AI interaction, such as prompt engineering and output evaluation, but also the ethical dimensions of AI usage, including academic integrity, privacy considerations, and responsible deployment. Institutions should also develop clear AI usage policies that provide guidance on acceptable and unacceptable uses of AI tools in academic work, thereby fostering a culture of responsible AI adoption.

For students, the positive relationship between AI adoption and employability skills highlights the professional value of developing AI competencies during their academic careers. The positive association between AI adoption and employability skills suggests that AI competencies may be relevant to students' perceived readiness for AI-augmented workplaces. For policymakers, the findings support the continued emphasis on technology integration in higher education, as exemplified by frameworks such as NEP 2020, and provide evidence for the allocation of resources toward AI literacy initiatives and infrastructure development in educational institutions. The study also highlights the need for multi-stakeholder collaboration among educators, technology developers, industry representatives, and policymakers to ensure that the integration of AI into higher education aligns with both academic standards and workforce requirements.

6.3 Future Research Directions

Several avenues for future research emerge from this study. First, multi-city and multi-institutional studies with larger and more diverse samples would enhance the generalizability of the findings and enable more nuanced analyses of how institutional, cultural, and regional factors influence AI adoption patterns. Second, longitudinal research designs that track changes in AI adoption, AI literacy, and employability perceptions over time would provide stronger evidence for causal relationships and enable the examination of how these variables evolve as AI technologies and educational contexts change. Third, Structural Equation Modeling (SEM) could be employed to validate the measurement model and test more complex mediating and moderating relationships, such as whether

AI literacy mediates the relationship between perceived ease of use and AI adoption, or whether the relationship between AI adoption and employability skills is moderated by academic discipline or prior technology experience. Fourth, discipline-wise comparisons could reveal how the nature of academic tasks and professional requirements across different fields of study influence the patterns and determinants of AI tool adoption. Fifth, qualitative research methods, including interviews and focus groups, could provide richer insights into the mechanisms through which AI adoption influences employability skill development and the contextual factors that shape students' AI adoption decisions.

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Appendix: Research Questionnaire

Title: Factors Influencing the Adoption of Artificial Intelligence Tools and Their Impact on Employability Skills among Undergraduate and Postgraduate Students

Respondent Consent: This questionnaire is for academic research purposes only. Your responses will remain confidential and anonymous.

Section A: Demographic Information

Tick one option wherever applicable.

1. Gender: Male / Female / Other / Prefer not to say
2. Age: 17–19 / 20–22 / 23–25 / Above 25
3. Level of Study: Undergraduate / Postgraduate
4. Faculty/Stream: Commerce / Science / Arts / Management / IT-Computer Science

Section B: AI Usage Patterns

Scale: Never / Rarely / Sometimes / Often / Always

- B1. I use AI for assignments.
- B2. I use AI for research.
- B3. I use AI for presentations.
- B4. I use AI for coding/problem-solving.

Section C: Perceived Usefulness (PU)

Scale: 1 = Strongly Disagree to 5 = Strongly Agree

- PU1. AI tools improve my learning efficiency.
- PU2. AI helps me complete academic tasks faster.
- PU3. AI improves the quality of my assignments.
- PU4. AI makes studying more productive.

Section D: Perceived Ease of Use (PEOU)

- PE1. AI tools are easy to learn.
- PE2. I can use AI tools without much effort.
- PE3. The interface of AI tools is user-friendly.
- PE4. It is easy to obtain useful responses from AI tools.

Section E: AI Literacy (AIL)

- AL1. I understand how AI tools generate responses.
- AL2. I know how to write effective prompts.
- AL3. I can identify inaccurate AI-generated information.
- AL4. I understand the limitations of AI tools.

Section F: Trust in AI (Trust)

- TR1. I trust AI-generated information for academic work.
- TR2. AI usually provides reliable answers.
- TR3. I verify AI-generated information before using it.
- TR4. I feel confident using AI for learning.

Section G: Ethical Awareness (Ethics)

- EA1. I am aware of plagiarism issues related to AI.
- EA2. I understand responsible AI usage.
- EA3. I am concerned about privacy while using AI tools.
- EA4. Students should follow ethical guidelines when using AI.

Section H: Adoption of AI Tools (AD)

- AD1. I regularly use AI tools for academic purposes.
- AD2. I intend to continue using AI tools.
- AD3. I recommend AI tools to other students.
- AD4. AI has become an important part of my learning process.

Section I: Employability Skills (EM)

- EM1. AI tools improve my problem-solving skills.
- EM2. AI enhances my creativity.
- EM3. AI helps me develop workplace-ready digital skills.
- EM4. Using AI makes me feel more prepared for future careers.