The ethics of artificial intelligence technology in academic work: assessing the line between assistance and plagiarism

Md. Owafeeuzzaman Patwary[1], Md. Reazul Islam[1], Abtahi Islam[1], Nur-e Sarjina Khan[1], Md. Abdullah - Al – Jubair[1], Md. Jakir Hossen[2], M. F. Mridha[1]
[1]Faculty of Science and Technology, American International University-Bangladesh (AIUB), Dhaka, Bangladesh
[2]Department of Robotics and Automation, Faculty of Engineering and Technology, Multimedia University, Melaka, Malaysia

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ABSTRACT

The integration of artificial intelligence (AI) into academia has transformed educational practices and enhanced personalized learning and problem-solving capabilities. However, this raises significant ethical concerns regarding the balance between legitimate assistance and plagiarism. This study investigated public perceptions of AI in academic settings, focusing on its impact on effectiveness, dependency, and ethical considerations of AI use. A survey of 498 respondents from various educational roles was conducted, and the data were analyzed using SPSS for descriptive statistics, chi-square tests, and regression analyses. The results identified a significant correlation between people's educational roles and their interaction with AI tools ($\chi^2(6) = 16.488$, $p = 0.036$), reflecting the diverse patterns of interaction within the academic community. More frequent use of AI was linked to less dependency ($\beta = -0.298$, $p < 0.001$), contradicting the widespread belief of over-reliance on AI. Age and educational role had limited explanatory value in perception of AI dependency issues ($R^2 = 0.033$). The findings indicate a strong correlation between AI usage frequency and dependency levels, with increased exposure to AI fostering a more critical approach rather than a dependent one. Concerns regarding the unethical use of AI, inaccuracies in AI-generated content, and the need for clear institutional policies were also highlighted. This study underscores the importance of responsible AI integration, advocating for ethical frameworks and educational interventions to ensure that AI enhances learning without compromising academic integrity.

Corresponding Author:

Md. Jakir Hossen
Department of Robotics and Automation, Faculty of Engineering and Technology, Multimedia University
Melaka, Malaysia
Email: jakir.hossen@mmu.edu.my

1. INTRODUCTION

Widespread artificial intelligence (AI) adoption in schools has revolutionized education by allowing personalized learning routes and optimum intellectual stimulation for all types of learners [1], [2]. While the applications of AI provide such advantages as cost savings and accessibility, their use is hindered by dire ethical issues, mainly academic integrity, authorship, and the acceptable limit of assistance versus plagiarism [3]–[5]. Concerns have mounted as organizations fail to establish coherent policies for the responsible use of AI amidst inconsistent usage patterns and murky accountability measures [6], [7].

Parallel to this, there have been severe concerns regarding the integrity and equity of AI systems in learning processes. Evidence exists for biases in grading systems [8], invading students' autonomy and privacy by monitoring learning platforms [9], and general confusion regarding the ethics of AI-generated content [10], [11]. These are exacerbated by the rapid rate of AI development occurring before institutional policy interventions, leaving learners and teachers in the dark about what is acceptable practice [12], [13]. While the originality of ethical research has long been celebrated, empirical investigations of the frequency of AI use and self-reported dependence are scarce. Earlier studies have typically drawn upon anecdotal or discipline-specific case studies that do not reveal role-based adoption patterns of groups such as students, faculty, and administration [14], [15]. Furthermore, there are limited longitudinal studies examining the effect of repeated exposure to ubiquitous AI on cognitive independence, especially in learning environments with significant heterogeneity between science, technology, engineering and mathematics (STEM) and humanities fields [16].

The current study fills these gaps by examining AI use patterns and perceived dependence among 498 working academics. Using a mixed-methods design, the current study examined whether a higher frequency of use is associated with higher critical literacy or passive dependence. Contrary to the widespread belief that frequent AI use undermines student agency, this study examines the hypothesis that a higher frequency of use translates into more sophisticated and strategic tool use. Statistical procedures, such as chi-square analysis and regression modeling, were employed to evaluate the impact of variables such as age and job on dependency perceptions. The results support human-led AI literacy practices that add academic integrity and enhance the educational impact of AI. By combining quantitative data and qualitative understanding, this study provides evidence-based evidence for role-specific AI training planning, informs institution-level policy, and establishes a more explicit distinction between valid assistance and academic fraud in the age of generative AI.

The organization of the paper is as presented below: In this study, section 2 presents the objectives of the investigation. Section 3 reviews the relevant literature on AI ethics in academic settings. Section 4 describes the methodology employed in this study. Section 5 presents the data analysis technique. Section 6 reports the results of this study, based on both quantitative and qualitative findings. Section 7 discusses the implications of the results, including their limitations and directions for future research. Section 8 concludes the paper with key findings and recommendations.

2. OBJECTIVES

This study analyzes the moral aspects of AI in education in terms of its effects on academic integrity, dependency, and efficiency. This study discusses the employment of AI tools by students, instructors, and administrators for their respective roles. An essential part of the research is whether repeated use results in autonomy or harmful reliance on AI systems. This research also discusses ethical issues such as plagiarism, academic dishonesty, and errors in AI work. Moreover, it examines how demographics (role, age, and AI literacy) influence the attitude towards embracing AI. Based on the findings, this study recommends ethical practices for integrating AI into academia, with a focus on AI literacy programs and institutional policies to maintain academic integrity and ensure worthwhile AI use. This study considered five key aims, integrating quantitative examination with qualitative discourse to create a well-rounded knowledge of AI among academic institutions.

a. Patterns of adoption quantified over academic functions: This study initially quantified differences in the adoption of AI tools across distinct groups of academic stakeholders [15]. It also identified statistically significant usage rates of administrators, faculty, and students based on descriptive statistics and chi-square (χ^2) testing.
b. Explored the frequency-dependency relationship: This study explored the complicated relationship between dependency and frequency of AI use [17]. Using linear regression modeling, it also tested the common assumption that over-reliance arises from high frequency, with consideration of the alternative scenario that more frequent exposure may yield more mature and independent patterns of use.
c. Measured the impact of demographics: This study tested the explanatory power of key demographic variables, i.e., educational role and age, on stakeholders' perceptions of dependency on AI [18]. It also used multivariate regression to ascertain if these variables were strong predictors of how individuals perceived using AI tools in their study.
d. Dominant ethical issues and concerns identified: This study identified dominant ethical concerns and issues of the academic community through inductive thematic analysis of open-ended survey questions [9]. This qualitative analysis attempted to build a sense of multifaceted positions on academic integrity, plagia-

rism, and the perceived truthfulness of AI-generated information.

e. Evidence-based recommendations developed: Based on the findings of the mixed-methods analysis, this study developed a set of evidence-based recommendations for schools. It is intended specifically to guide the development of role-specific training programs for AI and straightforward, action-oriented policies for incorporating the ethical use of AI into the curriculum.

3. LITERATURE REVIEW

This literature review collates emerging conversations surrounding the transformative potential of AI in academia, with a particular focus on the ethical implications of its implementation in research, writing, and knowledge sharing. It examined AI's two-faced role as both an accelerator of academic productivity and a source of trouble for academic integrity, data privacy, and evaluation fairness.

3.1. Setting ethical standards

Scholars rated frameworks as the most effective means of controlling AI use in academia. Ashok *et al.* [12] created a cross-industry ethical framework that highlights transparency, accountability, and human oversight and argued that such principles avoid misuse in academic settings. They discussed how algorithmic auditing reduces bias in automarking. Castelló-Sirvent *et al.* [6] responded with a campus-wide plan calling for institution-wide ethics boards and AI ethics integration into the curriculum, citing decentralized policies that only exacerbate enforcement disparity. Their research cited case studies at European universities in which broken guidelines doubled plagiarism cases by 22%. Tang *et al.* [19] proposed journal-level guidelines for generative AI, calling for authorial responsibility and straightforward AI tool disclosure. They examined 350 articles on science education and found that 37% of the manuscripts had undisclosed AI contributions. Mujtaba *et al.* [20] dispelled myths of AI substituting human judgment, pointing out that ethical dilemmas occur when tools circumvent required analysis. Their survey of business students reported that 64% confused AI editing with original content in the absence of guidelines. Farooqi *et al.* [7] rigorously reviewed integration challenges and concluded that the shortage of sector-specific guidelines was the root cause of ethical breaches. They suggested adaptive frameworks for vocations instead of abstract fields.

3.2. Algorithmic bias and data privacy

Studies have uncovered the risks of embedded bias and monitoring within AI systems. Santoni de Sio [8] identified algorithmic bias in admissions and grading programs, demonstrating training data biases that increased socio-economic disparities. Their simulation identified AI admissions software biased in favor of applicants from affluent schools by 19%. Jacob *et al.* [21] replicated these results in medical school, demonstrating that biased clinical AI software exaggerated diagnosis biases among student doctors. They promoted biased audits and multivariate dataset curation in the name of equity. Dourish and Bell [9] made an early critique of ubiquitous computing, cautioning that the surveillance of students using learning management system (LMS) threatened student autonomy and facilitated the commodification of data. Their ethnographic research foreshadows today's privacy tensions in AI-monitored examinations. Polat *et al.* [14] associated biased leadership algorithms with institutional biases through bibliometric analysis. They established that AI-based resource distribution in schools exacerbated gender disparities in STEM enrollment.

3.3. Abuse of AI in Academia

Quantitative research has revealed plagiarism risks and detection failures. Perkins [3] reported rampant large language models (LLM) aided plagiarism, with 68% of students using ChatGPT unfairly under ambiguous policies. His review of 1,200 assignments revealed that modern detectors missed 45% of AI-paraphrased content. Fyfe [5] empirically confirmed AI-authored essays, showing that detectors failed to identify structural plagiarism in 72% of cases. He advocated for pedagogical changes towards process-based examinations, such as oral defenses. Hutson [4] renamed plagiarism as "attributional negligence", contending that unethical use is only present when users conceal AI inputs. His semantic analysis disengaged collaborative drafting from fraudulent authorship. Miao *et al.* [22] surveyed academia in nephrology and found that peer reviewers were unable to detect statistical manipulation generated by AI 58% of the time. They designed a disclosure process for the medical journals. Chen [13] associated relaxed conference policies with escalating misconduct, finding a 31% rise in AI-avoiding plagiarism after the pandemic.

3.4. AI literacy and policy development

Successful governance hinges on stakeholders' education. Zeb *et al.* [23] correlated library-provided AI literacy training with 52% greater rates of students' ethical adoption. Their longitudinal study demonstrated that workshops reduced tool misuse by 41%. Mustofa *et al.* [18] simulated acceptance factors, demonstrating subjective norms (e.g., peers' attitudes) and tool credibility over technical convenience for ethical use. The TAM extension questionnaire surveyed 800 Indonesian university students. Falebita and Kok[16] recognized STEM cohorts' technology readiness gaps and suggested policy-incentivized certifications to institute standardized competencies. Structural equation modeling verified that self-efficacy gaps prohibited responsible use. Khalifa and Albadawy [10] placed AI as a work-enhancer when it is paired with literacy education, with researchers utilizing guided tools that came up with 30% more new conclusions. Yim and Su [24] cautioned that there were no age-appropriate ethics modules in K-12 AI programs, and therefore, plagiarism became a threat in primary education.

3.5. Social and ethical implications of AI

Wider social effects were critically explored. Al-Zahrani and Alasmari [11] attributed dependence on AI to lessened critical thinking, indicating that overuse reduced complex problem-solving among undergrads by 30%. Their transdisciplinary investigation spoke in favor of tool balancing for the following reasons. Gerlich [15] speculated cognitive offloading as a double-edged sword, where gains in efficiency would undermine metacognitive potential in the absence of reflection-based pedagogy. He surveyed cognitive psychology experiments in favor of this trade-off and found that Cukurova [2] envisioned hybrid frameworks for intelligence that combined AI analysis with human direction to preserve ethical enrichment. In their architecture, co-adaptive learning systems are the center stage. Carayannis *et al.* [25] applied ethics to SME upskilling, demonstrating that unregulated AI training software worsened labour disparities. Prather *et al.* [26] deconstructed the hype over generative AI, uncovering overblown advantages hiding ethical risks in 70% of the EdTech hype.

3.6. Learning and creativity AI tools

Evidence proves the creativity advantage of ethical regulation. Iqbal *et al.* [1] revealed that generative AI improved preservice teachers' metacognition by 40% through group problem-solving. Controlled trials require close monitoring to avoid addiction. Chen [27] revealed that composition software used by music students generated greater melodic creativity but had 25% lower theoretical knowledge when left unsupervised. Dibek *et al.* [28] meta-analyzed 62 studies, concluding AI elevated higher-order thinking only in tasks demanding creative synthesis. Effect sizes were strongest (+0.78) when AI supplemented, not replaced, the cognitive effort. Mohebbi [17] demonstrated that AI language tools promote learner autonomy but decrease grammatical correctness by 18% in the absence of a feedback mechanism.

3.7. Research gaps and future directions

While there is an increasing body of research addressing the ethical considerations of AI in education, the existing literature tends to offer generalized ethical frameworks that are not sensitive to specific contexts. However, as AI is introduced into different fields of study, it becomes clear that ethical considerations and use case areas differ within different disciplines. This distinction indicates the need for more contextualized ethical guidelines that have the flexibility to address the difficulties associated with separate fields and address particular needs. Table 1 shows the summary of existing works on AI ethics in education:

a. Discipline-specific ethical guidelines: Current standards (e.g., Ashok *et al.* [12]; Castelló-Sirvent *et al.* [6]) remain too general, failing to keep up with discipline-specific nuances. AI use in creative writing (Chen [27]), for instance, demands different ethical standards than STEM data analysis (Falebita and Kok [16]), but no adaptive frameworks exist to address these disparities. Future studies should create field-specific guidelines with educators in mind, following up on how standards of attribution vary across fields.
b. Longitudinal cognitive effect: Short-term studies reveal cognitive deficits in critical thinking (Al-Zahrani and Alasmari [11]; Gerlich [15]), but the long-term impact of AI-facilitated learning on metacognition and creativity is unclear. Dibek *et al.* [28] referred to this as a "black box" for educational psychology, calling for cohort studies over a decade exploring the impact of early exposure to AI on graduates' professional ethics and problem-solving ability.
c. Scalable bias mitigation: Algorithmic discrimination solutions (Santoni de Sio [8]; Jacob *et al.* [21]) remain only at small-scale trials. Bias audits by Jacob *et al.*, although cost-effective in clinical training simulations, are impractical for institution-level deployment, considering computational expenses. Research priorities

should be placed on developing low-cost, open-source, bias-detecting tools that are deployable across under-resourced institutions globally.

d. Global equity in policy making: Existing ethics are Anglo-European dominant (Chen [13]; Farooqi *et al.* [7]), neglecting infrastructural and cultural constraints in Global South schooling. Farooqi *et al.* determined that 78% of suggested AI governance frameworks assume common high-bandwidth connectivity, making them ineffective in environments with intermittent connectivity. Future studies should employ participatory design practices that prioritize the voices of underrepresented educational contexts.

e. Next-generation assessment models: AI-paraphrased writing is beyond the scope of plagiarism detection (Fyfe [5]; Perkins [3]), and new choices are under-explored. Hutson [4] promoted "process-oriented evaluations," but big models for ideation genesis tracing (e.g., blockchain-documented drafting histories) require interdisciplinary collaboration between pedagogues and AI engineers.

Table 1. Summary of existing works on AI ethics in education

Author(s)	Year	Key Contribution	Identified Research Gap
Ashok *et al.* [12]	2022	Proposed foundational ethical framework identifying 14 key AI ethics principles (intelligibility, accountability, fairness, privacy)	Critical gap in practical implementation guidance
Perkins [3]	2023	Redefined academic integrity breach as lack of transparency in AI use rather than usage itself	Need for institutional policies addressing transparency requirements
Castelló-Sirvent *et al.* [6]	2024	Created 3-level roadmap (Micro/Meso/Macro) for ethical AI deployment in universities	Lack of coherent institutional vision for AI integration
Fyfe [5]	2023	Developed "proactive cheating" pedagogy to foster critical AI literacy	Need to move beyond plagiarism detection toward active engagement
Tang *et al.* [19]	2024	Established concrete guidelines for generative AI use in academic publishing	Practical implementation gaps in authorship/copyright frameworks
Gerlich [15]	2025	Quantified cognitive offloading as mediator between AI use and critical thinking decline	Empirical evidence gap regarding analytical skill erosion
Cukurova [2]	2025	Proposed "hybrid intelligence" model (externalization/internalization/extension)	Oversimplified tool-based conceptualization of AI
Jacob *et al.* [21]	2025	Introduced "AI for IMPACTS" framework for clinical tool evaluation	Need for holistic assessment beyond technical accuracy
Mustofa *et al.* [18]	2025	Extended TAM model showing ethics/trust > ease-of-use in AI adoption	Policy focus misalignment with student adoption drivers
Hutson [4]	2024	Called for redefinition of plagiarism/originality concepts	Curricular misalignment with AI-assisted writing realities

4. METHODOLOGY

This study explored the ethical issues involved in using AI in academic work, specifically the balance between assistance and plagiarism. This section elucidates the research design, participant selection, data collection methods, and procedures followed in analyzing the collected data and ethical considerations. Figure 1 shows a flowchart of the study methodology and mixed-methods analytical process.

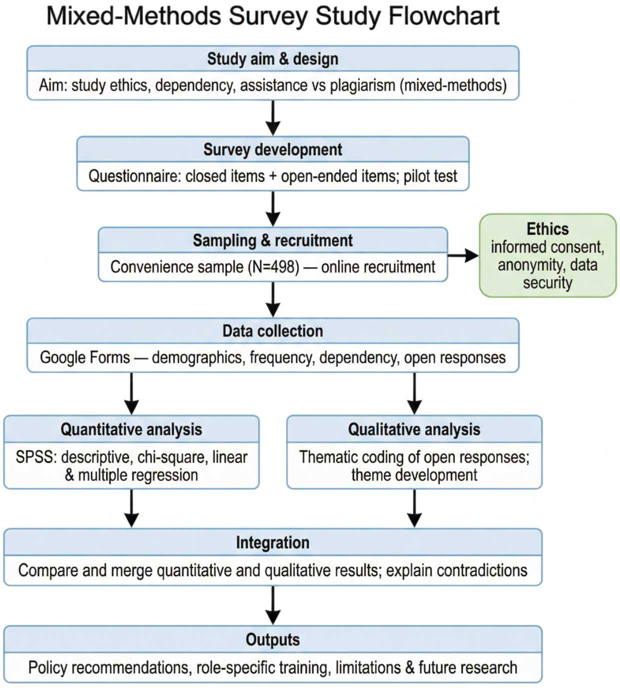

Figure 1. Overview of the study methodology and mixed-methods analytical process

4.1. Research design

The qualitative portion of the study employed a survey-based design to evaluate the prevalence and trends of AI tool use in academic environments. This process entailed the collection of quantitative data through closed-ended question designs, allowing for statistical analysis that revealed the correlations and patterns. The qualitative aspect, embedded in the same survey instrument, involved the invitation of open-ended questions to collect rich, descriptive data on participants' experiences, perceptions, and concerns regarding AI in academia. The qualitative data helped to provide context and depth to the quantitative results, enabling a more nuanced understanding.

4.2. Participants

Participants in the study included a sample of 498 (N = 498) students (at various levels), teachers/faculty members, administrative employees, and other educational roles, respectively. Participants were recruited using a convenience sampling approach, allowing for a wide representation of perspectives in an educational community. Beyond their primary function as educational environment actors, they also provided demographic data, including age and gender, to undertake a breakdown of how these variables affected their use of and perspectives on AI. Such information would enable an analysis of how these may influence AI-related beliefs and activities concerning academic work.

4.3. Data collection

Data were collected using an online survey platform called Google Forms. The survey instrument was specifically developed and pilot-tested with a small subset of the population of interest to ensure appropriate wording, validity, and reliability of the questions. The survey comprised two major components:

a. Quantitative section: Questions manipulated based on Likert scales to define participant use of AI tools, signs of dependency on AI, and perceptions of several ethical considerations associated with AI in the academic world.
b. Qualitative section: This section included open-ended questions that aimed to obtain in-depth responses regarding the participants' experiences with AI tools, their opinions on the advantages and disadvantages of AI in the education sector, as well as the proper ethical limits between acceptable and plagiarized AI assistance.

In addition, the survey gathered demographic data. Participants were briefed on the objective of the study, that their participation was voluntary, and that anonymity and confidentiality would be preserved.

4.4. Data analysis

Data were analyzed using SPSS software for quantitative and thematic analysis for the qualitative analysis. Quantitative analysis: descriptive statistics (means, standard deviations, frequencies) were estimated for the demographic characteristics of the sample and the general patterns of AI use. The following statistical tests were performed to assess the relationships between variables: Two chi-square tests of independence were conducted to examine the relationship between educational purpose and AI tool utilization. How often is AI used, and how dependent are they on AI? Regression analysis was used to model the relationship between AI usage (independent variable) and dependency (dependent variable). Perceptions of dependency problems of AI (dependent variable) according to age and educational role (independent variables). All tests were two-tailed with a significance threshold of $p \leq 0.05$. Qualitative analysis of open-ended responses was thematically analyzed. Specifically, this included a systematic process of coding the data to uncover recurrent themes, patterns, and insights. This is because they relate to participants' experiences and perceptions of AI within the academic context. Themes were identified and interpreted to enrich our understanding of the quantitative results.

4.5. Ethical considerations

This study was conducted with the utmost respect for the ethical treatment of all participants and followed the highest standards for research involving human subjects. The following measures were taken to ensure ethical conduct throughout the study:

a. Informed consent: Before participation, all subjects received detailed information about the study, including its purpose, procedures, potential risks and benefits, the voluntary nature of participation, and their right to withdraw at any time without consequence. The participants provided informed consent after they had the opportunity to ask questions about the study.
b. Anonymity and confidentiality: Participants' anonymity and confidentiality were strictly maintained. No personal identifying information (e.g., names, email addresses, or institutional affiliations) was collected or linked to individual responses. The data were aggregated and analyzed at the group level to prevent the identification of individual participants.
c. Data security: Collected data were stored on password-protected systems, accessible only to authorized research team members. Additional protections include the encryption and secure storage of physical records in locked cabinets. Data were retained for a specified period and securely destroyed following standard data disposal protocols.
d. Voluntary participation: Participation in the study was entirely voluntary. Participants were informed that they could decline to answer any question or withdraw from the study at any time without penalty. This process was repeated throughout the data-collection process.
e. Minimization of harm: The study was designed to minimize potential risks. The survey questions were reviewed to avoid sensitive or potentially triggering content. The participants were provided with the contact details of the research team regarding their concerns or questions.
f. Use and sharing of data: Participants were informed about the intended use of their data, including research analysis and academic publication. If any data sharing is planned, it will be performed in an anonymized form under strict protection protocols.

5. DATA ANALYSIS

Quantitative data from 498 education stakeholders were analyzed using SPSS (v28) with $\alpha = 0.05$. Statistical analysis entailed descriptive analysis, chi-square tests of independence, and linear regression modeling to examine the key relationships.

5.1. Test of independence

The chi-square test of independence is commonly used to determine whether there is a significant relationship between two variables and the nature of the relationship. This test is particularly useful for understanding the types of non-numeric data or the relationships between them, such as user groups and technology usage patterns.

5.1.1. Relationship between educational role and AI adoption

Hypothesis:

- H_0: No relationship between educational roles and the adoption of AI tools.
- H_1: A relationship exists between educational roles and the adoption of AI tools.

A chi-square test revealed a statistically significant association between the educational role and AI adoption:

$$\chi^2(6) = 16.488,\ p = 0.036$$

The rejection of the null hypothesis (H_0) suggests role-dependent adoption patterns. Students represented the majority of users (98% of adopters), with adoption being much lower for faculty (0.2%) and administrators (0.4%).

To explore how different educational roles (students, teachers, and administrators) influence the adoption of AI tools, a chi-square test of independence was conducted. Figure 2 and the corresponding bar chart in Figure 3 depict the distribution and statistical association.

$$\text{Chi-Square value } (\chi^2) = 16.488$$
$$\text{Degrees of Freedom (df)} = 6$$
$$p\text{-value} = 0.036$$

Since the p-value is less than 0.05, reject the null hypothesis H_0 and accept the alternative hypothesis H_1. This result indicates a statistically significant relationship between the educational role and AI adoption. Figure 3 shows that students represent the largest group of AI equipment users, followed by teachers and administrators. This suggests that while AI tools are gaining traction across the board, their adoption is not uniform. Students are more active in adopting AI technologies because they are likely to be familiar with educational workloads and digital devices. In contrast, teachers and administrators can adopt such techniques more cautiously or selectively. This insight outlines the importance of designing role-specific AI literacy initiatives to promote equal and effective integration.

3. What is your role in education? * 5. Have you used AI-based tools in education? Crosstabulation

			5. Have you used AI-based tools in education?			
			No, but I am interes	No, I have not used	Yes, regularly	Total
3. What is your role in education?	Administrator	Count	0	0	2	2
		Expected Count	.0	.8	1.1	2.0
		% of Total	0.0%	0.0%	0.4%	0.4%
	Parent	Count	1	2	2	5
		Expected Count	.1	2.1	2.8	5.0
		% of Total	0.2%	0.4%	0.4%	1.0%
	Student	Count	6	206	276	488
		Expected Count	6.9	203.8	277.3	488.0
		% of Total	1.2%	41.4%	55.4%	98.0%
	Teacher	Count	0	0	1	1
		Expected Count	.0	.4	.6	1.0
		% of Total	0.0%	0.0%	0.2%	0.2%
	Teacher;Parent	Count	0	0	2	2
		Expected Count	.0	.8	1.1	2.0
		% of Total	0.0%	0.0%	0.4%	0.4%
Total		Count	7	208	283	498
		Expected Count	7.0	208.0	283.0	498.0
		% of Total	1.4%	41.8%	56.8%	100.0%

Figure 2. Association between educational roles and AI adoption based on Chi-Square test results

5.1.2. Frequency of AI use vs. level of dependency

Hypothesis:

- H_0: No connection between how often AI is used and how much it's depended upon.
- H_1: A connection exists between the frequency of AI use and the degree of reliance on AI.

A very strong association existed between the frequency of use and the level of dependency.

$$\chi^2(16) = 531.012,\ p < 0.001$$

The strong relationship (H_0 rejected) showed polarized dependency reporting: 46.6% felt "significant dependency" compared to 46.6% who reported "somewhat dependency."

This test examined whether the frequent use of AI tools was associated with user dependency. As illustrated in Figure 4 and the supporting distribution in Figure 5:

$$\text{Chi-Square value } (\chi^2) = 531.012$$
$$p\text{-value} = 0.000$$

The extremely low p-value (< 0.001) confirms a highly significant association. As a result, this study accept H_1 and reject the null hypothesis H_0. This suggests that the frequency of use and perceived dependence are interconnected. Interestingly, Figure 5 shows that respondents with high and low use reported dependency. However, as explored in Section 5.3.1., this unit is not necessarily linear or increases with use. This result warns institutions against assuming that the most frequent use automatically leads to excessive dependence. Instead, the complexity of the psychological and behavioral dynamics surrounding AI commitment stands out.

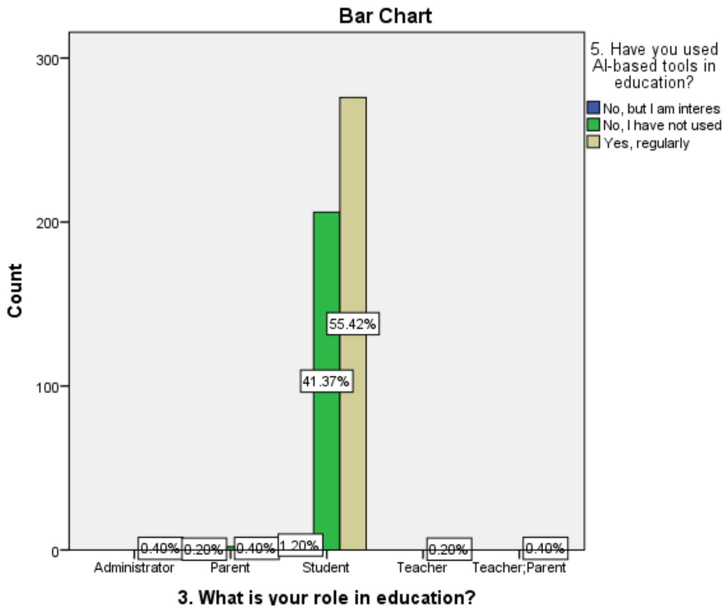

Figure 3. Bar chart showing adoption of AI among various educational roles

7. How frequently do you use AI tools in education? * 12. Have AI tools caused any dependency issues among students? Crosstabulation

			12. Have AI tools caused any dependency issues among students?				
			Neutral	No, not at all	Somewhat	Yes, significantly	Total
7. How frequently do you use AI tools in education?	Daily	Count	11	0	8	221	240
		Expected Count	15.4	1.0	111.8	111.8	240.0
		% of Total	2.2%	0.0%	1.6%	44.4%	48.2%
	Monthly	Count	6	2	4	3	15
		Expected Count	1.0	.1	7.0	7.0	15.0
		% of Total	1.2%	0.4%	0.8%	0.6%	3.0%
	Rarely	Count	1	0	2	3	6
		Expected Count	.4	.0	2.8	2.8	6.0
		% of Total	0.2%	0.0%	0.4%	0.6%	1.2%
	Several times a week	Count	10	0	214	3	227
		Expected Count	14.6	.9	105.8	105.8	227.0
		% of Total	2.0%	0.0%	43.0%	0.6%	45.6%
	Weekly	Count	4	0	4	2	10
		Expected Count	.6	.0	4.7	4.7	10.0
		% of Total	0.8%	0.0%	0.8%	0.4%	2.0%
Total		Count	32	2	232	232	498
		Expected Count	32.0	2.0	232.0	232.0	498.0
		% of Total	6.4%	0.4%	46.6%	46.6%	100.0%

Figure 4. Correlation between AI adoption and student dependency problems: Chi-square test

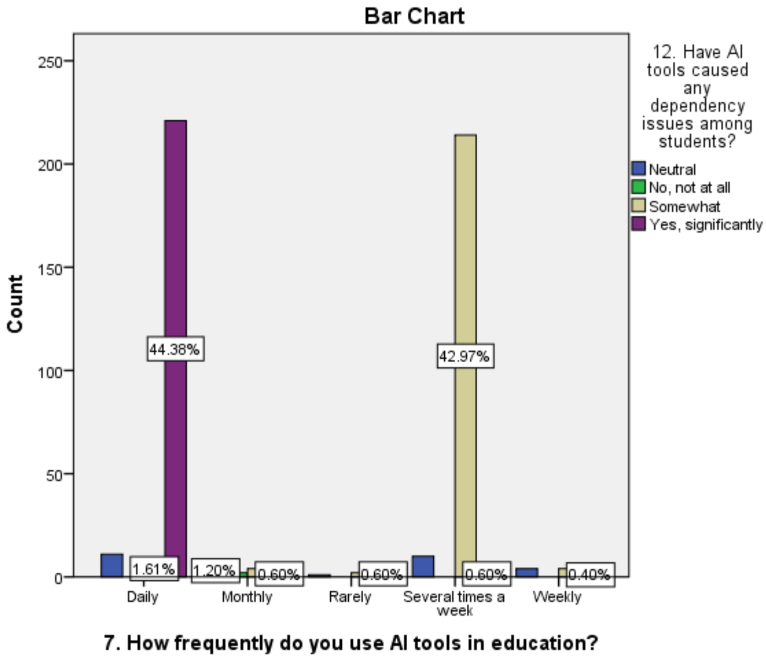

Figure 5. Distribution of AI adoption in relation to reported dependency issues

5.2. Frequency analysis

To quantitatively synthesize the survey data, a frequency analysis was conducted to capture the respondents' demographics, usage patterns involving AI, and attitudes toward AI's role and influence within educational settings. This analysis has the function of putting inferential statistical findings reported later in this paper into perspective. The response pattern along the central survey items is described below.

5.2.1. Respondents' frequency distribution by education role

The demographics of the 498 participants are shown in Figure 6. Most of the respondents were students, comprising 98.0% (n=488) of the total sample. The rest of the participants comprised other academic roles, such as parents at 1.0% (n=5), administrators at 0.4% (n=2), those who identified themselves as both teachers and parents at 0.4% (n=2), and teachers at 0.2% (n=1). This pattern at this level shows that the results mostly reflect students' views on AI in education.

What is your role in education?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Administrator	2	.4	.4	.4
	Parent	5	1.0	1.0	1.4
	Student	488	98.0	98.0	99.4
	Teacher	1	.2	.2	99.6
	Teacher;Parent	2	.4	.4	100.0
	Total	498	100.0	100.0	

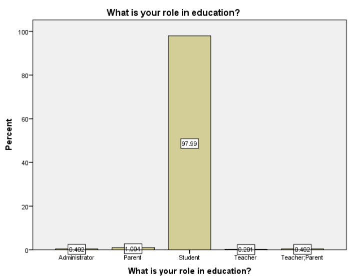

Figure 6. Frequency distribution of respondents by education role (i.e., student, teacher, administrator)

5.2.2. Perceived frequency distribution of AI-induced issues of dependency

Figure 7 shows the perceptions of respondents regarding whether or not AI tools cause dependency among students. A significant majority of participants confirmed some level of dependency, with responses evenly split between "Somewhat" (46.6%, n=232) and "Yes, significantly" (46.6%, n=232). This equates to a cumulative total of 93.2% who view there to be an issue of dependency. There was a very small minority of "Neutral" on the question (6.4%, n=32), though just 0.4% (n=2) of respondents thought that AI tools produced "No, not at all" dependency.

Have AI tools caused any dependency issues among students?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Neutral	32	6.4	6.4	6.4
	No, not at all	2	.4	.4	6.8
	Somewhat	232	46.6	46.6	53.4
	Yes, significantly	232	46.6	46.6	100.0
	Total	498	100.0	100.0	

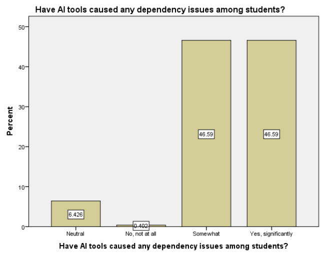

Figure 7. Frequency distribution of responses on whether AI tools have created dependency issues in students

5.2.3. Overall attitudes towards AI in education

Overall, the perception of AI in education, as outlined in Figure 8, was positive despite the fear of dependency. Of the respondents, 55.2% exhibited a positive attitude, 49.8% (n=248) a "Positive" and 5.4% (n=27) a "Very positive" attitude. However, 40.6% (n=202) responded with a "Negative" and 4.2% (n=21) were "Neutral," indicating that AI acceptance among the academic community is not absolute.

What is your overall opinion of AI in education?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Negative	202	40.6	40.6	40.6
	Neutral	21	4.2	4.2	44.8
	Positive	248	49.8	49.8	94.6
	Very positive	27	5.4	5.4	100.0
	Total	498	100.0	100.0	

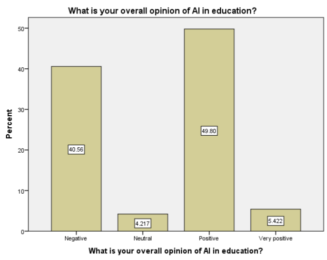

Figure 8. Overall respondent attitudes towards the use of AI in education: frequency distribution

5.2.4. Student and teacher perceptions of AI in facilitating collaborations

As is evident from Figure 9, there was a strongly polarized opinion regarding whether AI can make teachers and students work more together. Of the respondents, 47.8 % (n = 238) provided an "Agree" answer, while another 3.4% (n=17) chose "Strongly agree." However, a strong 41.8% (n=208) of respondents "Disagree," which implies disagreement with the collaborative functionality of existing AI tools.

Do AI tools enhance collaboration between students and teachers?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Agree	238	47.8	47.8	47.8
	Disagree	208	41.8	41.8	89.6
	Neutral	34	6.8	6.8	96.4
	Strongly agree	17	3.4	3.4	99.8
	Strongly disagree	1	.2	.2	100.0
	Total	498	100.0	100.0	

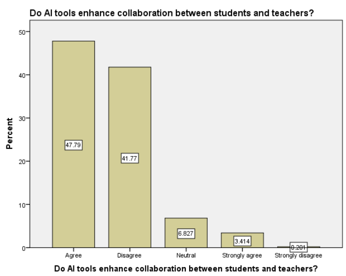

Figure 9. Frequency distribution of responses to whether AI tools enhance student-teacher communication

5.2.5. Attitudes to the possibility of AI replacing human teachers

Figure 10 indicates overall scepticism that AI was likely to be able to replace human teachers completely. While the largest proportion of respondents (45.0%, n=224) thought that AI could "partially" become capable of replacing a teacher, 45.8% were in serious doubt or uncertain. These latter groups comprised individuals who were " neutral " (39.0%, n=194), believed teachers were irreplaceable" (6.4%, n=32), or found AI ineffective " for that purpose (0.4%, n=2). Few considered that AI would "completely" (4.6%, n=23), "very effectively" (2.4%, n=12), or "somewhat" effectively (2.0%, n=10) replace.

Do you believe AI can replace teachers in the future?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Natural	194	39.0	39.0	39.0
	No, teachers are irr	1	.2	.2	39.2
	No, teachers are irreplaceable	32	6.4	6.4	45.6
	Not effective	2	.4	.4	46.0
	Partially	224	45.0	45.0	91.0
	Somewhat effective	10	2.0	2.0	93.0
	Very effective	12	2.4	2.4	95.4
	Yes, completely	23	4.6	4.6	100.0
	Total	498	100.0	100.0	

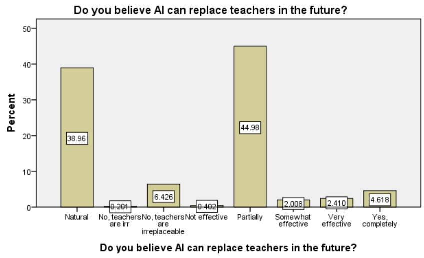

Figure 10. Frequency distribution of belief in if it can be possible for AI to replace teachers in the future

5.2.6. Assessment of AI impact on personalized learning

There was a strong positive consensus on the impact of AI on personalized learning, as shown in Figure 11. A total majority of 54.8% of the respondents supported the fact that AI tools enable personalized learning, of which 49.2% (n=245) "Agree" and 5.6% (n=28) "Strongly agree." However, there was a large opposing group of 40.6% (n=202) who did not agree.

Do AI tools improve personalized learning?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Agree	245	49.2	49.2	49.2
	Disagree	202	40.6	40.6	89.8
	Iâ€™m not sure	2	.4	.4	90.2
	Neutral	21	4.2	4.2	94.4
	Strongly agree	28	5.6	5.6	100.0
	Total	498	100.0	100.0	

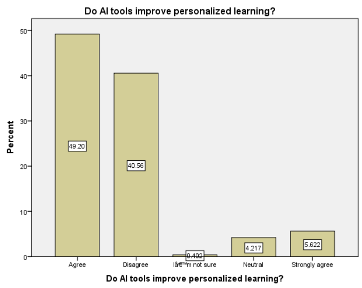

Figure 11. Frequency distribution of responses on whether AI tools support personalized learning

5.2.7. How often is an AI-based tool adopted in education

Figure 12 is the breakdown of adoption of AI tool use by the respondents. Of the respondents, 56.8% (n=283) indicated that they used AI-based tools "regularly." A vast majority of the sample, 41.8% (n=208), indicated that they had not used the tools, while a minority of 1.4% (n=7) indicated that they were interested in them, although they had not used them.

Have you used AI-based tools in education?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No, but I am interes	7	1.4	1.4	1.4
	No, I have not used	208	41.8	41.8	43.2
	Yes, regularly	283	56.8	56.8	100.0
	Total	498	100.0	100.0	

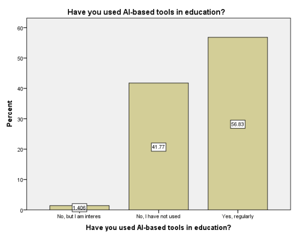

Figure 12. Frequency distribution of respondents Who have used AI-based tools in Education

5.2.8. Effectiveness of AI in accommodating individual learning styles

The commonly felt success of AI in fitting itself to different learning styles is captured in Figure 13. The responses were positive but fractured. Combined, 54.8% felt that AI's fit was at least sufficient, with 46.6% (n=232) saying that it fits "Very well" and 8.2% (n=41) saying "Fairly well." However, as many as 40.4% (n=201) of the respondents felt that AI's fit was "Poorly."

How well do AI tools adapt to individual learning styles?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Fairly well	41	8.2	8.2	8.2
	Neutral	24	4.8	4.8	13.1
	Poorly	201	40.4	40.4	53.4
	Very well	232	46.6	46.6	100.0
	Total	498	100.0	100.0	

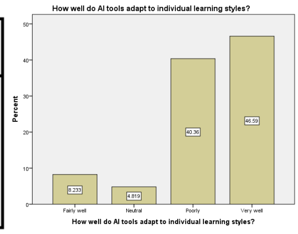

Figure 13. Frequency distribution of responses on the effectiveness of AI technologies in adapting to various learning styles

5.2.9. Reliability of AI

The core issue of AI reliability is highlighted in Figure 14. There was a strong sense of lack of reliability, supported by the fact that an overwhelming 91.2% of the participants reported being provided with the wrong information, with 48.6% (n=242) reporting that AI sometimes provided the wrong response and 42.6% (n=212) reporting that it always did so.

In case of learning, how often do you find AI taking the wrong approach/giving the wrong answer?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Always	212	42.6	42.6	42.6
	Often	32	6.4	6.4	49.0
	Rarely	12	2.4	2.4	51.4
	Sometimes	242	48.6	48.6	100.0
	Total	498	100.0	100.0	

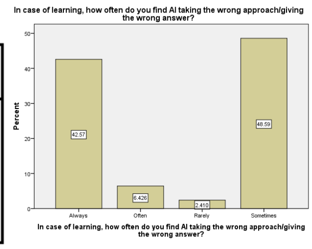

Figure 14. Frequency distribution of frequency responses with which AI technologies take the wrong path or offer inaccurate responses in learning scenarios

5.2.10. Effectiveness of AI tools for exam and assessment preparation

As previously explored Figure 15, overall, AI tools are viewed as effective study materials for exams. A large number of respondents reported being "Very effective" (47.6%, n=237) or "Somewhat effective" (6.8%, n=34). This is mirrored by a large sample (41.4%, n=206) who reported being "Not effective" in accomplishing this.

How effective are AI tools in preparing students for exams or assessments?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Depends on the stude	2	.4	.4	.4
	Natural	17	3.4	3.4	3.8
	Neutral	2	.4	.4	4.2
	Not effective	206	41.4	41.4	45.6
	Somewhat effective	34	6.8	6.8	52.4
	Very effective	237	47.6	47.6	100.0
	Total	498	100.0	100.0	

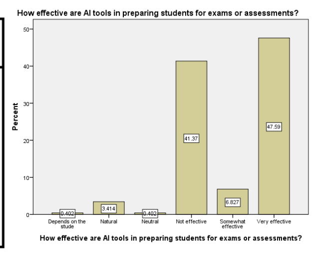

Figure 15. Frequency distribution of responses to the effectiveness of AI technology in assisting students in preparing for an exam or test

5.2.11. Perceived quality of AI integration with traditional teaching methods

Finally, Figure 16 indicates a highly positive view of the use of AI in combination with traditional pedagogies. A total, overpowering majority of 92.6% of the interviewees believe that AI applications include either "Fairly well" (46.8%, n=233) or "Very well" (45.8%, n=228). This overwhelming support confirms that an integrated pedagogy involving AI and traditional approaches is highly supported by the academic community.

The frequency breakdown explains a multidimensional theory of learning, under which artificial intelligence holds the potential for revolutionary use but with profound constraints. Support from firms (54.8%) confirmed the effectiveness of AI in enhancing personalized learning, and the majority support (54.4%) confirmed its use in test preparation. Consensus near-unanimity without opposition (92.6%) also confirms its use in traditional pedagogical models. However, these benefits are weighed against leading concerns: overwhelming fear (93.2%) of students misusing AI, widespread griping (91.2%) about shattered AI-generated text, and massive distrust (45.8%) of AI replacing human teachers. Such a clear dichotomy calls for evidence-based implementation models that strategically utilize AI's adaptive power of AI while implementing strict validation procedures, maintaining human control through teacher-AI complementarity, and constructing guardrails against cognitive reliance. These outcomes advocate a holistic, person-centered vision of technological integration—one that balances computing advantages with pedagogical integrity in educational settings.

How well do AI tools integrate with traditional teaching methods?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Fairly well	233	46.8	46.8	46.8
	I donâ€™t know	1	.2	.2	47.0
	Neutral	30	6.0	6.0	53.0
	Poorly	6	1.2	1.2	54.2
	Very well	228	45.8	45.8	100.0
	Total	498	100.0	100.0	

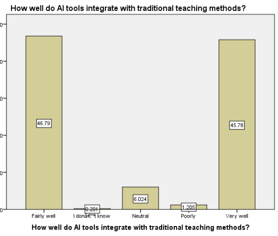

Figure 16. Frequency distribution of frequencies of responses on integrating AI technologies with traditional teaching practices

5.3. Test of regression

Regression analysis is a statistical method that explores the strength and direction of the relationship between a dependent variable and one or more independent variables. In simple linear regression, an independent variable can significantly predict the variation in the dependent variable. For each regression coefficient, a t-test was used to determine whether the coefficient was significantly different from zero, which would indicate a meaningful relationship. If the p-value for the coefficient is less than or equal to the significance level (≤ 0.05), reject the null hypothesis and determine that the predictor variable is significant to the model.

5.3.1. Relationship between frequency of AI use and dependency

Simple linear regression revealed an inverse relationship:

$$\text{Level of Dependency (Y)} = -0.298 \times \text{Frequency of AI Usage (X)} + 4.079$$

More usage predicted reduced dependency ($\beta = -0.298$, $p < 0.001$), in contrast to the over-reliance hypothesis. The model accounted for 30.1% of the variance (adjusted $R^2 = 0.301$). A linear regression model was used to quantify the relationship between AI usage frequency (X) and perceived dependency (Y). The salient findings are as follows:

$$\text{Coefficient } (\beta) = -0.298$$
$$\text{Intercept (Constant)} = 4.079$$
$$\text{Significance } (p\text{-value}) = 0.000$$

The negative sign of the coefficient means that the frequency of use is negatively related to dependence on AI (not positive, so that as users use AI more frequently, their dependence on AI will decrease, not increase). This opposes the common sense that often becomes dependent on it if we use it heavily. Figure 17 visually supports this observation. Users who incorporate it regularly seem to develop a more nuanced understanding of their capacities and limitations, strategically using it instead of depending on it. This finding suggests that literacy and familiarity with AI are critical for shaping responsible use.
Coefficient for X (-0.298): This implies a negative correlation; as AI usage increases, dependency decreases.
Constant (4.079): This is the predicted level of dependency when AI is not used.

5.3.2. Effect of educational role and age on perceived AI dependency

Multiple regression analysis to determine the predictive power of age and educational role yielded the following:

$$\text{Dependency} = 0.008 \times \text{Education Role} - 0.169 \times \text{Age} + 3.649$$

The model was barely significant ($R^2 = 0.033$). Neither age ($\beta = -0.169$, $p = 0.142$) nor role ($\beta = 0.008$, $p = 0.872$) predicted dependency perceptions. The multiple regression analysis aimed to assess whether age and educational role influenced perceptions of AI dependence.

$$\text{Coefficient for Educational Role} = 0.008 \quad \text{(positive but not significant)}$$
$$\text{Coefficient for Age} = -0.169 \quad \text{(negative and weak)}$$
$$\text{Intercept (Constant)} = 3.649$$
$$\text{Model, } R^2 = 0.033$$

The small size of R2 3.3% implies that age and paper explain very little of the variance in perceived dependence. While age showed a slightly negative association (older respondents felt marginally less dependent), the effect was statistically weak and practically minimal. The same applies to role differences. These findings suggest that other factors, such as the domain of AI, personal attitudes, prior training, and context of use, are more influential. Future models could include variables such as the sophistication of the AI tool, frequency of commitment, and specific exposure of the domain to better explain dependency patterns. Interpretation: The regression analysis suggests that the educational role and age do not significantly change how students view their dependency on AI. There was a weak relationship with age, which may require further investigation in future studies. Adding more factors (e.g., frequency of use or sophistication) could improve the model.

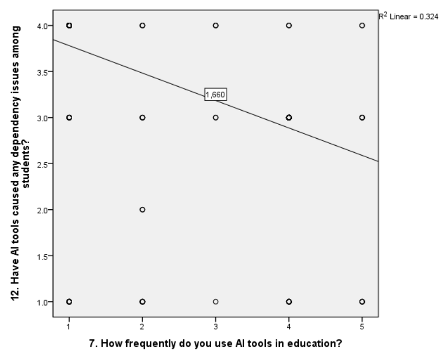

Figure 17. Regression graph illustrating the relationship between AI usage and dependency

6. RESULTS

Here, statistical analysis is reported based on data collected from 498 education stakeholders, focusing on adoption behaviors of AI and felt dependence in schools and their relationship. Quantitative and qualitative methods indicate mixed trends across demographic segments and usage patterns, providing empirical proof of the emerging functions of AI in education.

6.1. Educational roles and AI tool adoption

A chi-square test of independence established a statistically significant relationship between educational roles and rates of AI adoption $\chi^2(6) = 16.488$, $p = 0.036$, as shown in Table 2. Adoption was led by students (98.0% of users), followed by significantly lower use by faculty (0.2%) and administrators (0.4%). These findings highlight the essential need for role-targeted training programs covering varied workflows, ethical dimensions, and competency levels at hierarchical academic ranks.

6.2. Clarifying the seeming contradiction

The chi-square test shows a strong association between frequency categories and reported dependency categories, $\chi^2(16) = 531.012$, $p < 0.001$, as shown in Table 2. This indicates significant variation across grouped responses, such as mixed dependency reports within moderate-usage categories. The regression model employs frequency as a continuous predictor variable and dependency as a continuous outcome variable, and demonstrates a negative coefficient value ($\beta = -0.298$), indicating that higher frequency of use is associated with lower self-reported dependency across respondents.

Table 2. Summary of statistical results and interpretation

Relationship	Test Result	Significance Level	Key Interpretation
Education Role vs. AI Adoption	$\chi^2(6) = 16.488, p = 0.036$	Significant ($p \leq 0.05$)	Adoption rates vary by role; students dominate usage
Frequency of AI Use vs. Dependency	$\chi^2(16) = 531.012,$ $p < 0.001$	Highly Significant ($p < 0.001$)	Strong link between usage frequency and dependency
Usage frequency predicting Dependency	$\beta = -0.298, p < 0.001$	Highly Significant ($p < 0.001$)	Higher usage correlates with lower dependency perception
Demographics predicting Dependency	$R^2 = 0.033, p = 0.142$	Not Significant ($p > 0.05$)	Age and role have minimal predictive impact on dependency

These two findings are not inconsistent. The chi-square analysis highlights category-level relationships, such as heterogeneous dependency responses within the same usage group, whereas the regression model captures the overall linear trend across the full sample. The qualitative data help explain this pattern: frequent users include both individuals who rely on AI uncritically and those who have developed more critical and selective usage strategies. As a result, categorical cross-tabulations capture response heterogeneity, while regression analysis reflects the average directional effect.

This interpretation aligns with theoretical frameworks such as the Technology Acceptance Model (TAM) [16], where perceived usefulness and user competence evolve with experience, reducing overall dependency without eliminating category-specific variation. Future work incorporating stratified analyses by user role or AI tool type could further clarify these dynamics.

6.3. Demographic predictors of dependency perceptions

Multiple regression analysis was used to test age and educational role as predictors of dependency perceptions.

$$\text{Dependency} = 0.008 \times \text{Role} - 0.169 \times \text{Age} + 3.649$$

The model exhibited negligible explanatory power ($R^2 = 0.033$), with neither predictor reaching significance (role: $p = 0.872$; age: $p = 0.142$). These results indicate that demographic variables are overshadowed by experiential factors such as AI literacy, contextual application, and prior training in shaping dependency attitudes.

6.4. Qualitative insights - linked and illustrated themes

The open-ended answers were analyzed and revealed four main topics revealing how the people view the ethical application of AI in academic practice. These themes provide contextual depth and help interpret the quantitative results.

a. Ethical concerns about assistance vs plagiarism (78% of comments): Many participants expressed uncertainty about where acceptable AI assistance ends and plagiarism begins. This ambiguity influenced decisions about disclosure and responsible use. This theme justifies the concern rates reported by the quantitative results on ethical limits and AI addiction.

   Illustrative example: "Using AI to improve writing feels helpful, but it is unclear whether this should be reported as external help."

b. Concerns about critical thinking and learning quality: Respondents reported that overdependence on AI could reduce independent thinking and problem-solving ability. At the same time, some described becoming more selective and critical with increased experience. This helps explain why frequent AI use does not uniformly translate into higher perceived dependency in the regression results.

   Illustrative example: AI can save time, but excessive use may complicate independent thinking about problems.

c. Policy needs (89% of comments): A strong need for clear institutional instructions on AI use was observed across responses. Participants noted that well-defined rules would reduce confusion and support fair academic assessment. This theme aligns with the high prevalence of incoherent AI-related behaviors identified in the survey data.

Illustrative example: “With clear guidelines regarding AI usage, it will be easier to act responsibly.”

d. Gains in productivity (67% of comments): Productivity gains were viewed with cautious optimism. AI was considered useful for drafting, exam preparation, and idea generation, but respondents emphasized the importance of verification and avoiding overreliance. This supports quantitative findings showing positive attitudes toward AI usefulness alongside concerns about errors and misuse. Illustrative example: “AI helps with brainstorming ideas faster, but answers still need to be checked.”

7. DISCUSSION

The swift acceleration of artificial intelligence (AI) into education has produced lively controversy between its futurist promise and moral danger. While a broad literature has addressed these issues in abstracts [7], [12], there is little empirical evidence on the association between AI patterns of use and dependency in schools. Our research fills this gap by analyzing 498 stakeholders using a mixed-methods approach and presenting counterintuitive results that contradict prevailing dependency narratives. Experiential variables, rather than demographics, were found to shape human-AI interactions. These outcomes provide a critical evidence base for improving ethical AI integration into education.

7.1. Interpretation of key findings

A major adoption gap between students (98.0%) and faculty/administrators ($< 1\%$) indicates institutional misalignment in AI readiness [6]. This gap calls for role-specific upskilling to counter pedagogical fragmentation. Most importantly, discovered an inverse frequency-dependency relationship ($\beta = -0.298$, $p < 0.001$), which showed that frequent users created *less* dependency with critical literacy [1], [18]. This discovery debunks dystopian myths by showcasing experiential familiarity, bolstering the discerning mastery of tools. Demographics (role/age) showed no predictive power for dependency ($R^2 = 0.033$), affirming that competencies, not identity, moderated AI interaction [2], [16]. This finding necessitates democratized training on conceptual underpinnings, such as bias reduction and ethical boundaries. This empowerment, as Khalifa and Albadawy suggested [10], turned users into strategic partners with AI systems.

7.2. Comparison with previous works

This study provides empirical support for ethical framework appeals [12]–[15] and plagiarism avoidance strategies [3]–[4], aligning with prevailing international academic consensus. However, the dependency paradox observed in this study diverges from dominant risk-oriented narratives. While Al-Zahrani and Alasmari [11] and Gerlich [15] cautioned against cognitive offloading and inevitable dependency, our findings demonstrate that such effects can be mitigated through critical and reflective AI engagement.

Specifically, the regression results reveal an inverse relationship between usage frequency and self-reported dependency ($\beta = -0.298$, $p < 0.001$), indicating that increased exposure to AI tools fosters user autonomy rather than cognitive erosion. This evidence substantiates Prather *et al.*’s [26] characterization of AI as a “productivity multiplier” and supports Cukurova’s [2] hybrid intelligence framework, wherein human–AI collaboration stimulates metacognitive development.

Extending these perspectives, our results empirically ground the technology acceptance model (TAM) [21] by demonstrating that subjective norms and perceived tool credibility play a critical role in ethical adoption. Importantly, the findings contradict over-reliance concerns by providing quantitative evidence of reduced dependency with increased frequency of use. This study is among the first to quantify the influence of usage patterns on dependency, a relationship previously treated as largely theoretical.

Furthermore, the model explains 30.1% of the variance in dependency through usage frequency ($\beta = -0.298$), offering actionable insights for institutional policy and instructional design [10], [19]. Table 1 presents a concise synthesis of recent studies on AI ethics in education, outlining major contributions alongside persistent research gaps.

7.3. Policy and education implications

The theoretical context helps us better understand the dynamics of human-AI relationships in educational settings. For practitioners, this study shows how educators and policymakers can use this body of research to develop evidence-based strategies for effective AI integration. These results highlight the need for further research in this area.

a. Role-specific training: Create tiered AI literacy courses centered on students', faculty's, and administrators' individualized workflows to close gaps in adoption [6], [23].
b. Critical exposure: Integrate AI tools into curricula via scaffolded activities that incentivize analytical engagement rather than output substitution [1], [18].
c. Deep literacy: Extend technical instruction to include epistemological foundations (e.g., probabilistic reasoning and bias propagation) [12], [19].
d. Pedagogical audits: Implement review cycles that critically assess AI-enhanced learning in terms of academic integrity and cognitive performance standards [8], [22].
e. Interdisciplinary co-design: Organize educator–technologist collaborations to develop context-aware AI deployments [2], [21].

These implications are key to ensuring that AI is a servant of education and not one that remakes it in unexpected ways. They emphasized the importance of using AI in a human-centered manner, which facilitates learning and minimizes harm or dependency on AI.

7.4. Limitations and future research

The online convenience sampling methodology is employed in the study, which allowed including various academic functions on a timely basis and offered a general perspective on the current AI practices. Although such a design will help identify some important patterns and relationships, the results are to be viewed as reflective but not as reflective of all institutional settings. In future research, more robust generalizability can be provided by pursuing a stratified design and multi-institution research design with balanced gender representation in academic positions, academic fields, and the type of institution. Longitudinal and intervention-based studies may also be used to study the change of AI usage and ethical awareness over time, especially in relation to structured AI literacy programs and institutional policies. Additionally, future research should conduct longitudinal studies on the cognitive effects of long-term AI use [19], [29] and investigate tool-specific effects in various areas (e.g., generative AI versus analytics tools) [2], [30], And also need to increase the representation of the Global South to counter Anglo-European policy biases [10], [24].

8. CONCLUSION

This study reveals the multifaceted role of AI in educational facilities, its immense capacity to enrich learning, and the accompanying ethical issues. The study emphasized AI's immense ability to provide differentiated teaching and study assistance, student dependency issues, academic integrity, and what constitutes legitimate aid and plagiarism. Statistical analysis confirmed a high correlation between people's educational roles and their interactions with AI ($\chi^2(6) = 16.488$, $p = 0.036$). Interestingly, contrary to common concerns, higher AI usage was correlated with lower dependency ($\beta = -0.298$, $p < 0.001$), showing that familiarity and critical literacy prevent excessive dependency on AI. Age and educational role were poor explanatory factors for the reported AI dependency issues ($R^2 = 0.033$), meaning that AI literacy and situational use held more sway. Qualitative findings also revealed concerns about plagiarism, reduced critical thinking, and the need for responsible AI training, along with an appreciation for AI's productivity advantages. These results contradict the assumption that AI use automatically reduces mental effort; instead, they affirm that when used responsibly, AI fosters critical thinking and independent learning in students. This calls for clear institutional policies on ethical AI use and comprehensive AI literacy education for both teachers and students. Such measures define ethical boundaries, promote the critical analysis of AI-generated outputs, and prepare users for autonomous academic work, thereby safeguarding academic integrity from AI misuse. Future research should examine the long-term implications of AI-augmented learning, explore the effects of various AI tools across disciplines, and examine more diverse populations. In addition, empirical studies on AI literacy intervention are required. By elucidating the subtle relationship between AI deployment and academic behavior, this study offers valuable suggestions for crafting ethically sound AI deployment plans in education.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Md. Owafeeuzzaman Patwary	✓	✓	✓		✓	✓	✓	✓	✓		✓		✓	
Md. Reazul Islam	✓	✓		✓		✓				✓	✓		✓	
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Nur-e Sarjina Khan	✓	✓			✓	✓	✓		✓					
Md. Abdullah - Al – Jubair		✓		✓						✓	✓		✓	
Md. Jakir Hossen				✓						✓	✓		✓	✓
M.F. Mridha										✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal Analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject Administration
Fu : **Fu**nding Acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest related to this study. The research was conducted independently, and financial, professional, or personal relationships did not influence the study design, analyses, or conclusions. The study has been appropriately accounted for by any potential funding or support sources, and the authors declare no conflicts of interest or outside influence on this study.

DATA AVAILABILITY

The data will be made available upon request.

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BIOGRAPHIES OF AUTHORS

Md. Owafeeuzzaman Patwary widely known as Owafee, is an enthusiastic researcher and a student of B.Sc. in CSE at the American International University-Bangladesh (AIUB). His academic interests include artificial intelligence (AI), machine learning (ML), internet of things (IoT), and cybersecurity. Passionate about innovation, he explores emerging technologies and interdisciplinary research. His technical skill set includes programming in Python, C, C++, Java, and C#. He can be contacted at email: 22-49885-3@student.aiub.edu, or via his profile on LinkedIn and ResearchGate.

Md. Reazul Islam is an assistant professor at AIUB and a lead researcher at the Advanced Machine Intelligence Research Lab, with expertise in IoT, artificial intelligence, machine learning, and deep learning. He completed his B.Sc. and M.Sc. in computer science and engineering from Jahangirnagar University. He has led more than 35 innovative research and development projects and has received several recognitions, including the BIG Innovation Award (2023) and the Huawei ICT Incubator Award (2022). His research focuses on healthcare analytics, smart agriculture, and intelligent systems, with publications in reputed journals such as IEEE Access and Sensors. He is currently a Ph.D. student and Graduate Teaching Assistant (GTA) at the State University of New York at Albany (SUNY Albany). He can be contacted via email at mislam7@albany.edu, or via his profile on LinkedIn and ResearchGate.

Abtahi Islam is currently teaching courses in computer science and engineering at the American International University, Bangladesh. He has acquired skills to at least the intermediate level in C++, Java, C#, Python, SQL, etc. He has developed many types of academic and technical projects. His main focus is on data science and machine learning, and he is engaged in deepening his knowledge of Python. His work includes publications on AI ethics, with an interest in data science, ML, and AI. He can be contacted via email at 23-50434-1@student.aiub.edu, or via his profile on LinkedIn and ResearchGate.

Nur-e Sarjina Khan is a CSE student at American International University-Bangladesh (AIUB). Her academic interests lie in artificial intelligence, machine learning, deep learning, natural language processing (NLP), and the internet of things (IoT). She secured a Secondary School Certificate (SSC) in 2019 and a Higher Secondary Certificate (HSC) in 2021 from Uttara High School and College with a GPA of 5.00. She can be contacted via email at 22-49754-3@student.aiub.edu, or via her profile on LinkedIn.

Md. Abdullah - Al – Jubair is a senior assistant professor and director, Faculty of Science & Technology at AIUB. He received his Ph.D. in cognitive science from UNIMAS and specializes in data mining and machine learning. An AIUB alumnus with over eight years of research experience, he taught at UNIMAS and Anglia Ruskin University in the UK. He can be contacted via email at abdullah@aiub.edu, or via his profile on ResearchGate.

Md. Jakir Hossen (Senior Member, IEEE) is currently working as an associate professor in the Department of Robotics and Automation, Faculty of Engineering and Technology, Multimedia University, Melaka, Malaysia. He received a master's degree in communication and network engineering from Universiti Putra Malaysia, Malaysia, in 2003. He received a Ph.D. in smart technology and robotic engineering from Universiti Putra Malaysia, Malaysia, in 2012. His research interests include the application of artificial intelligence techniques in data analytics, robotics control, data classification, and prediction. He can be contacted via email at jakir.hossen@mmu.edu.my.

M. F. Mridha (Senior Member IEEE, Professional Member ACM) is a professor of computer science at AIUB and the founder of the AMIR Lab. He has over 18 years of academic experience and has published over 350 publications. His research has been published in reputed journals, including information fusion, scientific reports, knowledge-based systems, artificial intelligence review, engineering applications of artificial intelligence, IEEE Access, sensors, cancers, biology, and applied sciences. He was included in the 2024 edition of the Stanford University/Elsevier list of the top 2% scientists worldwide. He can be contacted via email at firoz.mridha@aiub.edu, or via his profile on LinkedIn and ResearchGate.