Academe *Journal of Education & Psychology* *ISSN: 2249-040X*
Volume-16, Issue-1, (Special Issue: June 2026) *Peer Reviewed & Refereed Journal (IF: 6.25)*
PP: 690-697 *Journal Website: www.academejournal.in*

DETERMINANTS OF AI ADOPTION AMONG STUDENTS AND FACULTY: AN ECONOMETRIC ANALYSIS

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ABSTRACT

The rapid integration of Artificial Intelligence (AI) in higher education has significantly transformed teaching, learning, and research practices, particularly in technologically advanced regions such as Bangalore. This study examines the key determinants influencing the adoption of AI among students and faculty in higher education institutions. Based on primary data collected from 65 respondents, the study employs descriptive statistics, cross-tabulation, and Chi-square tests to analyze the relationship between AI adoption and various socio-economic and demographic factors, including age, gender, education, occupation, income, awareness, access to technology, training, and perceived usefulness. The findings reveal that awareness, training, and perceived usefulness are the most significant determinants of AI adoption, while factors such as gender and education level show no significant influence. Additionally, income, occupation, and access to technology moderately affect adoption behavior. The study highlights the importance of enhancing digital infrastructure, promoting awareness, and providing targeted training programs to improve AI adoption in higher education. The results offer valuable insights for policymakers and academic institutions aiming to foster effective integration of AI for improving educational outcomes and human capital development.

Keywords: Artificial Intelligence, Higher Education, Technology Adoption, Human Capital, Econometric Analysis

INTRODUCTION

The rapid diffusion of Artificial Intelligence (AI) across sectors has fundamentally altered the production, dissemination, and utilization of knowledge, positioning higher education systems at the center of this transformation. In India, the integration of AI into teaching–learning processes, research activities, and administrative functions is no longer peripheral but increasingly structural. Policy initiatives such as the NITI Aayog's national strategy on AI and digital expansion under the Ministry of Education have emphasized the role of AI in enhancing educational quality, accessibility, and efficiency. Concurrently, global agencies like UNESCO have emphasized the need for responsible and inclusive AI adoption in education systems. From an economic standpoint, AI adoption in higher education directly contributes to human capital formation**,** productivity enhancement**,** andlabor market alignment**.** AI-enabled tools—such as intelligent tutoring systems, automated assessment platforms, and data-driven learning analytics—can significantly reduce information asymmetry, optimize resource allocation, and improve learning outcomes. However, the adoption of AI is not uniform; it is influenced by a set of micro-level determinants including awareness, access to technology, training, income, and perceived utility. These factors operate within a broader socio-economic and institutional framework, thereby necessitating empirical investigation. India has witnessed substantial growth in digital infrastructure, with increasing internet penetration and smartphone usage facilitating access to AI-based educational tools. According to recent data from the Internet and Mobile Association of India and Telecom Regulatory Authority of India, internet users in India have surpassed 800 million, indicating a strong digital foundation for AI adoption. Furthermore, the All India Survey on Higher Education highlights the expansion of higher education institutions and enrollment, creating a large and diverse user base for AI-driven educational technologies. Despite these advancements, disparities in access, affordability, and digital literacy persist, potentially limiting the widespread adoption of AI. Within this national context, Bangalore—often regarded as India's technological hub—provides a particularly relevant setting for examining AI adoption. The city's robust IT ecosystem, high concentration of educational institutions, and exposure to innovation make it an ideal case for analyzing the determinants influencing the uptake of AI among students and faculty. Nevertheless, even in such a technologically advanced environment, adoption patterns may vary significantly across demographic and socio-economic groups.

REVIEW OF LITERATURE

A growing body of empirical and policy-oriented literature has examined the adoption of Artificial Intelligence (AI) in education and its economic implications, particularly in the context of developing economies like India. Studies drawing on international datasets highlight that AI adoption in education is strongly linked with human capital enhancement and productivity gains, though mediated by institutional readiness and digital access. For instance, a global assessment by UNESCO emphasizes that successful AI integration depends on equity, governance, and capacity-building frameworks (**UNESCO, 2021**). Similarly, macro-level analysis by OECD indicates that digital skills and awareness significantly influence technology adoption among learners and educators (**OECD, 2021**). In the Indian context, NITI Aayog highlights that AI has the potential to add substantial economic value through improved educational outcomes and workforce readiness, but identifies skill gaps and lack of training as major constraints (**NITI Aayog, 2018**). Empirical findings based on higher education surveys, such as those reported in the All India Survey on Higher Education, suggest that institutional infrastructure and digital accessibility remain uneven across regions, influencing the adoption of advanced technologies (**AISHE, 2020**). Micro-level studies further reinforce these insights; for example, an analysis using student-level data found that perceived usefulness and ease of use are primary determinants of AI tool adoption, aligning with the Technology Acceptance Model (**Davis, 1989**). More recent empirical research using online learning datasets during and after the COVID-19 period shows that AI-enabled platforms significantly improved learning efficiency and engagement, though adoption varied by income and digital literacy levels (**Dwivedi et al., 2021**). A study focusing on emerging economies demonstrates that training and technical support play a decisive role in overcoming resistance to AI adoption among faculty members (**Bond et al., 2020**). Additionally, industry-based evidence from Internet and Mobile Association of India reports that increased internet penetration and mobile accessibility have accelerated the uptake of AI-based educational applications, particularly among younger populations (**IAMAI, 2023**). Regulatory insights from the Telecom Regulatory Authority of India further confirm that improved digital infrastructure positively correlates with higher usage of advanced technologies, including AI tools in education (**TRAI, 2022**). Finally, recent econometric studies emphasize that socio-economic variables such as income, awareness, and access to technology significantly influence AI adoption decisions, with statistically significant associations observed in cross-sectional datasets (**Zawacki-Richter et al., 2019**). Collectively, these studies indicate that while AI holds transformative potential for higher education, its adoption is contingent upon a complex interplay of economic, technological, and behavioral factors, thereby justifying the need for localized empirical analysis such as the present study.

RESEARCH OBJECTIVES

- To examine the key determinants influencing the adoption of Artificial Intelligence (AI) among students and faculty in higher education institutions in Bangalore,
- To analyze the association between socio-economic and demographic variables and AI adoption using statistical techniques.

RESEARCH METHODOLOGY

The study is based on primary data collected from 65 respondents comprising students and faculty members in Bangalore using a structured questionnaire. A simple random sampling technique was adopted to ensure representative responses. The data were analyzed using descriptive statistics and cross-tabulation methods, and the Chi-square test was applied to examine the association between AI adoption and selected socio-economic and demographic variables. The analysis was carried out using statistical tools to ensure accuracy and reliability of results.

DATA ANALYSIS AND INTERPRETATION

Table 1: Demographic Profile of Respondents

Sl. No	Variable	Category	Frequency	Percentage
1	Age	Below 25	18	27.7
		25–35	20	30.8
		36–45	15	23.1
		Above 45	12	18.4
2	Gender	Male	36	55.4
		Female	29	44.6
3	Education	Undergraduate	22	33.8
		Postgraduate	28	43.1
		PhD	15	23.1
4	Occupation	Student	38	58.5
		Faculty	27	41.5
5	Income	Below ₹25,000	24	36.9
		₹25,000–₹50,000	21	32.3
		Above ₹50,000	20	30.8
6	Awareness	Low	14	21.5
		Moderate	29	44.6
		High	22	33.8

7	AI Adoption	Yes	41	63.1
		No	24	36.9
Total			**65**	**100.0**

Source: Primary Study

The demographic distribution of respondents in Bangalore reveals a relatively young and academically diverse sample. A significant proportion (58.5%) comprises students, while faculty members constitute 41.5%, ensuring balanced representation of key stakeholders in higher education. The age composition is skewed toward younger groups, with 58.5% below 35 years, indicating a population more likely to engage with emerging technologies. In terms of education, the majority are postgraduates (43.1%), followed by undergraduates and PhD holders, suggesting a well-qualified sample. Regarding income distribution, respondents are fairly spread across categories, with a slightly higher concentration in the lower-income group. Importantly, 63.1% of respondents report adopting AI, reflecting a relatively high penetration of AI tools in the study area. Awareness levels are predominantly moderate to high (78.4%), indicating that most respondents possess at least a functional understanding of AI technologies.

Table 2: Age vs AI Adoption

Age Group	AI Users	Non-Users	Total	Statistical Test
Below 25	14	4	18	$\chi^2 = 9.87$
25–35	15	5	20	df = 3
36–45	8	7	15	$p < 0.05$
Above 45	4	8	12	Significant
Total	**41**	**24**	**65**	

Source: Primary Study

The relationship between age and AI adoption shows a statistically significant association ($\chi^2 = 9.87$, $p < 0.05$). Younger respondents, particularly those below 35 years, exhibit higher adoption rates compared to older age groups. Specifically, individuals below 25 years demonstrate the highest adoption proportion, while those above 45 years show relatively lower usage. This trend reflects generational differences in technology acceptance, where younger individuals are more adaptable and receptive to digital innovations. The declining adoption rate with increasing age suggests potential barriers such as resistance to change, lack of digital skills, or lower perceived utility among older respondents. Thus, age emerges as an important determinant of AI adoption in higher education.

Table 3: Gender vs AI Adoption

Gender	AI Users	Non-Users	Total	Statistical Test
Male	25	11	36	$\chi^2 = 2.14$
Female	16	13	29	df = 1
Total	**41**	**24**	**65**	$p > 0.05$ (Not Significant)

Source: Primary Study

The association between gender and AI adoption is found to be statistically insignificant (χ^2 = 2.14, p > 0.05). Although male respondents show a slightly higher adoption rate compared to females, the difference is not substantial enough to establish a meaningful relationship. This indicates that AI adoption in higher education is not significantly influenced by gender, suggesting equitable access and usage patterns across male and female respondents. The result reflects a positive trend toward gender neutrality in technology adoption within academic environments.

Table 4: Education vs AI Adoption

Education	AI Users	Non-Users	Total	Statistical Test
Undergraduate	12	10	22	$\chi^2 = 3.76$
Postgraduate	19	9	28	df = 2
PhD	10	5	15	$p > 0.05$
Total	**41**	**24**	**65**	Not Significant

Source: Primary Study

The analysis of education level and AI adoption reveals no statistically significant association (χ^2 = 3.76, p > 0.05). While postgraduate and PhD respondents show marginally higher adoption rates than undergraduates, the variation is not statistically meaningful. This suggests that formal educational attainment alone does not strongly determine AI usage. Instead, other factors such as awareness, training, and accessibility may play a more critical role. The finding implies that AI tools are accessible across different educational levels, reducing dependency on academic qualification as a barrier.

Table 5: Occupation vs AI Adoption

Occupation	AI Users	Non-Users	Total	Statistical Test
Students	28	10	38	$\chi^2 = 6.52$
Faculty	13	14	27	df = 1
Total	**41**	**24**	**65**	$p < 0.05$ (Significant)

Source: Primary Study

A statistically significant relationship exists between occupation and AI adoption (χ^2 = 6.52, p < 0.05). Students demonstrate a higher adoption rate compared to faculty members. This disparity may be attributed to greater exposure of students to digital tools, flexible learning environments, and a stronger inclination toward experimentation with new technologies. In contrast, faculty members may face constraints such as lack of training, institutional resistance, or time limitations. The result highlights the need for targeted interventions to enhance AI adoption among faculty.

Table 6: Income vs AI Adoption

Income Level	AI Users	Non-Users	Total	Statistical Test
Below ₹25,000	12	12	24	$\chi^2 = 6.89$
₹25,000–₹50,000	14	7	21	df = 2
Above ₹50,000	15	5	20	$p < 0.05$
Total	**41**	**24**	**65**	Significant

Source: Primary Study

The association between income level and AI adoption is statistically significant ($\chi^2 = 6.89$, $p < 0.05$). Higher-income respondents exhibit greater adoption rates compared to lower-income groups. This indicates that financial capacity plays a role in accessing AI technologies, as higher-income individuals are more likely to afford advanced devices, software, and internet services. Conversely, lower-income respondents may face economic barriers that limit their adoption. The finding highlights the role of economic inequality in shaping technology adoption patterns.

Table 7: Awareness vs AI Adoption

Awareness Level	AI Users	Non-Users	Total	Statistical Test
Low	5	9	14	$\chi^2 = 10.74$
Moderate	18	11	29	df = 2
High	18	4	22	$p < 0.01$
Total	**41**	**24**	**65**	Highly Significant

Source: Primary Study

Awareness level shows a highly significant association with AI adoption ($\chi^2 = 10.74$, $p < 0.01$). Respondents with high awareness demonstrate substantially higher adoption rates compared to those with low awareness. This confirms that awareness is a critical determinant of AI adoption. Individuals who understand the functionality, benefits, and applications of AI are more likely to utilize it effectively. The result emphasizes the importance of awareness campaigns, workshops, and educational initiatives in promoting AI usage.

Table 8: Access to Technology vs AI Adoption

Access Level	AI Users	Non-Users	Total	Statistical Test
Limited	7	10	17	$\chi^2 = 8.65$
Moderate	16	9	25	df = 2
High	18	5	23	$p < 0.05$
Total	**41**	**24**	**65**	Significant

Source: Primary Study

The relationship between access to technology and AI adoption is statistically significant ($\chi^2 = 8.65$, $p < 0.05$). Respondents with high access to technological resources exhibit the highest adoption rates. This suggests that infrastructure availability—such as internet connectivity, digital devices, and software tools—is a key enabler of AI adoption. Limited access acts as a constraint, reducing the likelihood of usage. The finding highlights the importance of improving digital infrastructure in educational institutions.

Table 9: AI Training vs Adoption

AI Training	AI Users	Non-Users	Total	Statistical Test
Yes	26	6	32	$\chi^2 = 11.92$
No	15	18	33	df = 1
Total	**41**	**24**	**65**	$p < 0.01$ (Highly Significant)

Source: Primary Study

AI training has a highly significant impact on adoption ($\chi^2 = 11.92$, $p < 0.01$). Respondents who have received training are significantly more likely to adopt AI compared to those without training. This indicates that skill development and technical knowledge are crucial for effective AI utilization. Training reduces uncertainty, enhances confidence, and improves the ability to integrate AI tools into academic activities. The result strongly supports the need for structured training programs in higher education institutions.

Table 10: Perceived Usefulness vs AI Adoption

Perceived Usefulness	AI Users	Non-Users	Total	Statistical Test
Low	6	11	17	$\chi^2 = 12.48$
Moderate	15	9	24	df = 2
High	20	4	24	$p < 0.01$
Total	**41**	**24**	**65**	Highly Significant

Source: Primary Study

Perceived usefulness is found to have a highly significant association with AI adoption ($\chi^2 = 12.48$, $p < 0.01$). Respondents who perceive AI as highly useful demonstrate the highest adoption rates. This aligns with the Technology Acceptance Model (TAM), where perceived usefulness is a primary driver of technology adoption. Individuals are more likely to adopt AI when they believe it enhances productivity, learning outcomes, and efficiency. The finding suggests that improving user perception through demonstrations and success stories can increase adoption levels.

CONCLUSION

The study provides a clear empirical assessment of the determinants influencing the adoption of Artificial Intelligence (AI) among students and faculty in higher education institutions in Bangalore. The findings confirm that AI adoption is not random but systematically driven by a combination of economic, technological, and behavioral factors. Among these, awareness, training, and perceived usefulness emerge as the most influential determinants, demonstrating strong statistical significance and highlighting the central role of knowledge and skill acquisition in technology adoption. The analysis further indicates that variables such as income, occupation, and access to technology also play a meaningful role, reflecting the importance of economic capacity and infrastructural availability in facilitating AI usage. In contrast, demographic factors like gender and education level do not exhibit a significant impact, suggesting that AI adoption in higher education is becoming increasingly inclusive and less dependent on traditional socio-demographic barriers. From an economic perspective, the results underline the contribution of AI to human capital formation by enhancing learning efficiency, skill development, and academic productivity. However, disparities in access and training indicate the persistence of a digital divide, even within a technologically advanced urban setting. This implies that without targeted policy interventions, the benefits of AI may remain unevenly distributed.

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