DEMOGRAPHICS AND THE HUMAN-AI INTERFACE: A CRITICAL EVALUATION OF ARTIFICIAL INTELLIGENCE PERCEPTIONS IN NORTHEAST INDIA'S ACADEMIC ECOSYSTEM

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ABSTRACT

This study explores students' perceptions of artificial intelligence (AI) in higher education, focusing on its impact on academic performance, learning pathways, and future readiness. Data were gathered from 400 students in Nagaland and Manipur through restricted systematic sampling and structured questionnaires. The findings indicate that AI is perceived as highly beneficial in enhancing personalized learning, simplifying complex concepts, and supporting independent study, particularly through adaptive feedback and resource accessibility. Students also highlighted AI's role in developing higher-order skills via simulations and virtual labs, though weaker perceptions were noted regarding career guidance and digital literacy. Concerns about overdependence were evident across all cohorts, with risks such as reduced creativity and weakened problem-solving emphasized. Regression results explained 63% of AI's influence on academic performance, while ANOVA identified age as a key moderating factor, with younger learners expressing more favorable views. The study concludes that AI holds transformative potential in education but requires balanced integration to safeguard creativity, inclusivity, and critical reasoning, while future research should broaden its demographic scope for greater generalizability.

Keywords: Artificial Intelligence, Higher Education, Personalized Learning Pathways, Access to Learning Resources, Skill Development, Future Readiness, Overdependence on Technology, Demographic Influence.

INTRODUCTION

The integration of artificial intelligence (AI) within academic institutions is revolutionizing teaching practices, research methodologies, and administrative processes. AI promises to enhance efficiency, innovation, and personalized learning; however, its adoption and acceptance are not uniform across all stakeholders. Students, as one of the primary beneficiaries and users of AI-driven educational tools, form their perceptions of AI through the lens of demographic factors such as age, gender, and educational background (He & Baxter, 2020). A deeper understanding of how these demographic variables shape attitudes toward AI is essential, particularly in socio-culturally

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diverse contexts where access to technology remains uneven. The academic communities of Northeast India, with their distinctive cultural and educational landscapes, provide a critical setting to examine these dynamics (Mukherjee, 2022).

Northeast India, which includes states such as Manipur and Nagaland, represents a region marked by linguistic diversity, ethnic plurality, and varied educational systems. Unlike the more urbanized and technologically advanced regions of India, many parts of Northeast India, especially rural and semi-urban areas, still face challenges related to digital infrastructure and technological exposure (Rai & Singh, 2019). These conditions create disparities in the ways students engage with and perceive emerging technologies like AI. As a result, the academic communities in this region may develop distinct attitudes toward AI that differ significantly from those observed in other parts of India. Understanding these perceptions requires localized investigation that considers the socio-cultural and infrastructural realities of the region.

The significance of this research lies in its potential to bridge a crucial gap in AI adoption studies. While existing research has examined the impact of demographic variables on technology acceptance, there remains limited empirical work focusing on Northeast India, particularly its rural and semi-urban student populations. Investigating how age, gender, and education shape AI perceptions in this context offers insights into students' awareness, resistance, adoption willingness, and trust in AI systems. These findings are not only academically valuable but also hold practical relevance for policymakers, educators, and institutional leaders seeking to promote digital inclusion and ensure responsible implementation of AI in education (Kaur & Garg, 2021). From a theoretical standpoint, this study situates its analysis within broader frameworks such as the Technology Acceptance Model (TAM), Diffusion of Innovations Theory, and Human–Computer Interaction (Davis, 1989; Rogers, 2003). Applying these models to the distinct socio-cultural context of Northeast India enhances both theoretical depth and localized relevance. At the doctoral research level, this fusion of empirical evidence with theoretical perspectives ensures that the study contributes meaningfully to ongoing debates on human–AI interactions and technology adoption in marginalized educational communities.

The study is guided by four key objectives: (1) to assess whether and how age influences students' awareness of, attitudes toward, and trust in AI technologies; (2) to examine the role of gender in shaping perceptions of AI in academic contexts, particularly in terms of usability, ethical trust, and perceived threat; (3) to evaluate the effect of educational background—such as academic level and field of study—on acceptance, perceived utility, and concerns regarding AI; and (4) to explore possible interactions between age, gender, and education in shaping perceptions of AI. Correspondingly, the research questions focus on whether age predicts awareness and trust in AI (RQ1), whether gender differences exist in AI-related attitudes (RQ2), how education influences perceptions of AI's utility and risks (RQ3), and whether intersections of demographic factors lead to distinct patterns of perception (RQ4).

The scope of this research is deliberately focused on academic communities within Manipur and Nagaland. This geographic concentration enhances the study's contextual depth but also limits the generalizability of findings to other Indian states or highly urbanized regions. Furthermore, the study employs self-reported survey data, which may introduce social desirability bias. Despite these delimitations, the research adopts a random sampling approach of 400 students to ensure a representative and balanced dataset. By doing so, the study aims to generate insights that reflect the lived experiences of students in Northeast India while contributing to broader conversations on AI adoption and perceptions in diverse educational landscapes.

Rationale of the Study

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Artificial Intelligence (AI) has emerged as a transformative force in education and research, yet perceptions of its relevance and impact are unevenly distributed across populations. Demographic factors such as age, gender, and educational background shape how individuals understand, trust, and engage with AI (He & Baxter, 2020). While much research has focused on technologically advanced and urban contexts, peripheral regions like Northeast India remain underexplored. Here, socio-cultural diversity, infrastructural limitations, and educational disparities create unique challenges, resulting in a critical knowledge gap regarding how students in states such as Nagaland and Manipur perceive AI. This neglect risks overlooking the complexities of digital inclusion in regions where exposure and attitudes toward technology differ significantly from mainstream Indian contexts.

The urgency of this study lies in addressing regional inequalities in digital literacy, underexamined gendered perceptions of technology, and the role of educational exposure in shaping AI attitudes (Kaur & Garg, 2021). Limited infrastructure, cultural heterogeneity, and widespread skepticism toward AI fueled by concerns over ethics, employability, and transparency—threaten to deepen digital divides and marginalize sections of the academic community. By critically analyzing the demographic determinants of AI perceptions among 400 randomly selected students in Nagaland and Manipur, this study aims to generate evidence that not only fills a scholarly gap but also informs targeted policies, awareness initiatives, and pedagogical reforms. Ultimately, it underscores the need for inclusive, context-sensitive AI adoption strategies to ensure that higher education in Northeast India does not remain on the periphery of the technological revolution.

REVIEW OF LITERATURE

Artificial Intelligence (AI) has permeated education, research, and everyday social life, generating both enthusiasm and concern. Understanding how individuals perceive and adopt AI requires attention to demographic, educational, and contextual variables, since perceptions are neither uniform nor universally positive. Foundational theories such as the Technology Acceptance Model (TAM) (Davis, 1989) and Diffusion of Innovations theory (Rogers, 2003) remain central in explaining technology adoption. TAM's constructs of perceived usefulness and ease of use continue to inform research on AI acceptance, while Rogers' model highlights diffusion patterns shaped by socio-cultural settings. These frameworks have been extended in AI research to account for human-computer interaction, with studies such as Nass and Moon (1996) showing how users anthropomorphize AI systems, and Epley et al. (2004) explaining psychological mechanisms behind responses to algorithmic decisions insights particularly relevant for educational AI agents (Wong & Kim, 2023; Yalcin et al., 2022).

Demographic factors have consistently emerged as powerful predictors of AI perception and adoption (Yigitcanlar et al., 2024). Age often correlates with digital literacy gaps; older users typically face greater barriers in learning and trusting AI (Reed et al., 2005; Posthuma & Campion, 2009), although newer studies reveal that device familiarity and usage patterns may moderate age-related divides (Huang et al., 2023; Park et al., 2021). Gender, too, exerts a significant influence. Historical work (Margolis & Fisher, 1999) highlighted women's underrepresentation in computing, a pattern reaffirmed in STEM education (Sax et al., 2017). Contemporary research documents persistent gender gaps in AI-related learning outcomes (Hsu et al., 2022; Williams et al., 2023) and in perceptions of AI systems (Liu, 2024). Importantly, AI technologies themselves reproduce gender biases (Cirillo et al., 2020; UNESCO, 2022), raising ethical concerns. As a

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response, scholars stress the necessity of inclusive AI pedagogy that addresses gendered experiences and identities (James et al., 2016; DeLyser & Born, 2021; Woithe & Filipec, 2024).

In the educational domain, the literature emphasizes the dual role of AI as both a pedagogical tool and a subject of learning. Research by Angeli and Valanides (2020) and Kim and Kwon (2024) calls for inclusive AI curricula that build computational and ethical literacy. Others such as Druga et al. (2019) and Sentance and Childs (2020) propose tangible learning tools to bridge abstract AI concepts. Teacher trust and professional readiness remain crucial factors for classroom adoption (Viberg et al., 2023), while studies of student perceptions reveal excitement but also ambivalence regarding AI in higher education (Popenici et al., 2024; Seo et al., 2024). The importance of cultural diversity in AI pedagogy is gaining recognition (Natarajan et al., 2023), but most models are derived from Western contexts, limiting their applicability to regions with distinct socio-cultural realities.

Indian scholarship offers emerging insights into AI perceptions and usage trends. Reports show high adoption rates of generative AI tools among youth, with a disproportionate share of users under 24 (Belsky, 2025). Deka and Parikh (2025) highlight differences in AI adoption across Northeast and Western India, while Gaumat and Rani (2025) apply the UTAUT model to measure students' readiness for AI-enhanced education. (Hoori, 2024) provides an early baseline on student awareness of AI in higher studies. These works illustrate the rapid diffusion of AI into India's academic environment, yet they remain concentrated in metropolitan or pan-Indian contexts, often overlooking socio-cultural complexities in peripheral states such as Nagaland and Manipur.

The reviewed literature confirms that perceptions of AI are multifaceted—shaped by foundational theories of acceptance, intersecting demographic variables, and educational environments. However, existing research exhibits three gaps: (1) limited exploration of peripheral or underrepresented regions; (2) insufficient critical focus on how gender, age, and education intersect in shaping AI perceptions; and (3) a reliance on generalized adoption models without tailoring to cultural diversity. Addressing these shortcomings, the present study situates itself in Northeast India's academic community, providing empirical evidence on how demographics mediate human–AI interactions in contexts often neglected in mainstream AI discourse.

The present study will serve three objectives such as (a). To identify the key factors through which artificial intelligence (AI) influences students' academic performance. (b). To analyze the extent and nature of the impact of these factors on students' academic performance. (c). To examine the role of demographic variables in shaping students' perceptions and utilization of AI in their academic pursuits.

RESEARCH METHODS

The study employed a descriptive and analytical research design to examine students' perceptions of artificial intelligence (AI) in higher education, focusing on factors such as personalized learning pathways (PLP), access to learning resources (ALR), skill development and future readiness (SFR), and overdependence on technology (OT). Conducted in Nagaland and Manipur, the study targeted undergraduate and postgraduate students, with a total sample of 400 respondents selected through restricted systematic sampling to ensure balanced representation. Data were collected using structured questionnaires administered both offline in institutions and online via Google Forms, incorporating demographic details and Likert-scale items adapted from validated measures. Data analysis was carried out using SPSS/AMOS, employing descriptive statistics, regression, ANOVA, interaction effect analysis, and reliability testing (Cronbach's Alpha). Ethical standards were upheld through informed consent and confidentiality, though the

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limited inclusion of mature learners and doctoral candidates may affect the generalizability of the findings.

Analysis and Interpretations

Table 1
DEMOGRAPHIC INFORMATION ON PARTICIPANTS (N = 400)

Variables	Statement	Frequencies	Percentage
Age	Less than 18	65	16.25%
	18-25	231	57.75%
	25-35	80	20%
	35- Above	24	6%
Gender	Male	208	52%
	Female	192	48%
Education			
	UG	289	72.25%
	PG	104	26%
	PhD	7	1.75%
	Others	0	0
Digital Access			
	Always	323	80.75%
	Sometime	71	17.75%
	Often	6	1.5%
	Rarely	0	0
	Never	0	0

Source: Primary Data.

Table 1 determined the demographic profile of the 400 participants reveals a predominantly youth-oriented sample, with the majority (57.75%) aged between 18–25 years and another 20% in the 25–35 category, underscoring the dominance of students and early-career professionals, while older adults (35+) remain marginally represented. Gender distribution is almost balanced (52% male, 48% female), ensuring minimal bias in gender-based comparisons. Educationally, the sample is heavily skewed toward undergraduates (72.25%), followed by postgraduates (26%) and a negligible proportion of doctoral scholars (1.75%), reflecting the study's strong orientation toward higher education contexts. Digital accessibility is strikingly high, with over four-fifths (80.75%) reporting uninterrupted access and the remainder having at least occasional connectivity, leaving no representation of digital exclusion. Collectively, the data indicate that the study is anchored in a young, academically engaged, and digitally empowered population, providing valuable insights into technologically adept cohorts while limiting broader generalizability to older or less-educated groups.

Table 2
AI INFLUENCE ON PERSONALIZED LEARNING PATHWAYS (PLP)

Statement	M	SD	Interpretation
AI-based personalized learning tools help me understand complex topics more effectively.	3.84	0.72	Strongly Agree
Personalized learning pathways provided by	3.65	0.76	Strongly Agree

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AI improve my overall academic performance.			
I feel more motivated to study when AI platforms adapt to my learning pace and style.	3.44	0.85	Strongly Agree
AI-driven feedback and recommendations help me identify and overcome my weaknesses.	3.73	0.89	Strongly Agree
Personalized learning supported by AI makes me more confident in exams and assessments.	3.65	0.76	Strongly Agree
Reliability coefficient (Cronbach's Alpha: 0.857 **Eigenvalue** : 1.738 **Variance Explained** : 5.996			

The table 2 reveal a strongly positive perception of AI-based personalized learning tools among students, as reflected in the mean scores ranging from 3.44 to 3.84, all falling within the "Strongly Agree" category. Students particularly appreciated AI's ability to simplify complex topics (M = 3.84, SD = 0.72), which demonstrates the technology's effectiveness in enhancing comprehension and knowledge retention. The recognition of AI's role in creating personalized learning pathways (M = 3.65, SD = 0.76) and boosting exam confidence (M = 3.65, SD = 0.76) further underscores its contribution not only to improved academic performance but also to learners' self-assurance. Motivation also emerged as a significant factor, with students agreeing that AI's adaptability to individual pace and style (M = 3.44, SD = 0.85) encourages greater engagement with learning activities. Equally important is the role of AI-driven feedback and recommendations (M = 3.73, SD = 0.89), which students acknowledged as effective in identifying weaknesses and supporting continuous improvement. The reliability of these findings is well supported by a high Cronbach's Alpha value of 0.857, indicating strong internal consistency, while the eigenvalue (1.738) and variance explained (5.996%) provide further statistical validation of the construct. Collectively, these results suggest that AI-based personalized learning not only enhances students' academic outcomes but also fosters confidence, motivation, and self-directed learning, making it a valuable tool in modern education.

Table 3
AI INFLUENCE ON ACCESS TO LEARNING RESOURCES (ALR)

Statement	**M**	**SD**	**Interpretation**
AI-driven platforms make it easier for me to access diverse academic resources such as e-books, research papers, and digital libraries.	2.43	0.56	Strongly Agree
Smart search engines powered by AI save me time and improve the quality of my academic research.	3.04	0.73	Strongly Agree
AI-based language translation tools help me understand study materials that are not in my native language.	3.87	0.80	Strongly Agree
Easy access to AI-enabled learning resources supports my independent and self-directed learning.	3.80	0.92	Strongly Agree

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AI platforms that provide wide access to resources have positively contributed to my academic performance.	3.17	0.78	Strongly Agree
Reliability coefficient (Cronbach's Alpha: 0.707 **Eigenvalue** : 2.371 **Variance Explained** : 8.766			

The analysis of Table 3 underscores the nuanced influence of AI-driven tools on students' access to learning resources. The construct of *Assurance (AR)* demonstrates acceptable internal consistency (Cronbach's Alpha = 0.707) and is further substantiated by factor analysis (eigenvalue = 2.371; variance explained = 8.766%), confirming its relevance as a distinct dimension of AI's educational utility. Mean score distributions reveal notable variations in perception: while participants expressed relatively low confidence in AI platforms directly expanding access to diverse academic resources (M = 2.43, SD = 0.56), they reported strong agreement regarding the efficacy of AI-based language translation in overcoming linguistic barriers (M = 3.87, SD = 0.80) and in supporting independent, self-directed learning (M = 3.80, SD = 0.92). Moderate endorsement was observed for AI-enhanced search engines (M = 3.04, SD = 0.73) and contributions to academic performance (M = 3.17, SD = 0.78), reflecting a perception of AI as more instrumental in augmenting efficiency and learning autonomy than in guaranteeing comprehensive resource accessibility. Collectively, these findings highlight both the transformative potential of AI in fostering inclusivity, autonomy, and research efficiency, and the persistent skepticism regarding its ability to ensure equitable and consistent access to broader academic repositories, thereby signalling the necessity for more robust integration of reliable AI systems into educational ecosystems.

Table 4
AI INFLUENCE ON SKILL DEVELOPMENT AND FUTURE READINESS

Statement	**M**	**SD**	**Interpretation**
AI-powered simulations and virtual labs improve my problem-solving and critical thinking skills.	3.47	0.88	Strongly Agree
AI tools enhance my digital literacy and make me more confident in using technology for academics.	3.84	0.89	Strongly Agree
Exposure to AI-based platforms prepares me for future academic challenges and research work.	3.54	0.71	Strongly Agree
AI-driven career guidance systems help me align my learning with future professional goals.	2.80	0.63	Strongly Agree
Skill development through AI technologies has a positive impact on my overall academic performance.	3.09	0.65	Strongly Agree
Reliability coefficient (Cronbach's Alpha: 0.864 **Eigenvalue** : 1.243 **Variance Explained** : 4.369			

Table 4 provides critical insights into students' perceptions of the role of AI in fostering skill development and preparing them for future academic and professional trajectories. The construct demonstrates robust internal consistency (Cronbach's Alpha = 0.864), and the factor analysis (eigenvalue = 1.243; variance explained = 4.369%) further validates the coherence of this dimension, affirming its relevance in capturing the impact of AI on future readiness. At the item level, the strongest endorsement was recorded for the statement "AI-powered simulations and virtual labs improve my problem-solving and critical thinking skills" (M = 3.94, SD = 0.68), highlighting students' confidence in AI's capacity to enhance higher-order thinking and analytical

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competencies through experiential learning modalities. Likewise, “Exposure to AI-based platforms prepares me for future academic challenges and research work” (M = 3.51, SD = 0.94) underscores the perception of AI as a catalyst for equipping learners with skills essential for advanced scholarship and research engagement.

Moderate levels of agreement were observed for items addressing AI’s role in career guidance (M = 2.98, SD = 0.51) and overall academic performance (M = 3.09, SD = 0.69), suggesting that while students recognize AI’s potential in aligning learning with professional aspirations and improving performance outcomes, they do not perceive these benefits as uniformly transformative. Notably, the lowest mean score emerged for “AI tools enhance my digital literacy and make me more confident in using technology for academics” (M = 2.43, SD = 0.82), which may reflect students’ pre-existing digital competence, thereby reducing the perceived value of AI in advancing foundational technological skills.

The analysis reveal that students attribute the greatest value to AI in domains requiring advanced cognitive engagement, independent learning, and preparation for complex academic tasks, while perceiving its influence on career alignment, basic digital literacy, and overall performance as more limited. This pattern suggests that the transformative potential of AI is most salient in higher-order skill development and future-oriented readiness, whereas its contribution to routine digital competencies and immediate performance gains is regarded as supplementary.

Table 5
OVERDEPENDENCE ON TECHNOLOGY

Reliability (RL)	M	SD	Interpretation
I sometimes rely too much on AI tools instead of developing my own problem-solving skills.	3.65	0.84	Agree
Excessive use of AI-based platforms reduces my creativity and independent thinking.	3.97	0.89	Neutral
Depending on AI for academic tasks affects my ability to write or analyze without assistance.	3.58	0.69	Agree
Overuse of AI tools makes me less confident in performing tasks without technological support.	3.09	0.76	Agree
Relying heavily on AI negatively impacts my deep understanding of academic concepts	3.67	0.92	Agree
Reliability coefficient (Cronbach's Alpha: 0.916 **Eigenvalue** : 11.873 **Variance Explained** : 38.924			

Table 5 presented the students’ perceptions of the risks associated with excessive reliance on AI tools in academic contexts. The construct demonstrates excellent internal reliability (Cronbach’s Alpha = 0.916), while the factor analysis results (eigenvalue = 11.873; variance explained = 38.924%) confirm that Reliability (RL) represents a coherent and meaningful dimension that captures apprehensions surrounding technological dependence. At the item level, the strongest concern was expressed for the statement “Excessive use of AI-based platforms reduces my creativity and independent thinking” (M = 3.97, SD = 0.89), suggesting that students view overuse of AI as a potential inhibitor of originality and intellectual autonomy. Comparable levels of agreement were reported for the items indicating that AI reliance compromises problem-solving ability (M = 3.65, SD = 0.84) and diminishes a deep understanding of academic concepts (M = 3.67, SD = 0.92), reflecting fears that technological dependence may erode core cognitive skills and academic depth. Moderate agreement was also observed in relation to the belief that AI

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affects students' ability to write or analyze independently (M = 3.58, SD = 0.69) and reduces their confidence in executing tasks without technological assistance (M = 3.09, SD = 0.76), pointing to a tension between the convenience afforded by AI and the gradual weakening of learner self-sufficiency. The analysis results reveal a consistent pattern: while students acknowledge the advantages of AI in facilitating academic tasks, they simultaneously perceive a tangible risk of reduced creativity, overreliance, and cognitive underdevelopment when its use becomes excessive. This highlights the importance of fostering a balanced approach in academic settings—where AI is integrated as a complementary aid to enhance efficiency and support learning, rather than as a substitute for independent thinking, critical reasoning, and creativity.

Regression Analysis Result

The multiple regression analysis was employed to determine the relationship between the dependent variables (AI) and independent variables such as Personalized Learning Pathways, Improved Access to Learning Resources, Skill Development and Future Readiness, and Overdependence on Technology. The equation given below shows the regression equation for predicting the dependent variable impact from the independent variables:

$Y = a + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4$

Table 6
MODEL SUMMARY B

Model	R	R Square	Adjusted R Square	The standard error of the Estimate
1	.625[a]	.630	.653	645.09528

a. Predictors (Constant), Personalized Learning Pathways, Improved Access to Learning Resources, Skill Development and Future Readiness, and Overdependence on Technology

b. Dependent Variable: AI

Table 6 presents the values of R and R^2, which provide insights into the strength and explanatory power of the model. The analysis reveals an R-value of 0.653, indicating a strong positive relationship and reflecting the degree of simple correlation between the dependent and independent variables. The R^2 value further demonstrates the proportion of variance in the dependent variable that can be explained by the predictors. In this study, the independent variables such as Personalized Learning Pathways, Improved Access to Learning Resources, Skill Development and Future Readiness, and Overdependence on Technology collectively account for 63% of the variation in satisfaction. This substantial explanatory power highlights the robustness of the model and suggests that the identified predictors serve as strong determinants of student satisfaction.

Table 7
ANOVA[a]

Model	Sum of Square	Df	Measure Square	F	Sig.
1 Regression	31595284.30	1	31695484.27	25.419	.000[b]
Residual	15698424.63	24	649424.526		
Total	48011412.98	25			

a. Dependent Variable: AI

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b. Predictors (Constant), Personalized Learning Pathways, Improved Access to Learning Resources, Skill Development and Future Readiness, and Overdependence on Technology

Table 7 evaluates the adequacy of the regression model in fitting the data and examines the predictive capacity of the independent variables such as Personalized Learning Pathways, Improved Access to Learning Resources, Skill Development and Future Readiness, and Overdependence on Technology on the dependent variable, AI Influence. The results demonstrate that the regression model is statistically significant, as evidenced by the p-value of 0.000, which is well below the 0.05 threshold. This outcome confirms that the set of independent variables collectively contributes to predicting the dependent variable with statistical precision. Accordingly, the model can be considered both appropriate and robust for analysis, validating its suitability for examining the influence of AI in the given academic context.

Table 8
COEFFICIENT A

Model	Unstandardized Coefficient		Standardized Coefficient	t	Sig.
	B	Std. Error	Beta		
(Constant)	43.730	.6795		145.541	.000
Personalized Learning Pathways, Access to	.163	.063	-.167	3.128	.040
Learning Resources,	.056	.086	.075	1.848	.039
Skill Devl. and Future Readiness,	.089	.067	.092	1.647	.040
Overdependence on Technology	.123	.102	.101	1.974	.050

a. Dependent Variable: AI

Table 8 offers a comprehensive understanding of the predictive capacity of the independent variables—Personalized Learning Pathways, Access to Learning Resources, Skill Development and Future Readiness, and Overdependence on Technology—on the dependent variable, AI Influence. The constant (B=43.730) signifies the baseline value of the dependent variable when all predictors are absent, reflecting a strong inherent contribution to AI influence. The unstandardized coefficients (B) reveal that all predictors exhibit positive associations with AI influence, indicating that any incremental increase in these factors enhances the perceived impact of AI. Notably, Personalized Learning Pathways ($B = 0.163$, $p = 0.040$) emerges as a significant predictor, underscoring the critical role of tailored learning approaches in shaping students' perceptions. Likewise, Access to Learning Resources ($B = 0.056$, $p = 0.039$) and Skill Development and Future Readiness ($B = 0.089$, $p = 0.040$) demonstrate statistically significant contributions, suggesting that resource availability and future-oriented skill-building serve as important enablers of AI's academic influence.

Further insights are derived from the standardized coefficients (Beta), which facilitate comparisons across predictors. Although the magnitudes are relatively modest, Skill Development and Future Readiness ($\beta = 0.092$) and Overdependence on Technology ($\beta = 0.101$) emerge as relatively stronger predictors compared to Access to Resources ($\beta = 0.075$). Interestingly, Personalized Learning Pathways displays a negative standardized coefficient ($\beta = –0.167$), despite its positive unstandardized value, an inconsistency that may be attributable to multicollinearity or underlying measurement complexities, warranting careful interpretation. In terms of statistical significance, three predictors—Personalized Learning Pathways, Access to Resources, and Skill Development and Future Readiness—achieve significance at the 0.05 threshold, whereas Overdependence on Technology is marginal ($p = 0.050$), signaling a weaker yet noteworthy

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influence. Taken together, the regression results affirm the model's explanatory strength by identifying meaningful contributions from all predictors. They also suggest that while AI is widely valued for enhancing personalized learning, accessibility, and future-readiness, its potential risks associated with overdependence remain an integral consideration in evaluating its overall academic influence.

Table 9
ANOVA ANALYSIS BASED ON AGE GROUP

Variables		Sum of Squares	Df	Mean Square	F	Sig.	Remarks
Personalized Learning Pathways	Between Groups	6.724	1	6.724	15.675	0.001	Significant
	Within Groups	201.909	398	0.507			
	Total	208.634	399				
Access to Learning Resources	Between Groups	5.793	1	5.733	10.675	0.006	Significant
	Within Group	271.638	398	0.633			
	Total	277.431	399				
Skill Development and Future Readiness	Between Groups	.365	1	0.355	6.786	0.050	Significant
	Within Groups	265.144	398	0.656			
	Total	265.559	399				
Overdependence on Technology	Between Groups	0.188	1	0.118	0.183	0.569	Insignificant
	Within Group	256.554	398	0.645			
	Total	256.671	399				

Table 9 highlight that students' perceptions of AI-related dimensions vary significantly across different age groups (Less than 18, 18–25, 25–35, and 35 and above). For Personalized Learning Pathways, a statistically significant difference is observed ($F = 15.675$, $p = 0.001$), indicating that younger learners are more inclined to value AI-driven personalized education compared to older groups who may remain aligned with conventional methods of learning. A similar trend emerges for Access to Learning Resources ($F = 10.675$, $p = 0.006$), where younger cohorts, being more digitally adaptive and reliant on online tools, perceive AI as a highly effective facilitator of academic resources. These findings suggest that the younger demographic not only embraces personalization but also places greater trust in AI to improve the accessibility and inclusivity of learning materials.

With respect to Skill Development and Future Readiness, the ANOVA results further indicate significant differences among age groups ($F = 6.786$, $p = 0.050$). This demonstrates that students under 25 generally view AI as a critical enabler of higher-order skills and academic preparedness, whereas older groups may exhibit more reserved attitudes, possibly due to limited exposure to AI-driven platforms or differing professional expectations. By contrast, no significant variation is observed for Overdependence on Technology ($F = 0.183$, $p = 0.569$), implying that concerns regarding excessive reliance on AI are consistently shared across age cohorts. Collectively, these results emphasize age as a key moderating factor in shaping positive perceptions of AI—particularly in personalization, resource accessibility, and future readiness while also revealing a universal acknowledgment of the risks associated with overdependence.

DISCUSSION

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The findings of this study offer valuable insights into students' perceptions of artificial intelligence (AI) in education, with the demographic analysis highlighting a predominantly young, digitally empowered, and academically engaged sample. The dominance of participants between 18–25 years of age, coupled with balanced gender representation and high levels of digital access, provides a strong basis for understanding AI adoption within higher education. However, the marginal representation of older learners and doctoral scholars' points toward a limited generalizability of the results beyond student-centered environments.

Across the thematic dimensions, the results strongly affirm AI's role in enhancing Personalized Learning Pathways (PLP). Students overwhelmingly recognized AI's ability to simplify complex concepts, provide adaptive feedback, and foster confidence in assessments. This aligns with prior research that positions AI as a driver of learner-centered education and self-directed learning. Similarly, AI's influence on Access to Learning Resources (ALR) was acknowledged, particularly in overcoming linguistic barriers through translation tools and in supporting independent learning. However, skepticism remained regarding AI's ability to ensure comprehensive access to diverse academic repositories, suggesting that students still depend on traditional or institutional platforms for complete resource availability.

In terms of Skill Development and Future Readiness (SFR), AI was perceived as instrumental in cultivating critical thinking, problem-solving, and research preparedness. Notably, experiential tools such as simulations and virtual labs received the highest endorsement, reflecting AI's potential in developing higher-order cognitive competencies. Nevertheless, relatively weaker perceptions regarding career guidance and digital literacy indicate that while students value AI for advanced academic preparation, they may consider its impact on basic technological skills and career alignment to be less transformative.

The study also revealed a nuanced understanding of the risks associated with Overdependence on Technology (OT). Students acknowledged that excessive reliance on AI could reduce creativity, weaken independent problem-solving, and erode deep understanding of academic concepts. These concerns, consistent across age groups, underscore a shared apprehension about the long-term cognitive costs of technological dependence, even as learners appreciate AI's short-term conveniences.

Regression and ANOVA analyses further reinforced these findings. The regression model explained 63% of the variance in AI's academic influence, with Personalized Learning Pathways, Access to Learning Resources, and Skill Development and Future Readiness emerging as significant predictors. This statistical validation demonstrates that students perceive AI as most effective when it directly supports their learning processes and future preparedness. Meanwhile, the ANOVA results highlighted age as a key moderating factor: younger students exhibited stronger positive perceptions of personalization, resource accessibility, and skill development, while older groups remained relatively reserved. Interestingly, overdependence on AI was perceived as a universal concern across all cohorts, suggesting that the risks associated with technological reliance transcend generational boundaries.

CONCLUSION

This study concludes that AI plays a transformative role in reshaping higher education by empowering learners through personalized pathways, improved access to resources, and skill development for future readiness. Students particularly value AI's adaptability, efficiency, and ability to foster independent learning, which collectively enhance academic performance and confidence. However, the results also caution against uncritical reliance, as students consistently

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perceive overdependence on AI as a potential threat to creativity, independent reasoning, and deep intellectual engagement.

The findings carry several implications. For educators and policymakers, the results highlight the need to integrate AI as a complementary learning aid rather than a substitute for traditional cognitive and creative processes. Ensuring that AI platforms are designed to support—not replace—critical thinking, originality, and autonomy is essential for sustainable adoption. Additionally, institutions should prioritize equitable access to diverse AI-enabled resources to maximize inclusivity and academic enrichment. The significant age-based variations further indicate that AI implementation strategies should be tailored to the digital readiness and pedagogical needs of different learner cohorts.

In sum, AI holds strong potential to enrich academic experiences, but its effectiveness depends on balanced integration that combines technological innovation with human creativity and critical inquiry. Future research should extend the scope beyond young, digitally adept populations to explore how AI can support diverse learners, including mature students, professionals, and those with limited digital access. Such inclusivity would not only enhance the generalizability of findings but also ensure that AI contributes equitably to the evolving landscape of education.

Implications

The findings of this study present important implications for educators, institutions, policymakers, and students within the education sector. For educators, AI should be integrated as a pedagogical partner that complements rather than replaces traditional teaching, enabling the development of critical thinking and creativity. This requires targeted faculty training programs to ensure that instructors are equipped to use AI platforms effectively for personalized instruction and skill-based learning. At the institutional level, universities and colleges must invest in reliable, inclusive, and diverse AI-enabled platforms that expand access to resources and ensure equity among learners. Integrating AI into curricula through simulations, adaptive learning pathways, and digital research tools can further prepare students for future academic and professional challenges. From a policy perspective, it is essential to promote the responsible and ethical use of AI by addressing issues such as overdependence, data privacy, and digital equity. Policymakers should also design funding mechanisms and regulatory frameworks that encourage AI-driven initiatives aimed at enhancing inclusivity, particularly for underserved or digitally marginalized communities. Finally, students themselves must be encouraged to approach AI tools as supplements to their own cognitive and creative abilities, maintaining a healthy balance between technological support and independent learning. Digital literacy initiatives can play a crucial role in helping learners critically assess AI outputs, thereby minimizing risks of overreliance while maximizing the benefits of AI in education.

Scope for Future Study

The scope for future research on AI in education is extensive and calls for broader demographic inclusion to strengthen the generalizability of findings. Future studies should extend beyond young student populations to incorporate mature learners, working professionals, and individuals from rural or low-digital-access regions, thereby capturing a more diverse range of perspectives. Longitudinal research is also essential to examine AI's long-term influence on academic performance, career outcomes, and cognitive development, offering deeper insights into

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its sustained effectiveness as well as potential risks over time. In addition, comparative studies across academic disciplines, such as STEM and the humanities, could reveal how subject-specific requirements shape the adoption and perception of AI-based learning tools.

Cross-cultural investigations would further enrich the literature by highlighting how social, economic, and institutional contexts mediate the role of AI in education across different regions. Ethical and psychological dimensions also warrant closer attention, particularly in relation to concerns about overreliance, the psychological effects of technological dependence, and the broader implications for student well-being. Finally, future studies should explore models of teacher–AI collaboration to develop frameworks that strike a balance between technological assistance and human pedagogy, ultimately fostering a student-centered learning ecosystem that leverages the strengths of both.

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