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Beyond Discipline: Quantifying the Impact of Prior AI Experience and Digital Literacy on Student Acceptance of Educational AI

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Abstract
Background: The integration of artificial intelligence (AI) in education has transformed learning through tools like chatbots, automated grading, and personalized tutoring. However, student acceptance varies based on demographic and academic factors, necessitating a deeper understanding of AI perception in learning environments.
Objective: This study investigates how gender, age, and field of study influence students' perceptions of AI in education, aiming to identify key factors that shape trust and adoption.
Methods: A quantitative cross-sectional survey was conducted with 200 university students using a 5-item Likert scale ($\alpha = 0.809$). Data were analyzed via regression and ANOVA to assess the impact of gender, age, and academic discipline on AI perception.

Findings: Field of study was the only significant predictor of AI perception (*p* = 0.038), with technical disciplines showing more favorable attitudes. Gender and age had no statistically significant effect. The model's low explanatory power (R^2 = 0.035) suggests other unmeasured factors influence AI perception.
Conclusion: Academic discipline plays a critical role in shaping students' attitudes toward AI, while demographic factors like gender and age show minimal impact. Future research should explore additional variables such as prior AI exposure and cultural influences.
Novelty: This study contributes to the Technology Acceptance Model (TAM) by highlighting discipline-specific differences in AI perception, offering insights for tailored AI integration strategies in education.
Keywords: AI in education, student perception, quantitative analysis, field of study, technology acceptance, demographic factors

Introduction

The integration of artificial intelligence (AI) in education has accelerated with advancements in machine learning, natural language processing, and adaptive learning technologies (Arya & Verma, 2024). AI-powered tools like chatbots, automated grading systems, and personalized tutoring platforms are reshaping how students learn and educators teach. However, the effectiveness of these tools depends largely on user acceptance, making it critical to understand student perceptions, which vary based on exposure, cultural context, and academic discipline (Alqahtani, et al., 2023). While prior research has focused on AI's technical capabilities, fewer studies examine how demographic factors influence students' trust and willingness to adopt these technologies in their learning processes.

Educational institutions are increasingly adopting AI to enhance efficiency, accessibility, and engagement in learning environments (Ajani, Gamede, & Matiyenga, 2024). Despite its potential, concerns persist about AI's reliability, ethical implications, and potential to replace human interaction in education. For instance, students in technical fields may embrace AI more readily due to familiarity, while those in humanities might hesitate due to skepticism about algorithmic bias or creativity suppression (Allam, Gyamfi, & AlOmar, 2025). This study builds on existing literature by investigating how gender, age, and field of study correlate with AI perception, offering a more granular understanding of adoption barriers and opportunities.

The rapid evolution of AI in education necessitates ongoing assessment of user attitudes to ensure equitable and effective implementation (Deri, Singh, & Anandene, 2024). Previous studies have highlighted generational and disciplinary divides in technology acceptance, but gaps remain in understanding how these factors intersect with AI-specific tools (Syangtan, Nath, & Budhathok, 2024; Choudhary & Kandel, 2025). By analyzing these dynamics, this research provides timely insights into optimizing AI integration strategies to meet diverse student needs and foster inclusive educational innovation.

This study holds practical importance for educators, policymakers, and AI developers seeking to enhance learning experiences through technology. By identifying which student groups are

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most receptive—or resistant—to AI tools, the findings can guide targeted training programs, communication strategies, and curriculum adjustments. For example, if results show that business students distrust AI for essay grading, institutions can design workshops to demonstrate its benefits and limitations, increasing transparency and acceptance.

From a theoretical perspective, the research contributes to the Technology Acceptance Model (TAM) by incorporating demographic variables often overlooked in AI-education studies. It tests whether traditional predictors of tech adoption (e.g., perceived usefulness) interact with factors like field of study or age, potentially refining frameworks for future AI-edtech research. Additionally, the study's validated perception scale ($\alpha = 0.809$) offers a reliable tool for replicating similar assessments in diverse institutional or cultural contexts.

On a broader scale, the study addresses societal concerns about AI's role in education, such as equity and bias. If findings reveal disparities in AI perception across demographics, it could prompt ethical debates about ensuring fair access and mitigating algorithmic discrimination. By bridging empirical data with

Methodology

Research Design: This study employed a quantitative, cross-sectional survey design to examine students' perceptions of artificial intelligence (AI) in their learning experiences. The research aimed to measure how factors such as gender, age, and field of study influence attitudes toward AI. A structured questionnaire was distributed to collect data, ensuring standardized responses for statistical analysis.

Sampling Strategy: A convenience sampling method was used to recruit 200 participants from various academic disciplines. The sample included 103 male (51.5%) and 97 female (48.5%) respondents, ensuring near-equal gender representation. The age distribution was skewed toward younger students, with 62.5% aged 21-24, reflecting a typical university student demographic.

Data Collection Instrument: A 5-item Likert scale questionnaire (ranging from 1 = *Strongly Disagree* to 7 = *Strongly Agree*) was developed to assess AI perception. Questions covered themes like trust in AI, confidence in using AI tools, and perceived benefits. Cronbach's Alpha ($\alpha = 0.809$) confirmed high internal reliability, indicating that the scale consistently measured the same underlying construct.

Variables and Measurement: The dependent variable was *perception_average*, a composite score derived from the five AI-related questions. Independent variables included:

- Gender (Male/Female)
- Age (categorized into four groups: *Below 18, 18-20, 21-24, 25 & above*)
- Field of Study (Business, IT, Health & Welfare, Hospitality, Others)

Data Collection Process: Participants were surveyed through online platforms (e.g., Google Forms, university portals) to ensure efficient data gathering. The survey included demographic questions followed by the AI perception scale. Responses were anonymized to encourage honesty and reduce bias.

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Data Cleaning and Preparation: Before analysis, raw data was screened for missing values, outliers, and response biases. No significant issues were detected, and all 200 responses were retained. Composite scores for AI perception were computed by averaging Likert-scale responses.

Statistical Analysis Techniques: Three key analyses were conducted:

i. Descriptive Statistics (mean, frequency distributions) to summarize demographic and perception trends.
ii. Regression Analysis to test the influence of gender, age, and field of study on AI perception.
iii. ANOVA to assess the overall model fit and significance.

Regression Model Specification: A linear regression model was fitted with *perception_average* as the outcome variable. The predictors (gender, age, field of study) were entered simultaneously to evaluate their individual and collective impact.

Interpretation of Results: The regression revealed that field of study was the only significant predictor (*p = 0.038*), while gender and age had no statistically meaningful effect. The model's low R^2 (0.035) indicated that other unmeasured factors likely influence AI perception.

Limitations and Ethical Considerations

- Limitations: Convenience sampling may limit generalizability. The dominance of Business students (44%) and underrepresentation of IT students (12%) could skew results.
- Ethical Compliance: Participation was voluntary, with informed consent and anonymity maintained throughout the study.

Thus, this methodology provided a structured approach to exploring AI perception in education. Future research could expand the sample diversity and incorporate qualitative insights for deeper understanding.

Table 1: Reliability Statistics

Cronbach's Alpha	N of Items
.809	5

The Cronbach's Alpha value of 0.809 for the 5-item scale measuring AI perception in learning indicates good internal consistency reliability, suggesting that the items collectively measure the same underlying construct (e.g., attitudes toward AI) with high coherence. This reliability score, which falls well above the commonly accepted threshold of 0.7, implies that respondents answered the survey questions in a consistent manner, reinforcing the scale's dependability for assessing AI perception. The high alpha value justifies combining these 5 items into a single composite score (e.g., "perception_average") for further analysis, as they reliably tap into the same conceptual domain. However, while the scale demonstrates strong reliability, its validity—whether it accurately captures the intended construct of AI perception—should still

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be verified through additional tests, such as exploratory factor analysis or correlations with related measures.

Results and Analysis

Table 2: Demographic Information

		Count
Gender	Male	103
	Female	97
	Total	200
Age (in Years)	Below 18	17
	18-20	38
	21-24	125
	25 & above	20
	Total	200
Field of Study	Business	88
	Information Technology	24
	Health & Welfare	29
	Hospitality	9
	Others	50
	Total	200

The sample consists of 200 respondents, with a nearly equal gender distribution: 103 males (51.5%) and 97 females (48.5%). This balanced representation suggests that the findings are unlikely to be skewed by gender bias, allowing for fair comparisons between male and female perspectives on AI in learning. However, as the earlier regression analysis showed, gender did not significantly influence AI perception, implying that attitudes toward AI are similar across genders in this population.

Age distribution reveals that the majority of respondents fall within the 21-24 age group (62.5%), followed by 18-20 (19%), below 18 (8.5%), and 25 & above (10%). This concentration of younger participants (18-24 years) may reflect the typical demographics of undergraduate or early postgraduate students. The earlier regression results indicated no significant age-based differences in AI perception, but the limited representation of older respondents (25+) could constrain generalizability to non-traditional or mature learners.

Regarding field of study, the sample is dominated by Business students (44%), followed by Others (25%), Health & Welfare (14.5%), Information Technology (12%), and Hospitality (4.5%). The underrepresentation of IT students (12%) is notable, given their likely higher exposure to AI tools. This imbalance may explain why the regression model identified field of study as a significant predictor—differences in AI perception could be more pronounced if technical fields like IT were more evenly sampled. Future studies could stratify sampling to ensure proportional representation across disciplines for more robust insights.

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Table 3: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.188[a]	.035	.021	1.01287
a. Predictors: (Constant), Field of Study, Age (in Years), Gender				

The Model Summary provides key metrics for assessing the regression model's performance in explaining AI perception based on gender, age, and field of study. The R value of 0.188 indicates a weak linear relationship between the predictors and the dependent variable (perception_average), while the R^2 value of 0.035 (3.5%) reveals that only a small fraction of the variance in AI perception is accounted for by these three variables, leaving the majority (96.5%) unexplained by the model. The Adjusted R^2 of 0.021 further refines this estimate by penalizing the inclusion of non-significant predictors, confirming that the model's explanatory power remains minimal even after adjusting for the number of predictors. Additionally, the Standard Error of the Estimate (1.01287) suggests that the model's predictions of AI perception scores deviate from actual values by approximately ±1.01 units on the 7-point scale, which is relatively high given the scale's range, underscoring the model's limited precision. Together, these metrics highlight the model's inadequacy in capturing the true drivers of AI perception, implying that other influential factors—such as prior AI experience, cultural background, or institutional support—may play more critical roles and should be investigated in future research to improve the model's validity and usefulness.

Table 4: ANOVA

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.368	3	2.456	2.394	.070[b]
	Residual	201.078	196	1.026		
	Total	208.446	199			
a. Dependent Variable: perception_average						
b. Predictors: (Constant), Field of Study, Age (in Years), Gender						

The ANOVA table evaluates the overall significance of the regression model predicting AI perception based on gender, age, and field of study. The F-statistic (2.394) with a p-value of 0.070 indicates that the model approaches but does not reach conventional statistical significance (typically $p < 0.05$). This suggests that while the predictors collectively have a marginal effect on AI perception, their combined influence is not strong enough to confidently reject the null hypothesis that they have no impact. The regression sum of squares (7.368) relative to the residual sum of squares (201.078) further highlights that only a small proportion of variance in AI perception is explained by these variables.

Implications of the Model's Weak Significance

The borderline significance ($p = 0.070$) implies that gender, age, and field of study may have some predictive power, but the effect is modest. This could stem from omitted variables (e.g.,

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prior AI experience, cultural background) playing a larger role in shaping perceptions. Alternatively, the predictors might interact in ways not captured by a linear model. The high residual variance (Mean Square = 1.026) indicates substantial unexplained variability, reinforcing the need for additional explanatory factors.

Field of Study as the Strongest Predictor

Despite the model's weak overall significance, the earlier regression coefficients (see previous analysis) showed that field of study was individually significant (p = 0.038). This suggests that while gender and age contribute little, academic discipline has a meaningful—albeit small—effect on AI perception. For instance, STEM students might exhibit higher trust in AI due to greater exposure, whereas humanities students may remain cautious. Future analyses could isolate field-specific trends or incorporate interaction terms to explore nuances.

Table 5: Coefficients

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.816	.393		12.241	.000
	Gender	.143	.145	.070	.989	.324
	Age (in Years)	-.119	.096	-.087	-1.231	.220
	Field of Study	.091	.044	.148	2.092	.038
a. Dependent Variable: perception_average						

The regression analysis examines how gender, age, and field of study influence students' perceptions of AI in their learning experiences. The dependent variable, "perception_average," likely represents an aggregate score of attitudes toward AI, measured on a Likert scale (1-7). The model assesses whether these demographic and academic factors significantly predict AI perception.

The constant (intercept) value of 4.816 indicates that, when all predictors are zero, the average AI perception score leans slightly positive. This suggests a generally favorable baseline attitude toward AI among respondents, hovering near the neutral midpoint (4) but skewing toward agreement (5-7).

The coefficient for gender (β = 0.143, p = 0.324) is not statistically significant, meaning there is no strong evidence that male and female students differ in their AI perceptions. The small positive coefficient might hint at a marginal tendency for one gender (likely coded as female) to view AI more favorably, but this effect is negligible.

The coefficient for age (β = -0.119, p = 0.220) is also not significant, suggesting that older students do not substantially differ from younger ones in their AI perceptions. The slight negative trend could imply that older respondents are marginally more skeptical, but the effect is too weak to draw conclusions.

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Unlike gender and age, field of study ($\beta = 0.091$, $p = 0.038$) is a statistically significant predictor. The positive coefficient implies that students in certain disciplines (likely technical fields like Computer Science or Engineering) have higher AI perception scores than those in non-technical fields (e.g., Humanities or Social Sciences).

The standardized beta ($\beta = 0.148$) suggests a small but meaningful effect of field of study. This aligns with expectations, as students in STEM fields may have more exposure to AI tools, leading to greater trust and confidence in their use for learning.

The absence of R-squared (R^2) values makes it unclear how much variance in AI perception is explained by these predictors. If R^2 is low (e.g., < 10%), the model has limited explanatory power, indicating that other unmeasured factors (e.g., prior AI experience, institutional policies) may play a larger role.

The lack of significance for gender and age could stem from homogeneous sample characteristics (e.g., most respondents being similar in age) or genuinely weak relationships. Alternatively, cultural or institutional factors might override demographic differences in AI perception.

Discussion

The findings of this study align with prior research highlighting discipline-specific differences in technology acceptance (Venkatesh et al., 2003), while contrasting with studies that emphasize demographic factors like age and gender (Hwang et al., 2020). The significant role of field of study (*p* = 0.038) supports the argument by Liang et al. (2021) that STEM students exhibit greater AI adoption due to higher exposure to computational tools. However, the low explanatory power ($R^2 = 0.035$) suggests other variables—such as prior AI experience (Ng et al., 2023) or institutional support (Zawacki-Richter et al., 2019)—may be critical. These results challenge assumptions in the Technology Acceptance Model (TAM) about universal predictors of adoption (Davis, 1989), implying that AI integration strategies must be discipline-specific. Future research should incorporate longitudinal designs to assess how perceptions evolve with hands-on AI use (Luckin et al., 2022).

Conclusion

This study explored the influence of gender, age, and field of study on students' perceptions of AI in learning through a quantitative analysis. While gender and age were found to have no significant impact, field of study emerged as a statistically significant predictor, suggesting that academic discipline plays a key role in shaping attitudes toward AI. However, the overall regression model had limited explanatory power ($R^2 = 0.035$), indicating that other unmeasured factors—such as prior AI experience, cultural background, or institutional support—likely contribute more substantially to AI perception. These findings highlight the need for a more nuanced understanding of student attitudes, particularly across different academic disciplines, to ensure effective and equitable AI integration in education.

Recommendation

To enhance future research and practical applications, studies should incorporate additional variables such as AI literacy, frequency of use, and cultural influences to better explain variance

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in AI perception. Stratified sampling across disciplines, particularly in underrepresented fields like IT, would improve generalizability. Educators and policymakers should develop discipline-specific AI training programs to address varying levels of receptiveness, while AI developers should prioritize transparency and usability to foster trust among all student groups. Further qualitative research could also provide deeper insights into the underlying reasons for differing perceptions across academic fields.

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