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AI and Learning: A Management Perspective from College Students of Kathmandu Valley, Nepal

Basu Dev Lamichhane
Assistant Professor
Tribhuvan University, Saraswati Multiple Campus, Kathmandu, Nepal
basudev.lamichhane@smc.tu.edu.np

Krishna Raj Acharya
Professor
Central Department of Economics, Tribhuvan University, Kathmandu, Nepal
krishna.acharya@rrlc.tu.edu.np

Prerna Pandey
Independent Researcher
prernapandey9844@gmail.com

Saujan Lamichhane*
Independent Researcher
saujanlamichhane999@gmail.com

Corresponding Author*
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Abstract
Background: With the quick integration of Artificial Intelligence in the global education system, it is quite essential that the impact of AI on student learning be determined. Although the studies have started in Nepal, a large gap is still present within the framework of student perceptions towards the influence of AI on learning.
Objectives: The objectives of this research were to examine the perceived effect of AI on the learning outcomes of college-going youth in the Kathmandu Valley, as well as to identify if the effect is considerably different for the chosen demographic: gender, age, and discipline.
Methods: In the current study, a quantitative, cross-sectional survey was administered to 319 college students using convenience sampling. The core instrument measured perceived impact

across six dimensions (learning effectiveness, outcome quality, memory retention, motivation, anxiety, and analytical skills) using a 7-point Likert scale combined into a composite dependent variable. Data analysis was done through descriptive statistics, testing the reliability of the scales using Cronbach's alpha, and independent sample t-test and one-way ANOVA analyses to test for mean differences across demographic groups.

Results: The overall aggregate result for the composite score (4.74 out of 7) reflected a mildly positive yet neutral-leaning attitude regarding AI's influence. The reliability analysis corroborated internal consistency for the overall composite scale. More importantly, the results for ANOVA tests did not yield any statistically significant differences for mean composite scores in any of the gender ($p=.882$), age ($p=.344$), or fields of study ($p=.269$) groups. Although some slight shifts did occur in certain descriptive groups (notably Health & Welfare students had the highest mean value), none actually proved statistically significant.

Conclusion: Results provide strong evidence for the existence of a certain consensus among college students in Kathmandu Valley on the integrated effects of AI on learning experiences, which do not seem to be confined within the usual demographic constraints. This sends out a strong signal for emerging approaches toward the integration of AI in education to not be demographically nuanced. However, the absence of significant differences points toward factors other than demographic differences becoming significantly crucial in influencing students' perceptions.

Novelty: Being one of the first studies to empirically investigate in the Nepalese setting beyond access and general attitudes to explore the perceived effects of AI on the multi-dimensional construct of learning outcomes, the methodical approach through the use of composite measurement and demographic analysis contributes to the local literature's refinement.

Keywords: Artificial Intelligence (AI), Learning Outcomes, Student Perceptions, Nepal Education, Demographic Analysis

Introduction

The integration of Artificial Intelligence into the educational sector is a global phenomenon that promises to revolutionize how knowledge will be delivered, personalized, and assessed (Adel, 2024; Yu, 2024). The international literature very suitably documents the potential of AI to improve learning outcomes through personalized tutoring, adaptive assessment, and intelligent content delivery (Mustafa et al., 2024; Lin et al., 2023). However, this potential is realized unevenly across diverse regional infrastructure, digital literacy, and socio-economic contexts. In Nepal, despite the growing global momentum, the adoption and impact of AI in education remain an under-researched area, especially when it concerns empirical evidence on its impacts related to student learning outcomes.

Initial studies conducted in the Nepalese environment, including the mixed-methodology study conducted by Poudel & Maharjan (2025), show there is indeed a massive digital divide regarding AI use between urban and rural areas, with students in urban areas being much better exposed to it. Though it brings out the issue of inequality, it does not, however, tackle the fundamental educational issue: Are AI tools able to increase learning efficiency, retention of skills, motivation levels, and analytical abilities of students? College-going students in the Katmandu Valley area of the Nepalese capital, being the chief group at the initial stage of AI implementation, would therefore be the most important group for acquisition of significant information on how this new technology is impacting the educational processes in the developing country.

This study thus aims to fill this important research gap by examining the perceived effect of AI on the educational outcomes of college students in Kathmandu Valley. It goes further than just studying adoption rates to study how AI affects academic skills. The research question to be addressed in this study is: How is the overall educational outcome for college students in Kathmandu Valley affected by Artificial Intelligence, and how does this compare for various important demographic groups?

Literature Review

The Global Paradigm of AI in Education

Internationally, the application of AI is viewed through the perspective of abetting a “sustainable multifaceted revolution” within the realm of education (Kamalov et al., 2024). Research analysis identifies its applications within three fundamental paradigms: the AI-directed paradigm, where the learner is portrayed as a “receiver”; the AI-supported paradigm, where the learner assumes the position of a “partner”; and the AI-powered paradigm, where the learner is characterized as a “leader."(Ouyang et al, 2023). It encompasses applications such as intelligent tutoring systems, automated assessment, analysis, and personalized educational pathways, all intended to boost the efficiency, engagement, and personalization of the educational process. The overarching benefit is that of improving the long-standing divide within education through the provision of quality solutions.

Relevant research conducted within the context of Nepal is still in its infancy but immensely insightful nonetheless. The study conducted by Poudel and Maharjan (2025) can well be said to provide foundational insight into the fact that although "the percentage of students' awareness about AI is high (90.7%)," its usage is divided. There "exposes a large digital divide where AI tools are being used more and more by city students compared to rural students." This brings the relevance of the current study into immediate focus, taking into account the topography of the study’s surroundings within the boundaries of the Kathmandu Valley, which is an urban area and therefore would naturally have fewer barriers to access and facilitate its potential assessment within the boundaries of impact and not access alone.

In addition, the scholarship from Nepal has started exploring the implications of AI, indicating the concerns over issues of academic integrity. This shows that they are aware of the threats

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that AI may pose. However, the optimism among the university students is worth noting, since most of them (62.7%) think that AI will be a solution in terms of reducing education inequality.

Theoretical Foundations: Learning Outcomes & Self-Efficacy

To develop an understanding of "learning outcomes," this research relies on the literature related to education and social cognitive theory (Chou et al., 2024). The role played by self-efficacy, described by Bandura, is essential in determining academic effectiveness, since self-efficacy is viewed as an individual's perception of his/her ability to perform the actions required to accomplish particular levels of accomplishment. The use of AI technology supports and helps to improve the academic self-efficacy level of the student (Lee et al., 2022). There is also an importance given in the literature to "critical thinking" and its identification as an essential skill related to "clear reasoning, analysis, and autonomy." The use of AI technology to support learning outcomes is essential, since it raises an important question regarding whether the use of AI technology will improve or impede the student's ability to develop essential higher-order skills, such as creative and critical thinking. The overall measure related to the outcomes covered in this piece includes effectiveness, quality, memory, motivation, concern, and analytical skills.

Demographic Variables as Key Differentiators

It has been indicated in literature that the experience of educational technology is not standard. Gender and technology diffusion can have complex differences in patterns of usage and attitude (Cai et al., 2017). Moreover, ‘age and field of study can be very powerful factors,’ too. “Students from more technical fields like IT might have more basic knowledge of AI and expectations than students from Business or Health Sciences.” It can well be assumed that at AI/ML programs, ‘the specific curricula in AI/ML programs with heavy emphasis on problem-solving in AI/ML and ethical judgment likely impart a view on AI in education very different from others.’ This study supposes that ‘field of study can be a very powerful determinant in determining perceived impacts,’ drawing on their sharply differing epistemic cultures.

Methodology

This research used a quantitative cross-sectional design to explore the correlation between the most influential demographic factors and the learning outcome impact of AI perceived among college students. The sampling frame consisted of college and university students enrolled in higher learning institutions in and around the Kathmandu Valley of Nepal. However, due to the limitations in practical realities of accessing a precise sampling frame, a non-probability sampling technique known as convenience sampling was considered for the research. A total of 319 respondents were considered for the survey, mostly in connection with professors and administrative personnel in different colleges, with the intent of accessing the survey questionnaire through an e-mail to the college groups concerned, and the calculated margin of

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error approximating around ±5.49% at a confidence level of 95% to obtain some reasonable research precision in the primary analysis.

A structured online survey was conducted to collect data for this study. The survey consisted of questions regarding participant demographics, familiarity with AI, and a set of six core questions measured via a 7-point Likert scale designed to generate a composite dependent variable (DV) for perceived AI effect on learning. This analysis plan is systematic. First, descriptive statistics can be used to examine characteristics of the sample and descriptive statistics for the composite DV. Then, Cronbach's alpha can be used to evaluate the reliability of the set of six questions.

Lastly, to examine whether participant perceptions differ in some way across demographic groups for this study's main question of whether participant perceptions are different across gender groups, by age groups, or by study groups, t-test and ANOVA tests were conducted to examine gender groups, age groups, and study groups separately.

Reliability Test

Table 1

Reliability Statistics

Cronbach's Alpha	N of Items
.709	6

Results

Perceived impact of Artificial Intelligence on learning outcomes between male and female respondents

Table 2

Group Statistics

	Gender	N	Mean	Std. Deviation	Std. Error Mean
ai_impact_mean	Male	158	4.7300	.99958	.07952
	Female	161	4.7453	.84205	.06636

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Table 3
Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
ai_impact_mean	Equal variances assumed	1.193	.276	-.149	317	.882	-.01538	.10341	-.21884	.18807
	Equal variances not assumed			-.149	306.132	.882	-.01538	.10358	-.21919	.18843

Analysis of male participants (N=158) yields a mean composite value of 4.73 (SD=1.00) on the scale measuring their perceptions of the effect of AI on their learning outcomes, where 1 denotes a strongly negative effect and 7 a strongly positive effect. A mean value of 4.73 is slightly above the theoretical mean of 4 ("Neutral") on the scale, indicating that male participants in the study have a slightly positive and cautious view of the effect of AI on their learning outcomes. A standard deviation of about 1.0 indicates moderate variability in their responses, indicating that though their mean is slightly positive, there is quite a spread of responses from negative to strongly positive.

The composite score mean for female respondents is 4.75 (SD = 0.84), which is not significantly different from those of male respondents. Again, this means that female perceptions are slightly above the point of neutrality, reflecting a cautious but slightly positive attitude toward the use of AI in their learning endeavors as well. One of the important points of divergence is that female perceptions are slightly tighter, as evidenced by their standard deviation being smaller (1.00 vs. 0.84), suggesting female perceptions are less divergent in comparison to those of males, reflecting less internal variation in their perceptions about AI use in learning. The number of individuals in both groups is remarkably similar, at 158 and 161, respectively, providing an excellent basis for comparison.

In Table 5, before comparing the means, Levene's Test for equality of variances was conducted to test a very important assumption. The test result was not significant (F = 1.193, p =.276), indicating no statistically significant difference in variance in composite scores between males and females. This inability to reject the null hypothesis of equal variances supports the standard t-test results that assume equal variances ("Equal variances assumed"). The subsequent t-test resulted in a t-statistic of-0.149 with 317 degrees of freedom, which is extremely small and thus suggests a very small difference between the two sample means.

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The two-tailed p-value for the t-test is .882, which is significantly greater than the standard alpha value of .05. Hence, we have reasons to not reject the null hypothesis. There are no statically significant reasons to show that there is any difference in the mean composite value for the perceived AI impact between males & females in this study. The mean difference of -0.01538 points is negligible, which is less than an infinitesimal value of two-hundredths of a point on this 7-point scale. The 95% confidence interval for this value lies between -0.219 & 0.188, which further strengthens the idea that the true value for this difference is likely to be zero, which covers the values of negligible negative & positive values.

AI's perceived impact on learning outcomes across different age cohorts

Table 4
Descriptives

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Below 18	26	4.9679	.45951	.09012	4.7823	5.1536	4.33	6.00
18-20	74	4.7815	1.20151	.13967	4.5032	5.0599	1.00	7.00
21-24	190	4.6702	.83834	.06082	4.5502	4.7901	2.50	6.33
25 & above	29	4.8621	.92589	.17193	4.5099	5.2143	3.17	6.00
Total	319	4.7377	.92201	.05162	4.6362	4.8393	1.00	7.00

Table 5
ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.835	3	.945	1.113	.344
Within Groups	267.498	315	.849		
Total	270.334	318			

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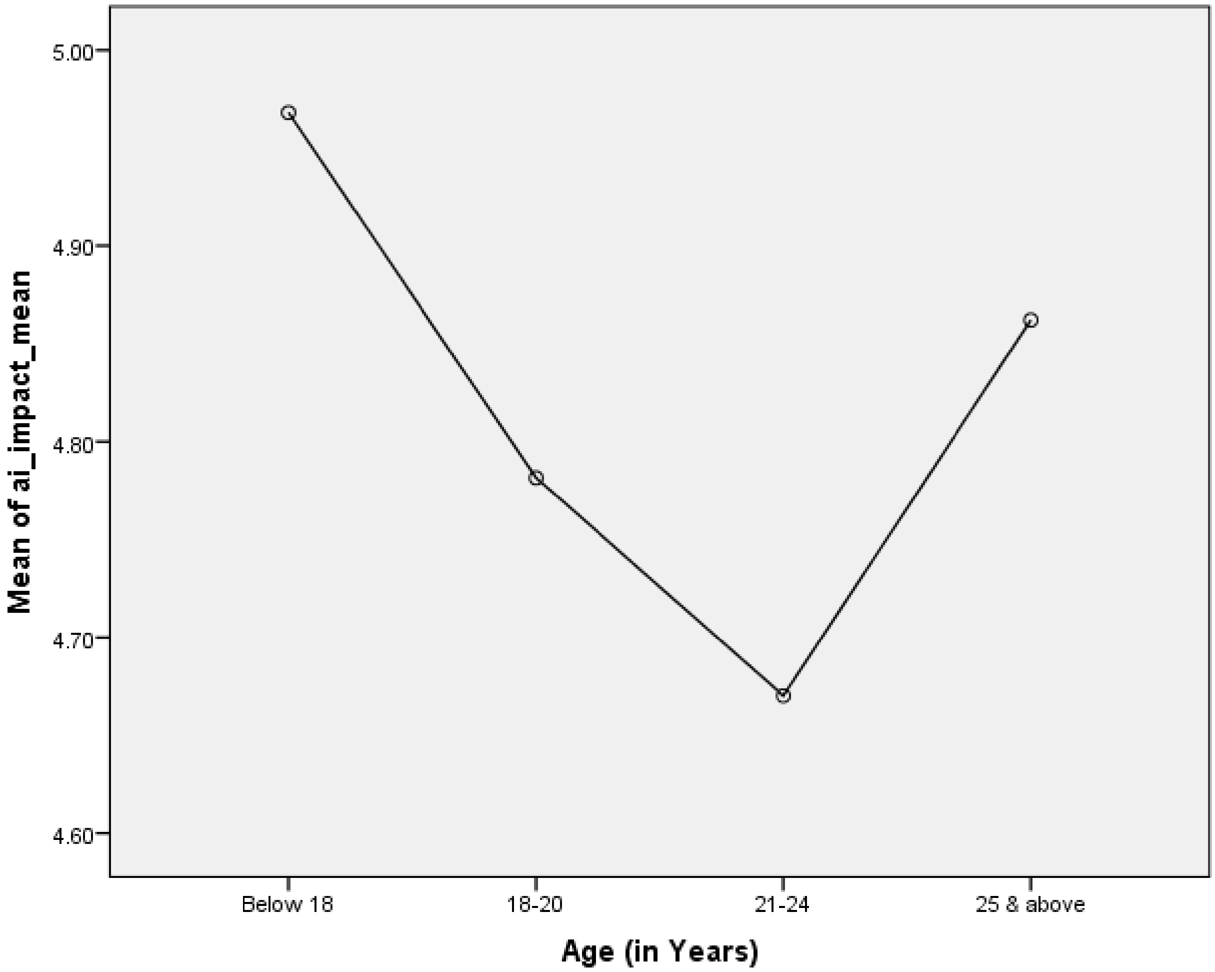

Figure 1: Means Plots

The study encompasses a whole group of 319 participants categorized by four different age groups. A bigger number, 21-24, comprises 190 respondents, followed by 18-20, which comprises 74 individuals. The smaller two are "Below 18," which comprises 26 people, and "25 & above," which comprises 29 people. For the whole population, the mean value concerning the impact of AI on learning is 4.74, having a standard deviation of 0.92, signifying that the whole group perceives it slightly above or rather close to being neutral, or maybe leaning slightly to the more positive side, given that it is a 7-point scale.

Analysis of the means for the groups shows an irregular trend with increasing age. The lowest age category ("Below 18") has been shown to have the most positive perception of AI's impact (Mean = 4.97, SD = 0.46). This slightly falls for the 18-20 age group (Mean = 4.78) to follow a trend of gradually reducing to 21-24 years (Mean = 4.67). Notably, however, the mean increases to 4.86 for those in the oldest age category ("25 & above"). The similarity of values across groups varies significantly, ranging from very low dispersion for those "Below 18" (SD = 0.46), implying general consensus on positive perceptions, to greatest dispersion for 18-20 years (SD = 1.20) ranging from 1 to 7 on this seven-point scale.

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A one-way ANOVA test was performed to verify whether these observed discrepancies in mean scores on A-scored subjects per age group were also significant. It appears from the outcome that the between-group Sum of Squares (2.835) is much smaller in comparison to the Sum of Squares of the within-group variation (267.498). This generates an F-statistic that is not significant ($F(3, 315) = 1.113$) with a probability of .344. As the probability is larger than the conventional level of .05, it is concluded that there are not sufficient grounds to reject the null hypothesis. In statistical terms, there appears to be no significant difference among the four age groups in their composite perception of the effect of AI on learning. This null finding is further reinforced by the complete overlap of the 95% CIs around the mean for each group. For example, the interval for the lowest-scoring age group, those from 21 to 24 years old (4.55-4.79) significantly overlaps with intervals for highest-scoring groups ("Below 18": 4.78 - 5.15; "25 & above": 4.51 to 5.21). That a true population mean for these age groups could well and truly be identical is suggested by such an overlap.

The means plot would graphically represent the non-linear trend as follows: a high beginning point for the youngest age group, a base passing through the 18-20 and 21-24 age groups, and a slight recovery among the 25+ age group. Nevertheless, in view of the non-significant ANOVA test, the U-shaped or "smile" in the trend shown in the graph should not be placed too much emphasis upon, insofar as a non-linear trend obtains. The graph essentially focuses on highlighting the descriptive statistic, that despite some minute variability, no age group's mean differs much from the total mean of 4.74. The flatness of the trend, in comparison to the error bars representing the SE or CI, would be the important visual point here.

Association of students' academic disciplines (e.g., Information Technology, Business, Health and Welfare, Hospitality, Others) with significant variations in their composite assessment of AI's impact on learning outcomes

Table 6

Descriptives

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Business	137	4.6460	.85354	.07292	4.5018	4.7902	2.50	6.17
Information Technology	54	4.6389	1.23147	.16758	4.3028	4.9750	1.00	7.00
Health & Welfare	42	4.9286	.90478	.13961	4.6466	5.2105	3.33	6.33
Hospitality	18	4.9074	.61893	.14588	4.5996	5.2152	4.00	5.67
Others	68	4.8382	.83207	.10090	4.6368	5.0396	2.67	6.50
Total	319	4.7377	.92201	.05162	4.6362	4.8393	1.00	7.00

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Table 7
ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.415	4	1.104	1.303	.269
Within Groups	265.918	314	.847		
Total	270.334	318			

The study analyzes the perceived effects of AI on learning outcomes for five different subject areas for 319 participants. The largest number of participants belong to Business graduates (N=137), followed by 'Others' (N=68), Information Technology (N=54), Health & Welfare (N=42), and Hospitality (N=18). The Grand mean is 4.74, which is consistent across all analyses and reflects a slightly positive perception. There is considerable disparity in the number of participants, with the number in Hospitality being very small.

The descriptive statistics show interesting patterns regarding the perception of AI's impact across academic disciplines. Accordingly, the most favorable composite scores are from students in Health & Welfare (Mean=4.93) and Hospitality (Mean=4.91), while students in Business (Mean=4.65) and Information Technology (Mean=4.64) report the least favorable-and almost identical-scores. The "Others" category falls in between (Mean=4.84). In terms of internal consensus, Hospitality students have the least variability in scores (SD=0.62), which would mean that there was a relatively unanimous positive view. On the other hand, IT students had the highest internal disagreement (SD=1.23); thus, their responses span from extremely negative, represented by 1, to extremely positive, represented by 7.

One-way ANOVA analysis was performed to determine the significance of the observed differences on the academic disciplines. It is observed that the variance of the means of the groups (Mean Square Between-Group = 1.104) is not significantly greater than the variance of the groups (Mean Square Within-Group = 0.847). It is found that the F-statistic is non-significant ($F(4, 314) = 1.303$), and its p-value is found to be .269. Since the obtained p-value is greater than the threshold of .05, it leads to the acceptance of the null hypothesis. It is concluded that there is no evidence of the combined perception of AI influence on learning being significantly different across the various disciplines.

Discussion

This present study examines whether demographic attributes-gender, age, and field of study-reflect significant differences in how university students perceive the holistic impact of AI on their learning outcomes. The findings based on a composite measure that was derived from these six key dimensions-conceptual learning effectiveness, motivation, skill preservation-fall consistently to support a conclusion of demographic similarity rather than divergence (Poudel

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& Maharjan, 2025). None of three independent variables had a statistically significant effect on the overall perception score. This discussion demonstrates an attempt to contextualize these no-difference findings within the larger frame of AI-in-education research, covering methodological considerations, most importantly, small sample sizes for particular subgroups, and hypothesizes further directions.

The non-significance on all three demographic variables implies a remarkable degree of consensus among the students on the integrated role of AI in their educational life. The average response on a 7-point semantic scale where 4 is a midpoint expressing a positive or negative response is 4.74. This is a rather positive response on a scale that is not very enthusiastic.

Gender & Age: A Homogeneous Experience. The fact that there's little difference in perception metrics for male and female respondents (4.73 vs. 4.75) dispels any notions of digital divides for technology acceptance for learning-related purposes among different sexes. This implies that differences in perceptions related to the usefulness, challenges, and ethical considerations of AI technology applications like ChatGPT might not differ by gender when one is placed in a learning milieu (Shahzad et al., 2024). There's also little variation across different age groups, ranging from "Below 18" to "25 & above," which implies that perhaps the concept of digital nativism has reached its maturity level to the point where differences due to small age groups within the university setting fail to create different perceptions of AI's effects.

Area of Study: The most fascinating finding of this null result is across areas of study. Going against expectations, students from Information Technology (IT), presumed to be the most technically savvy and thus positively inclined, showed the lowest mean (4.64), not significantly different from Business students, while Health and Welfare and Hospitality students showed the highest scores. It would appear that the benefit of AI is not necessarily one of technical knowledge and application but of problem-solving applications. An IT student can critically assess AI for its shortcomings in code or design, and a Health student can appreciate it for its ability to simulate scenarios and distill research information (Vieriu & Petrea, 2025). Notwithstanding such possible divergences of application, the aggregate result—their impact on learning—assess equally. This is consistent with studies showing that AI's benefit, such as customized education and information access, is generally attractive across disciplines.

It is also consistent with recommendations that have been proposed for studying with smaller samples. By employing an aggregate DV by combining the responses of several like-scale questions on a likert scale, it is possible to enhance the reliability of the measuring and thus the efficiency of the statistical analysis since it eliminates unpredictability due to unmeasured variables (Hopkin et al., 2015). It is also important to note that the provision of descriptive statistics, confidence intervals, and magnitude of results even if it is not significant is useful information for possible future studies or for use during meta-analyses.

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Conclusion

This particular study gives a crucial early result, which is that, at a macro level, a consensus among students regarding their views on the effect of AI on learning is quite evident across all demographics. This indicates that strategies regarding AI adoption in education could maybe be formulated on a unified student experience. However, the particular finding regarding a lack of diversity should be considered with the fact that it might lack statistical power due to the relatively small number of observations in each particular demographic. Additionally, the observed descriptive trends might be indicative of a more complex phenomenon that has yet to be unraveled. Thus, particular research initiatives, instead of a conclusive finding, may prove to be a wake-up call towards a more detailed, properly powered, and sufficiently enriched research endeavor. In particular, as the role of AI in education increasingly entrenches itself in the system, a comprehensive understanding of the complex dynamics among who the student happens to be, what they study, or how they use technology would soon prove indispensable towards ensuring these systems improve learning instead.

Transparency Statement: The authors confirm that this study has been conducted with honesty and in full adherence to ethical guidelines.
Data Availability Statement: Authors can provide data.
Conflict of Interest: The authors declare there is no conflicts of interest.
Authors' Contributions: The authors conducted all research activities i.e., concept, data collecting, drafting and final review of manuscript.

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