Use of AI and perceived equity among college students in the U.S.

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Abstract

As the popularity of Artificial Intelligence (AI) in various aspects of society increases, there are discussions within the educational sector about whether to ban or embrace AI. Amid this debate, it is important to better understand students' perceptions, an important stakeholder in this debate. The goal of the study is to answer the following research questions. 1) To what extent do students use AI? 2) What is the relationship between the usage of AI and the perceptions of inequity of AI? 3) Do inequity considerations of AI use vary by demographic characteristics? The authors surveyed a convenient sample of students at a university in the southeastern of the United States in 2024. The survey yielded 172 valid responses. The results indicate that there is a low AI use among students, there is inequity in the use of AI, and there is no relationship between AI use and students' demographics.

Keywords: Artificial Intelligence, inequity, educational sector, students' perceptions

1. Introduction

The popularity of Artificial Intelligence (AI) in various aspects of society, such as education, healthcare, transportation, and emergency management is on the increase (Jeffrey, 2020). AI is defined as "the simulation of human intelligence processes by machines, especially computer systems" (Craig et al., 2024). In the educational sector, teachers and students are increasingly utilizing AI for different purposes, including but not limited to, grading, correcting grammar, conducting research, and for detecting plagiarism (Cardona et al., 2023; Friedman et al., 2021). There are discussions within the educational sector about whether to ban the use of AI or embrace it. Those opposed to the use of AI cite reasons like inequity, plagiarism, ethical concerns, privacy issues, biases, etc. (Craig et al., 2024; Gao & Yu, 2024). Proponents argue that AI has the potential to revolutionize the educational sector, increase engagement, personalize student learning, enhance grading of assignments, and provide skillsets necessary for the future workforce (Cardona et al., 2023; Fošner, 2024; Riaz, 2023; Yee et al., 2023). Amid this debate, it is important to better understand some of these issues from the perspective of students, an important stakeholder in this debate. Specifically, this study is interested in the relationship between AI and inequity. Despite the importance of addressing potential inequities inherent in using AI in educational settings, little research has been done to better understand this relationship (Holstein & Doroudi, 2021). In this study, the authors adopt a more comprehensive definition of inequity—equity includes not only unequal access to AI among college students, but also the differential usage of AI by students in the classroom.

The goal of the study is to answer the following research questions. 1) To what extent do students use AI? 2) What is the relationship between the usage of AI and the perceptions of inequity of AI? 3) Do inequity considerations of AI use vary by demographic characteristics? To

answer these questions, the authors surveyed a convenient sample of students at a public university in the southeastern part of the United States in 2024. The online survey, which took 10 to 15 minutes to complete, consisted of 39 questions. The questions focused on students' perceptions of the extent of AI use in classrooms, concerns about inequity, the advantages and disadvantages of using AI, and privacy and ethical issues regarding AI usage. The survey yielded 172 valid responses. The authors use both descriptive statistics and regression analyses to answer the three questions. This study contributes to the ongoing debate by providing important insights into how students perceived inequity in the use of AI. In addition, it recommends policies aimed at addressing potential inequity concerns regarding AI use among college students. More broadly, the study contributes to higher education by discussing the implications of the findings for higher education practice. Finally, the study recommends future research topics related to AI and inequity in educational settings.

In the next section, the authors discuss relevant literature and then present the methodology including data collection and analysis. Following the methods section is the result section and then the discussion of the results. Finally, the authors conclude by reiterating the findings, offering some policy recommendations, discussing the study's limitations, and suggesting future research topics.

2. AI and inequity

Public perceptions of AI use, especially in educational settings are mixed (Taylor et al., 2025). Nevertheless, the use of AI or the concept of its use is important in the educational sector. As such, the integration of AI in education requires careful and sustained attention from educators, policymakers, and technology developers not only because of its institutional and business challenges but also due to its far-reaching implications for educational inequality.

The COVID-19 pandemic served as an unprecedented catalyst, dramatically accelerating the adoption of technology and digital pedagogy across all educational levels, from primary schools to higher education institutions (Garcia Ramos & Wilson-Kennedy, 2024). Prior to COVID-19, many schools were easing into the digital age; post COVID-19, there has been an accelerated adoption of technology, including Learning Management Systems and AI (Pantelimon et al., 2021; Schleicher, 2022). This rapid transformation highlighted both the remarkable opportunities that technology offers for innovative teaching and learning (Kramm & McKenna, 2023) and the imperative need for a better understanding of equity and accessibility in educational delivery, particularly for underserved and marginalized student populations (Basham et al., 2020; Chaaban, 2025; Garcia Ramos & Towns, 2023).

Learning outcomes can be achieved through personalized teaching strategies that thoughtfully address each student's unique needs, learning styles, prior knowledge, and cultural background. These adaptive approaches leverage AI's capacity to analyze student performance data, identify learning gaps, and provide targeted interventions in real time (Garcia Ramos & Wilson-Kennedy, 2024). However, an AI implementation that actively reduces existing barriers rather than amplifying them and promotes fair access to quality education for all students, regardless of their socioeconomic status, geographic location, or physical abilities, should remain a central, non-negotiable objective in any educational technology initiative (Basham et al., 2020).

Technology plays a critical role in accessible and equitable education system, particularly in several key areas: the thoughtful design of inclusive learning environments that accommodate diverse learner needs; the careful calibration of content difficulty and instructional complexity to

match student readiness levels; the selection and implementation of varied delivery methods that reach students through multiple modalities; and the ongoing development of technology-based pedagogical skills among educators to ensure effective integration of AI tools into teaching practice (Holstein & Doroudi, 2022). When implemented intentionally and with a commitment to equity, AI has the potential to democratize access to high-quality educational experiences and support the success of every learner.

Despite the inherent opportunities of AI, there are still many challenges and risks associated with implementing AI in the educational sector (Chaaban, 2025), such as algorithm bias. “Systematic, unwanted unfairness in how a computer detects patterns or automates decisions” is known as algorithm bias (Cardona et al., 2023, p. 8). Algorithm bias can lead to AI discrimination—the bias and injustice that can emerge from the operations of AI systems—in educational settings (Bostrom and Yudkowsky, 2014). For example, if AI algorithms are used in allocating resources to students from different socioeconomic backgrounds based on historical data, there is likely to be inequity in the resource allocation (Cardona et al., 2023). AI discrimination is a significant challenge that researchers and governments ought to address. Discrimination in AI has the potential to create inequities across various applications in multiple sectors, including personalized learning in education (Luusua et al., 2023). Hence, it is essential to develop ethical guidelines that can help to address inequities in educational settings (Chaaban, 2025).

2.1. AI and inequality in educational settings

AI has been present in classrooms for several years, including learning management tools such as Google Classroom, Canvas, ChatGPT, and Turnitin. For example, during the 2024-25 school year, a national survey conducted by the Center for Democracy and Technology (CDT) found that 85% of teachers and 86% of students in the U.S. reported using AI (2025). Previous research indicates that socioeconomic status has a significant influence on students' access to AI learning opportunities. The CDT survey also found that parents with higher incomes are more likely to indicate that their child uses AI compared to parents with lower income and/or those living in rural households (2025). Similarly, Brown et al. (2025) found a positive relationship between socioeconomic status and the frequency of AI use. Chklovski et al. (2019) observe that students from low-income households are often marginalized from AI-enhanced classes. Furthermore, Vandenberg et al. (2023) emphasize that students in rural areas have fewer opportunities to engage meaningfully with AI. This unequal level of AI use among students from various socioeconomic backgrounds is worrisome. In fact, as AI becomes increasingly integrated into K–12 education, concerns regarding equity and access are intensifying (Lee et al., 2025) because inequities can negatively affect motivation and engagement among students (Altugan, 2015).

Moreover, the recent widespread availability of generative AI tools, such as ChatGPT, and the rapid commercialization of similar technologies across sectors present new challenges and opportunities for both students and educators. AI technologies have advanced to a stage where sophisticated language models can respond to complex queries and generate coherent text across diverse genres, including essays, narratives, games, and poetry, while simultaneously facilitating discourse, synthesizing and elaborating content, generating computer code, and providing real-time feedback throughout these processes (Tate et al., 2023). In today’s rapidly evolving, information-driven world, educators must equip learners with the 21st-century competencies necessary to navigate complex sociocultural, linguistic, and civic challenges

(Xiaoling & Tan, 2025). These competencies encompass critical thinking and problem-solving abilities, digital literacy and technological fluency, effective communication and collaboration across diverse contexts, creativity and innovation, and cultural awareness and global citizenship.

Cultural backgrounds, including ethnicity, race, and socioeconomic status, have a significant impact on students' educational experiences. Many marginalized students encounter obstacles that limit their access to enriched programs, thereby perpetuating their disadvantages (Chklovski et al., 2019). A deep understanding of cultural influences is crucial for crafting effective education policies (Reed & Johnson, 2023). Through thoughtful implementation of AI, it is possible to create supportive educational environments that allow every student to succeed, ultimately helping to bridge existing gaps in education. A comprehensive empirical investigation conducted by Brown et al. (2025) examining AI usage patterns across higher education institutions revealed significant insights into the adoption and application of generative AI technologies among both student and faculty populations. The study identified three predominant use cases that transcended institutional roles: generating ideas (41% of the sample), explaining complex concepts (38%), and editing textual content (31%). These findings suggest a convergence in how different stakeholder groups conceptualize and operationalize AI tools in academic contexts, primarily as cognitive aids for ideation, clarification, and refinement rather than as complete content-generation systems. The study further revealed patterns within the academic community. Approximately one-quarter of students (25%) and nearly one-third of academic staff (31%) reported never using a generative AI tool, indicating that substantial portions of both populations remain either resistant to, unfamiliar with, or lacking access to these emerging technologies (Brown et al., 2025). This non-adoption may reflect concerns about academic integrity, technological literacy barriers, institutional policy ambiguities, or cultural philosophical opposition to AI integration in scholarly work.

2.2. Cultural capital theory

Cultural Capital Theory (CCT) illuminates how individuals perceive themselves and others within society, with a focus on social structures and access barriers (Reed & Johnson, 2023). For public administrators, understanding CCT is vital for delivering equitable services. They must ensure that AI resources are accessible to all students, tailoring information to diverse cultural contexts. By prioritizing this inclusiveness, they can better meet community needs and bridge the digital divide, allowing all students to benefit from technological advancements. Researchers, educators, and policymakers have increasingly dedicated their efforts to unraveling the intricate and multifaceted relationship between learning and the social world. This connection is not only complex but also fundamental for fostering effective educational practices (Altugan, 2015). One of the most pressing challenges in contemporary education is the integration of AI, which must consider the diverse cultural backgrounds of students. This task is particularly daunting, as AI continues to influence societal dynamics and has the potential to exacerbate existing inequalities.

CCT offers a valuable framework for analyzing how higher education administrators shape the impact of AI on equity and access within postsecondary institutions. Cultural capital encompasses the knowledge, skills, dispositions, and institutional competencies that are privileged within dominant academic structures (Bourdieu, 1986; Bourdieu & Passeron, 1990). As AI is integrated into admissions processes, advising systems, learning analytics, and student success initiatives, administrators serve as institutional gatekeepers who determine the selection, governance, and operationalization of these technologies. Such decisions shape which forms of

cultural capital are recognized and reinforced, especially when AI systems utilize historical institutional data that mirror existing social stratification (Benjamin, 2019; Williamson & Eynon, 2020).

AI tools can disproportionately benefit students who already possess dominant cultural competencies, such as familiarity with institutional norms, advanced digital literacy, or standardized academic pathways, while unintentionally marginalizing students from historically underserved backgrounds (Perrotta & Selwyn, 2020; Selwyn, 2019). Nevertheless, cultural capital theory also underscores the potential for administrators to act as equity-focused leaders by critically evaluating algorithmic bias, implementing inclusive data governance, and promoting culturally responsive AI practices. By expanding definitions of institutional success and embedding participatory decision-making processes that incorporate diverse student perspectives, administrators can use AI to redistribute cultural capital rather than merely reproduce it. This approach supports more equitable educational outcomes in a higher education landscape increasingly shaped by technology (Benjamin, 2019; Williamson & Eynon, 2020).

Students hailing from underserved communities face numerous barriers—stemming from socioeconomic status, gender, and race—yet their voices and experiences are often underrepresented in existing research (Cao et al., 2025). This lack of representation further complicates efforts to create equitable educational opportunities, highlighting the urgent need for inclusive approaches that acknowledge and address these disparities. Within the context of AI integration in STEM education, cultural capital becomes particularly salient as students from diverse backgrounds bring unique perspectives, problem-solving approaches, and lived experiences that can enrich computational thinking and technological innovation (Cao et al., 2025). According to Cao et al. (2025), when educators intentionally design AI-enhanced curricula that connect to students' cultural backgrounds, community contexts, and prior experiences, they create opportunities for learners to see themselves as legitimate participants in scientific and technological domains. This pedagogical orientation not only enhances student engagement and academic achievement but also contributes to the diversification of the educational sector by retaining talented individuals who might otherwise be marginalized by culturally unresponsive educational practices.

In the context of AI in higher education, CCT will posit that students with greater access to digital resources, familiarity with institutional technologies, and higher technological literacy are likely to have an advantage in adopting and utilizing AI tools. Similarly, students with higher cultural capital are more likely to receive recognition for their abilities than peers with lower cultural capital who are equally capable (Goldthorpe, 2007; Waller, 2018). Additionally, students' perceptions of inequity related to AI may affect their willingness to engage with these technologies in academic contexts. Prior research on first-generation and transfer students indicates that these groups often experience greater isolation and receive less institutional support during the transfer process compared to other students (Mobley et al., 2013). Such challenges are frequently attributed to individual characteristics, including lower academic aspirations, inadequate academic preparation, unclear educational goals, limited social networks, and low self-efficacy (Mobley & Brawner, 2019). These factors may compound or reflect the degree of success in transitioning from high school to higher education and in establishing the necessary connections for college success. Building on this framework, the present study investigates whether students' demographic and academic characteristics are associated with differences in AI use and whether perceptions of inequity are related to reported AI usage

behaviors. This study hopes to shed light on these questions and contribute to furthering our understanding of students' perceptions regarding AI use in educational settings.

3. Methods

3.1. Data collection and sample

The data used for this study were collected via an online questionnaire hosted on Qualtrics. The main objective of this study was to capture students' and faculty's perceptions of AI use in classrooms at a university in southeastern United States. This study focuses primarily on students' perceptions as they are a significant yet understudied stakeholder in the current debate about AI. The authors used perception-based measures to better understand how students from different backgrounds and experiences utilize AI and interpret their knowledge about AI in the educational setting. The use of perception-based measures in research is a common practice (e.g., Fošner, 2024; Jeffrey, 2020).

Consistent with CCT (Robbins, 2004), this study includes demographic and academic characteristics such as race/ethnicity, income, first-generation status, enrollment status, and transfer status as explanatory variables because these factors may reflect unequal access to technological resources, institutional support, and digital literacy opportunities (Mobley & Brawner, 2019; Valencia, 2010). Students from historically underserved backgrounds may experience different levels of exposure to AI technologies or varying perceptions regarding the fairness and accessibility of these tools (Mobley & Brawner, 2019). Accordingly, the empirical analysis examines whether these characteristics are associated with differences in AI use and perceptions of inequity of AI use among college students.

After designing the survey, the authors pretested it with three students and one faculty member. Using the feedback from the testers, which were mostly about improving the clarity and flow of the survey, the authors improved the survey. The authors distributed the survey via social media outlets and college/department websites from February 2024 to August 2024. Prior to administering the survey, the study was approved by the Institutional Review Board (IRB) of the authors' university. After IRB approval, the survey was sent to 68,442 students and 13,000 faculty members across various departments at the university. Participants in the survey had to be 18 years or older. The survey, which took between 10 to 15 minutes, consisted of 39 questions. The questions include demographic questions about the participants' age, race, gender, and income as well as questions regarding the perceptions of AI use in classrooms, the advantages and disadvantages of AI use, and the perceptions of the ethical and privacy concerns regarding AI use. The final dataset consists of 172 student responses out of an initial 214 student responses (the authors excluded 42 incomplete student responses).

The authors used a convenience sampling technique, which is a non-random sampling technique, employed when a researcher has easy access to participants and can collect information quickly from many participants (Bobrytska et al., 2024; Golzar et al., 2022). The reasons the authors used convenience sampling was because they had easy access to the participants (the authors are affiliated with the same university as the participants), and it was relatively cheap to design and distribute the questionnaire electronically and collect information from a large number of participants. There are advantages to using convenience sampling and they include easy access to participants, affordability, and ease of use (Golzar et al., 2022). Disadvantages of convenience sampling are that it is likely to be biased, and participants might

self-select into the study, which can limit the generalizability of research findings (Bobrytska et al., 2024; Golzar et al., 2022).

AI use for classwork was measured using the following questions: *Do you use AI for class assignments?* The response options were never, sometimes, about half of the time, most of the time, and always. Perceived equity issue was measured by the following question: *Do you think the use of AI among students can lead to inequity? Inequity can mean for example, some students have access to AI, while some students do not have access to AI.* Perceived privacy issues were measured by the question; *Do you think the use of AI among students can lead to privacy issues?* For both perceived equity issue and perceived privacy issue questions, the response option was a five-point Likert scale, from definitely not to definitely no. For perceived cheating, the authors used the following question: *In general, do you consider students' use of AI for class assignments cheating?* The response options were on a five-point Likert scale, from strongly disagree to strongly agree. Using the same Likert scale, perceived moral issue was measured using the following question: *In general, do you consider students' use of AI for class assignments morally wrong?*

Table 1 presents the summary statistics for the variables used in this study. As shown in Table 1, many student respondents were undergraduates (90%) and full-time students (84%). Close to half of the students were transfer students (47%) or first-generation students (49%). Regarding racial composition, Hispanic and White students were the majority groups, making up 33% and 34% of the sample respectively, followed by Black students (16%). Asians were among the minority groups making up only 8 percent of the sample. Most respondents identified as female (73%), followed by male (23%) and non-binary (4%). In terms of income, 59 percent reported earnings under $30,000 annually, with smaller proportions in higher income brackets.

The sample is largely representative of the university's student body and the student demographic of the state it belongs to along the lines of ethnicity and undergraduate student shares. Without revealing information linkable to the university and the state, Black students, full-time students, and first-generation students were overrepresented in our sample compared to the university and state averages. While such oversampling may lead to limited generalizability of our findings, it nevertheless provides important information about specific student groups typically underreported in other studies.

Table 1. Summary statistics (*N*=172).

Variable	Mean	Standard Error	Min	Max
AI use for classwork	1.52	0.78	1	5
Perceived equity issue	3.30	1.20	1	5
Perceived privacy issue	3.44	1.11	1	5
Perceived cheating	3.03	1.41	1	5
Perceived moral issue	2.78	1.41	1	5
Undergraduate	0.90	0.31	0	1
Full-time	0.84	0.36	0	1
Transfer	0.47	0.50	0	1
First generation	0.49	0.50	0	1
Asian	0.08	0.27	0	1
Black	0.16	0.36	0	1
Hispanic	0.33	0.47	0	1

Mixed race	0.06	0.23	0	1
White	0.34	0.47	0	1
Race unknown	0.03	0.18	0	1
Female	0.73	0.45	0	1
Male	0.23	0.42	0	1
Non-binary gender	0.04	0.20	0	1
Income under $30,000	0.59	0.49	0	1
Income $30,000-$49,999	0.20	0.40	0	1
Income $49,999-$74,999	0.09	0.29	0	1
Income $75,000-$99,999	0.04	0.20	0	1
Income $100,000-$149,999	0.05	0.22	0	1

3.2. Analytical methods and variable constructions

To answer the research questions regarding the extent of AI use and potential disparity across student groups, the authors focus on specific questions from the survey. Questions such as whether students believe that AI will lead to potential inequity or whether AI will lead to privacy issues reveal students' perceptions around AI use. The authors also look at students' self-reported use of AI as a measure of academic behavior. To paint a more nuanced picture of AI use, the authors provide a breakdown based on the reported purpose of its use. Students may use AI in class assignments to: (1) conduct research on a topic; (2) write a paper; (3) check for plagiarism; (4) figure out solutions to a problem; or (5) fix grammatical errors. These categories follow but also advance Brown et al.'s (2025) categorization of AI use in idea generation, concept explanation, and text editing.

To draw the relationship between AI use and AI perception, the authors regress AI use on the perceptions regarding potential issues surrounding AI, and a set of demographic and student variables as controls. Because AI use is coded as a frequency measure on a 1-5 Likert scale with 1 representing never using AI for schoolwork and 5 representing always using AI for schoolwork, the authors use an ordered logistic model rather than Ordinary Least Squares (OLS) to estimate the outcomes. Ordered logit is used when the dependent variable exhibits a categorical order in its values. Traditional OLSs are not suitable in this case because they require the dependent variable to be continuous with equal distancing between each of its values, and yet our categorical AI use variable cannot be interpreted as having equal distances between its values (Wooldridge, 2010). Instead, the ordered logit model assumes that beneath the categories of the values, there is a continuous scale, and hence estimates the relationship between the independent variables and the latent, underlying contiuous variable. It also sets invisible "cut-off" lines on this latent variable and looks at where the predicted values land in relation to these lines. Ordered logit coefficients therefore describe how much the changes in the predictor variables push the outcome variable to cross the threshold into the next category. They can be interpreted as the changes in the odds of being in a higher versus a lower category of the outcome variable, given a one-unit change in a predictor.

Sometimes respondents may use AI for specific purposes or under certain circumstances. Therefore, the authors constructed five dummy dichotomous variables to indicate if a specific reason was cited by the students as among their top three purposes of using AI for assignments. Once a reason was indicated by a student, the authors assigned a value of 1 to that variable and 0

otherwise. Because the dependent variable is a set of dichotomous variables, which OLS models are not suited for, the authors used logistic models to estimate the associations between the same sets of predictors and each of the five dummy dependent variables.

4. Results

To answer the first research question about the extent of students' use of AI, Table 1 presents summary statistics for the key variables used in this study. The outcome variable is students' use of AI technology for their schoolwork. The authors include students' perceptions related to AI use, particularly on equity, privacy, and moral issues, as well as their student information and demographic characteristics. On average, students report low use of AI for schoolwork, with a mean of 1.52 (standard deviation (SD)=0.78) on a 1-5 scale (1=never; 5= always). Regarding the perceptions of AI-related issues, students are generally more varied in their answers. On a five-point scale (1=Definitely not; 5=Definitely yes), students reported a mean of 3.30 (SD=1.20) for agreement with the statement on whether the use of AI will lead to inequity, a mean of 3.44 (SD=1.11) for the statement on whether it will lead to privacy issue, and 3.03 (SD=1.41) for the statement on whether it will lead to cheating, followed by a mean of 2.78 (SD=1.41) for the statement on whether it will lead to moral concerns.

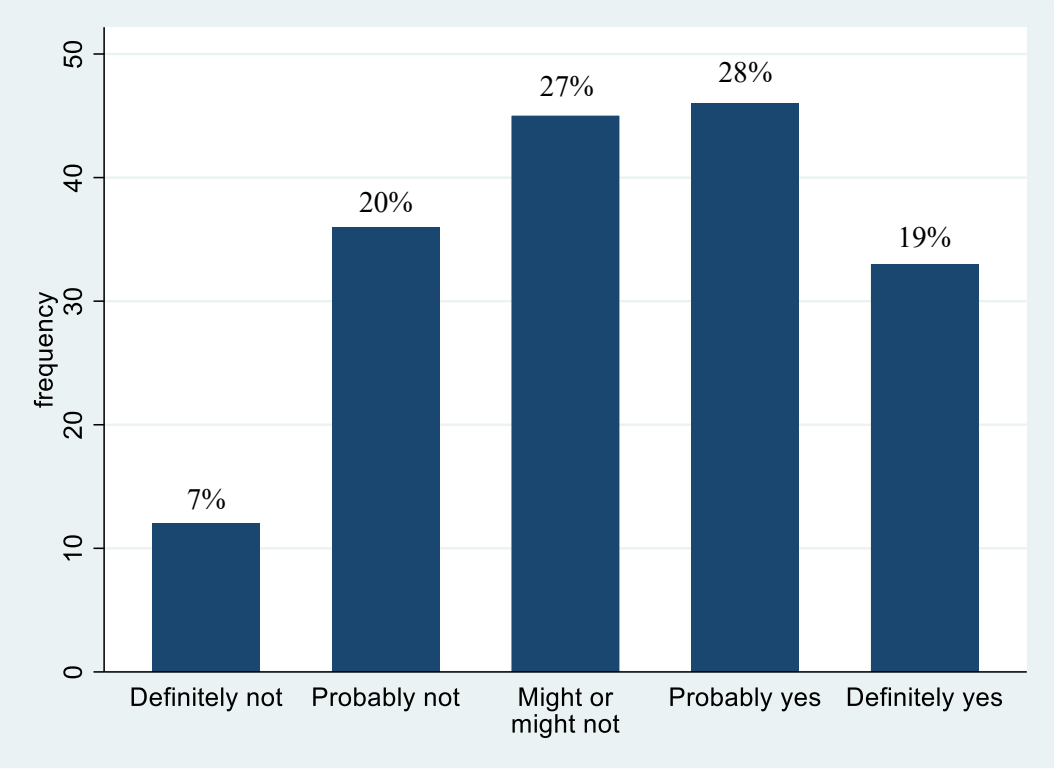

Figure 1. Frequency distribution of students' perceived AI use as it relates to equity issues.

Figure 1 presents the breakdown of how students perceive AI use as it relates to equity issues. Most students believed that the use of AI can lead to inequity with 28 percent answering *probably yes* and 19 percent answering *definitely yes*. Another 27 percent believed it *might or*

might not lead to inequity. When asked about whether they ever used AI for class assignments, according to Figure 2, most of the students responded *never* (60%), followed by *sometimes* (31%) and (5%). Overall, students tended to report little AI use for schoolwork.

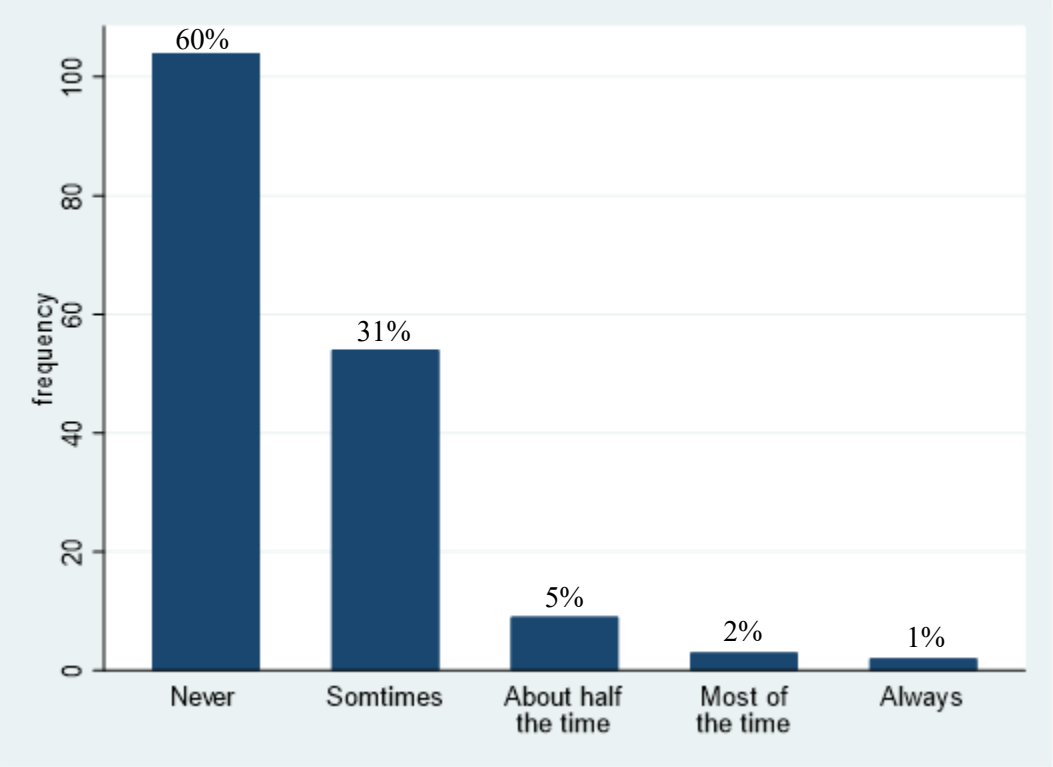

Figure 2. Frequency distribution of AI use for class assignments.

To answer the second research question—the relationship between the use of AI and perceptions of inequity of AI and the third research question—whether inequity consideration of AI use vary by demographic characteristics, the authors ran ordered logit for the overall AI use among students with different demographic characteristics, alongside the equity perception variable as the key explanatory variable. Table 2 reports the odds ratios, which were transformed from log odds for ease of interpretation. An odds ratio over 1 indicates a higher likelihood of crossing to a higher category of values in the AI use (on a scale 1-5) given a one-unit increase in each explanatory variable, and an odds ratio below 1 indicates a lower likelihood of crossing to a higher level of outcome values from a lower level.

The results show that being an undergraduate student, full-time student, transfer student, or female is associated with a higher chance of reporting higher levels of AI use. Compared to White students, all other racial/ethnic groups reported less AI use. Students making less than $100,000 annually reported using AI less frequently than those making between $100,000 and $150,000. However, none of these differences were statistically significant. Therefore, the authors found no meaningful disparities in AI use for class assignments based on students' demographic or academic characteristics. However, the relationship between perceived inequity and AI use is statistically significant at the $p < 0.1$ level. For each one-unit increase in a students'

perception that AI creates inequity, the odds of that student reporting AI use for class assignments decrease by 23 percent (OR = 0.77), suggesting that students who view AI as an unfair advantage are meaningfully less likely to use it.

Table 2. Ordered logit (odds ratio) estimates for AI usage for homework and perceived inequity of AI among college students.

	Odds Ratio (OR)	**Standard Error**	***p*-value**
Perceived Inequity	0.77*	0.11	0.06
Undergraduate	1.91	1.21	0.31
Full-time	1.89	0.98	0.22
Transfer	1.33	0.47	0.42
First generation	0.94	0.32	0.85
Race (reference = white)			
Asian	0.85	0.52	0.80
Hispanic	0.80	0.31	0.57
Black	0.44	0.23	0.12
Mixed race	0.28	0.24	0.15
Race unknown	0.50	0.46	0.45
Female	1.19	0.47	0.67
Non-binary gender	0.39	0.47	0.43
Income (reference = $100,000 - $149,999)			
Income under $30,000	0.48	0.32	0.28
Income $30,000-$49,999	0.62	0.44	0.50
Income $49,999-$74,999	0.29	0.25	0.16
Income $75,000-$99,999	0.41	0.43	0.39
N	172		
Pseudo R-squared	0.0469		

Note: Results are presented in odds ratios. *$p<0.10$. **$p<0.05$. ***$p<0.01$.

Finally, the authors examined AI use by specific purpose, running separate logistic regression models for five dichotomous outcomes—using AI for paper writing, generating research ideas, checking for plagiarism, finding solutions, and checking grammar. For each outcome, a baseline model included only perceived inequity as the explanatory variable (M1), followed by a second model that added demographic variables (M2).

In Table 3, the authors present the result of the logit estimates for specific AI usage for homework and perceived inequity of AI among college students. Results from Table 3 show that, in the baseline models (M1), higher levels of perceived inequity of AI are associated with less use of AI for research ideas and for grammar check at the $p < 0.1$ level. A one-unit increase in perceived inequity corresponded to a 21 percent decrease in the odds of using AI to generate research ideas (OR = 0.79) and a 24 percent decrease in the odds of using AI for grammatical assistance (OR = 0.76). However, these associations became statistically insignificant once demographic controls were added in M2. This suggests that the initial associations could be partially explained by underlying differences in students' backgrounds.

Table 3. Logit (odds ratio) estimates for specific AI usage for homework and perceived inequity of AI among college students.

	AI use for paper writing		**AI use for research ideas**		**AI use for plagiarism check**		**AI use for solution**		**AI use for grammar**	
	(M1)	**(M2)**	**(M1)**	**(M2)**	**(M1)**	**(M2)**	**(M1)**	**(M2)**	**(M1)**	**(M2)**
Perceived Inequity	0.79	0.71	0.79*	0.80	0.85	0.82	0.89	1.00	0.76*	0.75
Other demographic controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R-squared	0.012	0.068	0.014	0.090	0.010	0.080	0.003	0.115	0.017	0.076

Note: Results are presented in odds ratios. *p<0.10. **p<0.05. ***p<0.01.

5. Discussion

The goal of the study is to answer the following research questions. 1) To what extent do students use AI? 2) What is the relationship between the usage of AI and the perceptions of inequity of AI? 3) Do inequity considerations of AI use vary by demographic characteristics? In this section, the authors discuss the findings according to these three research questions. The results regarding the extent to which students use AI indicate that students on average reported a low use of AI (1.5 on a scale of 1-5). Similarly, most of the students said they have never used AI for class assignments (60%), while the rest of the students reported using AI for class assignments to varying degrees. This finding is not in line with research that indicates increased use of AI among students. For example, the study by Vilcarino & Langreo (2025) found that 86% of students use AI during the 2024-25 school year. Similarly, Rex (2023) reported that 56 percent college students use AI to accomplish their tasks. The reason for the low use of AI in this study may be because 47 percent of the students surveyed expressed some concern about AI leading to inequity issues.

Students reported a moderate concern over whether the use of AI will lead to inequity (3.3 on a scale of 5). Looking at the breakdown of the Likert scale responses, 47 percent of students responded with certainty that AI can lead to inequity, while 27 percent said AI use will not lead to inequity. The ordered logit result (Table 2) suggests that students' perception about AI leading to inequity increases is negatively associated with their use of AI for class assignments. This finding is in line with the argument of Lee et al. (2025) of a growing concern about AI leading to inequity and having detrimental effects on students. For example, inequity in educational settings has been found to reduce motivation and engagement among students (Altugan, 2015). The Logit results (Table 3) shed light on what students are using AI for. The results indicate that students with higher levels of perceived inequity of AI reported less use of AI for generating research ideas and for checking grammar. Although, these associations become statistically insignificant after controlling for students' demographics.

The results indicate that undergraduate students, full-time students, transfer students, and female students are more likely to use AI. When compared to White students, all other racial/ethnic student groups reported using AI less. Moreover, students making less than $100,000 tend to use less AI compared to students making between $100,000 and $150,000

annually. However, none of these associations are statistically significant, indicating little variation in AI use among student demographic groups. These results are somewhat encouraging in the sense that the demographic and culturally minority groups are not at a significant disadvantage compared to the dominant group when it comes to AI use. This finding may underlie a phenomenon where AI is becoming a prevalent tool in higher education that cuts across all groups.

Without concrete empirical evidence to state definitively, the potentially equalizing force of AI application could be attributed to a few reasons. First, the marginalized social groups are catching up with the dominant groups in their technological knowledge, skills, and competencies either through exposure to technology in primary and secondary education settings or socialization with their peers, demonstrating their strong self-efficacy. Second, the respondents in the sample may represent a specific group, consisting of individuals with academic competencies who self-select into pursuing higher education. Thus, although some may come from cultural minority groups, they are not representative of the group they come from. Third, higher education administrators in the institution where the survey was conducted have served as gap-bridging agents and equity-focused leaders by critically evaluating and implementing AI application and integrating AI in their curricula, pedagogical trainings, and student support programs, addressing the importance of cultural capital in students' college experience. Future research can delve deeper and discern the driving forces behind the data patterns observed.

6. Conclusion

The goal of the study is to answer the following research questions. 1) To what extent do students use AI? 2) What is the relationship between the usage of AI and the perceptions of inequity of AI? 3) Do inequity considerations of AI use vary by demographic characteristics? The results indicate that AI use among the students surveyed is low. Students also reported that there is inequity in the use of AI. The authors fail to find a significant relationship between AI use and demographic characteristics of students.

With regard to the finding of inequity in AI usage, it is important for policymakers to develop guidelines to ensure that all students have equal access to AI-based tools, especially for underserved and marginalized student populations (Basham et al., 2020; Garcia Ramos & Towns, 2023). When implemented intentionally and with a commitment to equity, AI has the potential to democratize access to high-quality educational experiences and support the success of every learner. Although our findings indicate some early signs of success in equitable incorporation of AI into educational settings, the evidence comes from one single higher education institution, which may not be generalized to other institutions. Also, what matters more is beyond just the use of AI. Equitable access to digital tools is better perceived as a means to an end. In the context of AI use in student learning, more equitable learning outcomes across demographic groups are what policymakers and administrators need to pay optimal attention to.

This study has some limitations that are worth mentioning. First, the sample was collected via convenience sampling, which limits our ability to generalize the findings. The implication of the lack of external validity is that the findings cannot be applied to other universities because the sample is not representative of the broader student population in the United States. Hence, there is a need for future researchers to use random sampling for data collection to avoid issues related to external validity. Second, the small sample size can also lead to the same issue of generalizability. Future research should consider collecting large samples.

Third, this study is based on perceptions and as a result, may not yield accurate results (Sadiq & Graham, 2016). Future research should consider using objective measures of inequity if available. All these limitations may threaten both the external and internal validity of our results, indicating that our findings only reveal associations between traits and academic behaviors among a specific group of students and should be treated with care when generalized to any broader population. Despite these limitations, this study provides important and useful insights on the relationship between AI use and inequity among our sampled college students.

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