Undergraduate Students' Appraisals and Rationales of AI Fairness in Higher Education

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Abstract

To measure learning with AI, students must be afforded opportunities to use AI consistently across courses. Our interview study of 36 undergraduates revealed that students make independent appraisals of *AI fairness* amid school policies and use AI inconsistently on school assignments. We discuss tensions for measurement raised from students' responses.

1 Introduction

Proficiency with AI tools, particularly generative AI (GenAI), is becoming necessary for job market candidates (Bowen & Watson, 2024; Microsoft, 2024). To develop proficiency, students must be afforded continuous opportunities to learn how to use AI in ways that augment (rather than stymie) their learning and reflect competencies desired in the modern workforce. Some universities have approached this demand by becoming *AI-native*: giving each student access to a chatbot and encouraging AI use (Singer, 2025). AI nativity implies a vision of policy coherence; that students and instructors alike will use AI tools in complementary ways that foster rich, flexible modes of learning, do not undermine each other's goals, and offer consistent ways to measure learning as it relates to students' assessments (and ultimately, the value of their degrees).

This paper contributes a depiction of ethical questions and tensions that arise when various actors within higher education have inconsistent visions of AI in education, and thus, develop diverging ideas about fairness and academic integrity. Drawing from a subset of interview data featuring undergraduate students' uses of AI in problem solving, we found that the vast majority of students believed that fair AI use in school coursework depended on a number of factors, many of which pointed to conceptions of cheating that have become hard to measure when AI is integrated inconsistently into coursework (Lee et al., 2024). Their confusions may create tensions for instructors, who have their own visions of how AI should be used on assignments, and for school administrators, who may expect that students take up AI tools for career and workforce development.

As issues of AI use in decentralized (Weick, 1976) university systems continue to surface (Dabis & Csáki, 2024; Goodier, 2025), we urge educators to pause and consider how such tools force students to reconfigure their judgments of what is fair and how learning is measured. These inconsistencies matter in educational measurement, as how students demonstrate learning on school assignments is in part a function of the tools that they use (Engeström, 2014). We explore these issues and answer:

RQ1: To what extent do students appraise AI use on school assignments as "fair"?

RQ2: What rationales do students give to justify whether AI use on school assignments is fair?

2 Background and Related Work

2.1 AI and Higher Education

The advent of GenAI chatbots (ChatGPT, Gemini, Claude), stirred mixed reactions in higher education. While some institutions initially sought to regulate or ban student access, others encouraged AI for teaching and learning (An et al., 2025). Nonetheless, trends suggest growing employer interest in hiring AI-literate workers (Microsoft, 2024), adding pressure on universities to equip students with AI knowledge and experience that aligns with workforce demand.

To address these demands, many institutions, including the Universities of Oxford, Arizona, Maryland, and Texas at Austin, as well as the entire California State University system (OpenAI, 2024;

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CSU, n.d.), have rolled out agreements with OpenAI to provide both students and employees with the advanced capabilities of ChatGPT Edu, implying usage expectations. However, there seems to be no agreement on productive use of AI.

McDonald et al. (2025) analyzed AI policies published by 116 US universities. They found that, while most (N=73, 63%) universities provided guidance for classroom use, encouraging adoption, guidance often focused on writing activities. Students and instructors within STEM fields, therefore, faced absent or vague recommendations at best. These policy inconsistencies may introduce wide variability in GenAI use among both instructors and students across disciplines, raising questions about fairness and educational value.

2.2 AI and Ethics in Higher Education

Although the surge of AI prompted discussions around transparency in data processing, hallucination-induced misinformation, academic fraud, and algorithmic bias (Memarian & Doleck, 2023; Pérez & Mattison, 2025; Zheng, 2024), institutions have yet to directly address the equally important issue of AI fairness. By *AI fairness*, we mean students' abilities to access AI, use it skillfully, and obtain outcomes that reflect their skill (Wang et al., 2024, p. 3). Wang and colleagues describe first, second, and third-order AI-divides that could result if components of their fairness definition are unmet. As students gain widespread access to AI tools, whether it be through personal accounts or institutional licenses, scholars must expand ethical discussion on what constitutes fair and appropriate use among students.

Ethical discussions about fair AI use in education are particularly consequential in cases where instructors integrate AI into their courses differently (Delaney et al., 2025). Some courses may intentionally integrate tools, such as discussion platform PackBack (Lantz et al., 2022), directly into student dashboards. Such tools provide structured opportunities to engage with AI in ways that support writing, self-reflection, and learning. In these cases, AI use is normalized as part of the learning environment. By extension, AI use across students is likely to exhibit less variation (in frequency and types of use) in AI-integrated courses than courses which have AI policies but do not incorporate AI tools directly. These courses may leave decisions about its use to instructor discretion. As a result, students may shoulder a larger ethical burden in courses where the teachers' policies conflict with their own beliefs, values, and ideals about the purpose of higher education.

Instructors for these courses may include AI-use statements in their syllabi either disallowing it or asking students to disclose when and how they use AI tools. Alternatively, an instructor may simply ignore AI, leaving the decision up to students' own judgement. In either case, AI use in such courses is unregulated, unobserved, and often undetectable (Ardito, 2024). This brings up questions about equitable awareness and AI skill development among students (Arum et al., 2025) but also leaves deeper issues of fairness unresolved.

Furthermore, this variation raises ethical questions about institutional consistency and how institutional AI-integration goals may infringe upon instructors' individual pedagogical values or beliefs about how these tools should or should not be used. When AI policies are lacking or unclear, students, instructors, and institutional leaders may hold contradicting views of what ethical use looks like. Moreover, instructors may unintentionally develop inconsistent rules or expectations for AI use among students, further complicating student beliefs about fairness.

Inconsistent AI policies among instructors and AI uses by students complicate measurement and assessment. If, for instance, half of the students in a writing course use an AI chatbot for their final essay, and half do not, scoring the final essay will become internally inconsistent, because it is likely unclear from the grader's perspective (1) who used AI and (2) to what extent and for what purpose users leveraged AI toward the final essay. For half the class, grades are a measurement of knowledge applied and distilled in the essay, and for the other half, grades are a partial measurement of learning and partial measurement of AI savviness. Thus, inconsistent AI policies increase threats to validity and assessment measurement precision (Zheng et al., 2025), and are worth examining in more detail.

3 Methods

3.1 Research Context and Participants

This study was conducted at a large university that serves mostly undergraduate students in the U.S. The university purchased chatbot subscriptions for all students and faculty. Faculty were encouraged to create their own AI course policies and syllabus statements that detailed if and how AI should be

used in their courses. Instructors were given flexibility to design AI policies as they pleased and ban AI use if they deemed appropriate.

We recruited 36 undergraduate students from various majors to study AI use during problem solving tasks. We hung flyers around campus in publicly-available locations, solicited open participation calls through email, and encouraged students to sign up using a QR code. The analysis we present in this paper emerged when variations of students' conceptions of AI fairness on school assignments during the study pre-interview arose with a higher frequency than we had anticipated.

3.2 Study Design and Data Collection

We focus on one subcomponent of a larger clinical interview study (diSessa, 2007) that explored how undergraduates used AI while problem solving. We first interviewed each student about their AI use and beliefs. To answer RQ1 and RQ2, we look at participants' responses to question six from our protocol: *"Do you think using AI on school assignments is fair?"* Importantly, members of the research team did not define fairness for the participant. Rather, we responded by deflecting the question (*"What do you think it means?")*

Our data consist of the 36 responses from participants, audiorecorded and transcribed by the research team. For anonymity, we refer to participants as P#, where # represents order (e.g., P4 was the fourth participant). In the event that the researcher did not understand the participant's initial response, or the participant did not appear to answer the question, we asked 1-2 probing questions until we understood their position. For example, P32 initially answered, *"Yeah, I'm kind of conflicted about it, because a lot of my math professors are aware of it, so they make changes."* The interviewer realized that P32 did not give an appraisal, and responded, *"Oh wow, that's interesting, but whether it's fair?"* P32 then said, *"Everyone's aware of it now, so it's becoming more fair…but if not everyone's using it, then I guess not."* We were satisfied that P32's new response gave an appraisal and moved on.

All interview recordings were autotranscribed by otter.ai. The initial error rate was around 9%, typical for recordings taken in consistent, quiet settings (Tran et al., 2023). Three members of the research team cleaned the transcripts to account for cross-talk discrepancies, speaker assignment errors, and errors that arose from abbreviations or acronyms (Matters & Shapiro, 2022).

3.3 Data Analysis

The unit of analysis encompasses students' responses to, "*Do you think using AI on school assignments is fair?",* including follow-up clarifying questions. Three researchers coded the data using an iterative process. During Phase 1, we individually coded participants' appraisals (RQ1) into "yes" "no" and "other." When meeting as a whole group to discuss coding agreements, we realized that a majority of participants did not give a clear yes/no answer. Rather, they gave some form of "it depends," and elaborated on what their appraisal depended on. During Phase 2, we re-coded the data into six appraisal categories based on what we learned in Phase 1: "yes," "yes/it depends," "it depends," "it depends/no," "no," and "unclear" (see Figure 1). We continued coding until we reached internal agreement on the definitions and codes applied (Cornish et al., 2016).

Following coding of appraisals, three researchers inductively (Saldaña, 2021) coded participant rationales (RQ2) in two rounds (Phases 3 and 4). During Phase 3, we induced rationales, converged on the definition of each, and discussed how many rationales should be assigned per participant. We concluded that some participants gave multiple, independent examples of fairness and maintained different rationales per context. For instance, P34 explained that she would not use AI to help her with math problem-solving, but would use it to help her write an essay outline. We therefore decided to apply multiple rationales per participant if the participant introduced a new context or idea and a different rationale than in a previous explanation. In Phase 4, we re-coded the data, resolving disagreements as needed and re-visiting the data to ensure internal consistency.

Figure 2 in the findings shows all appraisal codes, rationales, and code counts.

4 Results

4.1 RQ1: To what extent do students appraise AI use on school assignments as "fair?"

Figure 1 displays the distribution of AI fairness appraisals in our sample. 41.6% of participants (n = 15) responded that AI fairness depended on a number of contextual and organizational factors.

Only six students (16.7%) responded that using AI on school assignments was fair, and five students said that using AI on school assignments was not fair (13.9%). Two students (5.6%) gave unclear answers that did not contain an appraisal of fairness. We coded those instances as "unclear." P4, for instance, described AI in relationship to her ability to learn, but did not address fairness:

> *...It is kind of inevitable at this point…every student is going to be using AI…if you're not, you're just doing twice as much work as all your classmates. But…I don't think it's good. I think at the end of the day I… am glad I made it this far in my education before I was introduced [to GenAI] because if it was introduced earlier, I would never have learned how to think for myself. (P4, 10:52)*

Eight participants (22.2%) gave responses that contained multiple appraisals: they determined AI use on school assignments fell into multiple categories of "yes," "it depends," or "no." As an illustrative example, we observed P34 shift her explanation between "it depends" and "yes" as she considered the practicality of restricting AI:

> *I don't know. I use it sometimes, so I guess I should be saying fair. But I do feel guilty...Not really for math, because I'm still doing all the work. But for writing, I feel like it should be my organic thoughts. Although, at this point, now that it's so available, it's like, especially for young people, it's kind of impossible to tell them not to use it. And so, in that sense, I think a lot of teachers have to understand that they probably are going to use it, and they need to give guidelines for how to use it in a good way. (P34, 12:07)*

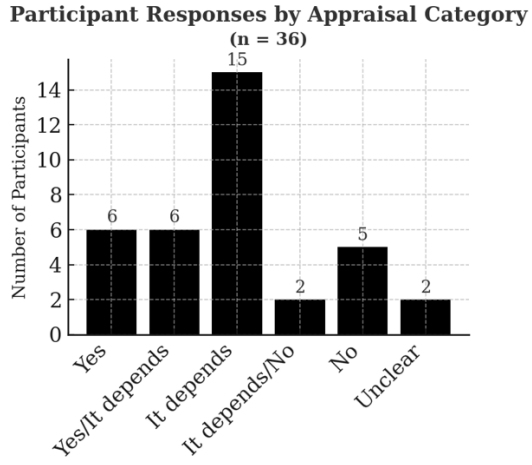

Figure 1: Distribution of undergraduate appraisals

P34, a junior-year civil engineering major, shifted from "it depends," where she reasoned that epistemic differences in school assignments influence her decision to use AI, to "yes" when thinking about the organization of technology in schools. Shifts in student appraisals of fairness suggest that (1) undergraduates may perceive fairness as a continuum between fair and not fair rather than discrete categories, and that (2) fairness appraisals can shift based on situation and context (diSessa et al., 2004).

4.2 RQ2: What rationales do students give to justify whether AI use on school assignments is fair?

Figure 2 shows students' AI fairness appraisals in relation to their rationales. Students asserted "yes," it is fair to use AI, for tutoring (n=2, 5.6%) or learning (n=1, 2.8%), and justified their beliefs by pointing to the ubiquity of AI (n=6, 16.7%) and the endorsement of AI by their institution (n=2, 5.6%). Additionally, some (n=3, 8.3%) expressed confidence that the designs of courses (e.g., in-class assessments, presentations, and projects) would assess students fairly, because assessments are conducted separately from homework assignments. P12 articulated:

> *My friends that were using [AI] were getting such good grades, but they weren't learning anything, or doing [homework] themselves. But when it came to the test, they were doing worse, and I was doing better…So I don't really think it's unfair anymore. (P12, 9:15)*

Students who believed that using AI on school assignments was unfair described issues of unequal access, either between students in their own courses (n=4, 11.1%) or compared to students in previous generations (n=2, 5.6%). Only one student reasoned that AI use was unfair because it hindered learning: *"I wouldn't say it's fair because then everybody's just going to copy paste what's in AI...and not use their mind."* (P18, 14:04). This student indicated earlier in the interview that she participated in higher education before AI (since 2017). It is possible that she compared AI use at present to her experience in 2017, before chatbots.

Most (94%, n=34) participants gave at least one rationale in the "it depends" category, suggesting that judgements of fairness depend on multiple factors including purpose of use, course instruction, and capabilities of free chatbots. Participant P28 offered: *"I would [not say using AI on school assignments is fair] because you get a limited amount of data use, like a phone plan."*

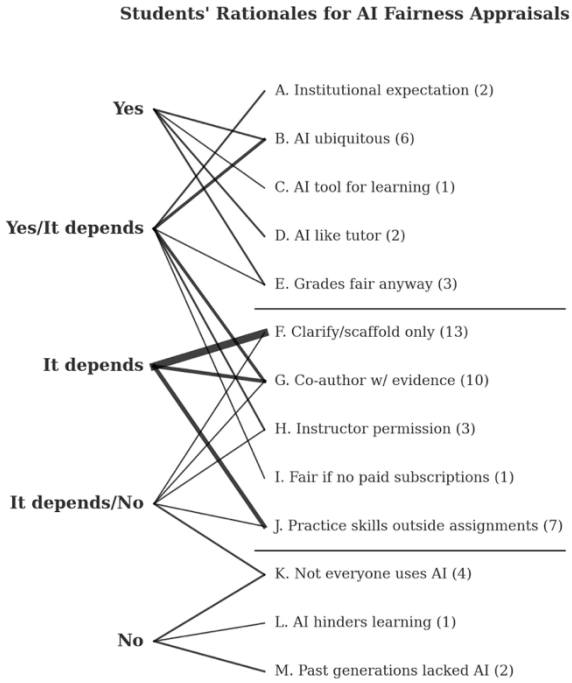

Figure 2: Distribution of rationales for AI fairness

Participants who said "it depends" cited socio-technical tensions in their courses. The first is about when AI is allowed to be used as a tutor: for practicing skills (e.g., learning a foreign language by conversing with AI) versus for tutoring on the content of graded assignments. P26 explained:

> *I think [using AI is] fair to a point where…new topics are introduced…My professor likes to put new topic questions on my homework. Which makes it difficult, because I don't know what's happening ...But personally, I don't really like [AI] too much. Especially writing...teachers say that it removes your voice… I would rather get docked the points.*

A second tension we observed is uncertainty about what forms of assistance AI should give on graded course assignments. Students' descriptions can be categorized by: (1) AI as a clarifier or scaffolder; (2) AI for overcoming impasses (3) AI as a deliverable co-author, and (4) AI as a personal tutor for anything unless their teacher specified a policy otherwise. We give illustrative examples:

> *When you're writing, some people will go give me ideas for writing a thesis on why recycling is bad. And [AI can] give you a couple ideas. And then you can write your own thesis based on some of the ideas or the wording or using it to check for grammar. (P5, a math teaching major, on scaffolding)*

> *I think if you're given a problem set… if you're stuck on a problem, then it's very helpful and I think it's valid to use. But I think if you're using it to write your whole…code program for you, then…it's like, defeating the purpose of learning. (P13, a computer science major, on overcoming an impasse)*

> *What I'll do is write an essay on my own, and then I'll ask [AI] to revise it and make it flow nicely…and make it sound more professional. And I think that's 100% fair. Like, I'd be scared of just putting in the prompt and being like, write an entire essay. But…if you can...make it your own words, then I think that's fair enough. (P11, a marketing major, on AI co-authoring)*

> *It depends how it's used. If the students aren't grasping the information, it's not really helping them in any way. But if it's in a way where they're...using it as a personal tutor, that would be fair. (P8, an engineering major, on AI as a tutor)*

Finally, some participants wished for instructors to clarify expectations on AI use in relation to academic integrity, even in light of a university-wide policy: "*tell the students what they expect to see in the class…if they don't want to see AI use, they should tell the students that."* However, this same participant later acknowledged that even given clear expectations, some students may not adhere to AI classroom policies: "*it's becoming such a powerful resource that students are going to use it regardless of what a professor says…we should try to incorporate it into classrooms and use it as a good resource. Not trying to ban it, because I don't think that's going to work*." His sentiments seem to reflect university-wide AI integration goals which encourage students and instructors alike to engage with AI for academic work.

5 Discussion

After studying 36 undergraduate students' appraisals and rationales for AI fairness on school assignments, we found a broad range of opinions, use cases, and ethical considerations that formed the foundations of students' judgments. Most were unsure if they should use AI on school assignments and varied in the socio-technical decision parameters they drew from when deciding when and how they would use AI. Although some expressed a desire for guidance from their instructors about what to do, others made determinations based on internal factors, such as whether they personally believed AI would help them learn, or how accessible AI chatbots are becoming as a publicly consumable resource. We

hypothesize that AI policy misalignments between the university and individual instructors may have caused students to become confused about AI fairness because they needed to navigate each course policy on a case-by-case basis.

Beyond AI policies, many students in our study drew from their own interpretations of fairness. Their appraisals did not draw from ethical considerations raised about AI by academia (e.g., model bias, data privacy, and data security), but rather their personal beliefs about whether AI tools helped them learn and the appropriateness of using novel technologies to "do school" (Pope, 2001). This suggests that in the wake of a decentralized university-wide policy stance on AI use in school, most students will do what "feels right" to them. This implies that while some students will not use AI at all, some may use it for everything, and some will make independent determinations based on a number of contextual factors (that should be studied in more detail in the future).

"Choose-your-own-adventure"-style AI fairness appraisals made by the undergraduates in our sample have implications for measurement and assessment. Particularly in courses with large student enrollments, instructors do not have time to peruse individual assessments and evaluate if and how AI was used. They likely do not have the resources to evaluate if students who use AI to complete course assessments score differently than students who do not. This implies, on the extreme end, threats to assessment precision and validity (Zheng et al., 2025). That is, a student who uses AI to complete an assessment from end-to-end could receive a better grade than a student who took time to learn the material but did not show mastery on the same assessment. In this case, the knowledge and skill gained (*purpose of learning*) by human students is measured unfairly against the perceived quality of a submitted deliverable (*purpose of work*) by a human extracting information from a large language model trained on most of the corpus of written human texts. Furthermore, if undergraduates can and do complete assessments programs with AI chatbots, it raises questions about the value and purpose of college degrees.

5.1 Limitations

Our study is limited in several ways. First, the broader purpose of our research was not to study fairness in a large population of students. As such, the deductive coding used reflects our intersubjective agreement (Krippendorff, 2018) on fairness in a small sample. Our aim was to illustrate through student narratives what fairness with AI looked like rather than to make claims about statistical power and generalizability (our study has neither of those elements). Nonetheless, larger samples and surveys with statistically validated constructs should be used to study how AI is appraised writ large (e.g., Paik et al., 2025).

Another limitation is that the question, "*Do you think AI use on school assignments is fair?"* was placed sixth in our interview protocol. Participants' answers to the preceding five questions could have influenced their appraisal (diSessa et al., 2004). We asked the first five questions to gain a baseline of students' AI beliefs and uses (e.g., question 1, "*How do you approach problem solving?*"; question 3, "*How, if at all, do you use AI with problem solving?*"). However, sometimes students gave off-topic responses that broached fairness. It is possible that these answers cued *a priori* conceptions of fairness that influenced the answer to the question that we ultimately studied.

5.2 Concluding Recommendations

While AI tools will continue to (rapidly) evolve and pose uncomfortable questions about the nature and fairness of learning, we put forth recommendations from our study. First, universities and instructors should have aligned AI use policies. This stands in opposition to policy flexibility recommended by An and colleagues (2025), and we acknowledge that faculty autonomy will make this difficult to achieve in practice, but our findings show that students rely on internal decision factors in absence of consistent guidance. Second, we recommend that instructors approach every course assessment with the perspective that at least one student will use AI, and ask themselves, "*Will students still achieve my desired learning outcomes with AI? Will their grades fairly reflect the desired learning outcomes?*" If not, they should consider redesigning their curriculum and assessments (Xie et al., 2024). Finally, we recommend that adults working at universities guide students to reflect on and assess their learning in a world with AI.

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