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# Generative AI in Higher Education: Uncertain Students, Ambiguous Use Cases, and Mercenary Perspectives

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## Abstract

**Background:** Students in higher education are using generative artificial intelligence (AI) despite mixed messages and contradictory policies.
**Objective:** This study helps answer outstanding questions about many aspects of AI in higher education: familiarity, usage, perceptions of peers, ethical/social views, and AI grading.
**Method:** I surveyed 733 undergraduates.
**Results:** Students reported mixed levels of experience with AI and tended toward nervousness over excitement. Most reported professors addressing AI but not integrating it. While 41% of students had used AI in ways explicitly banned, many more students (59%) reported ambiguous use cases. Students overestimated peer cheating, and this predicted their own cheating, as did general experience with and excitement about AI. Meanwhile, 11% of students reported false accusations, with first-generation students possibly at a higher rate. Pragmatic views about career and inequality may be affecting behaviors. Men consistently reported more involvement with AI than women.
**Conclusion:** Future research should focus on the hybrid collaboration of humans and AI and how AI might be leveraged to support and scaffold genuine learning.
**Teaching Implications:** AI will be relevant to many future careers, and students increasingly want it to be part of their education. Academic integrity will be a continuing challenge, and students need transparency.

## Keywords

artificial intelligence, generative AI, academic integrity, false accusations, detection, bias, ethics, inequality, workforce, educational technology

Imagine being a college student on your first day of a new semester. One professor says that using generative artificial intelligence (AI) is cheating, while the next says you will be using it extensively in the course, and yet another does not mention it. You are told you will be punished if an AI detector classifies your assessments as AI-generated. Some professors encourage you to use a grammar app to improve your writing, but others tell you that doing so counts as cheating. At home, one parent worries AI will atrophy your brain and abilities, while the other tells you that you need to learn prompt engineering to have any hope of landing a job in the new AI-infused economy. Pundits in the media say AI makes college obsolete, social media influencers advertise apps that can complete all your papers and online tests, and meanwhile some of your friends are showing off creative applications of AI for fun while others say AI will destroy the world. If you were a college student, you would probably find yourself confused, perhaps excited or nervous about this new technology, and likely unsure of where it fits in your future.

Generative AI is not new, but recent progress in transformer-based neural networks has produced large language models (LLMs) which—with significant reinforcement learning from human feedback—can be interacted with in a natural language context (e.g., chatbots) in a way that produces output at least superficially like human-written text (Abd-Elaal et al., 2022; Herbold et al., 2023). OpenAI's ChatGPT, for example, was made widely available in November 2022 and was labeled the fastest-growing consumer application in history (Hu, 2023; OpenAI, 2024a). Other LLMs—like Google's Gemini and Microsoft's Copilot—are becoming integrated into common office applications (Google, 2024; Microsoft, 2024). Meanwhile other writing, productivity, and "studying" services like Grammarly and Chegg are integrating these companies' models into their services, meaning these LLMs are becoming ubiquitous in students' lives (Melendez, 2024; Ortiz, 2023). Even social media applications like Snapchat, Instagram, and Facebook incorporate AI-powered chatbots (Duffy, 2024; Ortutay, 2024).

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So, how extensively are college students using AI at this point? It is hard to get exact data because the landscape is constantly changing and because students may not be aware of what counts as AI (e.g., some students have felt unfairly accused of cheating after using AI-powered Grammarly; Young, 2024). At the very least, the use of AI in higher education is proliferating. One national survey of U.S. college students in the Spring of 2024 found that 59% of students are regular users of AI, 17% have tried it, and 23% have never used it; this is up from Spring 2023 when those numbers were 43%, 26%, and 31% respectively (Bharadwaj et al., 2024).

In mid-2023, a U.S.-wide survey of high school students found that around half of them had used AI, and around half of those had used it for school assignments (Schiel et al., 2023). Collapsing across teens and young adults, another nationally representative survey in late 2023 found 51% of people 14–22 had used AI at some point, with 46% saying they used it to help with schoolwork (Common Sense Media, 2024). According to another extensive survey in early 2024, 69% of college-bound high school seniors had used AI, with 35% having used it for schoolwork; 26% admitted using it to "do" their work (e.g., writing essays, completing assignments), with 10% instead using it to "support" their work (Goebel et al., 2024).

Students lead instructors in the adoption of AI. For example, in a Spring 2024 survey, only 36% of instructors were regular users, 29% had tried it, and 36% had never used it (Bharadwaj et al., 2024). Furthermore, 44% of undergraduate students were paid users, while only 13% of instructors were, meaning students may be more aware than instructors of what frontier AI models can do. In the same survey, instructors who used AI regularly leaned toward believing AI would positively impact student learning, while nonusers leaned toward foreseeing a negative impact. For professional development, instructors report many fewer training opportunities related to integrating AI than training related to policy and academic integrity (e.g., detection, punishment); 39% of instructors reported no AI training. Very few professors seem to be integrating AI directly into their classes (e.g., only 18% of the AI-aware instructors in this survey encouraged AI usage).

It is easy to see the potential benefits of AI usage. For example, it could provide individualized instruction and tutoring, summarize and synthesize research, save instructors prep time (e.g., generating a bank of practice questions), and prepare students for an AI-enhanced workforce (Bond et al., 2024; Capraro et al., 2024; Cotton et al., 2023; Kasneci et al., 2023). The American Psychological Association's Guidelines for the Undergraduate Major recognize workforce preparation as a guiding principle and learning technological skills as a goal; teaching appropriate and ethical use of technology like AI can ensure students graduate with appropriate competencies (e.g., Goal 3.1, Goal 4.4; American Psychological Association, 2023). Additionally, neurodiverse students may find LLMs helpful support (Jang et al., 2024), and English as a Second Language (ESL) students may benefit from AI (Perkins, 2023; Warschauer et al., 2023).

However, alongside the benefits, many have pointed out potential downsides of AI in higher education, including issues of academic integrity, inequity of access and use, and algorithmic biases, as well as other social and ethical implications (Capraro et al., 2024; Cotton et al., 2023; Perkins, 2023; Rudolph et al., 2023). Academic integrity has received much attention as studies have shown that humans perform rather poorly at detecting AI-generated writing even when generated by early models (Clark et al., 2021; Liu et al., 2023; Shear et al., 2023); this held even when assisted by software like Turnitin's detection tool (Chaka, 2024; Perkins et al., 2023).

Indeed, there is reason to be skeptical that automated detection of AI-generated writing will be the answer when human detection is unreliable. For example, Sadasivan et al. (2024) demonstrate that even state-of-the-art automated detectors can be defeated with an automated paraphrasing attack, making it simple for machine-generated writing to pass as human-generated. False positives are more problematic, possibly leading to academic integrity processes that significantly undermine trust between students and their instructors or institution (Gegg-Harrison & Quarterman, 2024; Gorichanaz, 2023; Weber-Wulff et al., 2023).

Unfortunately, false positives may not happen to all students equally. Liang et al. (2023) found that automated detectors had a significantly higher false positive rate for ESL writers. The authors speculate about possible reasons (e.g., ESL speakers writing with less "perplexity"; i.e., less lexical richness and less complex syntax), though it could also be that the bias comes from imbalanced training sets (e.g., fewer ESL writing samples in the training data; Memarian & Doleck, 2023). Thus, AI in higher education has to deal not just with algorithmic bias in the output itself (Alenichev et al., 2023; Jain & Menon, 2023; Wan et al., 2023) but also in detection.

More recent work has trained automated detectors that achieved near-perfect performance. For example, a classifier trained on linguistic features and perplexity achieved near-100% accuracy, with just 1 false positive in 2000 essays (Jiang et al., 2024). In that study, automated detectors actually showed fewer, not more, false positives for ESL writers, likely because the researchers trained their classifiers with as many ESL writing samples as not; they also had a much larger sample size than Liang et al. (2023). However, they trained their detectors on a particular task (Graduate Record Examination essays); performance would presumably be worse when applied to general writing, so the issue of biased false positives may remain.

The concepts and norms around plagiarism and using sources are fuzzy even for experts (Pecarari, 2022) and can be challenging to learn for ESL students (Warschauer et al., 2023). Realistically, while generative AI may help level the playing field for ESL students relative to their peers, it may also present an additional risk of getting tangled up in unintentional academic integrity violations. This could also be true for first-generation students, another demographic that can face uncertainty around norms of writing and academic integrity (Ives & Castillo-Montoya, 2020; Stone, 2023).

Beyond academic integrity, AI introduces complicated social and career implications for students. AI is projected to play a substantial role in many careers (Lim & Lee, 2024; Schroeder, 2023). In one survey, college students leaned toward thinking they will need to know AI in their future careers (Bharadwaj et al., 2024). In another survey, 72% of college students said their institution should be preparing them *a lot* or *somewhat* for AI in the workplace, and AI is increasingly influencing student majors (Student Voice, 2024). A recent large study of AI usage by undergraduates taking a psychology course found that the primary motivation was value and convenience, a perception of increased performance, and learning value when using AI (Cavezos et al., 2024).

Beliefs about AI's role in education and society may, in turn, influence students' ethical views about using AI in classes in ways that are prohibited. Students may pragmatically feel justified using AI—even to cheat—if they think the technology is necessary for their success and that instructors are behind the times.

One survey of university students in early 2023 found that 61% thought AI tools would become the new normal; 11% of respondents said they intended to use or continue using AI to complete assignments and exams despite around half thinking AI usage constituted cheating or plagiarism (Welding, 2023). In a follow-up survey, half of the students again thought AI usage on exams and assignments was cheating, but many more students reported doing so (56% in late 2023, up from 22% in early 2023; Nam, 2023). A more recent survey of college students showed a substantial increase (from 39% in 2023 to 50% in 2024) in students who say they are *likely* or *extremely likely* to keep using AI tools even when banned (Bharadwaj et al., 2024). However, the reasoning behind this intention should be investigated further.

McCabe et al. (2001), summarizing a decade of research into college cheating, found that perception of peer behavior is one of the biggest motivators of cheating. Among other things, students may feel pressured to use AI to avoid being left behind or outcompeted by peers. Most college-bound high school seniors are concerned that other students using AI will negatively impact their college admissions, scholarship chances, and career opportunities (Goebel et al., 2024). Students may worry that AI will lead to a rich-get-richer scenario that increases inequality. For example, higher-performing college students in one study were significantly more likely to use AI than lower-performing students; of those not using AI yet, the lower-performing students were more likely to report the reason being a lack of access or knowledge (Schiel et al., 2023). The same study found that lower-performing students were significantly less likely to report having found errors in AI output, suggesting they use the technology less effectively. Likewise, among high school seniors, SAT high-scorers were much more likely than mid- or low-scorers to use AI in their college search process, writing scholarship essays, and so on (Goebel et al., 2024). Students may feel the need to use AI—even when banned or where rules are ambiguous—because of worries about AI-fueled inequality.

This speaks to a larger uncertainty and ambivalence about AI in general. A recent Pew poll of Americans asked across many use cases if AI's impact helps or hurts, and one-third to half of Americans report being unsure. In general, respondents with a college degree had a more positive view of AI's impact than those without a degree (the exception being privacy; Tyson & Kikuchi, 2023), yet the poll found that people 18–29 increasingly lean more concerned (42%) than excited (17%).

A different national survey in late 2023 asked U.S. teens and young adults about the expected impact of AI in the next 10 years, and the modal response was ambivalence (Common Sense Media, 2024). Young people worried about AI replacing jobs, spreading misinformation, and invading privacy. Demographic factors may interact with AI adoption and views. Some groups in the survey, such as LGBTQ, leaned toward expecting primarily negative impacts. Females were more likely (21%) than males (14%) to think the impact of AI would be negative. College-bound males (35%) were significantly more likely than females (21%) to self-report high levels of AI knowledge (Goebel et al., 2024). Male college students report the rise of AI influencing their career plans more than female and nonbinary students (Student Voice, 2024). Another study found men were more likely to have used AI to complete assignments or exams than women (64% vs. 48%; Nam, 2023). Gender differences in views about and experience with AI may cause downstream inequality in an AI-centric workforce (Capraro et al., 2024; Carvajal et al., 2024), but more research is needed.

Overall, there are many outstanding questions relating to AI in higher education. The present study contributes promising directions to begin answering those questions. For example, existing data on AI usage often focuses on users versus nonusers, or has focused on cheating, but many student behaviors fall into an ambiguous middle-ground where it is unclear what usage is allowed. Additionally, going beyond behavior to perceptions, beliefs, and ethical views around AI may help understand why students use AI and how they do; in particular, it is plausible that student behavior is motivated by what they think peers are doing, how they see AI fitting into a career, and whether they believe AI will have positive or negative societal outcomes. This paper will also report data relating to demographic differences and issues of inequality and bias.

## Method

### *Participants*

The survey was made available to undergraduates taking an introductory psychology course in late Fall 2023 and Spring 2024 at a large state university in the United States. The study was one option of many to fulfill a research requirement. A total of 740 began the survey, with 733 completing it. The sample comprised 64% (472) female students, 33% (246) male students, and 2% (16) transgender, nonbinary, and/or other students. The median age was 19, with 61% (449) first-year, 25% (180) sophomore, 9% (66) junior, and 5% (33) senior+. Roughly 28% (208) of the sample identified as a first-generation college student, and 8% (57) said English was not one of their first languages. The study was voluntary, anonymous, and IRB approved.

### Materials and Procedures

The survey—an unvalidated measure created for this study—was administered on Qualtrics, with participants taking it online at a time of their choosing on a device after signing up on the SONA recruitment platform. Participants were asked about the following topics:

- familiarity with text-based generative AI (ordinal: 1 *Not at all*, 2, 3, 4, 5 *Very*);
- excitement/nervousness about recent/long-term developments in AI (ordinal: 1 *Not at all*, 2, 3, 4, 5 *Very*);
- how many professors directly address AI, and how many require/integrate it? (ordinal: 1 *None*, 2 *Some*, 3 *Most*, 4 *All*);
- usage in classes in ways allowed / banned / ambiguous (ordinal: 1 *Not at all*, 2, 3, 4, 5 *A lot*);
- usage for fun, not directly related to a course (ordinal: 1 *Not at all*, 2, 3, 4, 5 *A lot*);
- usage at job (ordinal: 1 *Not at all*, 2, 3, 4, 5 *A lot*);
- moral acceptability of using AI in banned/ambiguous circumstances, if not caught (interval: 1 *Morally unacceptable*, 2, 3, 4, 5 *Morally acceptable*);
- percentage of peers using AI to cheat (ordinal: 1 *0-19%*, 2 *20–30%*, 3 *40–59%*, 4 *60–79%*, 5 *80–100%*);
- extent AI is relevant to future career / necessary during college education (ordinal: 1 *Not at all*, 2, 3, 4, 5 *Completely necessary*);
- see AI increasing/decreasing inequality in the near future / long term (interval: 1 *Increasing*, 2, 3, 4, 5 *Decreasing*);
- agreement with the statement "Jobs and industries care more about the product and output of work than they do about the process used to get there" (interval: 1 *Strongly disagree*, 2, 3, 4, 5 *Strongly agree*);
- false accusation of using AI (nominal: *Yes* [# of times], *No*);
- worry about false accusations (ordinal: 1 *Not at all*, 2, 3, 4, 5 *Very much*);
- demographics (age, year in school, course modality, first-generation status, ESL, gender); and
- additional peripheral questions not analyzed here (see Supplemental information; Stone, 2024a).

### Analysis

For all survey questions and raw data, see Stone (2024a). Most questions were conservatively treated as an ordinal scale for analyses, either because the scale points were obviously not equidistant (e.g., *None, Some, Most, All*) or because of a nonsymmetrical scale with only endpoints labeled (e.g., *Not at all* to *A lot*). A few items with symmetrical Likert-like scales (e.g., 5 points from *Strongly agree* to *Strongly disagree* or *Very comfortable* to *Very uncomfortable*) were analyzed as interval scale. Nonparametric tests, such as Spearman's rank-order correlation coefficient, Mann–Whitney $U$, and Wilcoxon Signed Ranks, were used for statistical tests with ordinal scale items.

Given the large number of variables and tests, the analyses herein should be considered exploratory. Results described as significant at the conventional $p < .05$ level are likely to include some false positives, whereas results at $p < .001$ (1/50th the usual threshold) can be interpreted more confidently and are marked with ** below. Statistically significant results are not reported below for effect sizes smaller than |.1| ($r$ or $r_s$) or 0.2 (Cohen's $d$), but see Supplemental information (Stone, 2024a) for smaller effects.

## Results

### Familiar but Nervous

More than 90% of respondents (669) were at least somewhat familiar with text-based AI ($M = 3.38$, $SD = 1.22$), but with significant variation (see Supplemental information for figures; Stone, 2024a). Likewise, there was mixed excitement about recent developments in AI ($M = 2.79$, $SD = 1.10$; scale from 1 = *Not at all* to 5 = *Very*) and similarly for long-term developments ($M = 2.65$, $SD = 1.13$). Nervousness about recent developments ($M = 3.50$, $SD = 1.08$) and long-term developments ($M = 3.82$, $SD = 1.07$) was significantly higher than excitement on those timelines according to a Wilcoxon Signed-Ranks Test, $z = -10.94$ and $-14.93$, respectively (both $p$s $< .001$**). Specifically, 53% (390) rated nervousness higher than excitement in the near-term (only 18%, 138, were in the other direction), and 65% (478) rated nervousness higher in the long-term (only 15%, 108, were in the other direction).

Students seemed unsure whether AI would increase or decrease inequality. On a scale of 1 *Increase* to 5 *Decrease*, 33% (227) answered 1 or 2 about the near future (whereas 19%, 141, answered 4 or 5); 36% (267) answered 1 or 2 about the long-term future (whereas 24%, 174, answered 4 or 5).

### Allowed, Banned, and Ambiguous Usage

Most students (63%, 463) had used AI in classes in ways explicitly allowed; very few (7%, 54) had done so *A lot* ($M = 2.37$, $SD = 1.32$). Sadly, 41% (306) of students reported having used AI in ways explicitly banned ($M = 1.72$, $SD = 1.02$) on a scale of 1 *Not at all* to 5 *A lot*); only a tiny proportion (2%, 15) selected *A lot*. Students were more likely (59%, 432) to have used it in ambiguous circumstances ($M = 2.18$, $SD = 1.20$).

Outside of their coursework, only a minority (24%, 118) had used it in the workplace ($M = 1.55$, $SD = 1.13$). Students were significantly more likely to have explored AI for fun ($M = 2.77$, $SD = 1.29$) than using it in school contexts, whether approved (Wilcoxon Signed-Ranks Test, $z = -7.23$, $p < .001$**), banned ($z = -15.85$, $p < .001$**), or ambiguous ($z = -10.42$, $p < .001$**).

Students varied in their perception of peers cheating with AI, with some overestimating and some underestimating relative to the roughly 40% that self-reported such cheating. Specifically, 15% (113) thought 0–19% of peers were cheating with AI, 29%

(212) thought 20–39% of peers were, 28% (208) thought 40–59% of peers were, 21% (157) thought 60–79% of peers were, and 6% (42) thought 80–100% of peers were.

What predicted cheating? The more familiarity students reported with AI, the more likely they used it in ways explicitly banned ($r_S = .32, p < .001^{**}$). Using AI in general (e.g., in ways explicitly allowed) also predicted cheating ($r_S = .56, p < .001^{**}$), suggesting that perhaps experience with the technology makes it more tempting to cheat with it. Furthermore, the more they thought peers were cheating with it, the more likely they were to do so themselves ($r_S = .32, p < .001^{**}$).

## Professors

Only 8% (57) had no professors who had addressed AI directly; most students reported some (32%, 235), most (39%, 289), or all (21%, 152) of their professors addressing it. However, this may be in only shallow ways (e.g., a syllabus statement). Those with more professors who had addressed AI reported themselves using AI more in ways that are allowed ($r_S = .10, p = .005$), banned ($r_S = .10, p = .008$), and ambiguous ($r_S = .14, p < .001^{**}$). Many fewer students reported any professors integrating it directly: 71% (517) reported none of their professors, and less than 3% (21) said most or all. Students whose professors had integrated AI reported using AI more, not just in ways that are allowed ($r_S = .38, p < .001^{**}$) but also in ways banned ($r_S = .24, p < .001^{**}$) and ambiguous ($r_S = .24, p < .001^{**}$).

## Ethical Positions on AI Cheating

On a scale of 1 *Morally unacceptable* to 5 *Morally acceptable*, most students (74%, 545) chose 1 or 2 with regards to using AI in ways that are explicitly banned, while only 8% (59) answered 4 or 5 ($M = 1.88, SD = 1.03$). However, the morality of using it in ambiguous circumstances was more mixed: 45% (333) answered 1 or 2, while 27% (196) answered 4 or 5 ($M = 2.71, SD = 1.21$).

The more familiar a student was with AI, the more excited they were about it ($r_S = .44, p < .001^{**}$), but also the more morally acceptable they found banned ($r_S = .26, p < .001^{**}$) and ambiguous ($r_S = .33, p < .001^{**}$) usage in coursework. The reported proportion of professors who have addressed AI did not predict students' moral positions about cheating ($r_s = .06, p = .100$). However, professors having integrated AI did predict students finding it morally acceptable to cheat ($r_S = .10, p = .008$).

## Role in Career and School

Students were mixed on their views of how relevant AI will be to future careers ($M = 2.70, SD = 1.14$) and likewise mixed on how necessary they think AI is in college education ($M = 2.57, SD = 1.14$). The more students thought AI would decrease inequality in the short term, the more they thought it relevant to their future career ($r = .13, p < .001^{**}$) and likewise necessary to learn in college ($r = .16, p < .001^{**}$). The same patterns hold for thinking AI will decrease long-term inequality ($rs = .14$ and $.15$, respectively, both $ps < .001^{**}$).

Respondents were also asked the extent to which they agreed with the following statement: "Jobs and industries care more about the product and output of work than they do about the process used to get there" on a scale of 1 *Strongly disagree* to 5 *Strongly agree* and the mean response was 3.88 ($SD = 0.98$), with 41% (298) selecting 4 and 30% (216) selecting 5. The more they affirmed this view, the more they thought it moral to use AI in ambiguous ways ($r = .16, p < .001^{**}$), but not necessarily in banned ways ($r = .07, p = .060$).

## Detection, False Accusations, and Bias

A worrying 11% (82) of students reported having been falsely accused of using AI when they did not. Of those, most (72%, 59) report it happening just once. The modal outcome was being cleared of the accusation; others received a warning or re-do, while only a few led to an F or course failure. Of the students who had never been falsely accused, 72% (469) reported at least some worry about false accusations (on a scale from 1 = *Not at all* to 5 = *Very much*, $M = 2.72, SD = 1.39$).

First-generation students were significantly more likely (15.4%, 32) to report being falsely accused than non-first-generation students (9.6%, 50), $X^2(1, N = 731) = 5.07, p = .024, V = .08$. First-generation students were not significantly different from peers in familiarity, excitement/nervousness, usage of AI, or thinking it will increase/decrease inequality (all $ps > .05$). First-generation students were significantly more likely ($M = 4.08, SD = 0.89$) than peers ($M = 3.80, SD = 1.00$) to agree that "Jobs and industries care more about the product and output of work than they do about the process used to get there", $t(422) = -3.70, p < .001^{**}, d = 0.29$.

ESL students were not more likely to report false accusations than students for whom English was a first language (6 and 76, respectively, 11%), $X^2(1, N = 731) = 0.03, p = .863$. Whether English was a student's first language did not predict their familiarity with AI, nervousness about AI, usage of AI, or thinking it will increase/decrease inequality (all $ps > .05$).

## Gender Differences

On the other hand, there were quite a few significant gender differences, with men consistently more involved with AI than women (Table 1). There were no gender differences in nervousness about AI, in using AI in ways explicitly banned, nor in believing the industry cares more about a product than process ($ps > .05$). Note that the small number of transgender, nonbinary, and other individuals meant that these groups could not be included in analyses (unless also identified as male/female), so future work should investigate gender minorities.

## Online Courses

There were few differences when narrowing to just those students taking exclusively online (87) or exclusively in-person

**Table 1.** Significant Gender Differences.

| | Male | | Female | | | | |
|---|---|---|---|---|---|---|---|
| Question | *M* | *SD* | *M* | *SD* | Test Statistic | *p*-Value | Effect Size |
| Familiarity | 3.65 | 1.21 | 3.25 | 1.20 | $U = 47011$ | $p < .001$** | $r = -.16$ |
| Excited, near-term | 3.20 | 1.17 | 2.60 | 1.00 | $U = 41224$ | $p < .001$** | $r = -.25$ |
| Excited, long-term | 3.02 | 1.19 | 2.47 | 1.04 | $U = 43457$ | $p < .001$** | $r = -.21$ |
| Usage, allowed | 2.57 | 1.32 | 2.28 | 1.31 | $U = 55722$ | $p = .004$ | $r = -.11$ |
| Usage, ambiguous | 2.36 | 1.26 | 2.10 | 1.16 | $U = 51648$ | $p = .011$ | $r = -.10$ |
| Morally acceptable, banned use | 3.01 | 1.17 | 2.57 | 0.92 | $t(405) = 4.91$ | $p < .001$** | $d = 0.42$ |
| Morally acceptable, ambiguous use | 3.01 | 1.23 | 2.57 | 1.18 | $t(716) = 4.76$ | $p < .001$** | $d = 0.37$ |
| Relevance to career | 3.02 | 1.20 | 2.55 | 1.07 | $U = 44927$ | $p < .001$** | $r = -.19$ |

*Note.* The nonparametric Mann–Whitney *U* test was used to compare genders on ordinal scale variables, and an independent-samples *t* test was used to compare genders on interval scale variables. Response options for all questions were on a scale of 1–5, with higher scores indicating more familiarity, excitement, usage, moral acceptability, and relevance, respectively. ** *p*-value below .001.

(248) courses. No difference was found in self-reported usage of AI in ways that are banned ($p = .190$) or ambiguous ($p = .515$). Asked how many of their professors had explicitly addressed AI (1 = *None*, 2 = *Some*, 3 = *Most*, 4 = *All*), in-person students ($M = 2.79$, $SD = 0.88$) answered significantly higher than online students ($M = 2.53$, $SD = 0.95$), Mann–Whitney $U = 9089$, $z = -2.30$, $r = -.13$, $p = .021$. There was, however, no difference in how many professors integrated AI ($p = .731$). When asked about the extent to which AI experience is necessary for college education (from 1 *Not at all* to 5 *Completely necessary*), online students ($M = 2.69$, $SD = 1.18$) answered significantly higher than in-person students ($M = 2.40$, $SD = 1.13$), $U = 9237$, $z = -2.06$, $r = -.11$, $p = .039$.

## Discussion

AI has become a fact of life in higher education, which will likely increase as the technology is further integrated into daily life and software. In the present study, the majority of students (> 60%) in an undergraduate psychology course were using AI in their classes, though generally not a lot. The technology is relatively new to consumers, and there is asymmetry in students' adoption, knowledge, training, and ethical views. In general, the more exposure to AI (general familiarity or through professors addressing/integrating it), the more usage and the stronger their feelings about it (positive and negative).

The fact that students reported significantly higher nervousness about AI than excitement may come from the mixed messages and contradictions they encounter. Overall, professors are at least addressing AI shallowly, but many fewer are integrating it into their pedagogical approach despite students wanting more experience with the tool. They see peers using AI to cheat, and some overestimate how common that is, which may, in turn, fuel fears of being left behind if they do not use it. Meanwhile, they worry about—or directly experience—false accusations of cheating, which may erode the student–educator relationship. As one respondent put it in a comment, "AI is creating a wall between students and professors, because while I have not had any explicitly say no use of AI, I have had myself and multiple friends get falsely accused of using it due to sentence structure, vocabulary choice, etc."

Some worry that false accusations may come from ambiguity about the allowed uses. The present study was novel in asking directly about ambiguous circumstances in addition to allowed/banned cases. While relatively few students were using AI in ways explicitly banned, they were more likely to use it in ways they consider ambiguous (~50% more students used AI for this). Some of that ambiguity may come from professors only addressing AI with surface-level policies that do not account for the wide variety of use cases (Nguyen et al., 2024). This ambiguity may be hard to avoid in the future, though, as AI is infused into more day-to-day applications; it will be hard for professors to stay aware of all that is available to students and address each use case explicitly.

Regardless of policy, some students may use AI in ways that are banned, as was the case for over 40% of this sample. Perhaps this should not be surprising: other recent work with a similar large undergraduate sample reported roughly 78% of students self-reported having cheated on exams, 95% having submitted someone else's work, and 69% having used unauthorized electronic resources (Cavazos et al., 2024). With AI specifically, students increasingly report intending to use AI even when banned (Bharadwaj et al., 2024; Nam, 2023; Welding, 2023). The present study showed that students with the most professors addressing or integrating AI were the same students using AI to cheat, with the correlation strongest for those with professors integrating AI. One possibility congruent with this is that introducing students to AI and giving them hands-on experience could indirectly lead to them using it to cheat; other recent work has shown the role of trying AI chatbots with the intention to use them (Ayanwale & Ndlovu, 2024; cf. Cavazos et al., 2024).

If so, the present study also offers one potential explanation for this choice: the overwhelming majority of students seem to have a somewhat mercenary, pragmatic view of the workforce they will be graduating into. Over 30% strongly agreed (and 40% chose the next closest response) with the statement about the industry not caring what tools are used to achieve an end result, and this correlates with moral views on utilizing

AI in banned and ambiguous circumstances. Students are worried about being left behind by their peers (Goebel et al., 2024), and as seen in the present study, many students overestimate how many peers are using AI to cheat, which may, in turn, pressure them to do so to stay competitive.

Professors may wish to identify when students are using AI, especially when banned in the course or assessment. There is evidence that instructors with experience with AI are often better at detecting AI-written essays (Shear et al., 2023). However, detecting AI-produced writing—by humans alone or by humans using algorithms—is not accurate enough to avoid a problematic rate of false positives. While near-perfect accuracy has been demonstrated for some detectors, that likely only applies to specialized detection models trained on massive datasets in specific circumstances but is unlikely to generalize to other writing contexts (Jiang et al., 2024).

Furthermore, with newer AI, the problem may be exacerbated. Jiang et al. (2024), for example, were able to detect essays generated by gpt-3.5-turbo whereas by May 2024, students already had access to a newer generation of OpenAI's LLM, ChatGPT 4o (OpenAI, 2024b), and further versions are on the horizon even as other LLMs already outpace GPT 4o on some benchmarks (Anthropic, 2024). Given that LLMs are trained to approximate human writing, it may become asymptotically more challenging to reliably distinguish AI from human writing, even before considering humanizing apps and automated paraphrasing tools that easily defeat automated detectors (Theorem 1, Sadasivan et al., 2024). For this reason, some scholars of psychology teaching have suggested moving to more interactive oral assessments (Newell, 2023).

While much of the research around AI and academic integrity has focused on distinguishing AI-written work from human-written, the reality facing instructors is likely an increasingly hybrid usage. In this human-in-the-loop process, AI is involved in various stages of work, making for a final product that inextricably blends human and machine-generated output (Zeng et al., 2024). When writing samples in one study shifted from human-generated to AI-generated sentences part way through, humans had trouble identifying where the AI writing began even for early LLMs (variations of GPT-2), so real-world hybrid authorship will likely remain challenging to identify (Dugan et al., 2023). Some psychology teaching and learning scholars have suggested incorporating an AI Contribution Statement for students to identify the role of AI in hybrid authorship (Albada & Woods, 2024), and APA has developed a framework for citing AI usage (McAdoo, 2024). However, these frameworks assume a good faith effort by students.

Meanwhile, when the instructor focuses simply on detecting AI usage as cheating, evidence suggests that processes may be biased and may lead to false positives that disproportionately affect some groups, and the present study reinforces this. Liang et al. (2023) found ESL writing was more likely to be falsely classified as AI-generated (cf. Jiang et al., 2024); here, I found that first-generation students may have been more likely to report false accusations. False accusations have real-world consequences for university and career trajectories and undermine the student–educator relationship (Gegg-Harrison & Quarterman, 2024).

On the positive side, AI tools have the potential to address inequities by leveling the playing field, for example, by reducing "linguistic taxes" that ESL students pay when using a second language for important tasks (Warschauer et al., 2023). Some evidence in the workplace already suggests an inverse skill bias, whereby AI may be most helpful to those with lower skills and experience (Capraro et al., 2024). Yet learning to use AI effectively—to prompt well and judge output (e.g., Richmond & Nicholls, 2024)—requires foundational writing skills that, if bypassed due to AI over-adoption too early, could make it harder for those students to progress to sophisticated usage (Warschauer et al., 2023).

The sophisticated usage of AI may be important in providing a competitive advantage in the workforce of the future (Koumpan & McOwen, 2024; Lim & Lee, 2024). The American Psychological Association suggests that skillful psychology students should demonstrate flexibility and adaptability to new systems and technology to be prepared for success in the workplace (Naufel et al., 2018). Students increasingly think experience with AI is relevant to their training and career (Bharadwaj et al., 2024; Goebel et al., 2024), yet we already see inequities in which students get experience with the technology. In the present study, male students were more familiar with AI than females, more excited about it, used it more in allowed and ambiguous ways, found it more morally acceptable to use in banned and ambiguous circumstances, and saw it as more relevant to education and career. As with other gender gaps in STEM, institutions may want to address this to ensure women enter the workforce similarly competitive in AI-relevant skills.

While the present study offers new insights and promising directions for future research, these results should be interpreted cautiously. First, the data comes from a convenience sample at one U.S. university and given the asymmetry in student populations and also in tech adoption and policies across faculty, institutions, and cultures (Ansari et al., 2023; Cambra-Fierro et al., 2024; Yusuf et al., 2024), the specifics may not generalize to all higher education. Likewise, this study measured many variables, and the nature of the analysis was exploratory. Taken with the usual null hypothesis significance testing caveats, results here with a *p*-value below .001** should be considered the most promising to confirm and investigate further.

Another limitation of this study is that AI usage, including cheating, was self-reported. Cavazos et al. (2024) provide evidence that students in a psychology course can accurately tell the difference between what counts as cheating with AI and what does not. Still, as with any self-report measure, the real rate may be higher or lower. Also, since respondents used their own devices, the environment during survey administration was not controlled.

Generative AI is here to stay, and higher education will need to adapt as the technology develops and is infused into domains previously thought exclusive to humans, like writing long text. Students currently appear unsure about AI and how it fits in their education and future. How institutions and professors frame AI may influence students' ethical views and usage going forward. Instructors may find it valuable to move beyond focusing on detecting AI-generated versus human-generated output and instead look into how AI will be integrated into a hybrid process of human and AI writing, coding, drawing, and learning. Future research should tackle questions of how and when AI can be utilized to support genuine learning, performance, psychological literacy, and intellectual growth, as well as identifying counterproductive use cases that may increase procrastination, interfere with memory, or decrease academic performance (Abbas et al., 2024; Bond et al., 2024; Richmond & Nicholls, 2024; Stone, 2024b; Walter, 2024).

## Consent to Participate

Participants completed an informed consent page.

## Data Availability

All data generated or analyzed during this study are included in this published article and its supplementary information files.


## Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.


## Ethical Considerations

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## Supplemental Material

Supplemental material for this paper is available online.

## Open Practices

For publishing their material, Stone received badges for Open Data and Open Materials. The public content may be retrieved from https://osf.io/rfp5k/?view_only=6c7f704f8621421d82ec35f1a19e9d34

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