AI and Academic Integrity: Exploring Student Perceptions and Implications for Higher Education

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Abstract

The emergence of generative artificial intelligence tools, such as ChatGPT, presents new challenges impacting student perceptions of academic integrity. While extensive research exists on academic misconduct and student perceptions of various infractions, there is limited understanding of how AI tools impact these views and whether their use constitutes a violation of academic integrity policies. This study explores university students' awareness and perceptions of academic misconduct, particularly concerning AI tool usage. A survey of domestic and international students enrolled at major universities in the United States received 277 valid responses. The results reveal high awareness of university integrity policies and significant concern about the use of AI for writing papers, with substantial variance in perceptions of misconduct severity. Notably, using AI to write entire papers is seen as major misconduct by a majority, while smaller AI-assisted tasks are viewed as less severe. Regression analysis highlights the importance of ethical education, revealing that students who view AI writing as cheating and those who believe cheating is unethical perceive academic misconduct more seriously. Conversely, student demographics (major, educational level, gender, international status), awareness of AI detection tools, and perceived ethics of AI use show complex, often non-significant relationships with perceptions of misconduct severity. These findings provide indication that education and clear policy about AI usage and academic misconduct could be useful in addressing a growing number of infractions in the face of emerging AI trends.

Academic integrity has been transformed by the emergence of generative artificial intelligence (AI), with new means of engaging in misconduct proliferating higher education (Song, 2024). Students, administrators, and instructors have taken different approaches to reacting to these changes. Some students have adopted these AI tools to complete assignments and write essays for them, a form of plagiarism that was termed by Chan (2024) as "AI-giarism." Most universities have acknowledged the risks posed by AI but have avoided making major institution-wide changes to policy, as some disciplines and courses embrace emerging AI tools and would suffer in the case of a restrictive ban (Carnegie Mellon University, 2024). Instructors have responded to a lack of uniform policy by enforcing course-specific rules regarding the permissibility of AI use.

Despite these developments, our understanding of how students perceive emerging AI tools and academic misconduct remains limited. The few existing studies that have emerged in recent years suggest complex views about AI use, where certain uses of AI may be viewed as permissible by some students, while others are viewed as universally impermissible (Chan, 2024). As the emergence of these AI tools, particularly large language models, is relatively new, there remains much to learn about student perceptions and how it informs intended use of these tools on academic assignments.

Enhancing our understanding of student populations views toward AI and what factors may influence perceptions of academic misconduct is critical. This study is particularly interested in the perceptions of international students, as this population is growing at many U.S. universities as the number of available domestic students is declining nationwide. Much of our understanding of student perceptions of misconduct has been forged from the perspectives of domestic students and instructors, leaving considerable gaps in our understanding of this unique student population, which is faced with additional barriers to learning in the United States, such as language, cultural, and learning differences, as well as a lack of adequate support (Wang et al., 2023). This paper seeks to broaden our awareness of student perceptions of academic misconduct in the age of generative artificial intelligence and what factors may result in differing views on this topic.

Literature Review

Academic misconduct has existed for as long as academia itself, with decades-old studies showing a high prevalence of cheating and other forms of misconduct on university campuses (Bowers, 1964; Harp & Taietz, 1965). As AI enters the classroom, educators have shown growing anxiety and concern about quality assessment in higher education. These concerns were quite substantial even before tools like ChatGPT emerged on the scene (Miao et al., 2021; Schiff, 2021), but have now reached a fever pitch (Eaton, 2024). This review of the literature explores the nature of academic misconduct, how it has been impacted by the emergence of artificial intelligence tools, and ways in which educators have sought to retain control in light of the emergence of these tools.

Academic Misconduct Defined

Academic misconduct has historically been defined as *the use of any unauthorized assistance that could give one student an undeserved advantage in their work* (Hugh & McCabe, 2006;

University of North Texas, 2024). Academic misconduct can include a range of behaviors, such as cheating, fabrication, forgery, plagiarism, or gaming, where an author misrepresents or exaggerates the significance of their findings (Biagioli et al., 2019; Tauginiene et al., 2019). Within this definition, the usage of any tools, including artificial intelligence tools, for the purposes of completing work, can be considered a potential instance of academic misconduct if their use is not explicitly permitted by the instructor (Abd-Elaal et al., 2019; Song, 2024). However, instructors are often uncertain how to develop an appropriate AI policy and students are frequently unaware that any policy might exist.

In recent decades, the rate of academic misconduct has increased substantially, owing to the accessibility of resources to support misconduct, such as the Internet. Some studies have estimated that over one-half of university students have conducted some form of misconduct during their time in higher education (Dar & Khan, 2021; McCabe et al., 2012). These types of infractions do not occur only at the lower, undergraduate level, but are also find in doctoral work, including dissertations (Singh & Remenyi, 2016). Potential acts of misconduct are frequently known among a student's peers, but they are often reluctant to report the misconduct to an instructor, in order to protect the student from recourse for their actions (Pupovac et al., 2019).

The terms "cheating" and "academic misconduct" can carry significantly distinct connotations for students. A study by Burgason et al. (2019) found that higher education students often disclosed that they had engaged in types of cheating, such as copying notes or looking up information from unauthorized sources, but that they did not view these behaviors as academic misconduct. The concept of academic misconduct carries the connotation that an institution's policies have been breached, which could lead to expulsion from the university (University of Cambridge, 2024). This may contribute to students' reluctance to label their behavior as misconduct, even though plagiarism falls under the definition of academic misconduct at most universities. In general, faculty and students define academic misconduct differently, with faculty having a broader definition compared to students, who view misconduct as encompassing only severe cases of cheating and impropriety (Hard et al., 2006; Parnther, 2020).

Student Perceptions of Academic Misconduct

Notably, views towards academic misconduct and the severity of different types of infractions can vary among different populations. Gender, age, grades, and time management skills of students can indicate whether a student is more likely to engage in misconduct (McGowan, 2016; Miles et al., 2022). A few recent studies have shown that the frequency of academic misconduct may be in some way predicted by personality traits of students. Ternes et al. (2019) note that some antisocial traits may portend a greater likelihood of academic misconduct. Stone et al. (2009; 2010) found that the Theory of Planned Behavior, which understands behavior as being predicted on the individual's attitudes and perceptions of subjective norms, is a strong predictor of the intention to engage in academic misconduct. A tendency to procrastinate may also be indicative of a greater likelihood of misconduct (Patrzek et al., 2015).

Other studies have suggested that students' backgrounds are not significant factors for academic misconduct, but rather environmental factors, like the academic discipline or quality of teachers (Khalid, 2015; Makarova, 2019). Several studies have found that students place blame on instructors for not adequately providing instruction on what constitutes academic misconduct and leaving too much up to the interpretation of the instructor (Baetz et al., 2011; Burgason et al., 2019; Perry, 2010). Studies that have tested approaches to better educate students have shown promising results, including Perkins et al. (2020), which saw a 37% reduction in academic misconduct following instruction, and a marginally significant positive outcome in the study of Benson and Enstroem (2023).

Artificial Intelligence and Academic Misconduct

The maturation of generative artificial intelligence technology has introduced a new threat to the academic landscape. The tools now exist for a student to compose an entire discussion board post or academic essay simply by pasting the prompt into a textbox and having a large language model do the work for them. The level of sophistication behind these models make it extremely difficult to police academic integrity violations, leading to calls to entirely rethink how we define and discuss academic integrity and misconduct (Yusuf et al., 2024; Zhang et al., 2024). Some academics have argued that the best approach to avoid academic misconduct in the present age is to abandon assignments that present easy opportunities to cheat and instead use assessments that require creativity, originality, or performance (Currie, 2023; Oravec, 2023).

Those who do aim to prevent academic integrity violations in the age of AI have some tools at their disposal. At the individual course level, instructors always have discretion about classroom conduct policy and may prohibit use of AI tools like ChatGPT (Perkins & Roe, 2023). There are detectors that can be used to identify potential usage of AI tools – though they are imperfect (Bellini et al, 2024). An understanding of a class's students and their perceptions about academic integrity, within the context of one's academic discipline and course set-up, can be beneficial in determining what policy should exist and what changes may be made to one's course to mitigate opportunities for plagiarism to occur (Perkins & Roe, 2023).

Existing research indicates that students have a clear understanding of the impermissibility of using direct AI-generated content for class assignments but may see more subtle uses of AI as more acceptable (Chan, 2023; Chan, 2024). For instance, copy-and-pasting assignment instructions and having a large language model produce a response is likely to be perceived as inappropriate, but crafting an individual response and then providing it to a large language model to expand and improve may be seen as okay. Other studies have suggested that those who are most likely to engage in academic misconduct involving AI tools are those who have already engaged in other forms of academic misconduct in the past (Tindle et al., 2023). Because these students have a pattern of misconduct relating both to AI and non-AI origins, it is possible that traditional methods of misconduct prevention may still be effective (Birks & Clare, 2023).

Prospect Theory and Risk-Taking with AI in Misconduct

A potential framework for understanding academic misconduct involving the use of AI tools is prospect theory. This theory emerged from the field of behavioral economics to explain why investors are willing to take risks, suggesting that when the benefits of a risk and perceived as much greater than the losses people are more likely to accept the risk (Levy, 1992). Given that AI use is difficult to detect, as outlined above, students may perceive the potential losses as minimal as odds of consistent detection are low, whereas the benefits of saving considerable time in completing assignments are tremendous. This framework of examining student intentions to engage in academic misconduct helps to inform the researchers' understanding of the current state of AI misconduct and guide the design of the research instrument for this study.

Research Problem and Questions

While a considerable body of literature exists on the topic of academic misconduct and student views towards various infractions, there is limited research on how the emergence of artificial intelligence tools like ChatGPT may impact student views towards misconduct or, indeed, if the use of these tools is viewed as a misconduct violation itself. While many universities have avoided ratifying a carte blanche prohibition of AI tools or including mention of large language models as a violation of academic integrity policy, many instructors have expressed deep concerns about the technology and sought to limit its usage (Bin-Nashwan et al., 2023). This study aims to examine the views of university students towards AI usage and academic misconduct, to address this existing gap in our understanding of the implications of these technologies. The research is guided by the following research questions:

1. What are the perceptions of university students towards various forms of academic misconduct, including the use of AI tools like ChatGPT?
2. What is the relationship between students' ethical beliefs about cheating, their beliefs about AI use risks, and their perceptions of the severity of academic misconduct involving AI tools?
3. How do demographic factors such as educational status, academic major, international/domestic student status, and gender influence student perceptions of academic misconduct involving AI tools?

Methods

This study utilizes a survey approach to address the research questions. A questionnaire consisting of ten multi-part questions (30 information items total) was developed based on the research questions, with some wording and organization adapted from existing surveys related to academic misconduct (Khalid et al., 2014; Schrimsher et al., 2011). The questions in this survey include the following:

Addressing Research Question 1:

- Whether the participant has read their university's academic integrity and misconduct policies (before today).
- Likert scales to indicate to what extent the following activities may be deemed academic misconduct (severity of misconduct): Using AI to generate paper ideas; using AI to write an entire paper; using AI to write a section of a paper; using AI to revise a paper that has

already been written by the student; copying sentences from a past paper; using Grammarly Pro; having a classmate help write a paper; using a paraphrasing tool.
- Awareness of issues with Grammarly Pro being identified as AI-generated content.

Addressing Research Question 2:

- A rank question with five options, where 1 represents the most serious potential misconduct and 5 represents the least: using AI to write a section of a paper; copying sentence from a past paper; having a classmate help write a paper; copying ideas from a website; using Grammarly Pro.
- Likert scales to indicate how strongly they agree with the following: That cheating on assignments is unethical; that cheating on assignments hurts other people; that cheating on assignments is okay as long as you do not get caught; that using AI to help write papers is cheating; that using AI on assignments is okay.

Addressing Research Question 3:

- Educational status (undergraduate/graduate)
- Academic major
- International/Domestic student status
- Gender identity
- Primary spoken language (at-home/outside of educational and work contexts)

This questionnaire was developed in an online survey platform and delivered electronically to participants. Participants included students enrolled in institutions of higher education who were at least 18 years of age at the time of completing the survey. The survey was distributed via email messages to students at several major universities in the United States and participants were encouraged to help distribute the survey to additional participants by disseminating the survey link. The survey remained open from April 1, 2024 until April 19, 2024. During this time period, 364 survey responses were received, of which 277 were valid and complete surveys. The data from these 277 responses were transferred from the online survey platform to a csv file for further analysis. This study was reviewed and approved by the Institutional Review Board (IRB) under protocol number IRB-24-142. All participants provided informed consent before completing the survey, ensuring that they were aware of the study's purpose, their voluntary participation, and the confidentiality of their responses. The research adhered to institutional ethical guidelines for human subject research.

Variable Definitions

The study utilized several variables in the statistical analysis to explore student perceptions of academic misconduct involving AI tools. These variables are defined as follows:

- **policy_aware**: Indicates whether the respondent is aware of their university's academic integrity and misconduct policies.
- **rank_ai_write**: Respondent's ranking of the severity of using AI to write academic papers or assignments.

- **rank_copying_past_work**: Ranking of the severity of copying sentences or sections from a past work previously submitted by the student.
- **rank_classmate_write_help**: Ranking of the severity of receiving help from a classmate to write academic work.
- **rank_copy_website_ideas**: Ranking of the severity of copying ideas or content from online sources or websites.
- **rank_grammarly_revise**: Ranking of the severity of using tools like Grammarly Pro to revise or assist in academic writing.
- **aware_grammarly_ai_detection**: Awareness that tools like Grammarly Pro can generate AI-detected content.
- **cheating_assignments_unethical**: Agreement level with the statement that cheating on assignments is unethical.
- **cheating_assignments_hurts_others**: Agreement level with the statement that cheating harms other people, not just the student.
- **cheating_ok_if_not_caught**: Agreement level with the idea that cheating is acceptable if not caught.
- **ai_writing_cheating**: Agreement level with the statement that using AI to assist in writing constitutes cheating.
- **ai_use_ethical**: Agreement level with the statement that using AI tools in academic assignments is ethical.
- **edu_status**: Educational status of the respondent (e.g., undergraduate, graduate).
- **major**: Academic major or field of study of the respondent.
- **student_type**: Classification of the respondent as a domestic or international student.
- **gender**: Gender identity of the respondent.
- **primary_language**: Primary language spoken by the respondent.
- **perceived_seriousness**: Overall perception of the seriousness of academic misconduct.

Correlation Analysis and Multicollinearity

The research employed rigorous statistical methods to identify significant predictors of students' perceptions of academic misconduct involving artificial intelligence tools. A critical step in this process was addressing the multicollinearity among predictor variables, which was first identified through correlation analysis and subsequently quantified using the Variance Inflation Factor (VIF).

Multicollinearity Analysis

Multicollinearity was assessed to ensure that the regression model's predictors were not unduly influencing each other, which could skew the results and interpretations. VIF values were calculated for each variable, with a commonly accepted threshold suggesting that VIF values exceeding 5 indicate potential issues requiring attention, although values above 10 are more conclusively problematic. But as can been seen in Table 1, there are a few attributes with a VIF score of infinity (Inf).

Table 1. VIF Scores Before Removing Highly Correlated Variables

Features	VIF
policy_aware	1.23
rank_ai_write	Inf *
rank_copying_past_work	Inf *
rank_classmate_write_help	Inf *
rank_copy_website_ideas	Inf *
rank_grammarly_revise	Inf *
aware_grammarly_ai_detection	1.12
cheating_assignments_unethical	1.16
cheating_assignments_hurts_others	1.26
cheating_ok_if_not_caught	1.23
ai_writing_cheating	1.35
ai_use_ethical	1.33
edu_status	1.25
major	1.27
student_type	1.92
gender	1.17
primary_language	1.29
perceived_seriousness	1.36
Intercept	0.00

Note: The ***** indicates the attributes with a VIF (Variance Inflation Factor) value of "inf" indicating that they are highly multicollinear.

This infinite VIF is caused by the perfect dependency among ranking variables (rank_ai_write, rank_copying_past_work, etc.) due to the constraint that they are limited to values 1 through 5. When four rankings are known, the fifth ranking is entirely predictable, creating a linear dependency. This is why the VIF was infinite. To resolve this, one ranking variable was removed to break the dependency. The choice of which ranking to exclude is arbitrary since any one of the rankings can be inferred from the others.

To resolve the issue, a stepwise approach was adopted:

1. Variables with infinite VIF values were identified and considered for removal.
2. “rank_ai_write" was removed, as it overlapped conceptually with other AI-related variables such as “ai_writing_cheating". Removing this variable ensured that each remaining variable contributed uniquely to the analysis.

This step was particularly effective because it reduced multicollinearity while maintaining the explanatory power of the model.

After removing 'rank_ai_write' the subsequent analysis and recalculated VIF values (Table 2) indicated a significant reduction in multicollinearity, affirming the decision's positive impact on the model's integrity and interpretability. The remaining variables could then be more reliably analyzed to understand their unique contributions to perceptions of academic misconduct seriousness.

This methodical approach ensures that each variable included in the model contributes meaningfully to understanding how various forms of academic misconduct, particularly those involving new technologies like AI, are perceived by students. This clarity is essential for developing targeted educational policies and interventions that address the nuanced challenges posed by digital tools in academic settings.

Table 2. VIF Scores After Removing Highly Correlated Variables

Features	VIF
policy_aware	1.23
rank_copying_past_work	1.86
rank_classmate_write_help	1.90
rank_copy_website_ideas	1.84
rank_grammarly_revise	2.29
aware_grammarly_ai_detection	1.112
cheating_assignments_unethical	1.16
cheating_assignments_hurts_others	1.26
cheating_ok_if_not_caught	1.23
ai_writing_cheating	1.35
ai_use_ethical	1.33
edu_status	1.25
major	1.27
student_type	1.92
gender	1.17
primary_language	1.29
perceived_seriousness	1.36
Intercept	0.00

Results

Of the 277 responses, 266 respondents (96%) indicated that they were familiar with their university's academic integrity policy before beginning the survey. 233 respondents (84%) indicated that they were aware that platforms like Grammarly Pro may use AI to revise writing, which could be identified by AI checker tools. The vast majority of respondents (91%) were graduate students (77% master's and 14% doctoral) while the remaining (9%) were undergraduate students. This difference may reflect the inherent interest and engagement of graduate students in topics like academic integrity, which are often more directly relevant to their advanced academic work and responsibilities. The student respondents came from over 30 different disciplines, including nursing, data science, and information science. Respondents skewed male (57%) compared to female (42%) and non-binary/not-listed (1%). The most common primary language was English, followed by Spanish, Telugu, Hindi, and Chinese. The respondent population also skews international (70%), owing to the recruitment approach that sought to attain a sizeable non-domestic student population.

Figure 1 shows the student respondents' ratings of the potential misconduct in various types of academic activities. For every activity, a plurality, if not outright majority, of respondents selected "major academic misconduct." There is, however, considerable variance, with "ChatGPT for Writing Entire Paper" and "Copying Sentences from Another Student" being the most commonly selected as major misconduct. Interestingly, there are some activities that many academic institutions would not consider misconduct – using ChatGPT to help generate some ideas and using Grammarly – that still had a plurality of respondents indicate that they should be consider major misconduct. For each activity, including the two major misconduct activities mentioned above, there were at least four (1%) respondents who indicated that they represented no academic misconduct at all.

Further analysis of some of the findings reveals some significant insights. A chi-square test comparing the responses for the activities, "ChatGPT for Writing Entire Paper," "Copying Sentences from Another Student," and "Having a Classmate Help Write Your Paper," show significant differences in the rating of severity, $X^2 = 121.33$, $p < .01$. "Having a Classmate Help Write Your Paper" has significantly more respondents indicating that this is not misconduct at all (22 respondents, compared to 4 respondents for each of the other two activities), and significantly fewer respondents indicating that it is major academic misconduct (125 respondents, compared to 232 and 205 respondents for the other activities). Additionally, there are significant differences in how students perceive the level of misconduct for using ChatGPT to write an entire paper versus just a paragraph, $X^2 = 72.91$, $p < .01$. While there is not a significant difference in the proportion who rate these activities as no misconduct at all (4 respondents versus 7 respondents), there are significant differences in the proportion who rate these activities as minor or moderate misconduct (23 respondents for writing entire paper versus 96 respondents for just a paragraph) and who rate them as major misconduct (232 respondents for entire paper versus 141 respondents for just a paragraph). This finding suggests that using AI to write small parts of a paper may be seen as more permissible/less severe than using these tools to write an entire paper, which is seen nearly universally as entirely impermissible.

There does not appear to be any difference in how international and domestic students perceive the seriousness of academic misconduct surrounding the use of AI tools ($X^2 = 1.12$, $p = .29$). 85% of international students rated "ChatGPT for Writing Entire Paper" as major academic misconduct, compared to 86% of domestic students. 52% of international students rated "Using ChatGPT to Write a Paragraph" as major misconduct, compared to 45% of domestic students. Similarly, there is no significant difference based on whether the student's primary language is English or another language, $X^2 = 0.50$, $p = .91$. 82% of primary English speakers viewed the use of "ChatGPT for Writing Entire Paper" as major misconduct, compared to 85% of those for whom English is a second language.

Figure 1. Respondent Ratings of Various Types of Potential Academic Misconduct

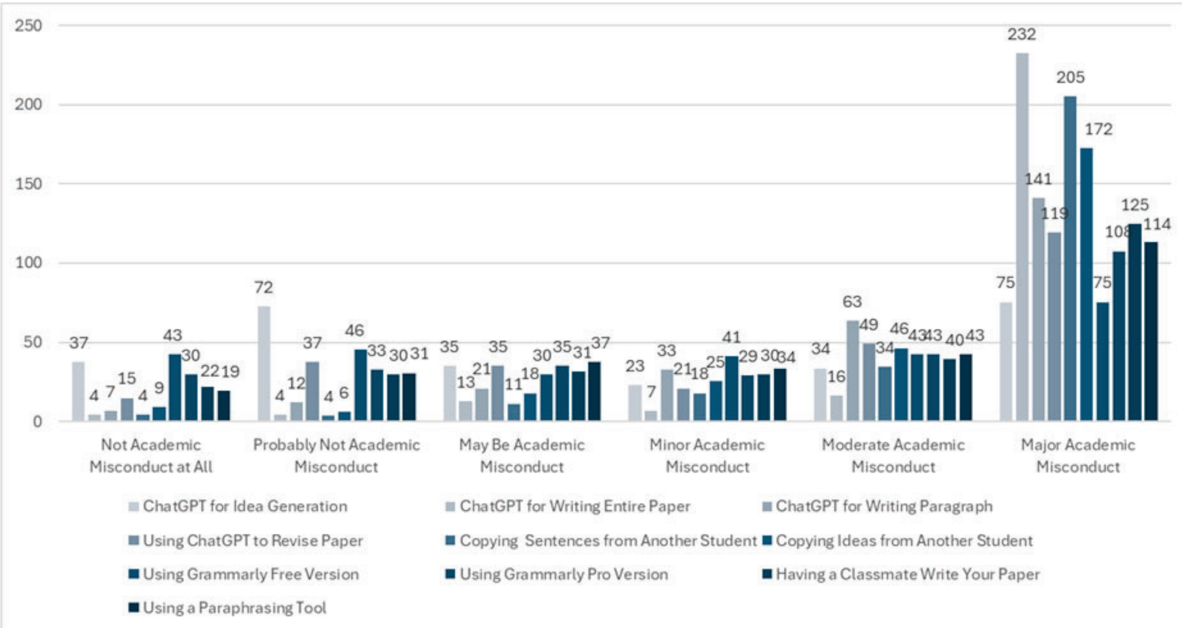
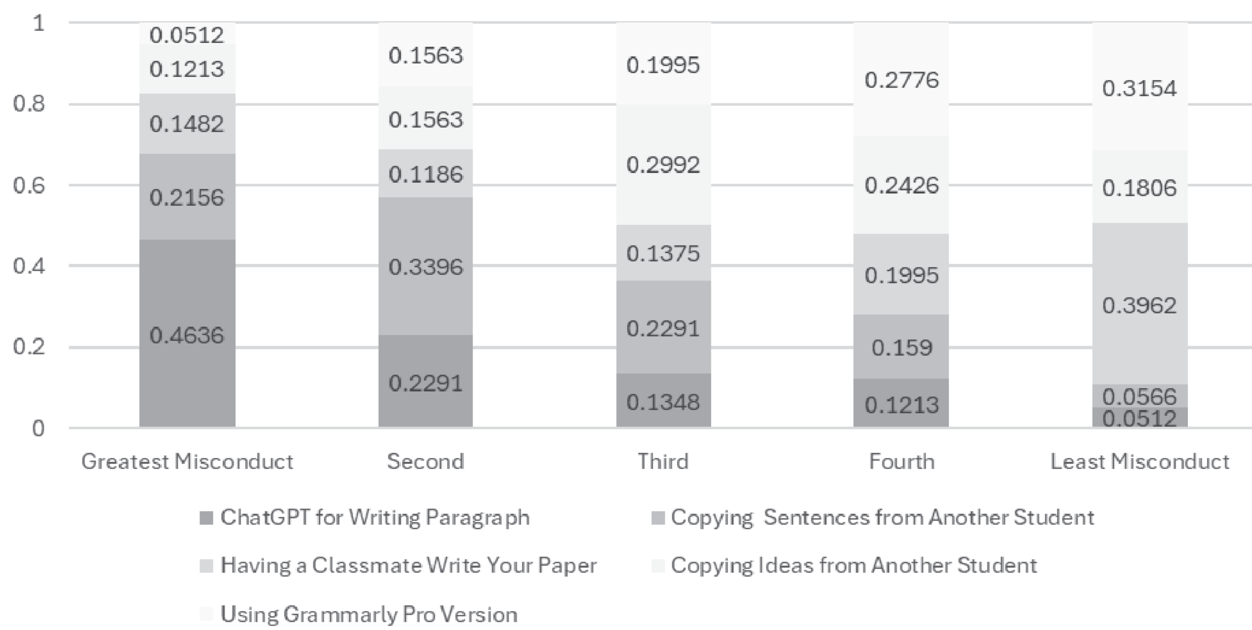


Figure 2 displays the percentage of respondents who ranked each of five activities as greatest, second greatest, third greatest, fourth greatest, and least misconduct. The use of ChatGPT for writing entire paragraphs was the clear top choice for misconduct, with it being selected as the greatest misconduct by 46% of respondents and as the second greatest by 23%, for a total of 69% in the top two. Copying sentences from other students was the clear second choice, with it being selected as the greatest misconduct by 22% of respondents and the second greatest misconduct by another 34%, for a total of 56% in the top two. The third greatest misconduct was copying ideas from another students, with it being the first choice for 12% of respondents, the second choice for 16%, and the third greatest choice for 30%, for a total of 58% of respondents in the top three. The fourth greatest misconduct was using Grammarly Pro Version, with 5% indicating it as the greatest misconduct, 16% as second greatest, 20% as third greatest, and 28% as the fourth greatest, for a total of 69% in the top four. This is compared to having a classmate help write your paper, which was indicated as the top misconduct for 15% of respondents, second greatest for 12%, and third greatest for 14%, and 20% as the fourth greatest for a total of 61% in the top four. Notably, “having a classmate help write your paper” brought the greatest divide in opinion, with 15% of respondents rating it as the greatest type of misconduct and 40% of respondents rating it as the least.

While there were no significant differences in what domestic and international students rated as the most serious types of academic misconduct, there were major differences in what they perceived as the least serious misconduct. 41% of domestic students rated “ChatGPT for Writing a Paragraph” as the most serious misconduct, compared to 47% of international students. 41% of domestic students rated “Copying Sentences from Another Student” as the second greatest misconduct, compared to 34% of international students. However, 59% of domestic students rated “Using Grammarly Pro” as the least serious misconduct, compared to 29% on international students. 14% of domestic students rated “Having a Classmate Help Write a Paper for You” as the least serious misconduct, compared to 42% of international students. This difference in ratings is statistically significant, $X^2 = 26.5$, $p < .01$. This finding suggests that international students view receiving classmate help on assignments as less serious compared to their domestic student peers.

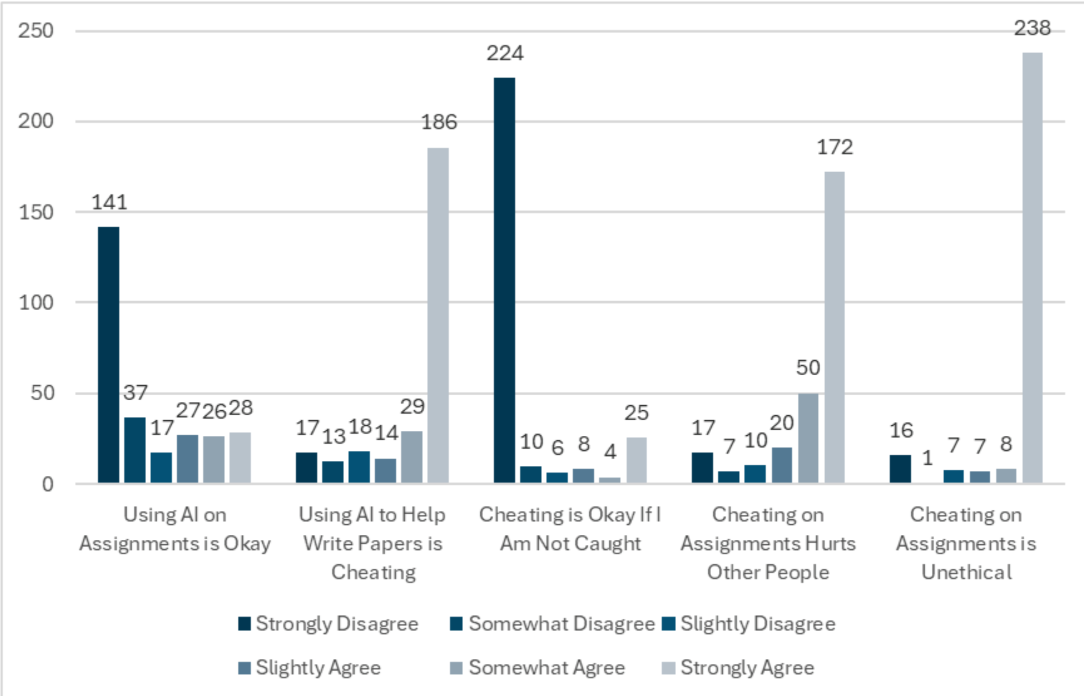
Figure 2. Ratings of Misconduct Severity for Various Activities



Lastly, Figure 3 shows how strongly respondents agree with a series of statements related to possible academic misconduct. For three statements, the vast majority of respondents "strongly agree": that using AI to help write papers is cheating, that cheating on assignments is unethical, and that cheating on assignments hurts other people than just the student. Of these statements, that cheating hurts other people stands out as distinct, as 25% of respondents only slightly or somewhat agreed with this statement compared to 16% and 5% for the other two statements. A chi-square test confirms this distinction, $X^2 = 62.12$, $p < .01$.

For the other two statements, a majority of respondents "strongly disagree": that using AI on assignments is okay and that cheating is okay if you are not caught. While responses to these statements are quite strongly clustered in either "strongly agree" or "strongly disagree," it is noteworthy that a sizeable percentage of respondents (29%) at least slightly agreed with the statement that "using AI on assignments is okay." The percentage strongly disagreeing with this statement was only 51%, much lower than with "cheating is okay if I am not caught" at 81%. A chi-square test verifies a significant difference between these groups, $X^2 = 65.50$, $p < .01$. This finding suggests some disagreement about the permissibility of using AI on assignments.

Figure 3. Agreement with Statements about Academic Misconduct



Regression Analysis

The regression analysis after refining the model to address multicollinearity offers an in-depth look at the factors influencing students' perceptions of academic misconduct seriousness. Below, both significant and non-significant predictors are discussed to understand their implications better. Table 3 presents the detailed regression results.

Table 3. Regression Output (Target variable = "perceived_seriousness")

Feature	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
const	2.31	1.06	2.19	0.03	0.23	4.39
policy_aware	0.29	0.30	0.97	0.33	-0.30	0.88
rank_copying_past_work	0.01	0.06	0.19	0.85	-0.11	0.13
rank_classmate_write_help	-0.01	0.05	-0.22	0.83	-0.11	0.09
rank_copy_website_ideas	-0.01	0.06	-0.24	0.81	-0.13	0.10
rank_grammarly_revise	0.02	0.07	0.25	0.80	-0.11	0.14
aware_grammarly_ai_detection	-0.28	0.14	-1.95	0.05	-0.56	0.00
cheating_assignments_unethical *	0.09	0.04	2.16	0.03	0.01	0.18
cheating_assignments_hurts_others	0.07	0.04	1.66	0.10	-0.01	0.15
cheating_ok_if_not_caught	0.01	0.04	0.15	0.88	-0.07	0.08
ai_writing_cheating *	0.19	0.04	4.89	0.00	0.11	0.27
ai_use_ethical *	-0.12	0.03	-3.65	0.00	-0.19	-0.06
edu_status	0.49	0.25	1.96	0.05	-0.00	0.99
major	-0.07	0.23	-0.32	0.75	-0.52	0.38
student_type	-0.32	0.28	-1.13	0.26	-0.87	0.24
gender	0.04	0.08	0.42	0.68	-0.13	0.20
primary_language	0.07	0.16	0.43	0.67	-0.24	0.38

Note: The * indicates significance at the 95% level ($p<0.05$).

Significant Predictors

Cheating Assignments Unethical (Coef: 0.09, P-value: 0.03): This significant positive coefficient indicates that students who view cheating as unethical tend to perceive academic misconduct as more serious than their peers. Considering that cheating is a type of academic misconduct, this finding is largely intuitive, though it does highlight the potential value of clearly stressing the unethical nature of cheating in the classroom in order to cultivate a culture that views all academic misconduct as a serious infraction.

AI Writing Cheating (Coef: 0.19, P-value: <0.01): This significant positive coefficient indicates that those who view AI written content as a form of cheating tend to take academic misconduct more seriously. In other words, those who are more cautious about the ramifications of AI use on their assignments are those who take a stauncher view towards academic misconduct overall. This finding may capture a growing unease about the impact of AI on the authenticity and originality of academic work, suggesting a need for clear guidelines and discussions on AI's role in education.

AI Use Ethical (Coef: -0.12, P-value: <0.01): This significant negative coefficient suggests that students who perceive the use of AI on classwork as ethical tend to view academic misconduct as less serious. As indicated earlier in this paper, not all uses of AI in the classroom are inherently unethical, but this finding those with stricter views on the ethicality of AI use are more likely to view academic misconduct as a serious issue.

Non-significant Predictors

Policy Awareness (Coef: 0.29, P-value: 0.33): Despite the positive coefficient, the lack of statistical significance suggests that simply being aware of university policies does not impact how seriously students perceive academic misconduct. This highlights the need for more engaging policy education that connects policy awareness with ethical implications.

Copying Past Work (Coef: 0.01, P-value: 0.85): The non-significance of this finding could reflect a nuanced understanding among students that while copying past work is a form of misconduct, it may be viewed as less severe compared to other forms like plagiarism or cheating on exams. It is possible that students see this as a lesser evil, or it may be a common practice that has become somewhat normalized in certain contexts.

Using classmate's help to write (Coef: -0.01, P-value: 0.83): The non-significance of this variable might indicate tolerance or acceptance of collaborative work, even when it borders on misconduct, reflecting a cultural shift towards more collaborative and less individualistic academic practices.

Copying ideas from a website (Coef: -0.01, P-value: 0.81): Similarly, this result could suggest that students do not view copying ideas from websites as severely as other types of misconduct, possibly due to the prevalence of information on the internet and ambiguity about what constitutes 'copying' in the digital age.

Using Grammarly to revise a paper/submission (Coef: 0.02, P-value: 0.80): This variable, representing how students rank the seriousness of using Grammarly to revise papers, also shows no significant impact on their perceptions of academic misconduct. This could imply that students see this type of tool as a legitimate aid rather than a form of misconduct, or it might reflect a general acceptance of technological aids in academic work.

Awareness of Grammarly-created content is detected as AI-generated (Coef: -0.28, P-value: 0.05): While nearly significant, the negative coefficient suggests that students who are aware of plagiarism detection tools might feel that these technologies reduce the severity of misconduct, perhaps giving a false sense of security or diluting personal accountability.

Cheating on Assignments Hurts Others (Coefficient: 0.07, P-value: 0.10): Despite its ethical implications, this variable did not significantly predict the perceived seriousness of academic misconduct (although it would be significant at a 0.1 level). The finding suggests that students' concerns about the direct consequences of cheating may overshadow their considerations of its broader impacts on others. This could indicate a need to emphasize the communal consequences of academic dishonesty in educational settings to enhance students' understanding of its wider ethical implications.

Cheating is Okay, If Not Caught (Coef: 0.01, P-value: 0.88): This variable's non-significance in predicting the perceived seriousness of academic misconduct suggests that students' ethical evaluations of cheating are not primarily influenced by the likelihood of being caught. The result indicates that considerations of personal integrity and ethical standards may play a more substantial role in shaping students' views on academic misconduct than the pragmatic concerns of detection and consequences. This finding underscores the importance of cultivating a strong ethical foundation in educational settings rather than relying solely on deterrence strategies.

Education Status (Coefficient: 0.49, P-value: 0.05): The positive coefficient suggests a trend that as educational achievement increases, so does the perception of the seriousness of academic misconduct. This indicates a potential pattern where higher education levels might be correlated with a stronger recognition of the implications of academic misconduct. However, the lack of statistical significance (although close) highlights that this observation is not conclusively supported by the data, suggesting that other factors might also play influential roles in shaping these perceptions.

Major (Coefficient: -0.07, P-value: 0.75): The coefficient for academic major suggests a very slight and statistically non-significant difference in how students from different majors (Library Science, Computer Science, Information Science, Linguistics) perceive the seriousness of academic misconduct. The negative coefficient implies a minimal reduction in perceived seriousness associated with these majors (Library and Information Science), but the high p-value clearly indicates that this effect is not statistically significant. This suggests that there is no substantial variation in perceptions of academic integrity across these specific disciplines, reinforcing the notion that ethical perceptions and education on academic misconduct can be uniformly applied across various academic fields without the need for major-specific adjustments.

Student Type (Domestic vs. International) (Coefficient: -0.32, P-value: 0.26): This negative coefficient suggests that compared to international students, domestic students perceive academic misconduct as less serious, although this result is not statistically significant. This lack of significant difference indicates that international status does not substantially influence perceptions of the seriousness of academic misconduct. This result highlights a need for academic integrity policies and education that effectively address and resonate with both domestic and international student populations, ensuring a consistent understanding of ethical standards across diverse student backgrounds.

Gender (Coefficient: 0.03, P-value: 0.68): The coefficient for gender suggests a minor difference in the perception of the seriousness of academic misconduct between genders, though this difference is not statistically significant. The high p-value indicates that gender does not have a substantial influence on how students perceive academic misconduct within this dataset. This finding suggests that perceptions of academic integrity might be relatively uniform across different genders, suggesting that perceptions of academic misconduct are gender neutral.

Primary Language (English vs. Other) (Coefficient: 0.07, P-value: 0.67): The coefficient indicates a slight difference in the perception of academic misconduct seriousness based on whether English is a student's primary language (non-English versus English), though this difference is not statistically significant. The high p-value signifies that primary language, whether English or another language, does not play a major role in shaping students' perceptions of academic misconduct.

The significant variables from this regression analysis indicate the critical role of ethical education and awareness in addressing academic misconduct, while the non-significance of many predictors highlights the nuanced and individualized nature of these perceptions. These insights are important for educators and policymakers aiming to cultivate a culture of integrity amidst the challenges posed by emerging technologies.

Discussion

What are the perceptions of university students towards various forms of academic misconduct, including the use of AI tools like ChatGPT?

Students' perceptions of academic misconduct vary significantly depending on the specific action in question. Traditional forms of academic dishonesty, such as copying sentences or ideas from a paper that a student in past version of a class wrote, are universally perceived as severe misconduct. The survey results show that university students generally have a high level of awareness regarding broad concepts of academic misconduct, with an impressive 96% of respondents reporting awareness with their institution's academic integrity policies. This indicates the effectiveness of the communication efforts of educators and institutions, or it could reflect that most respondents are graduate students. This corresponds with previous studies suggesting widespread awareness of general academic misconduct rules is related to instructors (Baetz et al., 2011; Burgason et al., 2019; Perry, 2010). Additionally, the result highlights that higher educational levels often correlate with increased awareness and stricter views on academic dishonesty (Perkins et al., 2020; Benson & Enstroem, 2023).

While perceptions of traditional academic misconduct are consistently high across all demographic factors, views on the use of AI tools vary. For instance, 45% of respondents saw using AI to generate ideas as a minor infraction, while 69% viewed using AI to write entire essays as a severe form of cheating. Furthermore, 60% of students did not consider using AI for grammar and spell-checking, including Grammarly free and pro versions, as misconduct. This suggests that many students see these tools as extensions of traditional aids like spell checkers and grammar guides, highlighting the need for more precise guidelines on the acceptable use of AI in academic settings. Oravec (2023) notes that the acceptance of such tools can be attributed to their integration into everyday educational practices, which blurs the line between helpful aids and potential misconduct.

However, using AI to write entire essays is viewed as severe misconduct, almost equating it with copying sentences from another student. Specifically, 46% of respondents rated "ChatGPT for Writing Paragraphs" as top misconduct, according to Figure 2. This nuanced perception indicates that students differentiate between various levels of AI assistance, suggesting a spectrum of acceptability depending on how the AI is used. These findings align with studies by Khalid et al. (2014) and Schrimsher et al. (2011), highlighting students' ability to discern varying degrees of severity in academic misconduct.

What is the relationship between students’ ethical beliefs about cheating and their perceptions of the severity of academic misconduct involving AI tools?

The relationship between students' ethical beliefs about cheating and their perceptions of the severity of academic misconduct involving AI tools is multifaceted. Students who view cheating on assignments as unethical (Table 3) also rate the use of AI tools as more unethical compared to those with more lenient views towards cheating (Coef. = 0.09, $p = .03$). Conversely, students who believe that using AI for classwork is acceptable tend to view academic misconduct as less serious (-0.12, $p < .01$). Overall, respondents showed greater leniency towards using AI for smaller parts of assignments, such as generating ideas or writing a few paragraphs. This study suggests that students who consider cheating more severe also tend to view AI-related misconduct more seriously. However, not all forms of AI use in assignments are perceived as misconduct. These findings, which highlight differing perspectives on various types of plagiarism and AI usage, align with previous research by Fyfe (2023) and Parker et al. (2023).

How do demographic factors influence student perceptions of academic misconduct involving AI tools?

The results regarding specific infractions involving AI technologies show some interesting points. Firstly, demographic factors do not significantly affect students' perceptions of AI tools. This finding contrasts with previous studies that indicate different populations, such as those based on gender, education levels, and language, may affect perceptions of academic misconduct (McGowan, 2016; Miles et al., 2022). However, this study shows that certain traits relating to ethical beliefs strongly influence perceptions of using AI tools in academic work. According to the results, many demographic factors did not show a significant statistical difference. Still, the results reveal that three factors—"cheating assignments unethical," "AI writing cheating," and "AI use ethical"—influenced students' perceptions of academic misconduct in the context of generative AI technologies. These results support previous studies suggesting that students' individual ethical beliefs may affect their perception of academic integrity (Patrzek et al., 2015; Stone et al., 2009; 2010).

Implications to educators and academic integrity

The emergence of AI tools like ChatGPT has introduced new complexities in maintaining academic integrity. The study reveals that while there is a general awareness of traditional forms of academic misconduct—96% of respondents noted in response to a survey question that they were familiar with their institution's academic integrity policies—the understanding and perception of AI-related infractions vary significantly. Specifically, 69% of students view using AI to write entire essays as severe misconduct, whereas 45% consider using AI to generate ideas a minor infraction, and 60% do not see the use of AI for grammar and spell-checking as misconduct. These statistics highlight the need for educators to provide more precise guidelines on the acceptable use of AI tools. The blurred lines between helpful aids and potential misconduct, as noted by Oravec (2023), require educators to clearly define what constitutes acceptable assistance versus academic dishonesty.

Educators face the challenge of updating their pedagogical approaches to address these nuances. They must ensure that students understand the ethical implications of using AI tools and the importance of maintaining academic integrity. This includes specifying acceptable uses, such as grammar checking, and prohibited uses, like generating entire essays. A multifaceted approach is required:

1. **Enhanced Communication of Policies**: Institutions should update and explicitly include guidelines on AI tool usage in their academic integrity policies. This information should be communicated clearly through orientations, workshops, and regular reminders. Regular updates and communication about these policies are essential. Chapman University has a list of existing policies and initiatives to communicate them to students at universities across the United States (https://libguides.chapman.edu/AI/policies).
2. **Feedback Mechanisms**: Establishing mechanisms for students to report concerns or uncertainties about AI tool usage can help institutions stay informed about emerging issues and adjust policies accordingly. Regular surveys and focus groups can provide insights into student perceptions and help tailor educational initiatives to address gaps in understanding. A survey from San Diego State University (2023) provides an example of an instrument that universities could use to evaluate the AI awareness of their students.
3. **Educational Interventions**: Workshops and seminars focused on ethical AI usage can help students understand the boundaries of acceptable use. Incorporating case studies and examples can illustrate the differences between permissible aids and misconduct. Integrating AI ethics into the curriculum can help students understand the broader implications of AI technologies. Mandatory courses or modules on digital literacy and ethical AI usage would be beneficial. Some universities have already begun to create learning modules on this topic, such as the AI Fundamentals microcredential at the University of North Texas (https://digitalstrategy.unt.edu/microcredentials/ai-fundamentals.html).
4. **Revising Assessment Methods**: Traditional assessment methods may need revision to reduce opportunities for misconduct. As suggested by Currie (2023) and Oravec (2023), designing assignments that require critical thinking and original analysis, which are less amenable to AI-generated content, is crucial. Additionally, institutions can use AI detection tools to identify potential misconduct. However, as Bellini et al. (2024) noted, these tools have limitations, and continuous improvement is necessary to keep pace with advancing AI technologies.

By implementing these methods, educational institutions can better navigate the challenges posed by AI tools and uphold the standards of academic integrity. This proactive approach will not only address current issues but also prepare institutions for future advancements in technology.

Limitations and Future Research

This study has several limitations to note. The reliance on self-reported data may introduce biases, as students may underreport their engagement in academic misconduct or overestimate their understanding of academic integrity policies based on social desirability. The sample may not be representative of all university students, limiting the generalizability of the findings. The wordings of some of the questions in the survey could be considered vague and could produce a response bias.

Additionally, the rapidly evolving nature of AI technologies means that students' perceptions and the associated ethical considerations may change over time, necessitating continuous monitoring and adaptation of academic integrity policies.

Further research can investigate the effectiveness of different educational interventions in enhancing students' understanding of ethical AI usage. Exploring the role of cultural and institutional differences in shaping perceptions of AI-related academic misconduct can also provide a more comprehensive understanding of this complex issue. Comparing the perception of AI writing tools as academic misconduct between faculty and students may reveal the gap between two stakeholder groups in the university.

Conclusion

This study offers valuable insights into the factors shaping students' perceptions of academic misconduct, particularly in the context of traditional infractions and emerging AI technologies. It highlights university students' general awareness of academic integrity policies and explores their nuanced views on AI-related academic misconduct. The findings suggest that individual ethical beliefs significantly influence perceptions of academic integrity, while demographic factors have little impact on students' views of AI tools in this context. This contribution enriches the existing literature by emphasizing the importance of individual learner characteristics in shaping students' perspectives on academic integrity, especially with the rise of generative AI technologies.

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