



Normalizing Deviance: A Statistical Analysis of Peer Interaction and the Perceived Usefulness of Generative AI in Academic Cheating

Menormalisasi Penyimpangan: Analisis Statistik terhadap Interaksi Teman Sebaya dan Persepsi Manfaat Generative AI dalam Kecurangan Akademik

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ABSTRACT

The rapid integration of artificial intelligence (AI) in higher education has created ethical dilemmas, blurring the line between utilizing technology as a learning tool and committing academic integrity violations. Consequently, this study investigates how peer interaction and the perceived usefulness of generative AI contribute to academic dishonesty among students. Employing a quantitative approach, data were collected from 81 sociology students selected via stratified random sampling to ensure proportional representation across academic batches using a 10-point rating scale questionnaire and analyzed through multiple linear regression. The results show that both independent variables simultaneously have a significant effect on academic cheating, with the perceived usefulness of AI acting as the most dominant predictor. Theoretically, this research validates differential association theory, illustrating the social learning of deviant behavior, indicating that academic cheating is a social behavior normalized by peer environments and strongly rationalized by the efficiency offered by AI. To address this normalizing deviance and ethically integrate AI into education, institutions must establish explicit guidelines regarding the boundaries of AI usage, redesign assessments to prioritize human critical thinking, and actively foster a strong culture of academic integrity.

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ABSTRAK

Integrasi artificial intelligence (AI) yang pesat di pendidikan tinggi telah menciptakan dilema etis, mengaburkan batas antara pemanfaatan teknologi sebagai alat pembelajaran dan pelanggaran integritas akademik. Berdasarkan hal tersebut, penelitian ini menyelidiki bagaimana interaksi teman sebaya dan persepsi manfaat Generative AI berkontribusi terhadap kecurangan akademik di kalangan mahasiswa. Dengan menggunakan pendekatan kuantitatif, data dikumpulkan dari 81 mahasiswa sosiologi yang dipilih melalui penarikan stratified random sampling untuk memastikan keterwakilan proporsional dari setiap angkatan menggunakan kuesioner dengan rating scale 10 poin, dan dianalisis melalui regresi linier berganda. Hasil penelitian menunjukkan kedua variabel independen secara simultan berpengaruh sangat

signifikan terhadap kecurangan akademik, dengan persepsi manfaat terbukti menjadi prediktor yang lebih dominan. Secara teoretis, penelitian ini memvalidasi teori asosiasi diferensial. Teori ini mengilustrasikan konteks pembelajaran perilaku menyimpang yang berindikasi pada kecurangan akademik, yaitu perilaku sosial yang dinormalisasi oleh lingkungan pertemanan dan dirasionalisasi secara kuat oleh efisiensi yang ditawarkan AI. Untuk mengatasi penyimpangan yang dinormalisasi dan diintegrasikan AI ke dalam pendidikan secara etis, institusi harus menetapkan panduan yang eksplisit tentang batasan penggunaan AI, merancang ulang asesmen untuk memprioritaskan kemampuan berpikir kritis manusia, dan secara aktif menumbuhkan budaya integritas akademik yang kuat.

Introduction

The development of artificial intelligence (AI) technology has penetrated various aspects of life, including in Indonesia. WriterBuddy noted that during the period from September 2022 to August 2023, Indonesia was recorded as one of the countries with the third highest number of visits to AI service websites globally, with approximately 1.4 billion visits to AI service provider websites, representing around 5.60% of total global traffic (Sarkar, 2023). The most visited tool was ChatGPT, with approximately 1.8 billion visits (Sarkar, 2023). The use of ChatGPT, QuillBot, and other automation tools is becoming increasingly widespread to support the learning process. Research by Supriadi et al. (2022) notes that AI-based innovations increase the speed and quality of student learning. Ideal academic integrity is when students adhere to existing integrity principles, namely honesty, rationality, objectivity, and openness, when using technology, rather than using it to take shortcuts (Patimah et al., 2024).

The trend of AI adoption in academic aspects offers potential usefulness such as accelerated task completion, ease of writing scientific papers, finding answers, and obtaining information, which can shift the line between utilization and misuse for cheating (Patimah et al., 2024). Academic cheating is defined as any form of action that violates ethics in the learning process, such as plagiarism, cheating, and data manipulation (Prabowo & Wardi, 2021). This practice not only damages academic integrity but also creates an unhealthy educational culture. Students no longer view the learning process as the goal but instead focus only on the result (Zubairi, 2023). Therefore, it is important to examine the factors behind this behavior. One factor that has come under scrutiny is the influence of peers or the student social environment.

Peers are individuals who have strong emotional and social ties with one another, especially on campus (Rahmarini & Totalia, 2025). This explains how cheating behavior can be learned and imitated through intensive social interaction. A meta-analysis by Zhao et al. (2022) shows that peer norms reinforce cheating behavior, especially in collectivist cultures. When students join groups that consider cheating to be normal, ideal academic values begin to erode. Students learn that when everyone does it, the action is no longer considered wrong. Over time, students internalize the deviant values of the group and incorporate them into their academic behavior (Lestari & Lestari, 2017).

A study by McCabe et al. (2001) shows that educational institutions with a strong academic culture that supports honesty tend to have lower rates of cheating. This culture includes the role of peers, as interactions between peers can influence the social norms within the group. The peer environment on campus also provides behavioral models that influence students' decisions to cheat. A meta-analysis by Zhao et al. (2022) found that descriptive norms and peer conditions increase the tendency for dishonest academic culture. On the other hand, the perceived usefulness of AI becomes a rational motivation that complements this social learning. Students who feel that AI helps them work faster, increases productivity, and reduces their study load will tend to be more permissive in using it. Davis (1989) explains that perceived usefulness is a strong predictor of technology adoption, which in the case of AI influences students' preferences for using the tool.

The International Center for Academic Integrity reveals that the most common forms of cheating today are copying in various ways, collaborating with peers, and involving digital sources in completing assignments. In this context, this includes the use of AI to complete assignments and cheat in online exams (Rettinger, 2020). This shows a shift in the value of cheating as technology advances. Nationally, Hartanto & Rohmah (2024) at tirta.id, with Jackpat, surveyed AI and academics from May 21-27, 2024. The survey involved 1,501 respondents aged 15-21 years, consisting of high school and university students. The results showed that 86.21% of respondents stated that they had used AI at least once a month to help complete academic assignments. Meanwhile, only 13.79% stated that they had never used AI at all to complete school or college assignments.

A review of the existing literature reveals several critical limitations, presenting an opportunity to further investigate the intersection of social dynamics and technological intervention. The detailed gap analysis of this research is summarized in Table I.

Table I Gap Analysis

Author(s) & Year	Focus on Previous Studies	Identified Research Gaps	Position of the Current Study
Maulana & Darmawan, (2023)	Reviews the ethical implications and discourse surrounding the use of ChatGPT in academic settings.	Does not empirically examine how peer interaction and social norms influence actual academic practices.	Incorporates peer interaction as a primary predictor to capture the social dimensions and normalization of AI usage.
Supriadi et al. (2022)	Highlights the educational benefits of AI from an optimistic and utilitarian perspective.	Overlooks the dark side of AI, leaving a void in quantitative empirical data regarding its negative impact on academic integrity.	Employs an explanatory quantitative survey approach to generate generalizable, empirical data specifically on AI-assisted cheating.
Zhao et al. (2022)	Investigates the cultural effects of peer cheating at the macro level (descriptive norms, collectivism, demographics) through a broad meta-analysis.	Fails to address AI as a modern medium for cheating. The broad meta-analytical approach misses specific, micro-level behavioral phenomena.	Utilizes primary survey data to provide a more focused, in-depth examination of AI-facilitated cheating at the micro level.
Rahmarini & Totalia, (2025).	Examines self-control, self-efficacy, peer environments, and the moderating role of religiosity in general academic cheating.	Focuses strictly on internal psychological factors and conventional peer dynamics, omitting the intervention of modern technology (Generative AI).	Expands the discourse on peer influence by coupling it with the perceived usefulness of AI to understand how technology actively normalizes deviant behavior.

This gap opens opportunities for studies that combine peer interaction and perceived usefulness of AI in a single framework. An explanatory quantitative approach is needed to obtain generalizable data. This model utilizes surveys to capture student perceptions. If this problem is not addressed, academic integrity will continue to deteriorate, damaging the reputation of institutions and public trust in the credibility of graduates. The main problem of this research lies in several interconnected gaps:

- A lack of understanding of how perceptions of AI usefulness and peer habits simultaneously influence the intention and practice of academic cheating.
- The reality is that these AI-assisted cheating practices are just beginning to emerge and play a role in students' daily academic lives.
- The fact that the specific relationship between perceived AI usefulness and AI-based cheating has not yet been comprehensively explored.

Peer Interaction

Peer groups have various essential functions in the social, emotional, and moral development of individuals (Santrock, 2007). The peer environment has a strong influence on the formation and change of individual behavior. Conformity is one of the main forms of this influence, namely the tendency of individuals to adjust themselves to group norms and behaviors to be socially accepted (Ramayanti & Musafiri, 2021). Conformity is defined as a person's desire to change their beliefs or behavior to fit group standards. This is reflected in adolescents' decisions, including in aspects of lifestyle, consumption, and academic choices (Lestari & Lestari, 2017). The process of conformity occurs through daily interactions. Sukaesih (2023) explains that interactions with peers play a key role in an individual's social and moral development. Through these interactions, individuals learn to understand patterns of reciprocal relationships, which cannot always be obtained from relationships with parents or other authorities.

Desiani (2020) explains that peers become a medium for individuals to learn how to observe the interests, needs, and views of others, thereby encouraging social adaptability. Individual behavior is often the result of a process of imitation in interaction, namely, passively copying the behavior of others. The influence of peers on behavior is not only positive but also has the potential for deviation if group norms lead to unethical actions (Sukaesih, 2023). This means that individuals imitate deviant behavior, including academic cheating, if it is considered normal within the group. The social environment of students, consisting of peers who interact with each other, influences academic norms and behavior, as well as aspects of peer interaction according to Riziq & Irmawita (2024): openness, cooperation, and honesty.

Perceived Usefulness

Perception is a cognitive process that enables individuals to interpret and give meaning to stimuli received from the environment. Perception in sociology and social psychology is not only individual in nature but is also influenced by other factors such as social, cultural, and previous experiences (Lase et al., 2025). Perceived usefulness is the extent to which a person believes that the use of technology will improve their performance in completing tasks or work. This concept was first introduced by Davis in the technology acceptance model (TAM) framework, which was later widely adopted and developed in numerous studies on technology acceptance (Moura et al., 2020).

According to Halim et al. (2023), this perception is subjective but influences users' decisions and preferences in choosing and using technology. According to Purwantini & Amalia (2021), the perception of usefulness is formed not only from initial information but also from direct experience in interacting with technology. When linked to AI, positive experiences such as relevant output results or ease of interface will reinforce the perception of usefulness and encourage continued use. As a result, the perception of usefulness is an important indicator in understanding the process of AI adoption by individuals. The higher the perception that AI provides real usefulness, the greater the likelihood that this technology will be adopted routinely, whether in academia, business, or everyday life. Kumala et al. (2020) formed the construct of belief in perceived usefulness. In this study on AI technology in the academic sphere, several key indicators were used, including working more quickly, increasing productivity, enhancing effectiveness, and making the job easier and more useful.

AI in Academia

AI in an academic context refers to technology that can mimic human cognitive processes to assist in writing and research (Diktiristek, 2024). Examples of commonly used AI technologies include ChatGPT, Google Gemini, Claude, Perplexity, and QuillBot. These tools are designed to improve the efficiency and quality of academic writing. The integration of AI in academic writing has brought significant changes to the way students and researchers compose scientific papers. These tools not only speed up the writing process but also improve the quality and accuracy of the content. It is important to understand that AI is a

tool, not a substitute for critical thinking and in-depth analysis. As highlighted by Shahzad et al. (2025), the use of AI must be accompanied by ethical understanding and academic responsibility. With the right approach, AI can be an asset in the academic world.

Although AI offers considerable usefulness, there are concerns regarding academic integrity and potential misuse. Some students may be tempted to use AI unethically, such as copying text without understanding it. According to Shahzad et al. (2025), ChatGPT dominates the use of AI in academic writing with a percentage of 77% of the total use of AI tools. A study by Khalil & Er (2023) shows that ChatGPT can generate text that is difficult to detect by traditional plagiarism tools. Lin (2023) states that although AI can help with writing structure and style, deep understanding still requires human intervention. Collaboration between AI and human writers is the ideal approach. This ensures that academic quality and integrity are maintained.

Academic Cheating

Mushthofa et al. (2021) emphasize that academic cheating is unethical and does not comply with academic norms. McCabe et al. (2001) add that academic cheating is complex behavior that violates the code of ethics of honesty in the learning process. This definition highlights its multifaceted nature, which includes not only cheating but also plagiarism, data manipulation, and unauthorized collaboration. For example, in the Indonesian context, Pramudyastuti et al. (2020) state that academic cheating has become a common phenomenon and involves deliberate dishonesty to obtain good academic results.

The common form of academic misconduct is plagiarism, which occurs when someone claims another person's work (writing, ideas, or research results) as their own without permission or proper attribution. The author copies someone else's writing and claims it as their own work (McCabe et al., 2006). Then, students paste or copy several sentences, data, or ideas from other people's books/websites, but do not write footnotes or proper citations (Patimah et al., 2024). Plagiarism with AI takes on a new, more complex dimension. AI technology can easily generate text that is like the original work, thereby potentially influencing students to use it unethically in completing assignments without going through the actual learning process (Diktiristek, 2024). The use of AI raises fundamental issues regarding unclear ownership of works. Unlike human work, which can be traced back to its sources, AI operates by predicting outputs based on probabilities derived from its vast training data. As a result, AI-generated text is often a compilation or synthesis of various sources that cannot be attributed or verified.

Another common form is cheating on exams, which includes various illegal ways of obtaining answers, such as bringing hidden notes, asking friends, or using cell phones or cheating sheets in exams or assignments (Susiatik et al., 2022). Plagiarism also includes not only direct copying but also the use of prohibited technology or materials to obtain answers. Students who engage in cheating deliberately take advantage of minimal supervision to achieve high grades instantly. The use of AI can be categorized as a form of modern cheating when it is used as prohibited technology or material to obtain answers for exams (Diktiristek, 2024). Its speed and complex results can facilitate academic cheating very easily. This unauthorized use of AI directly conflicts with the fundamental requirements of learning, which require students to work independently on their assignments with learning outcomes.

Differential Association Theory: Seven Propositions

One of the main principles in differential association theory is that individuals learn values, attitudes, and techniques of deviance through interaction with social groups. If a student is in a social circle that is permissive of using AI for academic cheating, they are likely to adopt a similar attitude. Students may begin to believe that everyone else is doing it and that cheating is not a serious matter. Even students who initially have good academic grades can be influenced by their peer group. When students see that cheating with the help of AI yields better results in less time, they may begin to consider and eventually do the same.

Sutherland formulated nine main propositions in Differential Association Theory to explain how deviance is learned (Hisyam, 2021). Of these nine propositions, the first seven will be used as they can be linked to the research variables. These propositions assert that deviant behavior is learned through communication, especially in intimate or close relationships. This learning process includes not only the techniques of committing violations but also the moral justification that accompanies them. When applied to students, this justification can take the form of a belief that everyone else is cheating, so that deviance is not just an act but a social process that is learned gradually.

The first proposition states that criminal behavior stems from learning processes rather than innate genetic factors (P1). The second proposition emphasizes that the learning of deviant behavior occurs in verbal and social interactions with others (P2). The third proposition states that the learning of deviant behavior occurs primarily in intimate groups (P3). The fourth proposition mentions that learning includes techniques, motives, and justifications for deviant actions (P4). The fifth proposition talks about the value or norm orientation that underlies the action (P5). The sixth proposition emphasizes that a person becomes deviant when exposed to more definitions that support the violation than those that oppose it (P6). The seventh proposition explains that the influence of differential association depends on the frequency, duration, priority, and intensity of the relationship (P7) (Hisyam, 2021).

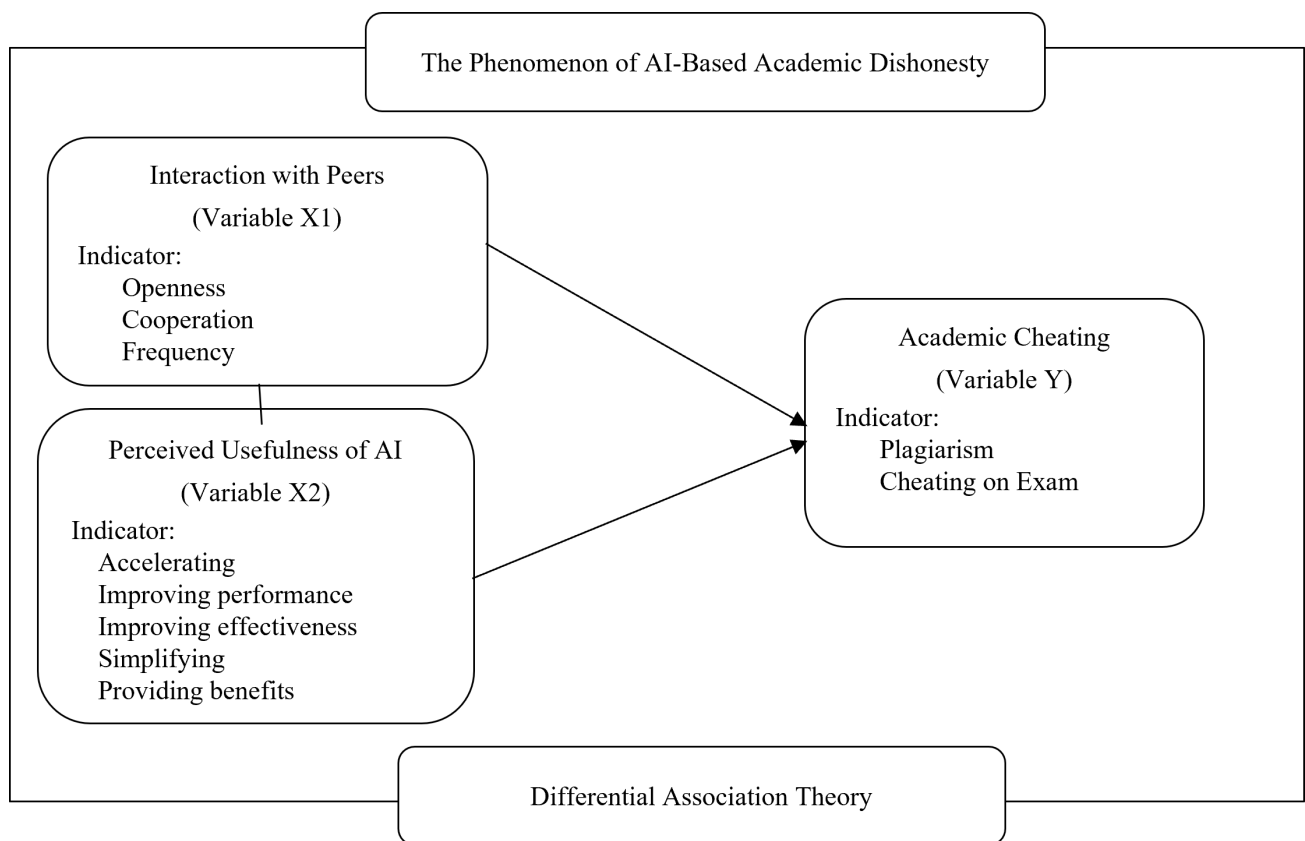


Figure 1 Thinking Framework

Method

This study uses a quantitative approach because it aims to test the relationship between variables objectively and measurably. The use of a quantitative approach allows researchers to identify patterns and the strength of the relationship between perceived usefulness, peer environment, and academic cheating. The population in this study consists of all active students from the 2022, 2023, and 2024 cohorts in the sociology study program at University X. This population was selected because, socially

and academically, the prospective respondents are involved in the use of digital technology, including AI, in their daily learning activities. The sampling method used in this study is probability sampling with the proportionate stratified random sampling technique. This method was chosen so that each stratum (class) is represented proportionally, thereby increasing the representativeness of the sample to the population.

The research instrument, in the form of a questionnaire, was developed based on the operational indicators of each variable. This questionnaire uses a rating scale. The rating scale in this study is categorized as an interval scale. Data measurement for the variables in this study uses a 10-point rating scale. The rating scale was chosen because of its ability to produce interval data that is more sensitive and accurate for parametric statistical analysis such as regression analysis (Morris, 2012). Respondents were instructed to choose the number that best represents their level of agreement or conformity with a given statement. In its application, the highest score (10) indicates the most positive response (highly applicable), whereas the lowest score (1) represents the most negative response (highly inapplicable). This broader range allows respondents to express the intensity of their feelings or opinions with greater precision, thereby capturing nuanced responses that might be lost on scales with fewer points (Dawes, 2008). The instrument design considered varied wording, including combining positive and negative statements so that respondents would not answer carelessly and to detect the consistency of respondents' answers (Pujihastuti, 2010). Thus, some statements were formulated in negative forms to prevent mechanical response patterns.

The application of multiple linear regression is driven by the explanatory objective of this research, which aims to determine the magnitude of both the simultaneous and partial effects of each independent variable on the dependent variable. This analytical method is highly appropriate for quantitative studies involving multiple predictor variables and a single criterion variable. According to Field (2018), regression analysis facilitates the prediction and interpretation of linear relationships among variables while also enabling the formulated hypotheses to be tested measurably and objectively.

The data collected from the questionnaires initially underwent editing, coding, and tabulation processes to ensure accuracy and completeness. Subsequently, the data were analyzed using the Statistical Package for Social Sciences software version 27. The first analytical phase involved descriptive statistics to determine data distribution, including the mean, median, and standard deviation for each variable. The second phase required that the data satisfy several classical assumptions prior to hypothesis testing (Field, 2018). This included normality testing, multicollinearity testing by assessing variance inflation factor and tolerance values, and heteroscedasticity testing through scatterplot examinations. The third phase involved conducting multiple linear regression analysis to generate regression coefficients, significance values, and the coefficient of determination to measure the magnitude of the independent variables' influence on the dependent variable.

Results and Discussion

The results of the descriptive statistical analysis show that female respondents were the majority group, numbering 60 people or 74.1% of the total sample. Meanwhile, there were 21 male respondents, equivalent to 25.9% of the total respondents. Based on the data obtained, respondents were dominated by students from the class of 2024, numbering 28 people or 34.6% of the total sample. Next, respondents from the class of 2022 numbered 27 people (33.3%). Meanwhile, respondents from the class of 2023 were the smallest group, although the difference was not significant, with 26 people (32.1%). The even distribution of respondents across classes shows consistency with the sampling technique used, namely stratified random sampling.

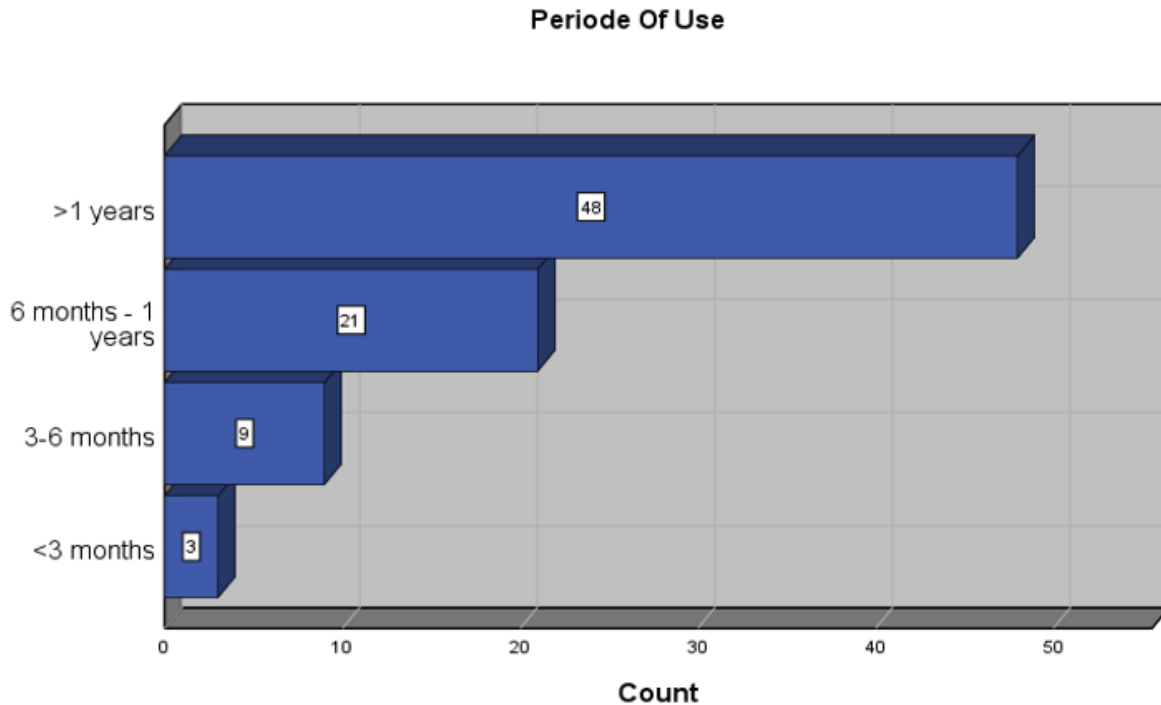


Figure 2. Frequency of Respondents Based on AI Usage Duration

The results of the descriptive statistical analysis show that most respondents, namely 48 people (59.3%), have been using AI for more than a year. The second largest group is users with a duration of 6 months to 1 year, totaling 21 people (25.9%). Meanwhile, respondents with shorter usage durations, namely 3-6 months and less than 3 months, numbered only 9 people (11.1%) and 3 people (3.7%), respectively. This indicates that most of the samples in this study were not new users but individuals who already had significant experience and familiarity with AI technology.

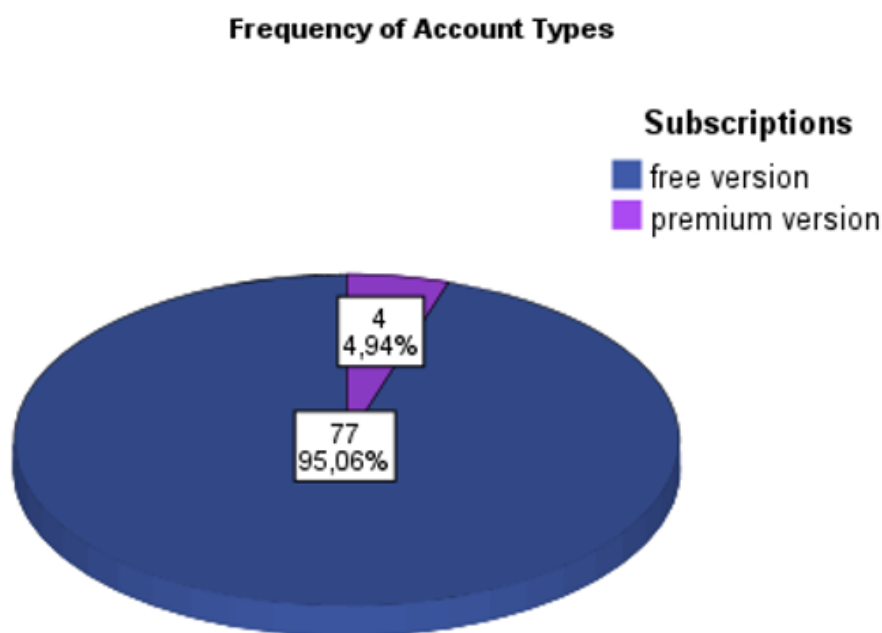


Figure 3. Frequency of Respondents Based on Account Types

Descriptive statistical calculations show that the majority of respondents, namely 77 people or 95.1%, are users of free AI services (free version). On the other hand, only a small number of respondents, namely 4 people or 4.9%, chose to use paid services (premium version). Many popular AI platforms today offer very capable functionality in their free versions. These features are often more than sufficient to meet general needs.

To provide a deeper insight into this high familiarity and usage intensity, the analysis further identifies the specific characteristics of AI adoption. The research recognizes that students typically integrate various tools into their workflow rather than relying on a single application. Therefore, the data were analyzed using a multiple-choice format to determine the rankings of the most frequently used AI services, the sources from which students obtain information, and the practical functions of AI in their academic lives. The following section presents the distribution and hierarchy of these tables.

Table II Ranking of Most Used AI Services by Respondents

Ranking	Type of AI Used	Total of 81 Responses	Percentage
1	Chat GPT	74	91,4
2	Gemini	43	53,1
3	Perplexity	40	49,4
4	QuilBot	21	25,9
5	Claude	17	21,0
6	BlackBox	1	1,2

Source: Data processed by author (2025)

Table III Ranking of Information Sources regarding AI by Respondents

Ranking	Source of Information AI Platform	Total of 81 Responses	Percentage
1	Friends	62	76,5
2	Social Media	53	65,4
3	Internet	40	49,4
4	Lecturers	14	17,3

Source: Data processed by author (2025)

Table IV Ranking of AI Functions for Academic Purposes by Respondent

Ranking	Academic Function	Total of 81 Responses	Percentage
1	Creating references and citations	64	79,0
2	Answering questions or assignments	54	66,7
3	Searching for ideas/materials	50	61,7
4	Summarizing material	40	49,4
5	Creating KTI	19	23,5

Source: Data processed by the author (2025)

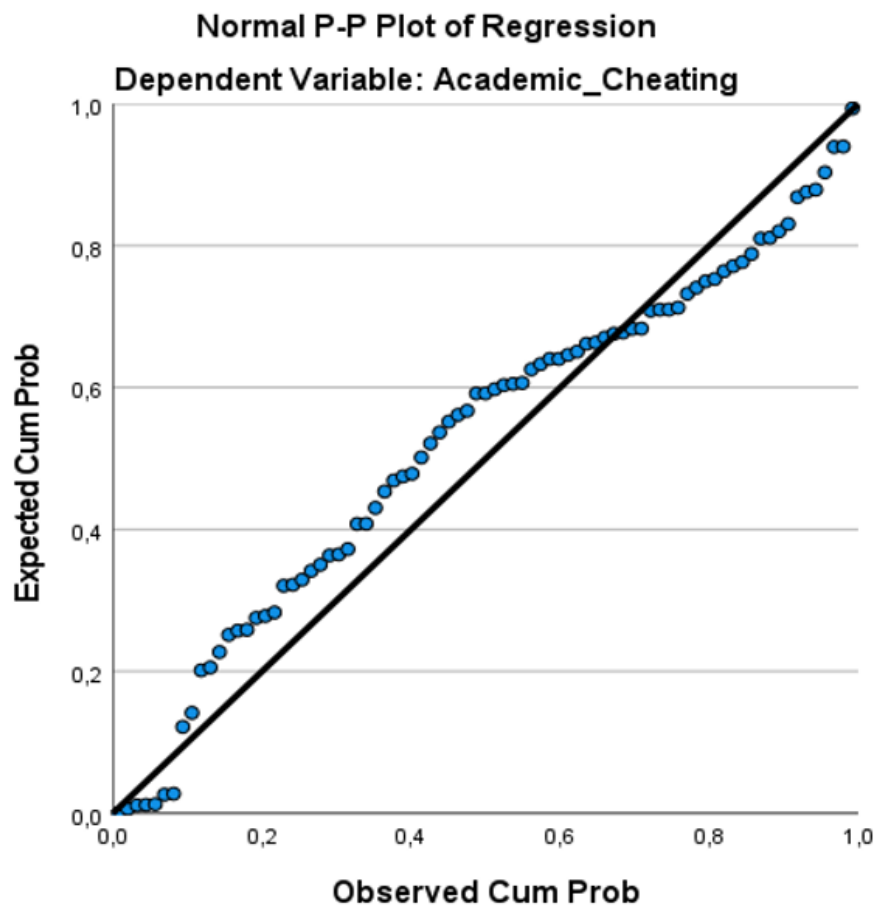
The reliability test was conducted using Cronbach's alpha method with the help of the SPSS program. The instrument is considered reliable if the Cronbach's alpha value is > 0.70 . A value above 0.70 indicates that the items in a variable have good internal consistency. Reliability was tested based on trial data conducted on 30 students outside the main sample.

Table V Reliability Test

Variable	Cronbach's Alpha Decision	Cronbach's Alpha Results	Decision
X1: Peer interaction	> 0,700	0,844	Reliable
X2: Perceived usefulness of AI	> 0,700	0,755	Reliable
Y: Academic Cheating	> 0,700	0,800	Reliable

Source: Data processed by the author (2025)

The reliability test results show that Cronbach's Alpha value exceeds the minimum threshold of 0.70, indicating a high level of reliability. This means that all items have strong internal consistency in measuring the aspects of peer interaction. This instrument can be relied upon to produce stable and consistent data over time and is declared reliable and suitable for use in the subsequent stages of research analysis. After ensuring that, the next stage of analysis is hypothesis testing through regression analysis. To proceed with the regression analysis, the data must satisfy certain feasibility criteria. Consequently, classical assumption tests, including normality and linearity, must be executed first.

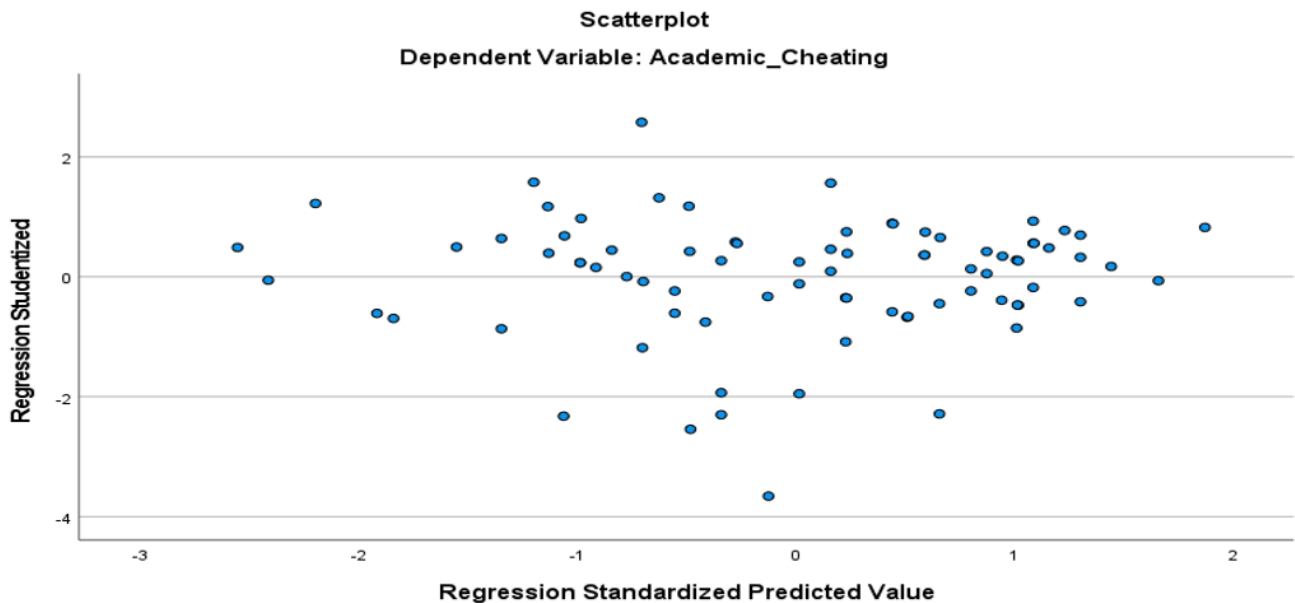
**Figure 4 P-P Plot Regression**

The normal P-P plot shows that most points track the diagonal expected normal line, with slight deviations at the tails. The tight clustering around the line confirms adherence to a normal distribution. Since the data has met this normality prerequisite, the subsequent step is to conduct a multicollinearity test to ensure there is no strong correlation between the independent variables.

Table VI Heteroscedasticity Test

Coefficients ^a Dependent Variable Y					
Model	Standardized Coefficients Beta	T	Sig.	Tolerance	VIF
(Constant)		,847	,400		
X1	,208	2,076	,041	,512	1,954
X2	,614	6,126	<,001	,512	1,954

The interpretation of the results indicates that the tolerance values for both independent peer interaction (X1) and perceived usefulness (X2) are 0.512 each, which is well above the critical threshold of 0.10. Furthermore, the VIF values are 1.954 each, which is well below the common problematic threshold ($VIF < 10$). This indicates that there is no significant multicollinearity between the independent variables. Consequently, the non-multicollinearity prerequisite for the multiple regression analysis in this study is fulfilled. With the absence of multicollinearity confirmed, the next step is to conduct a heteroscedasticity test to ensure that the variance of the residuals remains constant across all observations.

**Figure 5** Frequency of Respondents Based on Account Types

Based on the scatterplot, the data points are distributed randomly along the prediction axis and scattered above and below the zero line without any systematic pattern, such as funneling or clustering, which would indicate an increase or decrease in variance relative to the predicted values. The range of values does not show an increasing concentration of variance at specific predicted values; hence, no evident symptoms of heteroscedasticity are apparent. As a result, visually, the homoscedasticity assumption for this multiple regression model can be considered fulfilled. With the homoscedasticity assumption satisfied, all prerequisite classical assumptions for the multiple regression model have been successfully met. Consequently, the analysis advances to the simultaneous hypothesis testing (F-test) to determine whether peer interaction and the perceived usefulness of using AI collectively influence academic cheating.

Table VII ANOVA F-Test (Simultaneous Testing)

ANOVA ^a					
Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	6430,565	2	3215,282	58,225	<,001 ^b
Residual	4307,312	78	55,222		
Total	10737,877	80			

Source: Data processed by author (2025)

The table above can be interpreted based on the significance value; it is known that the significance value (Sig.) obtained is <0.001. This value is clearly smaller than the specified significance level, which is well below the significance level of 0.05, with a value of < 0.001. This finding indicates a statistically significant result. The results suggest that the independent variables (peer interaction and perceived usefulness) together have a significant effect on the dependent variable (academic cheating).

Table VIII Model Summary

Model Summary ^b				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,774 ^a	,559	,589	7,431

Source: Data processed by author (2025)

Based on the data analysis results presented in the Model Summary table, the R-squared value is 0.559, and the focus is the adjusted R-Squared value of 0.589. The main interpretation of this analysis centers on the adjusted R-squared value of 0.589. This figure can be interpreted as meaning that the combined (simultaneous) contribution of the independent variables (peer interaction and perceived usefulness) to the rise and fall of the dependent variable (academic cheating) is 58.9%. The results show that the regression model proposed in this study can explain nearly 59% of the total variation that occurs in variable Y. This indicates that variables peer interaction and perceived usefulness are relevant predictors and play a significant role in explaining the phenomenon measured by variable academic cheating. The consequence of this finding is that there is a residual effect that cannot be explained by this regression model. This residual effect is 41.1%, which is obtained from a simple calculation (100% - 58.9%). This figure of 41.1% represents the contribution of other factors or variables that theoretically could also influence variable Y but were not included or studied in this research model.

Table IX Coefficients T-Test

Coefficients ^a						Collinearity Statistics	
Model	Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	T	Sig.	Tolerance	Vif
(constant)	4,111	4,856		,847	,400		
X1	,159	,77	,208	2,076	,041	,512	1,954
X2	,884	0,144	,614	6,126	<,001	,512	1,954

Source: Data processed by author (2025)

The significance value (Sig.) for variable peer interaction is 0.041. Since this value is less than 0.05, it can be concluded that variable peer interaction (X1) partially has a significant effect on variable academic cheating (Y). The significance value (Sig.) for the variable perceived usefulness (X2) is

<0.001 . Because this value is much smaller than 0.05, even smaller than <0.001 , it can be concluded that the variable perceived usefulness partially has a significant effect on academic cheating (Y). Overall, the T-test results show that both independent variables, peer interaction and perceived usefulness, are statistically significant predictors of the dependent variable, academic cheating. The above results also show a difference in strength, clearly indicating that the beta value for the variable perceived usefulness (0.614) is higher than the beta value for the variable peer interaction (0.208). In fact, the influence of perceived usefulness is almost three times stronger than that of peer interaction. In conclusion, although both independent variables, peer interaction and perceived usefulness, have a significant effect on the dependent variable, academic cheating, the variable perceived usefulness has a much more dominant and stronger influence.

Based on the results of the multiple linear regression analysis shown in the table above, the regression equation is $(Y = 4.111 + 0.159X_1 + 0.884X_2)$. The constant value of 4.111 indicates that if the variables peer interaction (X_1) and perceived usefulness (X_2) are zero, then the value of the dependent variable academic cheating (Y) is 4.111. Variable X_1 has a regression coefficient value of 0.159 with a significance of 0.041 (<0.05), which indicates that X_1 has a positive and significant effect on Y. This shows that every one-unit increase in X_1 will increase the value of Y by 0.159 if other variables remain constant. Meanwhile, variable X_2 has a regression coefficient value of 0.884 with a significance of <0.001 (<0.05), which indicates that X_2 also has a positive and significant effect on Y. This result shows that every one-unit increase in X_2 will increase the value of Y by 0.884 with other variables remaining constant.

Meanwhile, based on the results of the description of the variables tested, the categories indicate a positive level, where variables X_1 , X_2 , and Y are in the medium to high category. Peer interaction (X_1) shows that there are strong and positive social norms related to the use of AI. The data consistently describe an environment in which students actively share knowledge, collaborate on group assignments, and help each other when there are technical difficulties. Overall, the peer interaction variable (X_1) creates a social environment that is very conducive to the normalization of practices that border on academic cheating because it provides a model of behavior (Zhao et al., 2022). This is in line with the research of Rahmarini & Totalia (2025) that peers are one of the variables that support academic cheating.

The perception of AI usefulness (X_2) indicates the extent of rationalization based on AI functions, assuming speed, ease, efficiency, and usefulness, which in academic terms leads students to use AI. This shows how the perception of usefulness plays a role in the use of technological products, in this context AI, which is consumed by society (Alshammari & Babu, 2025). The more beneficial a product or service is, the more it will be used (Mauliza & Purba, 2023). The usefulness alters students' moral calculations, as the rewards gained from using AI, such as getting better grades and reduced stress, feel far greater than the acceptable risks. This perception is the motive for the adoption of behavior measured in variable Y. The influence of these two variables does not work independently but rather creates a strong constructive collaboration. Peer interaction (X_1) creates a smooth, safe, and socially acceptable environment for behavior. Meanwhile, the perception of usefulness (X_2) serves as a strong internal motivation that encourages students to move quickly down that path. It is this combination of a normalizing environment and rationalizing motivation that significantly influences academic cheating (Y).

However, this study has limitations in terms of population and sample originating from a single study program, which will have academic cultural characteristics, types of assignments, and study pressures in social study programs that may differ from other study programs. Based on the results of the coefficient of determination (adjusted R-squared analysis), the two independent variables in this study (peer interaction and perceived usefulness) were able to explain 58.9% of the variation in academic cheating. This means that there is still a remaining influence of 41.1% that is explained by factors other than those included in this research model.

When examined through Sutherland's differential association theory, this phenomenon is explained through seven points of interaction association. Edwin Sutherland's differential association theory explains

the formation of deviant behavior through seven main propositions, beginning with the basic principle that criminal behavior can be explained by social mechanisms that occur, which can be summarized as students entering intimate friendship groups (P3) where they communicate intensely (P2). Through this interaction, respondents learn techniques for using AI and develop strong rationalizations based on its usefulness (P4). This process collectively redefines the rules of academic integrity (P5), leading to the dominance of definitions that support the extensive use of AI (P6). Because these interactions are very frequent and intense (P7), academic cheating using AI becomes a learned and inevitable outcome (P1).

This study reveals that academic cheating using AI is contagious social behavior, not just a decision made by one student. Initially, a student may feel hesitant or afraid to break the rules, but their peer environment changes everything. Through daily interactions on campus or in chat groups, an intensive learning process takes place, such as sharing tips, prompting tricks, and ways to paraphrase AI results to pass detection. As a result, actions that should be considered serious violations gradually become commonplace and normal because everyone is doing them, so feelings of guilt are slowly eroded by the habits of the group.

This behavior, already considered normal by peers, is further reinforced by a strong perception of personal benefit, namely, the significant cognitive advantages offered by the technology itself. Students experience firsthand how AI can cut down the time needed to complete assignments from hours to minutes with instant results. This experience of efficiency and convenience becomes a logical reason for them to justify cheating as a strategic step in dealing with their academic workload. They no longer see themselves as cheaters, but rather as students who work efficiently, even though their methods violate academic integrity.

The combination of peer support and instant convenience creates a behavioral pattern that is difficult to stop. Students are trapped in a cycle where their environment continues to teach and normalize new ways of using AI, while the instant results of this technology continue to provide practical satisfaction. This phenomenon shows that academic cheating in the digital age is the result of complex social adaptation, where the line between genuine learning and simply completing assignments is becoming increasingly blurred due to environmental pressures and technological convenience. The implications of this research for the world of education are that conventional approaches focused on detection and punishment are no longer adequate to tackle AI-based academic cheating. Effective intervention requires a shift in values, targeting the root of the problem, namely the normalization of deviant behavior.

Conclusion

Peer interaction (X1) and perception of AI (X2) were found to have a positive and significant effect on students' tendency to commit academic cheating (Y), both simultaneously (simultaneously) and individually (partially). These findings statistically support and accept the proposed hypothesis. The F-test results show a significance value of <0.001 , confirming that peer interaction and perception of AI usefulness together are significant predictors of academic cheating. The adjusted R-squared value of 0.589 indicates that the two independent variables can explain 58.9% of the variation in academic cheating behavior. This indicates that the results make a strong and relevant contribution.

In addition, peer interaction (X1) was found to have a significant effect (Sig. = 0.041), while the perception of AI usefulness (X2) was found to have a significant effect (Sig. < 0.001). Beta coefficient analysis shows that the perception of AI usefulness (beta = 0.614) has a more dominant and stronger influence than peer interaction (beta = 0.208). This study empirically validates Sutherland's main proposition, which states that deviant behavior (academic cheating) is the result of a social learning process that occurs in intimate groups (peer groups). The friendship environment has been proven to effectively teach techniques and rationalizations for committing violations. This study also found that among the two variables, the perception of the usefulness of AI (X2) has a more dominant influence. This is evidenced by the standardized beta coefficient value, where X2 (beta = 0.614) shows a much stronger

influence than X1 ($\beta = 0.208$). This means that even though the social environment creates conditions that normalize behavior, the main driver that encourages students to commit academic fraud comes from their personal belief in the real usefulness provided by AI, such as efficiency and improved task quality.

The presence of artificial intelligence (AI) in higher education can no longer be viewed exclusively as a computer science achievement or a mere technological disruption. AI has become deeply integrated into everyday life, creating a new social reality. From a social science perspective, this technological innovation interacts directly with the students' social structures. While algorithms and sophisticated AI systems provide technical convenience, how these technologies are adopted, rationalized, and utilized for academic cheating heavily depends on group dynamics (peer interaction) and the individual's construction of meaning regarding the technology (perceived usefulness).

The rapid acceleration of scientific and technological innovation, if unmatched by ethical adaptation, critical awareness, and institutional regulation, can trigger what social sciences term the "normalization of deviance," a condition where cheating is gradually accepted as a new cultural norm. Therefore, responding to the challenges of AI in the educational realm demands a multidisciplinary approach synergizing technological literacy with the reinforcement of social integrity values. Understanding this intersection serves as the philosophical and practical foundation for the recommendations proposed in this study.

Educational institutions and educators must implement structural adaptations to address the rapid advancement of artificial intelligence. Universities and faculties are advised to integrate AI ethics, boundaries, and integrity guidelines directly into the curriculum through clear regulations and specific modules. Concurrently, educators should redesign evaluation methods by shifting away from AI-vulnerable tasks such as standard descriptive essays towards authentic assessments like oral exams, social phenomenon case studies, and process-based grading. This strategic shift will effectively diminish the perceived benefits of relying on AI for academic dishonesty.

At the individual level, students are strongly encouraged to foster critical and reflective awareness regarding their AI consumption. The findings indicate a positive dependency on AI driven by its perceived usefulness in facilitating academic cheating. Students must recognize that while AI offers immediate convenience, excessive reliance on these tools poses a significant threat to the development of vital competencies. Cultivating independent critical thinking, analytical writing, and argumentative skills remains essential to prepare for their future professional careers.

Finally, future researchers are recommended to adopt a mixed-methods approach, utilizing in-depth interviews to further explore the underlying rationalization processes of student behaviors. To enhance the generalizability of the findings, subsequent studies should expand the population and sample beyond a single sociology program, acknowledging that different disciplines may possess distinct academic cultures and pressures. Moreover, future research models should incorporate additional external variables that potentially influence academic cheating, such as the impact of social media, lecturer supervision, academic pressure, and individual ethical comprehension.

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