frontiers | Frontiers in Education

TYPE Brief Research Report
PUBLISHED 07 July 2025
DOI 10.3389/feduc.2025.1551721

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RECEIVED 03 January 2025
ACCEPTED 18 June 2025
PUBLISHED 07 July 2025

CITATION
Sun R, Tang M, Zhou J, Loan NTT and Wang C-Y (2025) The dark tetrad as associated factors in generative AI academic misconduct: insights beyond personal attribute variables.
Front. Educ. 10:1551721.
doi: 10.3389/feduc.2025.1551721

The dark tetrad as associated factors in generative AI academic misconduct: insights beyond personal attribute variables

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The rise of generative artificial intelligence (AI) tools has reshaped the academic integrity landscape, introducing new challenges to maintaining honesty in scholarly work. Unlike traditional plagiarism, which typically involves copying existing text, generative artificial intelligence-generated content often appears sufficiently original to evade detection systems. This underscores the necessity of investigating the factors that contribute to such misconduct. This study explores the factors associated with Generative AI academic misconduct among university students in Taiwan, focusing on personality traits from the Dark Tetrad—Machiavellianism, narcissism, psychopathy, and sadism—alongside other personal attribute variables. Data were collected from 812 participants ($Mean_{age}$ = 24.86), comprising 439 females and 373 males, including 362 undergraduates and 450 graduate students. The results indicate that narcissism, psychopathy, and sadism significantly are significantly associated with Generative AI academic misconduct, while gender, educational level, grade point average, and Machiavellianism are not significant associated factors. These findings highlight the limited relevance of traditional personal attributes as associated factors in the context of generative AI and emphasize the need for targeted interventions to address personality-driven behaviors in mitigating the risks of academic misconduct.

KEYWORDS

generative artificial intelligence, Dark Tetrad, academic performance, gender, educational level

1 Introduction

Academic misconduct has long posed significant challenges to higher education institutions (Perkins et al., 2020). It is generally defined as a failure to maintain honesty and integrity in academic work, encompassing actions such as using unauthorized assistance during examinations, neglecting proper citation practices, and assigning authorship to individuals who did not meaningfully contribute (Kidwell and Kent, 2008). Based on 12 years of data, McCabe and the International Center for Academic Integrity found that student cheating was alarmingly widespread, with 43% of graduate students and 68%

of undergraduates admitting to dishonest behaviors such as cheating on assignments or exams (McCabe et al., 2012). Common types of academic misconduct include violations of academic originality such as ghostwriting, plagiarism, data fabrication, deceit, and, more recently, the misuse of generative artificial intelligence tools (Pudasaini et al., 2024; Nerdynav, 2023).

The advent of generative artificial intelligence tools has profoundly altered the academic integrity landscape. ChatGPT, for instance, was developed by OpenAI to generate contextualized responses to open-ended questions. Claude, another large language model by Anthropic, is widely employed by students to assist with their goal-directed academic tasks, especially in essay writing and code generating. In such a case, students can now produce sophisticated, AI-generated work with minimal effort (Song, 2024). Unlike traditional plagiarism, which typically involved copying existing text, generative artificial intelligence generated content often appears original enough to evade standard detection systems (Pudasaini et al., 2024; Demers, 2023). Tools like ChatGPT and Claude complicate the distinction between authentic student output and AI-generated material, posing new challenges for both automated detection and human evaluation (Kumar et al., 2024; Liu et al., 2023). Yet, as Song (2024) observes, there is a notable gap in research on best practices for the ethical integration of generative artificial intelligence into academic environments. As educational institutions confront these challenges, it becomes essential to investigate the factors driving students to rely on generative artificial intelligence for dishonest academic practices.

Previous research has identified several personal attributes that influence academic misconduct. The role of gender remains contested: while some studies report that males are more prone to cheating (Yu et al., 2017; Jereb et al., 2018; Denisova-Schmidt et al., 2019), others find no significant gender differences (Bokosmaty et al., 2019). Educational level also matters. At more advanced levels of study, the impact of academic anxiety on misconduct appears to diminish. Doctoral students, for example, are often more aware of academic norms and more fully understand the negative consequences of misconduct. As a result, they are less likely to engage in such behaviors–even under heightened stress–compared to students at lower educational levels (Su and He, 2023; Burgason et al., 2019).

Academic performance also appears to shape misconduct tendencies. Students with lower academic achievement are generally more likely to engage in dishonest behaviors than their higher-achieving peers, potentially due to increased academic pressure or low self-confidence (Miles et al., 2022; Chamorro-Premuzic and Furnham, 2004; Smith et al., 2007; Yukhymenko-Lescroart, 2023). Among those who cheat, a "desire to get ahead" stands out as a key motivator, reflecting the perception that unethical actions can confer competitive advantages (Simkin and McLeod, 2010).

Beyond personal attributes, dark personality traits may offer deeper insights into why individuals engage in academic misconduct (Playfoot et al., 2024). The Dark Tetrad–comprising Machiavellianism, Narcissism, Psychopathy, and Sadism–provides a framework for examining personality-driven unethical behaviors (Paulhus et al., 2021). These traits share a common core characterized by low empathy and a predisposition toward aggression (Gómez-Leal et al. 2024; Paulhus and Williams, 2002; Wang and Bi, 2024), yet each exhibits distinct features. Machiavellianism involves cynicism, manipulation, and a willingness to use unethical means for self-gain. Narcissism is typified by grandiosity, superiority, and a need for admiration. Psychopathy is associated with callousness, impulsivity, and a lack of empathy. Sadism involves deriving pleasure from others' suffering (Jones and Paulhus, 2013; Paulhus et al., 2021).

Several studies connect these dark traits to higher rates of academic dishonesty (Lingán-Huamán et al., 2024; Greitemeyer and Kastenmüller, 2023). Some research indicates strong correlations between cheating and both Machiavellianism and psychopathy, but not narcissism (He et al., 2023). Others find that Machiavellianism and narcissism are positively related to self-reported cheating, whereas psychopathy is not (Esteves et al., 2021). Nevertheless, most studies focus on the Dark Triad rather than the full Dark Tetrad, highlighting the need to explore all four traits.

Building on the identified gaps in existing literature, this study aims to provide a more comprehensive understanding of academic misconduct in the context of generative AI usage. While previous research has predominantly focused on the Dark Triad –Machiavellianism, Narcissism, and Psychopathy– this study expands the investigation to the full Dark Tetrad framework by incorporating Sadism. Additionally, the research examines a broader range of personal attributes, including age, gender, educational level, and academic performance. In summary, this study seeks to explore the relationships between generative AI academic misconduct and various influential factors, including the Dark Tetrad, age, gender, educational level, and academic performance.

2 Method

2.1 Participants and procedure

The participants in this study were university students in Taiwan, comprising both undergraduate and graduate students. Data were collected from users of Taiwan-based social media platforms, such as Facebook group and Dcard, specifically targeting student groups. Participants provided demographic information, including their gender and education level (undergraduate or graduate). The survey was open for responses from November 18, 2024, to December 18, 2024. A total of 812 participants were recruited (M_{age} = 24.86, SD_{age} = 5.98), including 439 females and 373 males. Among the participants, 362 were undergraduates and 450 were graduate students. This study received approval from the University Research Ethics Committee for Human Subject Protection.

2.2 Measures

2.2.1 Dark Tetrad

The dark personality traits were assessed using the Traditional Chinese version of the Short Dark Tetrad scale (Chang et al., 2021). The scale consists of a total of 25 items, measures Machiavellianism with 7 items, narcissism with 7 items, psychopathy with 5 items, and sadism with 6 items. Each rated on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). An example item is: "People often say that I am uncontrollable." In this study, good internal consistency was found for the scale ($\alpha = 0.872$). The Confirmatory Factor Analysis (CFA) results yielded acceptable fit indices ($\chi^2_{(269)} = 1126.294$, $p < 0.001$, CFI = 0.903, RMSEA = 0.063, SRMR = 0.064).

2.2.2 Academic performance

Participants were asked to report their average grade point average (GPA) score from the previous semester, based on a 4.3 scale. The reported GPA scores were required to fall within the range of 0–4.3.

2.2.3 Generative AI academic misconduct

The generative AI academic misconduct scale was specifically developed to assess the frequency of students' engagement in generative AI-related academic misconduct. The initial item pool was generated through semi-structured discussions with five undergraduate students, five master's students, and three doctoral students, all of whom had a strong understanding of generative AI and reported either personal experiences or observations related to academic dishonesty. Based on these discussions and a review of emerging literature and media reports on AI-related academic misconduct (Whittle and Harrer, 2025; Hall, 2025; Danesi, 2024; Chelli et al. 2024; Hua et al., 2024), a preliminary list of potential behaviors was compiled. This list was reviewed by two experts in educational psychology and one expert in AI ethics to assess content relevance and face validity. After incorporating their feedback, the scale was refined to include four representative items. The finalized scale comprises four items, each rated on a 5-point Likert scale (1 = never, 5 = always). These items assess the frequency of the following behaviors: (1) using generative AI to fabricate references, (2) creating AI-generated artistic works (e.g., music or paintings), (3) generating false internship or employment verification documents, and (4) fabricating research data or results. In the current study, the GAIAM scale demonstrated excellent internal consistency ($\alpha = 0.944$). Confirmatory factor analysis supported its unidimensional structure, indicating good model fit ($\chi^2_{(2)} = 4.083$, $p = 0.130$; CFI = 0.999; RMSEA = 0.036; SRMR = 0.004).

2.3 Data analysis

Descriptive statistics, Pearson's correlation, linear regression, and Cronbach's alpha were calculated using SPSS 20.0. CFA was conducted using Mplus 8.0. Following Hair et al. (2009), the criteria for a good model fit were set as follows: comparative fit index (CFI) > 0.90, root mean square error of approximation (RMSEA) < 0.07, and standardized root mean square residual (SRMR) < 0.08.

3 Result

3.1 Descriptive statistics and correlations

As shown in the Table 1, generative AI academic misconduct (GAIAM) exhibited significant positive correlations with narcissism ($r = 0.333$, $p < 0.01$), psychopathy ($r = 0.374$, $p < 0.01$), and sadism ($r = 0.344$, $p < 0.01$). Narcissism was positively correlated with Machiavellianism ($r = 0.097$, $p < 0.01$) and psychopathy ($r = 0.421$, $p < 0.01$), while psychopathy displayed significantly positive correlations with sadism ($r = 0.460$, $p < 0.01$). Additionally, GPA demonstrated negative correlations with psychopathy ($r = -0.116$, $p < 0.01$) and sadism ($r = -0.109$, $p < 0.01$).

3.2 Hierarchical linear regression

As shown in Table 2, hierarchical linear regression was conducted to investigate the influence of personal attributes, academic performance, and Dark Tetrad traits on Generative AI academic misconduct (GAIAM). The results, presented in the table, indicate that narcissism ($\beta = 0.200$, $p < 0.001$), psychopathy ($\beta = 0.199$, $p < 0.001$), and sadism ($\beta = 0.187$, $p < 0.001$) were significantly positively associated with GAIAM. In contrast, gender, education level, GPA, and Machiavellianism were not significantly associated with GAIAM. The model accounted for 21.5% of the variance in GAIAM ($F = 31.519$, $p < 0.001$). Multicollinearity was assessed using the variance inflation factor (VIF), with all values below the recommended threshold of 10, indicating no severe multicollinearity issues (Hair et al., 2009).

4 Discussion

The findings of this study emphasize that, in the context of Generative AI academic misconduct (GAIAM), personality traits–especially those aligned with the Dark Tetrad–are more strongly associated with GAIAM than traditional personal attribute factors. This conclusion underscores the unique nature of GAIAM, where the absence of effective detection systems may reduce the relevance of variables such as gender, educational level, and GPA. In essence, what meaningfully differentiates students who engage in GAIAM from those who do not is not their demographic or academic background, but rather their underlying disposition to achieve goals by any means necessary.

The significant positive relationship between narcissism and GAIAM aligns with theoretical perspectives suggesting that narcissistic individuals feel entitled to success and are willing to resort to unethical means to attain it. Such individuals often seek recognition and dominance (Paulhus and Williams, 2002), which makes them more likely to exploit AI tools for academic advantage. Psychopathy's association with GAIAM similarly reflects its established link to impulsivity and moral disregard (Jones and Paulhus, 2013). Those high in psychopathy may engage in misconduct without considering ethical implications, consistent with their inclination toward risk-taking and impulsivity (Paulhus et al., 2021). Finally, the strong link between sadism and GAIAM reveals a distinctive mechanism: some individuals may derive satisfaction from undermining norms and using AI tools to deceive evaluators (Buckels et al.,2013). Buckels et al. (2013) highlight that sadistic individuals find pleasure in causing disruption or harm, which may explain their involvement in GAIAM.

In contrast, the non-significant results for Machiavellianism suggest that GAIAM may not align with the calculated, strategic

TABLE 1 The results of descriptive statistics and correlations.

Variable	1	2	3	4	5	6
1. GAIAM	–					
2. GPA	−0.041	–				
3. Machiavellianism	−0.005	−0.007	–			
4. Narcissism	0.333**	0.012	0.097**	–		
5. Psychopathy	0.374**	−0.116**	0.034	0.421**	–	
6. Sadism	0.344**	−0.109**	0.087*	0.271**	0.460**	–
Mean	6.55	3.72	26.74	20.29	11.86	12.58
SD	4.16	0.719	4.142	5.840	4.704	5.668

GAIAM, Generative AI academic misconduct. $^{*}p \leq 0.05$, $^{**}p \leq 0.01$.

TABLE 2 The results of hierarchical linear regression.

Variable	Generative AI academic misconduct (GAIAM)			
	B	β	*T*	VIF
Intercept	1.205		1.015	
Gender[a]	0.368	0.044	1.321	1.144
Education level[b]	−0.459	−0.055	−1.738	1.022
GPA	0.046	0.008	0.250	1.034
Machiavellianism	−0.054	−0.053	−1.690	1.020
Narcissism	0.142	0.200	5.726***	1.245
Psychopathy	0.176	0.199	5.252***	1.468
Sadism	0.137	0.187	4.982***	1.440
F	31.519***			
R^2	0.215***			

[a]Male = 0, Female = 1; [b]Undergraduate = 0, Graduate = 1. $^{***}p < 0.001$.

nature of this trait. Playfoot et al. (2024) provide a plausible explanation, noting that self-reported unethical behaviors, such as cheating, are susceptible to underreporting–particularly among Machiavellian individuals who excel at concealing their misconduct (Playfoot et al., 2024). The Dark Tetrad measure of Machiavellianism, characterized by secrecy and manipulation (e.g., "It's not wise to let people know your secrets"), supports the notion that these individuals may adeptly obscure their unethical actions, complicating accurate assessments of their true involvement in GAIAM. In addition to potential underreporting, limitations in the measurement of Machiavellianism should also be considered. The Traditional Chinese version of the Short Dark Tetrad scale used in this study has shown some validity concerns, particularly in the Machiavellianism subscale (Chang et al., 2021). CFA results from prior validation research indicated that five items in the Machiavellianism subscale had factor loadings below 0.50 (Chang et al., 2021), raising questions about the scale's ability to fully capture the construct within the Taiwanese cultural context. These psychometric limitations may have further contributed to the non-significant findings.

Notably, personal attributes such as gender, education level, and GPA were not significantly associated with GAIAM. This finding contrasts with previous research suggesting that lower academic achievement and education levels are linked to a greater likelihood of academic misconduct (e.g., Miles et al., 2022). One possible explanation is that, in digital contexts where misconduct is difficult to detect, individuals high in dark personality traits may perceive fewer social consequences for their actions (Suler, 2004; Udris, 2014). This perception may reduce their sense of accountability and, in turn, increase the likelihood of engaging in antisocial behaviors such as GAIAM. This phenomenon is commonly referred to as toxic online disinhibition (Suler, 2004), which previous studies have found to be associated with the link between dark personality traits and antisocial online behaviors such as cyberbullying (Kurek et al., 2019). Given the current lack of reliable AI output detection systems, individuals high in dark traits may feel especially emboldened in academic contexts involving generative AI. In such environments, the influence of dark traits may be amplified, potentially diminishing the observed associations between GAIAM and more traditional factors such as GPA or education level. However, we acknowledge that our study did not directly measure toxic online disinhibition, and this interpretation remains speculative. Future research should empirically examine this proposed mechanism.

These findings underscore the importance of addressing underlying personality dispositions associated with GAIAM, rather than relying solely on traditional demographic or academic indicators. Educators and counselors may consider implementing personalized interventions–such as coaching, targeted workshops, or student support programs–for students exhibiting traits like narcissism, psychopathy, and sadism, with the aim of reducing their likelihood of engaging in unethical behaviors. In this context, generative AI (GAI) should not be viewed solely as a threat to academic integrity but also recognized as a powerful educational tool. When responsibly integrated into curricula and counseling practices, GAI can enhance student engagement by fostering motivation, strengthening digital literacy, and supporting constructivist learning principles (Tan and Maravilla, 2024). As Tan and Maravilla (2024) emphasize, such integration promotes ethical academic behavior by enhancing students' autonomy, competence, and relatedness–core components of intrinsic motivation. These qualities position GAI as a valuable asset in both instructional design and student development initiatives.

This study has several limitations. First, we were unable to conduct a formal pilot test of the GAIAM scale due to resource constraints. Although the items were informed by student interviews and expert feedback, future research should pilot the scale to further validate its reliability and clarity. Second, we did not assess or weight the severity of each type of misconduct. While some behaviors may be relatively minor, others could involve legal implications. Future studies should consider incorporating perceived severity ratings. Third, the use of self-reported academic performance may have introduced response bias. Triangulating self-reports with institutional records or faculty assessments may help improve the validity of academic performance measures. Fourth, the cross-sectional design of this study limits the ability to draw causal inferences. Longitudinal research is needed to explore how the relationships between personality traits and academic misconduct evolve over time.

Another important limitation lies in the cultural specificity of our sample. All participants were recruited from Taiwan, a collectivist society that emphasizes social harmony, adherence to norms, and interpersonal sensitivity (Markus and Kitayama, 1991). As such, the prevalence and expression of GAIAM may differ from those observed in more individualistic cultures, such as the United States, where autonomy and personal agency are more strongly emphasized (Chang et al., 2021). For example, because GAIAM is difficult to detect through automated systems, peer reporting may become a key mechanism for detection. However, students in collectivist cultures may be less likely to report peers due to a desire to preserve group harmony, whereas those in individualistic cultures may be more willing to report misconduct in order to protect their academic standing or gain a competitive advantage. Future research should address these limitations by incorporating cross-cultural comparisons, adopting longitudinal designs, and validating behavioral severity distinctions. In particular, investigating how cultural norms influence the expression and social perception of misconduct in tech-mediated academic environments will be critical for generalizing findings beyond East Asian contexts.

Despite some limitations, this study makes significant contributions to the understanding of GAIAM. By examining AI-facilitated academic misconduct through the lens of the more comprehensive Dark Tetrad framework, this study extends prior research beyond the Dark Triad. The results indicate that personality traits such as narcissism, psychopathy, and sadism are stronger associated factors of GAIAM than conventional personal attributes like gender, education level, or GPA. This pattern likely arises from the current lack of effective detection mechanisms for AI-driven misconduct, allowing personality-driven motivations to exert a greater influence on students' decisions to engage in GAIAM.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Ethics Committee of Sichuan Normal University, Sichuan Normal University, Chengdu, China. The studies were conducted in accordance with the local legislation and institutional requirements. The ethics committee/institutional review board waived the requirement of written informed consent for participation from the participants or the participants' legal guardians/next of kin because written informed consent was waived because this study utilized anonymous online surveys, ensuring no personal identifying information, such as names, was collected. Instead, participants provided their consent through an online consent form. The study involved only adults aged 18 or older, who were deemed capable of making informed decisions about their participation. Participants were also informed that they could withdraw from the study at any time if they disagreed with the consent form or felt uncomfortable.

Author contributions

RS: Conceptualization, Investigation, Software, Writing – original draft, Writing – review and editing. MT: Conceptualization, Investigation, Software, Writing – original draft, Writing – review and editing. JZ: Writing – review and editing. NL: Writing – review and editing, Data curation. C-YW: Conceptualization, Supervision, Writing – original draft, Writing – review and editing, Data curation, Methodology.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that Generative AI was used in the creation of this manuscript. During the preparation of this work the authors used ChatGPT in order to revise and refine the manuscript to ensure that the sentences flow smoothly and are free from grammatical errors. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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