Computers in Human Behavior Reports 18 (2025) 100681

Contents lists available at ScienceDirect

Computers in Human Behavior Reports

journal homepage: www.sciencedirect.com/journal/computers-in-human-behavior-reports

The role of moral intention and moral obligation in predicting attitudes toward avoiding AIgiarism: A protection motivation theory perspective

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ARTICLE INFO

Keywords:
AIgiarism
Plagiarism
Protection motivation theory
Moral intention
Moral obligation

ABSTRACT

Traditional methods of combating plagiarism have proven ineffective due to the dual use of AI chatbots to plagiarize and avoid detection. Therefore, there is a growing rationale to focus on moral responsibility towards protecting academic integrity. This study investigated the impact of students' moral intentions and moral obligations on their attitudes toward avoiding AI-assisted plagiarism (AIgiarism). Data was collected from a representative group of 263 students and analyzed using "partial least squares structural equation modeling" (PLS-SEM) and "artificial neural network" (ANN). The results revealed that students' moral intentions and obligations positively influenced their attitudes towards avoiding AIgarism. "Protection motivation theory" (PMT) constructs positively predicted students' moral intentions. Moreover, the results of the ANN analysis showed that moral obligation and intention were the most critical factors influencing students' attitudes toward avoiding plagiarism. This study will help educational institutions develop AI-supported anti-plagiarism solutions in areas such as identification, instilling moral responsibility, and creating an environment of trust and support.

1. Introduction

The misuse of artificial intelligence chatbots is challenging our moral principles. AI chatbots, while useful in many ways, represent an easy means of misinformation and plagiarism (Yigci et al., 2024). Data and results are being fabricated at an alarming rate (Kim et al., 2024). References are often fake and incorrect (Gravel et al., 2023) and copyrights are frequently violated (Lucchi, 2023). A recent study on ChatGPT found that 55 % of evaluated references were fake, and 43 % were incorrect (Walters & Wilder, 2023). In another study in a medical context, forty-one out of fifty-nine evaluated references (69 %) were fabricated, even though they appeared authentic (Gravel et al., 2023). Inconsistent reference formats were also reported. Such malpractices vary depending on the source type. For instance, one study indicated that all journal article references were incorrect, and webpage references referred to fake links. Book references, however, were found to be authentic (Giray, 2024). The legitimacy and authorship of AI-generated content are not the only concern; our creativity and critical thinking are also threatened (Pereira et al., 2024). AI chatbots can create content that may appear original while being indistinguishable from human-written content (Hayawi et al., 2024; Khalil & Er, 2023). Even though rewritten and sugarcoated, the generated text may still match existing ones in the literature. Such persuasive contents, for sure, stimulate misinformation and plagiarism (Dwivedi et al., 2023).

The concept of plagiarism varies across institutions and cultures; hence, finding a standard or agreed-upon definition of plagiarism seems unrealistic (Sousa-Silva, 2020). It is commonly called cheating, misrepresentation, fabrication, academic fraud, or academic malpractice (Hayawi et al., 2024; Hayes & Introna, 2005). According to the Merriam-Webster dictionary, plagiarism originated from the Latin word "*plagiarius*" which means "kidnapper." Today, plagiarism is the practice of using others' ideas or work and presenting them as your own. It is said to be dishonesty related to copyrights and authorship involving theft of ideas and content and depriving the original authors of due credit (R. Farooq & Sultana, 2022; Helgesson & Eriksson, 2015; Liddell, 2003; C. Park, 2017, pp. 525–542). Some studies also associated plagiarism with lying, insulting, and stealing (Liddell, 2003). Plagiarism is divided into appropriation, misrepresentation, cheating, and self-plagiarism (Sarlauskiene & Stabingis, 2014). AI plagiarism, also called AIgiarism (Khalaf, 2024, pp. 1–12), uses advanced AI tools to commit plagiarism and evade detection and penalties.

Various reasons contribute to committing plagiarism. A significant

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https://doi.org/10.1016/j.chbr.2025.100681
Received 26 November 2024; Received in revised form 14 April 2025; Accepted 28 April 2025
Available online 19 May 2025

factor is the easy access to "information and communication technology" (ICT) and the World Wide Web (www) (Jereb et al., 2018). Likewise, students highlighted a lack of foreign language skills, time pressure, and insufficient knowledge about plagiarism as key reasons (Eret & Gokmenoglu, 2010). Reasons also include laziness, subject-related knowledge gaps, the simplified availability of internet resources, and lack of penalty (Kampa et al., 2024). In general terms, plagiarism is facilitated by technological, institutional, academic, personal, and external factors (Husain et al., 2017).

The detection of plagiarism and other types of academic misconduct has been a key application area for "natural language processing" (NLP) research. Foltýnek et al. (2019) systematically reviewed existing plagiarism methods and systems in this context. According to their findings, detection methods can be categorized into lexical, semantics-based, and area-based approaches. Another study presented a text-comparison method by comparing the two texts to one-dimensional strings and repeating a shift to discover word matching (Sakamoto & Tsuda, 2019). Additional studies compared various existing machine learning-based methods for detection performance (Solanki et al., 2024; Vasuteja et al., 2024, pp. 245–251). Bhattacharjee and Dutta (2013) specifically focused on a detection method for identifying mathematical equations. Numerous plagiarism detection systems like Turnitin, iThenticate, and CrossCheck (Bahuguna et al., 2024) are currently in use. Foltýnek et al. (2020) evaluated fifteen systems, ranking Urkund, StrikePlagiarism, and Turnitin as the top performers.

Even though all these systems and methods exist, generative AI technology seems to challenge the status quo. AI Chatbots can generate a sophisticated text output without being caught by traditional plagiarism detection tools (Ciaccio, 2023; Khalil & Er, 2023). Writers, either manually or now using AI paraphrasing tools, can reword content to bypass detection (Ciaccio, 2023; Steponenaite & Barakat, 2023, pp. 434–442). Either form, however, is unethical (Ciaccio, 2023).

So, our academic and scientific integrity is at risk if the conventional approaches are proven inefficient and policies are ineffective and outdated (Goel & Nelson, 2024). Thus, a gap is created between the ethical concerns raised by AI systems (Akgun & Greenhow, 2022; Kooli, 2023; Murtarelli et al., 2021; Ryan, 2023), and the moral responsibility to avoid mistakes. A key issue is when students commit plagiarism and use evasion techniques to escape detection (Pudasaini et al., 2024). To address this duality issue, self-paced solutions are essential.

This study focuses on the fact that AI systems are preprogrammed and unintentional. At the same time, humans are morally responsible for their actions and mistakes (Wilson et al., 2022), and plagiarism is a moral and behavioral development problem (R. Farooq & Sultana, 2022). Therefore, it should be addressed from that perspective. Prior studies focused on the use of protective systems (e.g., anti-plagiarism software) to deal with the problem of plagiarism (Lee, 2011) and AI detection tools (Chaka, 2024). Khalaf (2024, pp. 1–12) also examined attitudes toward AI plagiarism. On the other hand, our research employs the "protection motivation theory" (PMT) (Rogers, 1975) from health psychology to predict students' moral intention to avoid AI plagiarism in academic settings. With the help of the theoretical framework, the study puts forward that students tend to avoid AI plagiarism, 1) if they perceive it as a threat to their moral principles, 2) if they are convinced that sticking to moral principles will assist them in preventing AI plagiarism, 3) if they believe that they can prioritize their moral responsibility.

Compared to other studies in the field, the key distinguishing feature of this study is its focus on the effects of a moral component rather than solely relying on policies and detection tools. This approach sets the study apart, as much of the research on generative AI overlooks the moral implications and their impact on academic integrity. Educational institutions and practitioners should recognize that traditional solutions are no longer sufficient and instead develop sustainable strategies that prioritize moral values and principles to counter the inevitable challenges posed by generative AI tools to our academic integrity.

This study has several key contributions: (1) It investigates the pressing issue of AI-driven plagiarism from two key dimensions, understanding the threat and assessing coping mechanisms and it explores the role of enhanced morality (moral intention) as a sustainable preventive mechanism; (2) It emphasizes how attitudes toward plagiarism can encourage students to seek legitimate solutions; and 3) It applies a hybrid approach combining both PLS-SEM and ANN to analyze data. The hybrid approach has the benefit of providing methodological rigor for this study. It also enables finding linear and non-linear correlations between the different constructs participating in the anti-AI facilitated plagiarism solutions; 4) applying PMT to analyze AIgiarism threats, prevention capabilities, and behavioral intentions.

2. Theoretical background

"Protection motivation theory" was initially introduced by Rogers (Rogers, 1975), who explored how individuals understand the effect of fear appeals and how they cope. Subsequent revisions to the theory added persuasive communications focusing on cognitive processes that facilitate behavior change (Rogers, 1983). Two fundamental dimensions form the PMT, "threat appraisal" and "coping appraisal," in which behavioral options to avert a threat are assessed (Boer & Seydel, 1996). Threat appraisal is "how severe and how likely a threat results in undesirable consequences, whereas coping appraisal is the perceived capability of engaging in protective behavior" (Khan et al., 2024). Averting such a threat rests on following a given adaptive behavior. The effectiveness of that behavior is determined by response efficacy (e.g., assistance from peers or instructors) and self-efficacy (e.g., prior knowledge of the topic of concern). An appropriate response may require time and resources (response cost) (Boer & Seydel, 1996). For an effective strategy, the perceived threat should outweigh maladaptive responses, while coping appraisal should surpass the response cost (Boer & Seydel, 1996; Maddux & Rogers, 1983). The result of these appraisal-mediated processes is the intentions or decision to execute or refrain from specific coping strategies (Floyd et al., 2000).

PMT has been widely employed in various contexts, including health (Chenoweth et al., 2009, pp. 1–10; Estebsari et al., 2023; Hedayati et al., 2023; Milne et al., 2000; Rakhshani et al., 2024; Seow et al., 2022; Venkatesh et al., 2003) and security (Dodge et al., 2023; Hassan et al., 2024; Jamil et al., 2024; Khan et al., 2024; Sulaiman et al., 2022) as well as environmental settings (Kothe et al., 2019; Meso et al., 2013) used it to examine the effectiveness of security training completed by college students (Lee, 2011). investigated the use of PMT to understand students' intentions to adopt anti-plagiarism systems. The study found that PMT constructs—such as "vulnerability, severity, self-efficacy, response efficacy, and response cost"—along with moral obligation and social influence, are strong predictors of students' intentions. Additionally, research shows that participants with lower intentions to plagiarize hold more negative views toward plagiarism and perceive it as socially unacceptable (Camara et al., 2017).

In the "ethical decision-making" (EDM) theory, moral intention, which is also referred to as "moral motivation," is "the motivation or commitment to act according to one's moral values" (Lankton et al., 2019). Plagiarism is a moral issue, often condemned as dishonesty and a violation of academic standards (East, 2010). It causes emotional and moral distress (Vehviläinen et al., 2018), possibly due to the risk of dismissal and reputational damage (King & ChatGPT, 2023). Based on this understanding, avoiding plagiarism could stem from a moral disposition rather than dire warnings about failing grades (Wilhoit, 1994). Establishing firm moral intention strongly predicts subsequent behavior (May & Pauli, 2002). This means choosing the moral decision (e.g., refraining from plagiarism) over another solution (e.g., committing plagiarism) representing a different value (Lankton et al., 2019). When faced with a dilemma, moral intention serves as a guiding force. Consistent with this, moral intention influences a person's decision to buy pirated software (Moores & Chang, 2006). Subsequently, a person's attitude toward plagiarism is influenced by ethical surroundings. If they have a negative attitude toward plagiarism, they are unlikely to plagiarize, and vice versa (R. Farooq & Sultana, 2022). Our study conceptualizes moral intention as a mediator between "Protection Motivation Theory" (PMT) constructs and students' attitudes toward avoiding AI-facilitated plagiarism. This aligns with previous findings where students' behavioral intention to use anti-plagiarism software mediated the relationship between PMT constructs and actual adoption (Lee, 2011). Fig. 1 presents the research model.

3. Hypothesis development

3.1. Threat appraisal

Threat appraisal evaluates perceptions of threat based on severity and vulnerability (Floyd et al., 2000). The perception of vulnerability relates to a person's evaluation of the likelihood of exposure to a harmful threat (Venkatesh et al., 2003). Therefore, when a person perceives vulnerability as higher, the likelihood of adopting the defended adaptive behavior increases (Meso et al., 2013). Previous research shows that perceived vulnerability strengthens faculty members' behavioral intentions to use anti-plagiarism software (Lee, 2011). Across studies, positive correlations between previewed vulnerability and behavioral intention were reported in various contents (Chenoweth et al., 2009, pp. 1–10; Lee, 2011; Luu et al., 2017; H. T. Nguyen & Tang, 2022). Similarly, this study posits that a student's perceived vulnerability is positively linked with their moral intentions to avoid AI plagiarism.

Perceived severity is defined as the assessment of potential harm resulting from an event (Meso et al., 2013). In the context of AI plagiarism, such harm may include expulsion and damage to one's professional reputation (King & ChatGPT, 2023). According to Rogers (Rogers, 1975), individuals evaluate the likelihood and severity of exposure to the harmful event, assess their ability to cope with it, and adjust their attitudes accordingly. Therefore, the more severe the perceived consequences of maladaptive actions, the more likely individuals will adopt recommended adaptive actions (Lee, 2011). Previous studies have explored the association between perceived severity and behavioral intention. For instance, studies have found a relationship between perceived severity and a student's intention to embrace proper information security actions (Meso et al., 2013), enroll in e-learning courses (H. T. Nguyen & Tang, 2022), utilize anti-plagiarism systems (H. T. Nguyen & Tang, 2022), adopt protective technology (Chenoweth et al., 2009, pp. 1–10), and use AI avatar services (J. Park et al., 2024). This is even though perceived severity and vulnerability do not always lead to stronger behavioral intentions (A. Farooq et al., 2019, pp. 1–8). While acknowledging the mixed findings, the present study posits that perceived severity and vulnerability will significantly impact the moral intention of individuals to adopt measures against AI-facilitated plagiarism.

H1. Perceived vulnerability is positively related to the moral intention to avoid AI plagiarism.

H2. Perceived severity is positively related to the moral intention to avoid AI plagiarism.

3.2. The coping-appraisal

The coping appraisal process assesses one's ability to manage and prevent the perceived threat, comprising variables like response costs, response efficacy, and self-efficacy (Floyd et al., 2000). Self-efficacy refers to "the individual's perception that he or she will be able to effectively use a given protective response to prevent or mitigate the effects of a given criminal threat" (Clubb & Hinkle, 2015). Response efficacy is "the belief that the adaptive response will work, meaning that taking the recommended protective action is effective in averting an undesirable threat" (Floyd et al., 2000; Prentice-Dunn & Rogers, 1997).

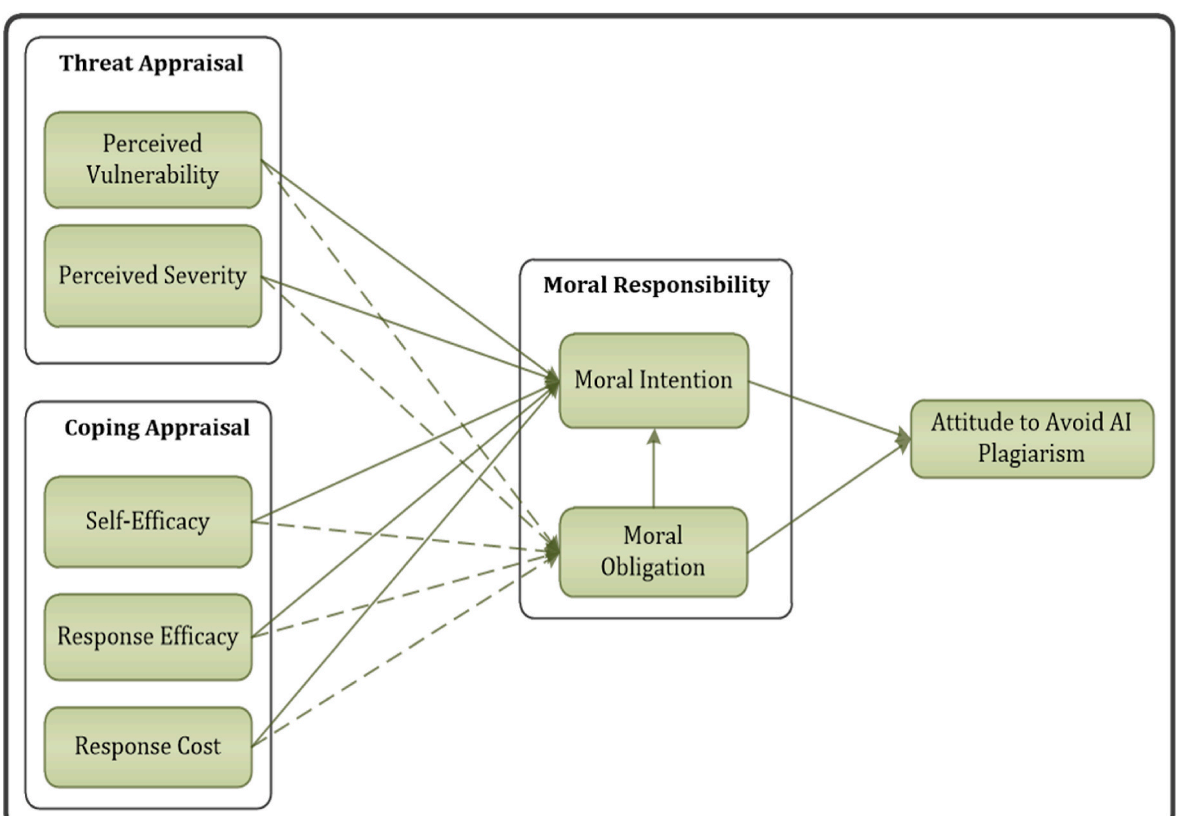

Fig. 1. Proposed research model.

Response costs are "associated with the recommended behavior" (Meso et al., 2013). In cybersecurity, response efficacy and self-efficacy are significant determinants of protective intent (Li et al., 2019). Similarly, they also strongly impact students' intention to use anti-plagiarism systems (Lee, 2011). Based on the above discussion, this research proposes the following hypotheses.

H3. Self-efficacy is positively related to the moral intention to avoid AI plagiarism.

H4. Response efficacy is positively related to the moral intention to avoid AI plagiarism.

H5. Response cost positively correlates with the moral intention to avoid AI plagiarism.

3.3. Moral intention and moral obligation

Moral intention refers to "the likelihood that individuals will engage in a moral action" (Kumar et al., 2020) and reflects their motivation to act according to moral values (Schwartz, 2016). When examining the influence of moral values on actual behavior, behavioral intentions and ethical judgment should be considered (Huang et al., 2022). Although intentions do not always lead to action, intention is a key predictor of behavior and offers opportunities to address plagiarism before it occurs (Camara et al., 2017). It was also discussed in the existing literature that individuals make ethical judgments by evaluating whether an issue is ethically appropriate or inappropriate (Jones, 1991; Lin & Clark, 2021). Therefore, in the plagiarism scenario, lower behavioral intention indicates a greater likelihood of ethical behavior (Leonard et al., 2017). According to the "Theory of Reasoned Action" (TRA) and "Theory of Planned Behavior" (TPB),"a person's beliefs about a given behavior

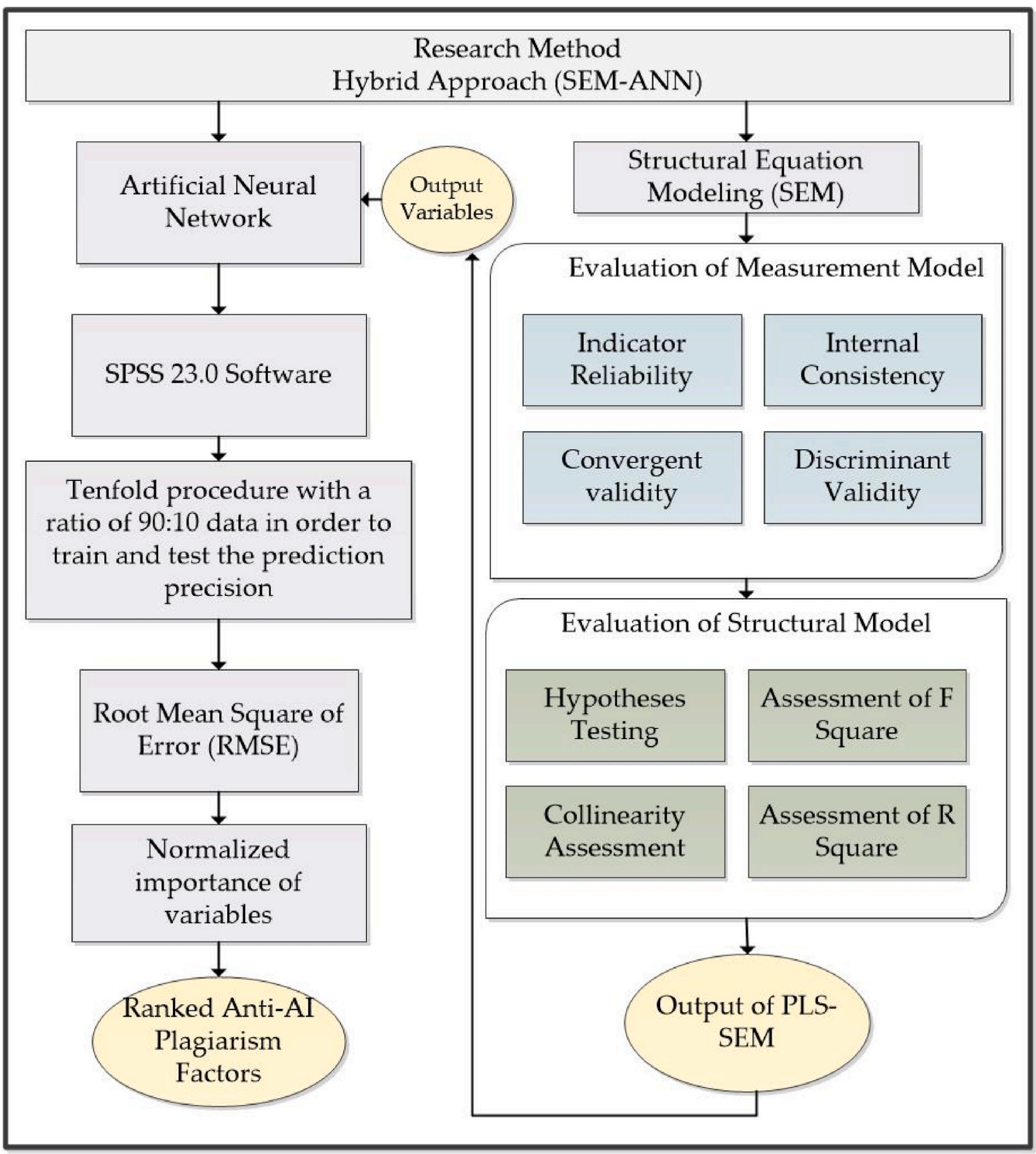

Fig. 2. The two-stage research method.

will determine their attitude toward the behavior" (Ajzen, 1985; Ajzen, 1985; LaCaille, 2020). Adding moral obligation to the Fishbein-Ajzen model (Fishbein & Ajzen, 1977) has significantly improved the prediction of behavioral intention (Gorsuch & Ortberg, 1983). One's sense of moral obligation correlates with one's intentions to behave ethically or unethically (Beck & Ajzen, 1991; Chen, 2016; Gorsuch & Ortberg, 1983). In software piracy, moral obligation also strongly influences users' attitudes towards software piracy (Peace & Galletta, 1996) and their intentions (Hashim et al., 2018; Yoon, 2011). This makes us assume that the attitude toward AI plagiarism avoidance is influenced by students' moral responsibility (moral intention and moral obligation). In contrast, moral obligation is a precursor to moral intention. Accordingly, this study posits the following three hypotheses.

H6. Moral intention has a positively significant relationship with the attitude toward AI plagiarism.

H7. Moral obligation has a positively significant relationship with the attitude toward AI plagiarism.

H8. Moral obligation has a positively significant relationship with moral intention.

4. Methodology

The methodology shown in Fig. 2 followed in this paper is like the approach used by Asadi et al. (2021) and Mohd Rahim et al. (2022). It follows a two-stage process involving "Partial Least Squares Structural Equation Modeling" (PLS-SEM) and "Artificial Neural Networks" (ANN) for data analysis. For the initial stage, the PLS-SEM analysis identified which variables significantly predicted the moral intention and attitude toward AI plagiarism. However, these predictors are not considered important, which may limit the required knowledge for higher learning institutions (HLI) to allocate resources for mitigating AI plagiarism. Nevertheless, the important determinants of PLS-SEM hypotheses testing are used as input neurons for the ANN model. For the second stage, an ANN is utilized to evaluate the hypothesized relationships and rank them by importance (Almufarreh, 2024). The existing literature also recommends the combined approach of PLS-SEM and ANN (Al-Qaysi et al., 2025; Asadi et al., 2021; Mohd Rahim et al., 2022; Salifu et al., 2024).

4.1. Sample and data collection

This study employed the quantitative research design in which a questionnaire with a 5-point Likert-type scale was used as a fundamental tool for data collection. The study data was collected from university students in Somalia. The questionnaire was distributed electronically via Google Forms to the students. Respondents with prior experience using AI chatbots were targeted. Their demographics are shown in Table 1. A purposive sampling method was used to select participants. Purposive sampling selects respondents expected to provide the most valuable and relevant information (Campbell et al., 2020). This method assumes that the selected group adequately represents the population of interest and is likely to meet the study's objectives (Mohd Rahim et al., 2022). The nascent development of AI chatbots in Somali higher education could further justify using the purposive sampling method. A recent study indicates a heightened interest in using generative AI for academic purposes (Abdi et al., 2025).

G*Power software was used to ensure a sufficient sample size for the research (Ashour, 2024). Following Cohen's parameters (Cohen, 1988; Faul et al., 2007). The sample size is determined as a function of the required power level, the effect size, and the prespecified significance level. Concerning this, GPower 3.1.9.2 recommended a minimum sample size of 264 respondents to achieve 80 % power, with an effect size of 0.17 at a significance level of 0.05.

Table 1
Participant demographics.

Characteristics		Frequency (n = 263)	Percentage (%)
Gender	Male	170	64.6 %
	Female	93	35.4 %
Age	20–24 years	230	87.5 %
	25–29 years	24	9.1 %
	30–40 years	5	1.9 %
	41–50 years	4	1.5 %
Marital status	Married	21	92.0 %
	Single	242	8.0 %
Educational level	Undergraduate	233	89.7 %
	Master	27	10.3 %
	PhD	1	0.4 %
Frequency of Use	Frequently	36	13.7 %
	Rarely	112	42.6 %
	Occasionally	93	35.4 %
	Very frequently	22	8.4 %

4.2. Measures

The constructs measured in this study included moral obligation (MO) (Gorsuch & Ortberg, 1983; Hashim et al., 2018), "perceived severity" (PS), "perceived vulnerability" (PV), "response efficacy" (RE), "self-efficacy" (SE), "response cost" (RC), "moral intention" (MI) (Floyd et al., 2000; Lee, 2011; Norman et al., 2015), and attitude (ATT) (R. Farooq & Sultana, 2022; Khalaf, 2024, pp. 1–12). Appendix A shows the original questionnaire's constructs and measurement items. To ensure content validity, validated measurement items were used (Hair et al., 2013), and concise language was used following Hinkin's guidelines (Hinkin, 1998). The measurement items of PS, PV, RE, SE, and RC were adapted from (Hu et al., 2022; Lee, 2011) to fit the study context. The "moral obligation" was measured with four items derived from (Lee, 2011; Uzun & Kilis, 2020). The moral intention was measured using four items adapted (Zhang et al., 2023). Attitude toward plagiarism was evaluated using five measures adopted from (Mavrinac et al., 2010).

5. Results

This study used PLS-SEM using SmartPLS 4 to test the measurement model and assess the linear relationships in the research model. Since PLS-SEM cannot handle non-linear relationships (Chong, 2013), the ANN method was considered (see Fig. 3 for types of analytical approach). ANN can tolerate and learn from noisy data and can handle non-linear along with non-compensatory relationships (Albahri et al., 2022). However, ANN is less effective in hypothesis testing, an area where PLS-SEM excels (Chan & Chong, 2012; Sabbir et al., 2021). Thus, the two approaches complement each other.

5.1. Measurement model

The measurement model was tested by examining the internal consistency (composite reliability) and construct validity concerning criteria presented by (Hair Jr et al., 2021) (Hair Jr et al., 2021a). The composite reliability values shown in Table 2, ranging from 0.759 to 0.839, comfortably fit within the recommended threshold value of

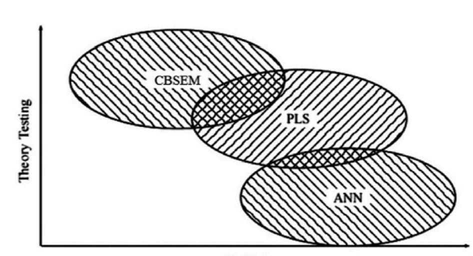

Fig. 3. Types of analytical approaches (Henseler et al., 2009).

Table 2
Reliability and construct validity.

Constructs	Indicators	Loadings	CR	AVE
Attitude	ATT1	0.792	0.777	0.539
	ATT2	0.700		
	ATT4	0.706		
Moral Intention	MI1	0.745	0.766	0.522
	MI3	0.728		
	MI4	0.693		
Moral Obligation	MO1	0.654	0.755	0.507
	MO2	0.754		
	MO3	0.724		
Perceived Vulnerability	PV1	0.755	0.778	0.541
	PV2	0.813		
	PV3	0.627		
Response Cost	RC2	0.801	0.760	0.519
	RC3	0.771		
	RC4	0.567		
Response Efficacy	RE2	0.738	0.814	0.594
	RE3	0.837		
	RE4	0.733		
Self-Efficacy	SE2	0.828	0.814	0.594
	SE3	0.734		
	SE4	0.727		
Severity	PS1	0.791	0.788	0.554
	PS2	0.757		
	PS3	0.681		

0.70–0.90 (Hair et al., 2019). For indicator loadings, a threshold above 0.70 is recommended since this indicates that the factor explains more than half of the variance (Hair Jr et al., 2021b). The factor loadings in this study satisfied the criteria, except for six items with loadings in the range of 0.567–0.70, which is still relatively high. Moreover, values between 0.40 and 0.70 could be retained if their removal does not improve the constructs' validity or internal consistency (Hair et al., 2011; Hair Jr et al., 2021a).

Constructs were examined for convergent and discriminant validity. All constructs demonstrated satisfactory convergent validity since all AVE values were higher than the threshold of 0.50 (Fornell & Larcker, 1981). Discriminant validity needs that constructs be distinct both conceptually and statistically (Henseler et al., 2016). Fornell-Larcker criteria introduced in Table 3 indicate that each construct measures a distinct concept. Further, discriminant validity is assessed using the "heterotrait-monotrait" (HTMT) values. An HTMT value lower than 0.85 indicates adequate discriminant validity (Hair et al., 2019). The HTMT values in Table 4 indicate that discriminant validity is well established.

5.2. Structural model

After establishing the validity and reliability of the constructs, the next step is to evaluate the structural model shown in Fig. 4. The structural model is used to evaluate the predictive capabilities and the relationships among research constructs (Saihi et al., 2024). This study utilizes the bootstrapping function of Smart PLS to perform the significance testing for the constructs' relationships (Hair Jr et al., 2021b).

The structural model was first assessed for collinearity. Collinearity is computed through the "variance inflation factor" (VIF) value. If a VIF value is greater than or equal to 3.3, it suggests the existence of collinearity (Kock & Lynn, 2012). Table 5 shows the collinearity analysis generated using SmartPLS. The table shows that the VIF values fall below the specified threshold. Hence, there are no collinearity issues in the relationships of model constructs.

Table 4
Heterotrait-Monotrait ratio (HTMT).

	ATT	MI	MO	PV	RC	RE	SE
MI	0.776						
MO	0.850	0.738					
PV	0.563	0.584	0.729				
RC	0.608	0.410	0.595	0.621			
RE	0.443	0.679	0.645	0.444	0.443		
SE	0.454	0.656	0.593	0.611	0.324	0.658	
PS	0.667	0.672	0.777	0.644	0.852	0.598	0.537

Validating the structural model helps researchers determine if the study data support their hypothesized relationships (Urbach & Ahlemann, 2010). Moral intention strongly influences attitude ($\beta = 0.304$, $p < 0.000$), while moral intention ($\beta = 0.304$, $p < 0.000$) and moral obligation ($\beta = 0.369$, $p < 0.000$) also have a significant and positive effect on attitude. Factors such as "perceived vulnerability" ($\beta = 0.127$, $p = 0.016$), "response efficacy" ($\beta = 0.223$, $p = 0.002$), "self-efficacy" ($\beta = 0.187$, $p = 0.002$), "severity" ($\beta = 0.187$, $p = 0.006$), and "moral obligation" ($\beta = 0.372$, $p = 0.016$) all significantly impact moral intention. However, "response cost" has no significant effect on moral intention ($\beta = 0.009$, $p = 0.442$).

Two additional criteria assessed for a structural model are R-square and F-square. R-square, which examines the explanatory power of a model and ranges between 0 and 1 (Hair Jr et al., 2021a). Higher R-square values suggest a stronger capability to explain variance in a dependent variable (Urbach & Ahlemann, 2010). In this study, the R-square and R-square adjusted values were created for two dependent variables, ATT (Attitude) and MI (Moral Intention. The adjusted R-square values indicate that the model explains 31.5 % of the variance in attitude (ATT) and 27.9 % of the variance in moral intention (MI).

Researchers can assess the impact of removing a specific construct on the R-square value of an endogenous construct using a metric known as the F-square effect size (Hair et al., 2019). According to Cohen (Cohen, 1988)F-square values 0.02, 0.15, and 0.35 correspond to small, medium, and significant effects. About the given criteria, MI has a small effect on ATT (F-square = 0.123), and MO has a medium effect on ATT (F-square = 0.188). Similarly, RE, SE, PS, and MO have small effects on MI (F-square = 0.039, 0.038, and 0.02 respectively). PV, on the other hand, has a negligible or no effect on MI (F-square = 0.011), while RC exhibits no effect on MI (F-square = 0).

5.3. Artificial neural network

SPSS 23.0 was employed to conduct the ANN analysis. Significant predictors from the hypothesized relationships in the PL-SEM were extracted for use in the neural network analysis. Two ANN models, Model A (Fig. 5) and Model B (Fig. 6), were developed based on the structure of the proposed model. For Model A, moral obligation,

Table 3
Fornell-Larcker Criterion.

	ATT	MI	MO	PV	RC	RE	SE	PS
ATT	0.734							
MI	0.441	0.722						
MO	0.482	0.372	0.625					
PV	0.332	0.331	0.376	0.736				
RC	0.338	0.231	0.271	0.339	0.721			
RE	0.279	0.414	0.349	0.274	0.256	0.718		
SE	0.279	0.397	0.307	0.375	0.175	0.438	0.764	
PS	0.394	0.388	0.405	0.374	0.477	0.384	0.335	0.745

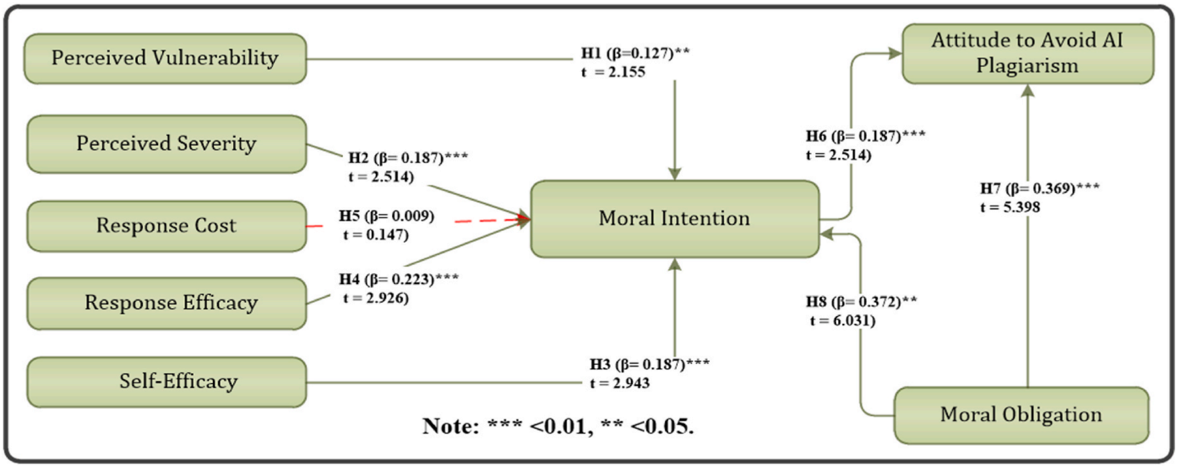

Fig. 4. The structural model.

Table 5
Hypothesis testing.

Hypotheses	Path	β	T statistics	Collinearity	P values	Decision
H1	PV→ MI	0.127	2.155	1.379	0.016	Supported
H2	PS→MI	0.187	2.514	1.62	0.006	Supported
H3	SE→MI	0.187	2.943	1.353	0.002	Supported
H4	RE→MI	0.223	2.926	1.327	0.002	Supported
H5	RC→MI	0.009	0.147	1.351	0.442	Rejected
H6	MI→ATT	0.304	4.489	1.135	0.000	Supported
H7	MO→ATT	0.369	5.398	1.135	0.000	Supported
H8	MO→ MI	0.372	6.031	1.292	0.016	Supported

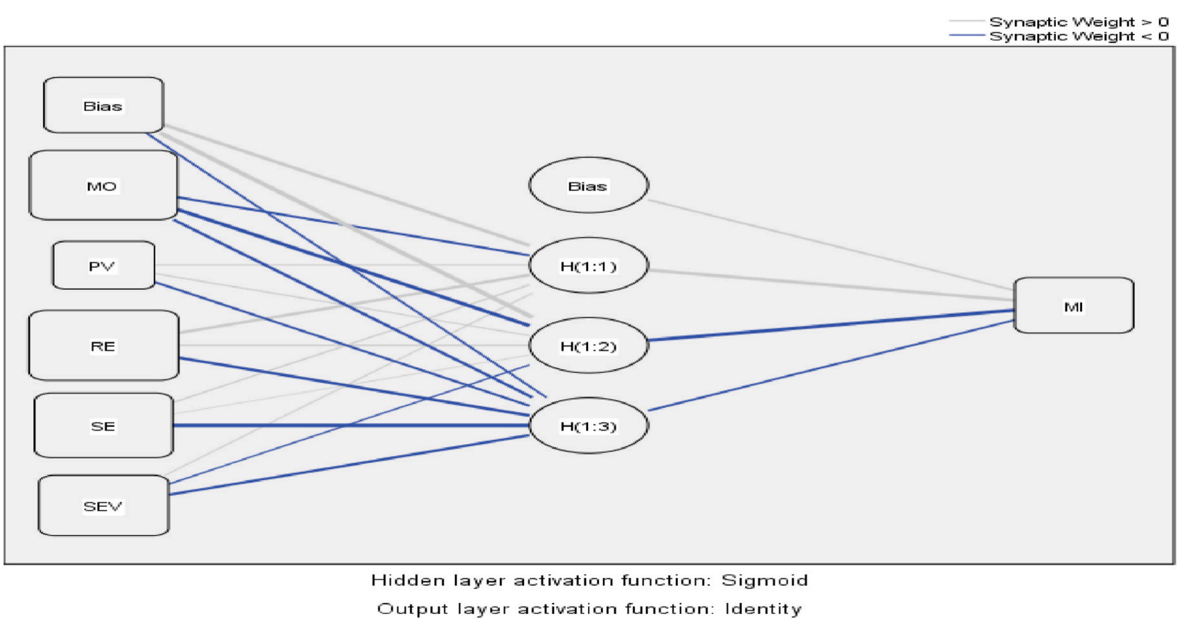

Fig. 5. ANN Model A (PS (SEV), PV, RE, SE, and MO as input variables).

perceived vulnerability, self-efficacy, response efficacy, and severity made the input layers. For Model B, moral intention and moral obligation were input layer variables. Two variables, moral intention and attitudes, represented the output layer in the study. The "sigmoid function" was utilized as the activation function for both the hidden and output neurons. To avoid overfitting, a ten-fold cross-validation technique was employed in ANN models, where 90 % of the data was used for training and the remaining 10 % for testing (Al-Sharafi et al., 2023).

Table 6 shows the "Root Mean Square of Error" (RMSE) that was calculated to determine the predictive accuracy of the models (Almufarreh, 2024). The RMSE indicates the error in the testing and training phases. The mean RMSE values of the two models were small for the two ANN models: 0.613 and 0.594 for training, and 0.594 and 0.556 for testing data. The standard was 0.025, 0.014 for training data, and 0.109 0.076 for testing and training all hidden nodes. This indicates a considerable level of accuracy of the ANN models in predicting the

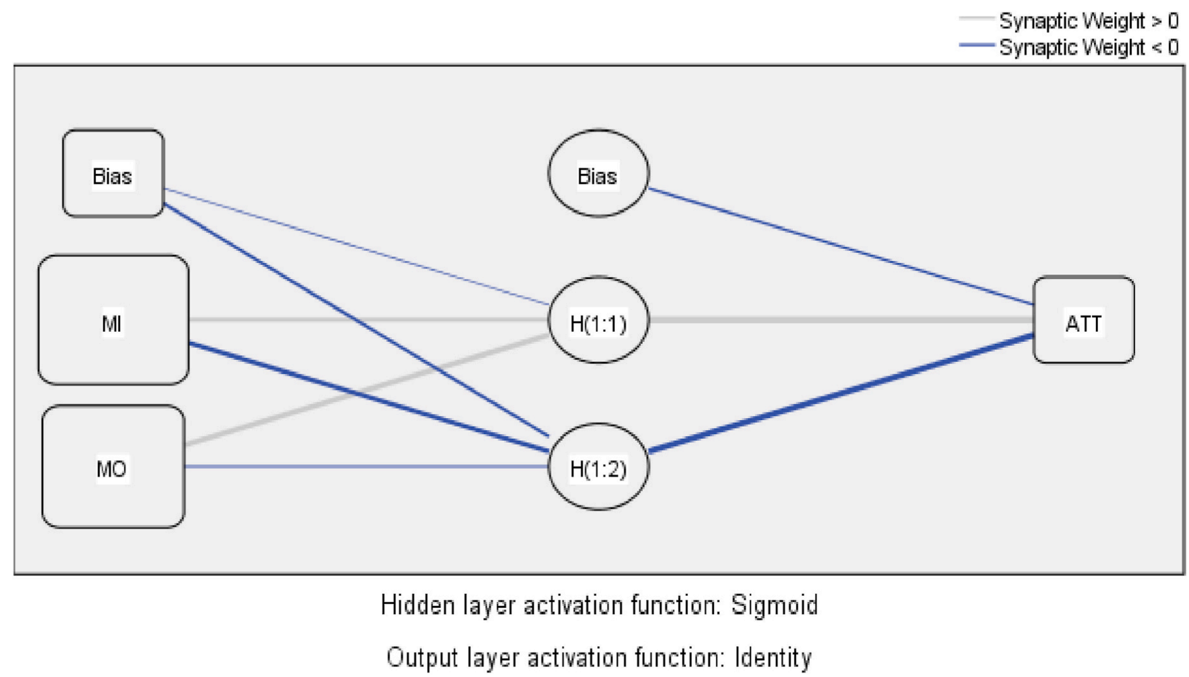

Fig. 6. ANN Model B (MO and MI as input variables).

Table 6
The results for RMSE in the ANN method.

Network	Training	Testing	Training	Testing
1	0.617	0.572	0.580	0.549
2	0.623	0.404	0.587	0.602
3	0.572	0.384	0.600	0.597
4	0.610	0.698	0.583	0.548
5	0.591	0.638	0.588	0.527
6	0.605	0.571	0.597	0.544
7	0.601	0.685	0.592	0.523
8	0.609	0.601	0.632	0.638
9	0.635	0.656	0.593	0.370
10	0.671	0.703	0.584	0.663
Mean	0.613	0.591	0.594	0.556
SD	0.025	0.109	0.014	0.076

Table 7
Sensitivity analysis.

Variables	Importance	Normalized Importance (%)	Ranking
MI	0.512	100	1
MO	0.488	95.34	2
SE	0.223	43.56	3
PS	0.216	42.23	4
MO	0.215	41.98	5
RE	0.198	38.75	6
PV	0.149	29.01	7

endogenous constructs of moral obligation, perceived vulnerability, response efficacy, self-efficacy, and moral intention.

The sensitivity analysis indicated the relative relevance of each predictor, where the importance of an exogenous variable is the degree to which its value varies compared to other exogenous variables in the research (Al-Sharafi et al., 2023). The importance of the predictors should be divided by the maximum value of the predictor to calculate their normalized importance (NI) (Asadi et al., 2021). Based on this, the relative importance of each predictor in the evaluated model was calculated. As shown in Table 7, moral intention is the most influential predictor (NI = 100 %), followed by moral obligation (NI = 95 %), Self-efficacy (NI = 43 %), severity (NI = 42 %), moral obligation for Model A (NI = 41 %), response efficacy (NI = 38 %), and perceived vulnerability (NI = 29 %).

6. Discussion

Plagiarism is described in a moralistic tone, for instance, as "a moral issue" (East, 2010), "a moral offense" (Tulus, 2020) and "moral distress" (Vehviläinen et al., 2018). Invading other people's intellectual property and claiming it as one's own is wrong and unlawful. Despite this, it has become a widespread problem, often committed by individuals who take advantage of loopholes or ignore strict rules and potential consequences. While these rules are set for everyone, the intention to commit plagiarism is a personal matter. Morality can also be seen as an individual trait, where actions reflect one's moral integrity, such as adherence to principles and persistence in upholding them despite the temptation to rationalize violations (Schlenker, 2008). Academic dishonesty, like cheating and plagiarism, is related to lower levels of moral integrity (Ampuni et al., 2020).

Plagiarism can be examined through the lens of "Protection Motivation Theory" (PMT). PMT was initially proposed by Rogers (Rogers, 1975) to address fear-arousing communication regarding health-related behaviors and attitudes (Boer & Seydel, 1996). Since then, the theory has been used in various contexts beyond health, including cybersecurity (Arpaci, 2024; Green et al., 2024; Jamil et al., 2024) and environment (Hosseinikhah Choshaly, 2024; Keshavarz & Karami, 2016; Kothe et al., 2019; Madadizadeh et al., 2024; Rainear & Christensen, 2017). Research has also shown that PMT can be successfully applied to the acceptance of anti-plagiarism software (Lee, 2011). Concerning this, the present study also employs PMT to investigate how increased moral responsibility helps avoid AI-facilitated plagiarism.

PMT consists of various elements that are classified under two primary cognitive processes, including threat and coping appraisal (Shillair, 2020, pp. 1–3). Threat appraisals involve "evaluating maladaptive responses, with a specific focus on vulnerability and severity" (Arpaci, 2024). Perceptions of high severity and vulnerability may increase the likelihood of protective action (Lee, 2011). Perceived severity can be contextualized at the individual level as the damage caused by AI-facilitated plagiarism, leading to shallow learning and overreliance on AI-generated content. On the other hand, the perceived vulnerability could be conceptualized as the likelihood of a threat occurring without protective action, like the absence of guiding rules or moral responsibility.

The findings of this study show that both PS and PV substantially impact students' moral intention to avoid AI plagiarism, with *p*-values of 0.01 and 0.00, respectively. This is due to PS assisting students in acknowledging the problem of plagiarism, like academic dishonesty, and reduced moral leadership (Lee, 2011). For vulnerability, it is common for people to seek protection if they feel defenseless. In this context, students' perception of vulnerability fuels their moral intention towards avoiding plagiarism, as they recognize the potential risks of engaging in such behavior.

In the coping appraisal process, belief in response efficacy and perceived self-efficacy in executing the response are key factors that promote protection motivation (Shillair, 2020, pp. 1–3). When response effectiveness is higher, the possibility that a person will activate an adaptive behavior will increase (Lee, 2011). Self-efficacy determines the quality of this response. For instance, if individuals believe they can perform recommended actions, they adopt them (Bandura, 1977; Schwarzer, 1992, pp. 217–243). Likewise, students may consider remaining in an academic circle dedicated to learning if they believe it will effectively give them the support that substitutes the need for committing plagiarism. Their decision could be influenced by how refraining from AI plagiarism fits within their environment and the group to which they belong. This has something to do with the collaborative dynamics and cultural norms present in student groups. Today, with the emergence of AI, we cannot ignore that the intensity of academic group work has decreased. Examples are platforms like ChatGPT and Gemini, which are often self-centered and involve limited responses from others. Put in another way, responses could be represented as the moral use of generative AI itself, which could necessitate training and guidance from others. Effective training, without a doubt, will cater to self-reliance and, thereby, plagiarism avoidance. The concept is strengthened by the significant relation between response efficacy and moral intention to avoid plagiarism with a *p*-value of 0.002. Similarly, Lee (2011) reported a positive link between the two constructs. Therefore, the emphasis should be put on assisting students in avoiding plagiarism rather than waiting to punish them after the fact. Response cost is the effort required to implement a recommended coping strategy (Rogers, 1975), not a punitive consequence of action. Students can reduce the need to commit plagiarism by investing sufficient effort and time in a subject matter. The magnitude of the required effort is predicted by factors such as the complexity of the subject and the proximity of the deadline. Additionally, factors like one's moral stance may confound the interaction of the RC predictor. Therefore, the insignificant relationship between RC and MI is understandable.

The strong influence of MI on ATT ($\beta = 0.304$, $p = 0.000$) underscores the critical role that positive attitudes play in fostering moral responsibility in academic settings. It is quite ideal that moral intention fuels positive attitudes in resisting plagiarism. If the students recognize they succeed with the help of the available resources, the environment is supportive, and the instructor is on their side, which are the results of positive attitudes, they will stick to their higher standards with confidence. Their moral intentions and positive attitudes are further elevated if they perceive morality as an obligation (MO). This concept is evidenced by the significant influence that MOs exert on both MI and ATT.

7. Conclusion

The concept of plagiarism varies across cultures and institutions, and definitions of plagiarism vary accordingly. It involves fraud, cheating, misrepresentation, and denying original authors due recognition (Farooq & Sultana, 2022; Hayawi et al., 2024; Hayes & Introna, 2005; Liddell, 2003). AI plagiarism, or "AIgiarism," is the use of AI tools to commit plagiarism or escape detection (Khalaf, 2024, pp. 1–12).

This study examines AI-driven plagiarism from the perspective of attitudes and moral responsibility. The constructs of "Protection Motivation Theory" (PMT) were to set a theoretical foundation for the study. We explored the role of enhanced morality as a preventive measure against AI plagiarism and highlighted how negative attitudes toward plagiarism can motivate students to seek legitimate solutions (Camara et al., 2017; R. Farooq & Sultana, 2022). The study also utilized a two-stage approach using PLS-SEM and ANN to analyze linear and non-linear relationships and increase the robustness of the findings (Arpaci, 2024). The results signified the relevance of moral responsibility as a significant aspect in minimizing academic dishonesty, and students will most likely behave ethically when they see AI plagiarism as a genuine threat to their integrity.

7.1. Theoretical implications

This study may contribute to the growing literature on the ethical use of artificial intelligence (Fu & Weng, 2024; Homayouni et al., 2024, pp. 1–6; Memarian & Doleck, 2023; A. Nguyen et al., 2023) by enhancing the "Protection Motivation Theory" (PMT) with the concept of moral responsibility. Our approach challenges conventional methods of combating plagiarism that rely solely on detection and punitive measures. While traditional strategies emphasize academic consequences as deterrents, their effectiveness remains debatable, as they often overlook the underlying moral dimensions of plagiarism. This research argues that plagiarism is not only an academic violation but also a moral transgression, necessitating a more comprehensive framework.

From this perspective, perceived severity extends beyond academic penalties to encompass behavioral and ethical consequences. PMT also introduces the vulnerability component, which, in this study, assesses students' awareness of the likelihood of facing negative outcomes due to plagiarism. Students' level of vulnerability reflects their awareness of plagiarism-related consequences and influences their willingness to adopt preventive measures. However, awareness alone does not translate into action unless coupled with response efficacy, the belief that adopting a recommended protective action will effectively mitigate a potential threat (Floyd et al., 2000; Lee, 2011; Prentice-Dunn & Rogers, 1997).

Considering these findings, educators and higher education policymakers should reconsider their current decision-making models to better integrate moral responsibility into plagiarism prevention strategies. Furthermore, using a hybrid PLS-SEM and ANN technique enhances methodological rigor by demonstrating that linear and nonlinear interactions must be considered to fully capture the complexity of plagiarism-related behaviors.

7.2. Practical implications

The results provide significant insights for educators, policymakers, and academic institutions in formulating successful plagiarism prevention initiatives. Universities should emphasize moral values by integrating ethics-oriented courses and cultivating an academic atmosphere that promotes self-regulation and responsibility. Secondly, instead of depending only on detection and disciplinary actions, institutions need to establish AI literacy programs that educate students on the ethical use of AI technologies. Instructors should actively include students in talks about the moral issues and implications of AI-driven plagiarism, emphasizing that academic integrity is a moral obligation rather than just a compliance issue. Finally, the paper recommends that institutions allocate resources toward adaptive learning strategies that allow students to complete academic assignments without resorting to AI-assisted plagiarism.

7.3. Limitations and future research

Despite the valuable contributions, this study is not free from limitations. First, the research sample is limited to Somali universities in

Mogadishu. The respondents' exposure to the use of AI may differ according to geographical differences. To address this issue, comprehensive cross-country investigations are required. Similarly, the resource-constrained nature of the Somali context (Webersik, 2008) may also impose a further limitation. Thus, future studies may consider retesting the research model in more resource-rich settings for comparison. Furthermore, the findings rely on the protection motivation theory to determine students' behavior. Extending the research model with UTAUT constructs could capture the impact of social context and expectations on respondents' behavior (Lai et al., 2024). While the hybrid approach of PLS-SEM and ANN strengthens methodological validity, this study adopts a cross-sectional design, limiting the ability to track changes in moral attitudes over time. Longitudinal studies should be conducted to track how students' attitudes and moral intentions evolve, particularly in response to changing academic policies and advancements in AI plagiarism detection technologies. Future research should also investigate institutional interventions, such as AI literacy programs (Czerkawski & Durgut, 2024, pp. 165–174; Kong et al., 2022; Tzirides et al., 2024), ethics-driven curricula (Southworth et al., 2023), to examine their impact on students' willingness to engage in academic integrity practices.

CRediT authorship contribution statement

Ismail Mohamed Ali: Writing – original draft, Methodology, Data curation. **Ibrahim Arpaci:** Writing – review & editing.

Declaration of Competing interest

The author declares no conflicts of interest related to this manuscript. The research was conducted independently, with no financial or personal relationships that could influence the study's outcomes or interpretations.

Appendix A. Measurement Items

Perceived Vulnerability (Hu et al., 2022; Lee, 2011)	
PV1	"I could be vulnerable to Internet plagiarism when using AI chatbots (e.g., ChatGPT)."
PV2	"I could be susceptible to Internet plagiarism when using AI chatbots."
PV3	"Students in my class are likely to commit Internet plagiarism when they use AI chatbots for their studies."
PV4	"I feel at risk that AI chatbots can give me fake answers."
PV4	"AI chatbots can likely affect my learning ability."
Response Cost (Hu et al., 2022; Lee, 2011)	
RC1	"There is too much overhead associated with AI chatbots in learning."
RC2	"It takes considerable time and effort to understand the content provided by AI chatbots."
RC3	"Using AI chatbots may cause distrustful relationships between me and my learning goals."
RC4	"Using AI chatbots reduces my self-reliance as it can effortlessly generate content."
RC5	"Using AI chatbots can make me lazy as it creates no challenge."
Perceived Severity (Hu et al., 2022; Lee, 2011)	
PS1	"AI plagiarism may seriously undermine the standards of academic integrity."
PS2	"AI plagiarism committed by classmates influences honest students to imitate their behavior."
PS3	"There is a high chance for me to provide good grades to those who plagiarize without detecting their plagiarism."
PS4	"My image will be seriously damaged if the plagiarism I committed is publicized."
Self-Efficacy (Hu et al., 2022; Lee, 2011)	
SE1	"I feel confident using the AI chatbot."
SE2	"I have the necessary skills for using AI chatbots."
SE3	"I feel confident operating ChatGPT functions."
SE4	"I feel that AI chatbots are important to me."
SE5	"It would be easy for me to use the anti-plagiarism software myself."
Response Efficacy (Hu et al., 2022; Lee, 2011)	
RE1	"Effective use of AI chatbots will help my students avoid Internet plagiarism."
RE2	"Effective use of AI chatbots will save time when studying."
RE3	"Effective use of AI chatbots will prevent language errors in my writing (assignments, essays, projects)."
RE4	"Effective use of AI chatbots will help me to make accurate calculations."
Moral Intention (Zhang et al., 2023)	
MI1	"I tend to contemplate moral issues during my studies proactively."
MI2	"I strive to make moral decisions as quickly as possible."
MI3	"I adhere to moral principles without wavering in decision-making."
MI4	"I am inclined to engage in behaviors that align with moral standards."
Attitude (Mavrinac et al., 2010)	
ATT1	"Plagiarists do not belong in the scientific community."
ATT2	"The names of the authors who plagiarize should be disclosed to the scientific community."
ATT3	"In times of moral and ethical decline, it is important to discuss issues like plagiarism and self-plagiarism."
ATT4	"Plagiarizing is as bad as stealing an exam."
ATT5	"Plagiarism impoverishes the investigative spirit."
Moral Obligations (Lee, 2011; Uzun & Kilis, 2020)	
MO1	"If my colleagues do not take any actions to counteract Internet plagiarism, it is my duty to persuade them to adopt them."
MO2	"I think I have to take action to cope with Internet plagiarism if it deteriorates the academic integrity of my institution."
MO3	"Plagiarism goes against my principles."
MO4	"I would not feel guilty engaging in plagiarism."

Data availability

Data will be made available on request.

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