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An Exploratory Factor Analysis of Vulnerability and Protective Factors Influencing University Students' Unethical Intention to Use AI Tools

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Abstract

The rapid integration of AI tools in higher education presents both opportunities and challenges in the contemporary education setting, mainly regarding students' ethical and responsible use. This study aims to explore the underlying factors that influence students' unethical intention to use AI tools through a Vulnerability–Protection framework, which considers factors that lead to unethical usage (vulnerability) and factors that prevent unethical usage (protection). Data were collected from 522 undergraduate and postgraduate students across eight universities, comprising four public and four private institutions, in the Colombo District, Sri Lanka. Exploratory Factor Analysis (EFA) was conducted to identify primary dimensions, and reliability analysis was used to assess internal consistency. Results discovered a seven-factor structure, including four vulnerability factors: perceived ease of use/usefulness, institutional pressure, peer influence, and task pressure, and two protective factors: AI literacy and ethical awareness. Perceived usefulness and ease of use were identified as the strongest drivers of AI adoption, while protective factors provided a barrier for unethical usage. The findings highlight a relationship between different cognitive, social, and ethical factors of AI use, highlighting the importance of improving AI literacy, ethical awareness, and supportive institutional practices. These insights offer practical guidance for universities to promote responsible and knowledgeable AI adoption while mitigating risks related to academic integrity.

Keywords: *AI usage, Behavioral Intention, Exploratory Factor Analysis, Higher Education, Vulnerability–Protection Framework*

1. Introduction

Artificial intelligence (AI) technologies are driving massive transformations across global education systems because it is quickly spreading to every aspect of education (Bouteraa et al., 2024). Teaching, learning, and assessment practices, especially in higher education, are changing with AI (Rodway & Schepman, 2023). From automated feedback tools to generative language models, AI now plays a significant role in how students access information, complete academic tasks, and navigate complex learning environments (Ali et al., 2024). As in many developing countries, in Sri Lanka, the use of AI in universities has accelerated as digitalization and technology have become increasingly integrated into the education sector. While AI offers clear benefits, including improved efficiency, enhanced learning support, and greater accessibility, it also raises growing concerns about academic integrity, ethical use, and students' readiness to use such tools responsibly (Wang et al., 2025).

A core challenge is that the way students approach AI is changing significantly (Vieriu & Petrea, 2025). Some use AI critically and ethically, guided by skills such as AI literacy and an understanding of responsible use. However, the majority may use AI impulsively, opportunistically, or when under time pressure and peer pressure (Abbas et al., 2024; Baek et al., 2024). These patterns suggest that some factors are available that could unintentionally push students into uncritical or ethically questionable use of AI (Acosta-Enriquez et al., 2025; Theoharakis et al., 2025). On the other hand, some research provide evidences there are some other factors that encourage students to use AI more responsibly (Wang et al., 2025).

Although previous research has examined individual predictors of technology use, particularly through established models such as the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh & Davis, 2000) and the Theory of Planned Behavior (TPB) (Ajzen, 1991), there is limited understanding of how multiple factors interact simultaneously to influence students' behavioral intentions to use AI in both vulnerable and protective ways. Furthermore, many existing models assume well-defined theoretical structures, but empirical evidence is insufficient to confidently specify such relationships, especially in emerging contexts such as Sri Lanka (Weerasinghe & Abeysinghe, 2024). This gap highlights the need for a more exploratory approach that practically explains how different factors from different theoretical models naturally cluster into meaningful factors that explain student intention

To address this gap, the present study introduces a new exploratory conceptual direction, called the vulnerability and protective approach to behavioral intention of using AI tools. Rather than examining pre-specified theoretical constructs, this study examines how the influencing factors of AI usage can be reorganized into developing vulnerable and protective dimensions. Furthermore, how these dimensions influence behavioral intentions to use AI. Therefore, this study aims,

(1) To identify the underlying factors that constitute vulnerability to unethical usage among university students in Sri Lanka.

(2) To identify the underlying factors that constitute the protection of preventing unethical usage among students in Sri Lanka?

The study uses exploratory factor analysis (EFA) to originate factor structures for vulnerability and protection using pre-identified items from different theories and frameworks, such as perceived usefulness (PU), perceived ease of use (PEOU), social influence (SI), institutional pressure (IP), AI literacy (AIL), and ethical awareness (EA).

This exploratory approach seeks to identify the underlying factor structure of vulnerability-related items (PU, PEOU, SI, IP) (Acosta-Enriquez et al., 2025; Alshammari & Al-Mamary, 2025; Theoharakis et al., 2025) and protective-related items (AIL and EA) (Asagar, 2025; Wang et al., 2025) using EFA. Apart from that, the study will assess the reliability of the factors developed from EFA.

2. Literature Review

2.1. AI Usage in Higher Education

AI is no longer something distant or futuristic in university settings; students are using AI right now in their learning environments, supporting tasks ranging from writing assistance to data analysis, translation, tutoring, and information retrieval (Wang et al., 2025; Yan et al., 2024). Especially with tools like ChatGPT and other generative AI tools. This deep accessibility of generative AI tools has reshaped the way students approach coursework, complete assignments, make decisions, and even prepare for exams (Kim et al., 2022; Vieriu & Petrea, 2025). While AI is more helpful in academic tasks, it also produces considerable ethical and integrity issues in academia. Students tend to misuse AI for their brains, letting it do the coursework as it sees fit, rather than thinking for themselves. This may create serious ethical problems like unauthentic works, plagiarism issues, dependency on AI tools, cognitive offload, etc. (Cross et al., 2023; Karabacak et al., 2023; Nikolic et al., 2023). As a result, scholars have called for frameworks that not only promote the use of AI but also ensure responsible and ethical use in academic settings.

In developing countries like Sri Lanka, where digital literacy and institutional guidelines are still evolving, understanding students' behavioral intentions to use AI is especially important. Behavioral intention, generally conceptualized as the likelihood that an individual will engage in a given behavior, remains one of the strongest predictors of technology adoption. However, BI is not formed in isolation; it is shaped by psychological, contextual, and ethical influences that can increase the risk of uncritical use or reinforce protective behaviors (Elbaz, 2024; Muhammad Waqas et al., 2025). Therefore, this study explores these opposing effects through a lens of risk, safety, and security.

2.2. Vulnerability Factors in AI Usage

One of the strongest reasons students are attracted to AI is simply how useful they find it. In many educational contexts, students believe that generative AI is able to improve their performance, streamline difficult tasks, and save time (C. Wang et al., 2025). When something feels powerful and useful, it's easy to rely on it, even if it poses a risk. As with vulnerability factors, increasing the likelihood of uncritical, impulsive, or ethically risky AI use.

One of the most important factors that positively influences the intention to engage in unethical behavior is ease of use (Alshammari & Al-Mamary, 2025). Perceived ease of use is described as the extent to which individuals believe that using a technology will be effortless. If a tool feels intuitive and does not require much effort, students are more likely to adopt it. This “low-friction” approach can be a double-edged sword. On the one hand, that ease encourages adoption. On the other hand, it can reduce the amount of reflection or critical judgment a student applies when using the tool. Although initially a positive predictor in technology adoption models such as TAM, in the context of AI ethics, ease of use can inadvertently encourage shortcuts or overreliance (Wu et al., 2024).

Another factor that can influence the behavioral intention is the perceived usefulness of the AI tool. Perceived usefulness refers to the belief among students that AI tools will improve academic performance or efficiency (Alshammari & Al-Mamary, 2025). Although PU has traditionally been associated with high usage, its effects can also display a risk of over-reliance. When AI is readily available, students may grab it not just for meaningful tasks, but simply because it’s there. Without careful reflection, this “grab whatever you can” mentality can lead to overreliance, especially under tight deadlines or heavy workloads. When students perceive AI as essential for completing assignments quickly or accurately, they may prioritize usefulness over critical evaluation, originality, or ethical considerations. Therefore, PU operates as a double-edged factor in AI-supported learning contexts (Li, 2023).

The TAM, developed by Davis (1989), has long been used to explain how individuals adopt new technologies. In TAM, perceived ease of use and perceived usefulness are key predictors that shape users’ behavioral intention to adopt a system. PEOU reflects the degree to which a user believes that interacting with a technology will be easy, while PU indicates a belief that using the technology will improve performance or efficiency. Traditionally, TAM positions BI as a consequence of these perceptions, capturing an individual’s ability to engage with technology (Li, 2023). In the context of AI tools in higher education, this construct is highly relevant. Students who perceive AI as useful and easy to implement are naturally more inclined to use it, without fully considering the potential ethical or academic implications. Therefore, in the present study, PEOU and PU are conceptualized as risk factors, conditions that may increase the likelihood that students will impulsively or opportunistically use AI, while BI serves as the dependent variable, reflecting students’ intention to use AI. Using TAM constructs in this way aligns with their theoretical role but reframes them in an exploratory context that accounts for both practical adoption and potential ethical risks, providing a solid foundation for examining behavioral intentions toward AI tools.

Another vulnerability factor identified in the literature is social influence (Korchak et al., 2025). Social influence refers to the pressure students feel to use AI tools from peers, instructors, or the academic culture. Since students are not operating within the vaccine, their peers, educators, and academic culture strongly shape their choices (Korchak et al., 2025; Uludağ et al., 2025). In many university environments, peer groups normalize the use of AI, often without clear guidance or limits. Students may adopt AI due to social comparison, fear of failure, or collective norms rather than informed judgment. This creates a risk for unregulated or opportunistic use, especially when formal policies on AI are unclear or inconsistent. Johnston et al. (2024) report that many students feel peer pressure to use generative AI. Some believe that there should be institutional policies about when it is appropriate to use AI, which highlights how much influence the academic community has over individual AI decisions.

Another important factor influencing students' use of AI tools is institutional pressure. Universities often impose tight deadlines, high expectations for assignment quality, and heavy course loads, which create an environment in which students are forced to work efficiently under time constraints (Salah et al., 2024). Such pressures can push students to turn to AI tools as a practical solution to manage competing demands, meet deadlines, and deal with multiple modules simultaneously. Studies on academic stress and technology use show that high workload and performance expectations increase students' reliance on digital tools, including AI, as a strategy (Misra & McKean, 2000; Zheng et al., 2023). In the context of AI use, IP can be seen as a risk factor, increasing the likelihood that students will use AI not only for support but also sometimes as a shortcut to meet institutional demands. By shaping the perceived need for AI, institutional structures indirectly influence behavioral intentions, highlighting the critical role of the academic environment in students' ethical and practical engagement with AI technologies (Singh et al., 2020).

Visually, these factors create an environment where students may use AI impulsively or opportunistically, increasing the risk of unethical practices or shortcuts in their academic pursuits. Identifying these triggers is essential to understanding not only the motivations behind AI use but also the situations in which safety factors are critical in guiding responsible behavior.

2.3. Protective Factors in AI Usage

Protective factors represent skills, behaviors, or attitudes that reduce the likelihood of risky AI use and strengthen responsible, informed, and ethical adoption. Based on the literature, AI literacy has been found as a strong protective factor. The concept of AI literacy has evolved as a bridge between students' understanding of AI and their ability to use these technologies ethically in educational contexts. Research consistently shows that, unlike general literacy, AI literacy functions as more than technical knowledge and acts as a broader framework that shapes how students access, evaluate, and implement AI tools in their academic work (Casal-Otero et al., 2023).

AI literacy incorporates the knowledge, awareness, and competencies needed to understand how AI works, its limitations, potential biases, ethical risks, and appropriate applications (Casal-Otero et al., 2023; Ng et al., 2021). Students with higher AI literacy are better able to evaluate AI outputs critically, resist misinformation, and avoid misuse. AI literacy also includes understanding institutional guidelines, privacy concerns, data governance issues, and the importance of maintaining academic integrity when using AI-generated content. Thus, AI literacy acts as a major protective barrier against irresponsible usage. The literature presents a variety of approaches designed to conceptualize AI literacy, but most frameworks share common core elements. Previous research established that AI literacy encompasses technical, evaluative, and ethical knowledge related to AI systems (Al-Zahrani, 2024; Ng et al., 2021). This broad definition recognizes that responsible AI use requires understanding not only how AI works but also its limitations, potential biases, and ethical implications.

The reviewed literature reveals both mergers and deviations in approaches to AI literacy. While the majority of research agrees on the importance of integrating technical knowledge with ethical understanding, there are some differences in how these components should be planned, taught, and evaluated (Bhullar et al., 2024; Bouteraa et al., 2024). Some approaches emphasize broad frameworks that integrate all aspects of AI literacy, while others focus on specific skill areas or educational contexts. Therefore, it can be identified a significant gap between measuring AI literacy and assessing ethical behavior. While many studies have developed sophisticated approaches to measuring AI literacy, few have examined whether higher AI literacy leads to more ethical AI use (Carolus et al., 2023). This represents a critical area for future research, particularly emphasizing AI literacy as a protective factor in ethical behavioral intention to use AI tools.

Ethical Awareness (EA) represents a critical dimension of protective factors, reflecting students' ability to recognize, evaluate, and respond to moral and ethical considerations associated with AI use (Asagar, 2025). Unlike AI literacy, which primarily equips students with knowledge and skills to navigate technology effectively, ethical awareness emphasizes the values, judgments, and ethical reasoning that guide students' decisions. It includes sensitivity to issues such as fairness, transparency, accountability, academic integrity, and the broader societal consequences of AI use.

Students with high ethical awareness are more likely to question whether their use of AI aligns with moral principles and institutional expectations (Migdadi et al., 2024). For example, they consider the implications of submitting AI-generated content as their own work, the potential biases embedded in AI outputs, and how reliance on AI may affect their learning or the academic experience of others. This reflective approach encourages deliberate decision-making rather than impulsive or convenience-driven usage.

Even when students face strong vulnerability factors such as tight deadlines, social pressure, or the perceived usefulness of AI, the presence of ethical awareness can guide them to act responsibly. It encourages them to critically evaluate situations, balance efficiency with integrity, and choose actions that uphold academic standards (Shrestha, 2025).

Moreover, ethical awareness is closely linked to the development of professional and personal responsibility. In higher education, students are preparing for careers where AI is increasingly integrated into professional practice. Cultivating ethical awareness ensures that students not only use AI responsibly in their academic work but also develop habits and moral frameworks that can transfer to professional contexts, where decisions may have broader societal consequences (Shrestha, 2025).

Ethical awareness is not distinctive; it can be fostered through structured educational interventions, reflective practice, case studies, and institutional guidance. When combined with AI literacy, it forms a comprehensive protective system: literacy provides the tools and knowledge for competent AI use, while ethical awareness provides the moral compass that guides how those tools are applied. Together, they empower students to engage with AI in ways that maximize benefits, minimize risks, and uphold the values of honesty, fairness, and responsibility (C. Wang et al., 2025).

Importantly, ethical awareness functions as a complementary protective factor that strengthens the impact of AI literacy (Alnsour et al., 2025). Ethical awareness reflects students' sensitivity to ethical issues surrounding AI, including fairness, transparency, accountability, and the moral implications of using AI-generated content. While AI literacy equips students with the knowledge needed to navigate AI tools effectively, ethical awareness provides the moral compass that guides the application of that knowledge toward responsible choices (Chan, 2023a; H. Wang et al., 2024). Students who possess strong ethical awareness are more likely to consider the consequences of their AI use on themselves, their peers, and the integrity of the academic environment (Shrestha, 2025).

Together, AI literacy and ethical awareness form a powerful protective barrier against irresponsible AI usage. AIL provides the analytical and procedural competencies, while EA ensures those competencies translate into ethical decisions. This dual combination helps students navigate AI tools confidently, mitigate risks, and engage with AI in ways that support learning, creativity, and integrity rather than undermine them.

2.4. Vulnerability-Protective Perspective

Examining vulnerability and protective factors side by side provides a nuanced lens for understanding students' engagement with AI. Rather than categorizing students simplistically as either "AI adopters" or "cheaters," this perspective acknowledges that their behavior is shaped by both real opportunities and tangible risks. Vulnerability factors explain why students may be drawn toward AI tools: these technologies are perceived as useful, easy to use, socially encouraged, and readily available. Protective factors, on the other hand, reveal how students can regulate or restrain their use, guided by skills, critical reflection, and ethical awareness. Together, these dimensions illuminate the interplay between motivation and restraint, highlighting the conditions under which students may adopt AI responsibly or risk overreliance and misuse.

This vulnerability–protection framework is grounded in actual student behavior. It captures how students discuss AI, the ways they incorporate it into their academic work, and the challenges they face in balancing efficiency with ethical considerations. The framework is particularly valuable in contexts where universities have yet to establish clear AI guidelines. In such settings, the absence of shared norms or strong literacy programs may lead students to rely predominantly on convenience or peer behavior, increasing the likelihood of misuse or dependence. By considering both vulnerability and protective factors together, the framework provides a more realistic and actionable understanding of student decision-making than models that focus solely on either risk or competence.

Despite the growing literature on AI use in education, several gaps remain. Many studies assume that theoretical constructs, such as AI literacy or ethical awareness, naturally align with students' perceptions, without empirically validating how these constructs manifest in actual behavior. Furthermore, few studies have examined vulnerability and protective factors in a unified model, limiting our understanding of their interaction. Research also remains contextually narrow, with limited evidence from non-Western universities or environments where institutional policies, resources, and student experiences differ. Finally, most studies focus on self-reported intentions to use AI ethically rather than on actual usage patterns, leaving a gap in our knowledge of real behavioral outcomes.

In light of these limitations, there is a clear need to explore how students' perceptions cluster into risk-oriented and protective dimensions and how these dimensions influence their intention to use AI. Employing exploratory factor analysis enables researchers to uncover these latent structures empirically, rather than relying solely on theory. By doing so, it becomes possible to understand not only the factors that drive AI adoption but also the mechanisms that help students exercise caution and ethical judgment. Such insights are crucial for universities seeking to support responsible AI use: rather than simply discouraging AI, institutions can strengthen protective factors like literacy and ethical awareness, equipping students to navigate AI tools in ways that enhance learning while maintaining integrity.

3. Methodology

This study adopted a positivist research philosophy as it seeks to identify the underlying latent factors through a quantitative measurement (Creswell & Creswell, 2018). A cross-sectional survey design was adopted to examine how risk and safety factors influence students' behavioral intentions to use AI tools in academic settings (Creswell & Creswell, 2018). A structured questionnaire was developed using previously validated items from the literature on technological acceptance, academic integrity, moral psychology, and AI literacy. As the current study explores how these items cluster into dimensions relevant to vulnerability and protection in practice, an exploratory approach is considered more appropriate. Because the research wanted to discover latent structures rather than validate a fixed theoretical model. Therefore, exploratory factor analysis was used to identify the underlying factor structure of the vulnerability and protective factors (Nz, 2019).

The target population for this study comprises undergraduate and postgraduate students enrolled in both state and private universities in Western Province. For categorization, the study includes four state universities in Western province, which are the University of Colombo, University of Sri Jayewardenepura, University of Moratuwa, and University of Kelaniya, operating under the direct administration of the University Grants Commission (UGC), established by the Universities Act No. 16 of 1978. These institutions are recognized as fully-fledged public universities governed by the UGC (Universities Act, No. 16 of 1978, 2009).

Similarly, the study selected four private institutions operating in Western province, which have been officially recognized as Degree-Awarding Institutes under Section 25A of the same Act. To match the selected state universities, private institutes were selected under the criteria of the number of degree programs available. Selected institutes are the National School of Business Management (NSBM), Sri Lanka Institute of Information Technology (SLIIT), National Institute of Business Management (NIBM), and Colombo International Nautical and Engineering College (CINEC). Among the UGC degree awarding institutes, the above four universities have more diversified degree programs. Therefore, they were selected by assuming that they would be the best matches. These institutions are authorized by the UGC to offer degree programs within Sri Lanka’s higher education framework (Universities Act, No. 16 of 1978, 2009).

According to the most recent UGC statistical report (2022), a total of 49,500 students were enrolled in undergraduate programs for selected universities (including both internal and external students), and 19,141 students were enrolled in postgraduate programs, bringing the total to approximately 68,641 students in selected state universities (UGC, 2022). In the private sector, data from the British Council (2024) indicated that 20,052 students were enrolled in private degree programs. This number reportedly increased to 42,000 students by the year 2025, as stated in a recent article by the Daily News (Francisco, 2024).

Therefore, based on data from the 2021/2022 academic year, the estimated total student population across selected state and private universities in Western province stands at approximately 88,693 students. This figure serves as the foundational population for the present study, capturing the landscape of higher education enrolment within the Western province.

Data were collected from 522 students, using a non-probability purposive sampling approach (Saunders et al., 2019). This sample size exceeds the commonly suggested minimum requirement for factor analysis (5–10 participants per item), ensuring adequate statistical power for EFA (Yong & Pearce, 2013).

A structured survey was conducted to capture students' self-reported perceptions of AI literacy, ethical awareness, and perceived usefulness, ease of use, social influences, institutional pressures, and behavioral intentions. These variables were informed by prior studies on technology adoption, academic integrity, and ethics, but how they were integrated into vulnerability and safety dimensions was intentionally left open to empirical discovery. Therefore, EFA was used to investigate how these items naturally clustered together in students' minds, providing a data-driven basis for the model tested in the subsequent analysis.

3.1. Instrument Development

The questionnaire was administered in a self-administered format, enabling respondents to fill it out on their own without the researcher's direct participation. The data collection process was executed from July to the end of August 2025.

The questionnaire consisted of three main sections, each designed to assess a different set of constructs related to students' engagement with AI tools. As vulnerability factors, the study included 16 items representing students' risk-oriented motivations to use AI, derived from four well-established constructs as represented in Table 1.

Table 1: Vulnerability factors list

Construct	***Factor ID***	***Vulnerable factor items***
Perceived ease of use	*V1*	*Ease of use of AI tools and technologies*
	V2	*Ease of learn by AI tools and technologies*
	V3	*Clear and understandable interaction with AI tools and technologies*
	V4	*Becoming a skillful person by using AI tools and technologies*

Perceived usefulness	*V5*	*Efficient learning using AI tools and technologies*
	V6	*Accomplishing academic tasks quickly using AI tools and technologies*
	V7	*High accessibility and no limitations to using AI tools and technologies.*
	V8	*Receiving higher scores using AI tools and technologies*
Social influence	*V9*	*Influence of classmates*
	V10	*Influence of lecturers*
	V11	*Influence of well-known people and social media*
	V12	*Influence of parents and family members*
Institutional pressure	*V13*	*Having strict guidelines for coursework*
	V14	*Having strict enforcement of academic integrity*
	V15	*Availability of policies and rules regarding assignments, exams, and usage of technology*
	V16	*Pressure from the educators to generate high-quality assignments*

These constructs were selected because they have consistently been shown to influence technology use across educational and occupational contexts. Items were adapted from prior literature on the Technology Acceptance Model (TAM), social influence in digital behavior, and institutional determinants of academic conduct. Together, these items were expected to capture various psychological and contextual forces that may push students toward relying more heavily on AI tools, especially under time pressure, academic workload, or social expectation.

The second group consisted of 9 protective factors representing students' protective characteristics, which may help them regulate or limit inappropriate AI use. These items reflected two key constructs. The following Table 2 displays the constructs and their factors.

Table 2: Protective factors list

Construct	***Factor ID***	***Protective factor items***
AI literacy	*P1*	*Understanding of human-machine interaction that AI performs*
	P2	*Understanding of how AI generates information using big data*
	P3	*Understanding of the limitations and opportunities of using AI*
	P4	*Ability to assess the advantages and disadvantages that AI entails*
	P5	*Reliability of information generated by AI*
Ethical awareness	*P6*	*Awareness of using fully AI-generated content is cheating in terms of academic*
	P7	*Awareness of ethical practices using AI tools in academics*
	P8	*Following the ethical guidelines provided by the university*
	P9	*Avoiding malicious and unethical practices situationally*

These constructs were included because growing literature suggests that literacy and ethical reflection help students critically evaluate AI outputs and make informed choices rather than relying solely on convenience or pressure.

Behavioral intention to use AI tools was measured using three items adapted from the TAM. Given that BI is a central predictor of actual behavior in TAM research, it was used as the dependent variable in the final regression analysis.

All items were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Prior studies have shown that Likert-type scales are effective for measuring psychological perceptions and provide sufficient variability for factor analysis.

3.2. Ethical Consideration

The study followed standard ethical guidelines for research involving human participants. All respondents were informed about the study's purpose, the voluntary nature of participation, anonymity, and their right to withdraw without consequence. No identifiable or sensitive personal data was collected. Data were stored securely and used solely for academic purposes.

4. Results and Discussion

4.1. Preliminary Data Screening

Table 3: Normality values

Factor	Skewness	Kurtosis
VF10	.668	.138
VF11	.177	-.610
VF12	-.211	1.228
VF13	.157	1.338
VF14	-.972	3.112
VF15	.346	2.259
VF16	-.898	.854
PF1	-.273	-1.337
PF2	-.393	-1.156
PF3	-.943	.381
PF4	-.828	.224
PF5	.707	-.786
PF6	1.092	.053
PF7	-.774	2.005
PF8	-.587	.330
PF9	-1.084	1.613

Before conducting the main statistical analyses, a series of preliminary screening processes were done to ensure that the data met the necessary assumptions for EFA and reliability testing. These processes included checks for missing values, outliers, and normality assessment.

The initial stage involved examining the dataset for missing values across all questionnaire items. The inspection revealed that the dataset contained **no missing values**, indicating that all 522 participants completed every item in the survey instrument. As a result, no data imputation or case deletion techniques were required, and the full sample was retained for subsequent analyses. The absence of missing data enhances the validity of the results and supports the robustness of the factor extraction process.

To determine whether the data met the assumption of normality required for factor analysis, **skewness and kurtosis values** were examined for each survey item. All values fell within the acceptable threshold of **±2** (Leguina, 2015)**,** indicating that the data approximated a normal distribution. This level of normality is considered satisfactory for analyses such as PCA and EFA, specially with a sample size exceeding 500 participants.

4.2. Exploratory Factor Analysis

After the preliminary screening, the data were directed to the main analysis. The main analysis was done using SPSS. To determine whether the items were appropriate for factor extraction, two standard statistical tests were performed: the **Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy** and **Bartlett's Test of Sphericity.** The KMO value obtained was **0.784,** which exceeds the recommended minimum threshold of 0.60. According to Kaiser's (1974) classification, values between 0.70 and 0.79 are considered **"middling",** indicating that the correlations among items are sufficiently compact and the sample size is adequate for producing reliable factors. Thus, the data were believed suitable for EFA. Bartlett's Test of Sphericity was significant (P<0.001), indicating that the correlation matrix was not an identity matrix and that meaningful relationships exist among the measured variables. This further confirms the suitability of applying factor analysis.

Table 4: Result Summary of Items.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		***.784***
Bartlett's Test of Sphericity	*Approx. Chi-Square*	*10764.384*
	df	*253*
	Sig.	*0.000*

Table 5: Cronbach's Alpha Value

Cronbach's Alpha	N of Items
0.842	25

After establishing that the data were suitable for factor analysis, an EFA using PCA with Varimax rotation was conducted to identify the underlying structure of vulnerability and protective factors associated with students' behavioral intentions toward AI tool usage. From the initial reliability calculation for all factors, which indicated 0.84, it was the most acceptable value of the variable analysis (Yong & Pearce, 2013).

Table 6: Total Variance Explained

Component	**Initial Eigenvalues**		
	Total	% of Variance	Cumulative %
1	6.764	29.410	29.410
2	3.598	15.642	45.053
3	2.335	10.152	55.204
4	1.888	8.207	63.411
5	1.452	6.315	69.726
6	1.167	5.072	74.798
7	1.048	4.554	79.352
8	.732	3.181	82.533
9	.701	3.047	85.581
10	.654	2.842	88.423
11	.514	2.234	90.656
12	.431	1.873	92.529
13	.372	1.616	94.145
14	.302	1.312	95.457
15	.276	1.199	96.656
16	.202	.880	97.535
17	.138	.602	98.137
18	.110	.480	98.617
19	.104	.451	99.068
20	.090	.393	99.461
21	.052	.228	99.689
22	.048	.207	99.896

23	.024	.104	100.000

The Total Variance Explained table indicated that **seven components** had eigenvalues greater than 1.0, satisfying Kaiser's criterion for factor retention (Finch, 2020). Together, these seven components accounted for **79.35%** of the total variance, which is considered a strong and acceptable level of explanatory power in social science research. The substantial proportion of explained variance (79.35%) indicates that the measured items provide a strong representation of the constructs under study. Extracting seven components aligns with both statistical criteria and the conceptual framework, distinguishing vulnerability and protective factors. The extraction of several components also suggests that students' attitudes and behaviors regarding AI tool usage are multi-dimensional, capturing diverse influences such as cognitive readiness, ethical awareness, time pressure, perceived usefulness, and institutional expectations.

Next, the Principal Component Analysis with Varimax rotation, seven distinct components emerged, representing the latent structures underlying the vulnerability and protective items. Factor loadings greater than 0.50 were considered significant for interpretation, and items that loaded cleanly onto a single factor were retained (Finch, 2020). The extracted factors were examined in the context of the study's conceptual framework to identify which components corresponded to vulnerability factors and which corresponded to protective factors.

Overall, the EFA results reveal a **multi-dimensional structure** comprising **four vulnerability factors** and **two protective factors,** consistent with the conceptual framework of the study.

Table 7: Rotated component matrix

	1	*2*	*3*	*4*	*5*	*6*	*7*
VF5	*.898*						
VF7	*.896*						
VF6	*.879*						
VF2	*.777*						
VF1	*.758*						
VF4	*.693*						
VF3	*.679*						

VF8	*.505*						
PF8		*.907*					
PF9		*.889*					
PF7		*.807*					
PF1			*.917*				
PF2			*.888*				
PF3			*.800*				
PF4			*.689*				
VF16				*.788*			
VF14				*.737*			
VF13					*.807*		
VF15					*.755*		
VF12						*.772*	
PF6						*.709*	
VF10						*.577*	
VF11							*.870*

The internal consistency of each factor was assessed using **Cronbach's alpha**, which measures the reliability of items within a factor. Reliability analysis ensures that the items grouped under each factor consistently capture the same underlying construct, providing confidence in the factor scores used in subsequent analyses.

The protective factors (Components 2 and 3) and the primary vulnerability factor (Component 1) all demonstrated **high reliability (α > 0.89),** indicating that the items consistently measure the intended constructs. This suggests that students' perceptions regarding AI literacy, ethical awareness, and perceived ease of use/usefulness form coherent and internally consistent dimensions.

Table 8: Summary of factor interpretation

Factor	***Type***	***Items***	***Description***	***Cronbach's Alpha***
Component 1	*Vulnerability*	*VF1–VF8*	*Perceived Ease of Use / Usefulness*	*0.908*
Component 2	*Protective*	*PF7–PF9*	*Ethical Awareness*	*0.891*
Component 3	*Protective*	*PF1–PF4*	*AI Literacy*	*0.890*
Component 4	*Vulnerability*	*VF10, VF12, PF6*	*Institutional Pressure*	*0.460*
Component 5	*Vulnerability*	*VF13, VF15*	*Peer / Social Influence*	*0.664*
Component 6	*Vulnerability*	*VF14, VF16*	*Task / Performance Pressure*	*0.712*
Component 7	*Vulnerability*	*VF11*	*Residual Specific Vulnerability*	-

Component 6 (Task/Performance Pressure) exhibited good reliability (α = 0.712), while Component 5 (Peer/Social Influence) showed acceptable reliability (α = 0.664). Although slightly lower than the ideal threshold of 0.70, these values are considered sufficient for exploratory research, especially given the small number of items in these factors.

Component 4 (Institutional Pressure) had a low reliability (α = 0.460), suggesting that the three items grouped under this factor may not consistently measure the same construct. This could be due to the diversity of institutional contexts or differences in students' perceptions of time pressure, workload, and governance. Researchers are advised to interpret findings related to this factor with caution and consider potential refinement in future studies.

Component 7 consists of a single item (VF11), and therefore, Cronbach's alpha is not applicable. Single-item factors are sometimes retained in exploratory analyses if the item shows a strong loading and conceptual relevance.

Overall, the majority of factors demonstrated sufficient reliability to be used as composite scores in subsequent analyses. The high-reliability factors (Components 1, 2, and 3) provide a robust basis for examining the influence of vulnerability and protective dimensions on students' **behavioral intentions** to use AI tools. Factors with lower reliability (Components 4 and 5) should be interpreted cautiously in regression analyses, and their findings may indicate areas where additional measurement refinement is needed in future research.

5. Conclusion

This study explored students' behavioral intention to use AI tools through a Vulnerability–Protection framework, which considers both factors that increase vulnerability to risky AI usage and factors that mitigate such risks. Using survey data from 522 undergraduate and postgraduate students across public and private universities in Colombo District, the study employed Exploratory Factor Analysis and reliability testing to explain the underlying dimensions of vulnerability and protection.

The analysis revealed a seven-factor structure comprising four vulnerability factors: perceived ease of use/usefulness, institutional pressure, peer/social influence, and task/performance pressure, and two protective factors: AI literacy and ethical awareness, with one residual item representing specific vulnerability. The findings indicate that students are primarily driven to use AI tools by their perceived utility and ease of use, in line with the Technology Acceptance Model, while external pressures and social norms further support this tendency. At the same time, protective factors such as ethical awareness and AI literacy provide a counterbalance, equipping students to use AI responsibly and ethically. The majority of factors demonstrated good to excellent reliability, although institutional pressure exhibited lower internal consistency, suggesting variability in how students perceive academic demands.

Despite these insights, the study has limitations. The sample is geographically limited to the Colombo District, which may affect generalizability. Some factors, particularly institutional pressure and peer influence, showed moderate reliability, indicating the need for further refinement in future research.

The study offers practical implications for higher education. Universities can enhance AI literacy and ethical awareness through targeted curricula, workshops, and guidelines, empowering students to critically evaluate AI outputs and adhere to academic integrity. Addressing workload and deadlines thoughtfully can reduce the external pressures that drive risky AI use, while fostering a positive peer culture can encourage responsible adoption.

In conclusion, students' intentions to use AI tools are shaped by a dynamic interplay of cognitive, social, and ethical factors. Recognizing both vulnerability and protective dimensions provides a holistic perspective, highlighting the importance of equipping students with knowledge, ethical competence, and supportive institutional environments. By adopting this approach, educators and policymakers can foster responsible, informed, and ethical engagement with AI technologies in higher education.

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