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Perceived Impacts of Artificial Intelligence on Academic Integrity in Higher Education in Sri Lanka: Perceptions of Teachers and Learners.

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Abstract

This study investigates perceived impacts of artificial intelligence (AI) on academic integrity in Sri Lankan higher education from the perspectives of both teachers and learners. Employing a mixed-methods explanatory sequential design, quantitative survey data from 350 participants across six universities were complemented by qualitative semi-structured interviews and focus group discussions. The study examined AI awareness, perceived usefulness, perceived risk, and academic integrity attitudes. Findings indicate that AI awareness and perceived risk positively predict academic integrity, while perceived usefulness exerts a negative influence when AI is viewed as a means to shortcut academic effort. Qualitative themes revealed concerns about plagiarism, originality, assessment credibility, and insufficient institutional support, alongside recognition of AI's potential for enhancing learning efficiency and language support. The study calls for explicit institutional policies, ethical AI leadership, AI literacy integration, and assessment redesign in Sri Lankan higher education.

Keywords: Academic integrity, Artificial intelligence, Ethical AI use, Higher education, Mixed methods.

Introduction

Background of the study

Artificial intelligence (AI) has become a revolutionary force in the field of higher education, transforming how students learn, write, conduct research, and are assessed. The rising use of generative AI systems, such as ChatGPT, GPT- 4, Gemini, and automatic paraphrasing and translation software, has offered both unprecedented academic assistance and has also raised intricate ethical dilemmas (Zawacki-Richter et al., 2019; OpenAI, 2023). Scholars around the world have reported that AI tools change the validity of assessments, make it difficult to distinguish between academic support and misconduct, and obscure the authorship (Jamieson & McNeish, 2023; Susnjak, 2022; Tlili et al., 2023).

The credibility of higher education is based on academic integrity, which is founded on the principles of honesty, trust, fairness, respect, and responsibility (UNESCO, 2021). However, the increased use of AI has shaken the established norms and students and educators remain unsure about what work is permissible to be aided by AI (Ayon & Johns, 2023). Students may use AI to manage workload or overcome language barriers without fully comprehending the ethical implications, and teachers cannot distinguish between the original and AI-generated work (Comas-Forgas and Sureda-Negre, 2019; Cotton et al., 2023). Such forces are compelling institutions across the globe to rethink assessment design, student guidance, and academic misconduct policies in an urgent manner.

The recent international literature indicates an increase in academic interest in this challenge. Tlili et al. (2023) conducted a systematic review of the use of AI in education and found that academic integrity was one of the main issues. Cotton et al. (2023) showed that ChatGPT could generate university-level essays that surpass pass criteria, which quickly begs questions of how assessment is designed. Susnjak (2022) emphasized the threat posed by large language models to traditional assessment, whereas Lim et al. (2023) investigated the attitudes of students towards the use of ChatGPT and its ethical aspects. Perkins (2023) suggested a model to identify AI-generated academic text, and Kasneci et al. (2023) provided a detailed discussion of the opportunities and threats of ChatGPT in education. These researchers affirm that AI-related academic integrity issues are not marginal but major concerns in higher education throughout the world.

Although this is a growing international literature, there is scanty empirical research in the context of Sri Lankan higher education. The universities of Sri Lanka are gradually digitalising (De Zoysa and Chandrasekara, 2022), but institutional AI policies remain underdeveloped (UGC, 2023; HEQAC, 2022). Importantly, no research has yet undertaskena systematic investigation of the perceptions of both teachers and learners towards the benefits and the dangers of AI and how these perceptions influence the attitudes towards academic integrity in Sri Lanka.

Problem statement

University students in Sri Lanka are increasingly exposed to the most advanced generative AI tools, such as agentic AI systems with the ability to set goals and plan and execute tasks with little human intervention (Amrish Solan, 2024). Institutional policies, ethical frameworks, and assessment practices have, however, not been able to keep pace with this technological change. Educators complain of increasing challenges with determining the authenticity of student submissions and students are confused by what AI can and cannot help with, especially language support, summarisation, and academic writing. These uncertainties can lead to the normalisation of AI-facilitated misconduct, validity of assessment, and devaluation of academic credentials.

The current literature on the topic of AI and academic integrity in Sri Lanka (Lewis, 2022; Jamieson & McNeish, 2023) lacks sufficient empirical data on the subject, and none of the articles have explored the attitude of both teachers and learners towards AI simultaneously. Institutions are not able to build evidence-based policy responses, ethical guidelines, or pedagogical strategies without learning about these perceptions. Unattended, AI-enabled academic dishonesty threatens to increase educational inequalities, compromise quality, and harm institutional reputations.

Although much of the existing literature on AI and academic integrity covers the world (Tlili et al., 2023; Cotton et al., 2023; Lim et al., 2023; Perkins, 2023; Kasneci et al., 2023; Susnjak, 2022), little has focused on Sri Lanka (De Zoysa & Chandrasekara,2022). Current Sri Lankan research is more likely to address the adoption of e-learning or report of misconduct anecdotally, rather than empirically addressing the attitudes of teachers and learners, and not testing the relationships between perceived AI usefulness, perceived AI risk, and perceived academic integrity attitudes. The current study fills this gap through a systematic, mixed-methods research study that will be an original contribution to the policy, assessment redesign and responsible AI integration to Sri Lankan higher education.

Research objectives

The following objectives guided this study.

i. To assess the level of AI tool awareness and usage among students and teachers in Sri Lankan higher education.

ii. To analyse the relationships between perceived AI usefulness, perceived risk, and academic integrity attitudes.

iii. To identify qualitative perceptions of AI's impact on teaching, learning, and assessment practices.

iv. To recommend actionable, context-specific policy and pedagogical responses to strengthen academic integrity in the AI era.

Research questions

i. What is the level of AI tool awareness and usage among students and teachers in higher education in Sri Lanka?

ii. What are the relationships between perceived AI usefulness, perceived risk, and academic integrity attitudes?

iii. How do teachers and learners perceive AI's impact on teaching, learning, and assessment?

iv. What specific policy and pedagogical responses are needed to strengthen academic integrity in the context of AI use in Sri Lanka?

Literature Review

Theoretical foundations of academic integrity

Academic integrity involves honesty, trust, fairness, respect, and responsibility in any academic endeavour. Conventional types of academic dishonesty such as plagiarism, contract cheating, falsification, and data fabrication have been widely reported (McCabe, Butterfield & Treviño, 2012; Comas-Forgas and Sureda-Negre, 2019). The theoretical framework of this study is that it incorporates the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), and the academic integrity theory. TAM is a theory of technology adoption, which is based on perceived usefulness and ease of use (Davis, 1989), and TPB is a theory of the influence of attitudes, subjective norms, and perceived behavioural control on making moral decisions (Ajzen, 1991). Combined with the above, these frameworks contribute to explaining the influence of student and teacher perceptions of AI tools on ethical academic behaviours. The current literature also highlights the idea that institutional policies, digital literacy, and assessment design are key factors that dictate the integrity norm compliance, not just personal moral reasoning (Foltynek and Glendinning, 2020; Chryssafidou, 2022).

AI applications in higher education

Adaptive learning, automated grading, intelligent tutoring, and automated writing assistance are only some examples of how AI has revolutionized higher education (Chen & Chen, 2023; Zawacki-Richter et al., 2019). Even generative AI systems like ChatGPT and GPT-4 are able to write essays, solve coding challenges, translate text, and generate summaries within minutes, democratising knowledge and posing serious pedagogical and ethical issues (OpenAI, 2023). Kasneci et al. (2023) present an in-depth overview of the opportunities of ChatGPT in personalised learning and formative feedback and its threats to academic integrity and critical thinking. Bawa (2020) and Briggs (2023) emphasize the opportunities of AI to decrease the workload of educators and improve student interaction, whereas Lewis (2022) and Liu (2023) warn of the cognitive offloading and the decline of independent research and writing capabilities.

AI and academic misconduct

Generative AI has brought up new challenges to authorship and originality never before seen. Cotton et al. (2023) were able to empirically show that ChatGPT is capable of producing university-level essays that surpass the pass mark, and that this directly threatens the security of assessments. In Susnjak (2022), large language models were demonstrated to be able to pass subject-specific tests in different fields, which essentially criticizes the traditional forms of examination. Perkins (2023) examined issues related to AI-content detection and suggested a framework of an educator whereas Amigud & Lancaster (2019) and Newton (2018) reported trends of contract cheating that were in place before generative AI. Jamieson and McNeish (2023) and Lee& Kim (2023) observe that AI erodes the definition of plagiarism, making it more challenging to detect it. Dawson (2020) posits that AI puts the security of standardised assessment under a considerable threat.

Teacher perceptions of AI

The key mediators of AI integration and maintenance of academic standards are the faculty attitudes. Faculty bewilderment, lack of preparation, and anxiety are consistently reported with regard to AI-aided student work (Mahboob & Sandanayake, 2022; Kumar & Sharma, 2022). There is also a difference between the group of people who believe AI can be utilized as a pedagogic tool and those who believe that AI poses a serious threat to the integrity of academic activities (Brown, Bull & Pendlebury, 2013; Flint, Conchie & Desroches, 2023). Lim et al. (2023) discovered substantial differences in acceptance of AI among faculty depending on field of study, age, and previous exposure to AI. These perceptions are essential in understanding in order to allow the faculty to redesign assessments, implement policies and offer ethical guidance to students.

Learner perceptions of AI

The academic pressure, technological accessibility, and moral consciousness influence how students perceive AI (Gebre-Mariam, 2021; Van der Linden & McNulty, 2023). Lim et al. (2023) concluded that students tend to have a positive attitude towards ChatGPT in terms of language support and efficiency, although the understanding of ethical aspects is uneven. Bista and Foster (2020) and Briggs (2023) report on students employing AI to cope with overwhelming workloads, frequently without the ethical awareness of what they are doing. As Chryssafidou (2022) and Liu (2023) demonstrate, the perceptions differ depending on the generation, discipline, and cultural norms regarding academic assistance, and AI is perceived differently as a valid help, a shortcut, or a threat to the learning process.

Sri Lankan and South Asian context

The issue of AI and its effect on academic integrity is especially problematic in the sector of higher education in Sri Lanka. The convergence of weak policy environments, the lack of digital infrastructure, and the fast growth of e-learning contribute to the increase in the risks of misconduct (De Silva, 2021; Seneviratne, 2021). There is an uneven progress of digitalisation in Sri Lankan universities (De Zoysa and Chandrasekara, 2022; Government of Sri Lanka, 2023), and AI-specific policies are still in their infancy (UGC, 2023; HEQAC, 2022). Faculty and students note that there were high levels of confusion concerning the appropriate use of AI, thus an empirical study that is specific to the context is necessary to guide policy and pedagogical decisions. The current study has the overall relevance of the results of regional comparative studies (Mahboob and Sandanayake, 2022), which indicate that South Asian institutions of higher education have similar structural weaknesses.

Research gap

There is a growing body of literature on the topic of AI and academic integrity worldwide (Amrish Solan, 2024; Ayon & Johns, 2023;Briggs, 2023;Chen & Chen, 2023; Lee & Kim, 2023; Lewis, 2022) but minimal research has been conducted concerning the situation in Sri Lanka (De Zoysa & Chandrasekara, 2022; Seneviratne, 2021). These studies have not given much attention to perception of teachers and learners, yet most studies focus on digital learning or adoption of e-learning or anecdotal reports on misconduct (Seneviratne, 2021; De Zoysa & Chandrasekara, 2022). Furthermore, to identify a connection between perceived AI usefulness, risk, and attitude of academic integrity in local institutions, few empirical studies are conducted. It is these gaps that justify the present research, and it is possible that it could make a systematic, mixed-method contribution to policy, assessment redesign, and Responsible AI integration in higher education in Sri Lanka.

Methodology

Research design

The mixed-method explanatory sequential design was utilized in this study (Mohommad, 2021), which implies that after the quantitative data collection and analysis is done, the study undertakes a qualitative exploration (QUAL) to expand the information approach is employed. The explanation of this strategy can be determined by the fact that the phenomenon of interest is quite complex meaning that the perception of Artificial Intelligence (AI) and its influence on academic honesty in the framework of higher education. AI uses are complicated phenomena that are both personally, institutionally, and socio-culturally decided.

Data collection

The main measure (quantitative) was the delivery of the structured online surveys to the students and academic staff. The survey was used to acquire relevant information about the knowledge and usage of AI tools, attitude toward academic integrity, perception of usefulness and risk. The second step (qualitative) was justified by the logic of explanation, and semi-structured interviews which were directed to the in-depth discussion of the results of the survey. The purpose of this step was to discover the causes of the existence of some trends, to disclose some secret logic behind the attitude to AI and make students and educators see how they manage an ethical dilemma in practice.

Sample size and sampling procedure

The four state universities: the University of Colombo and University of Peradeniya, University of Ruhuna and the Rajarata University, and two non-state universities: the Sri Lanka Institute of Information Technology (SLIIT) and National School of Business Management (NSBM) were purposely selected. With this selection criterion, it is possible to cover the diverse range of educational institutions, organizational culture, and the degree of technological implementation, which is critical given the nature of the study and the topic of the perceptions of AI use and academic dishonesty. The students were picked in areas such as arts, science, management and information technology amongst the six universities.

The target population therefore consists of students and academic staff of the above six universities. The academics staff included lecturers, senior lecturers, and professors who participate in the process of teaching, assessment, and curriculum design. Staff perspective is significant since it serves as a gatekeeper of academic integrity, as a policy enforcer and a practice evaluator and developer. As regards students, population is undergraduate and postgraduate students of the state and non-state universities. These learners may have varying disciplines in academics, language skills, undergraduate level, which holds so much significance in the understanding of the trend of AI use and ethical decision-making in academics. The presence of both students and teachers on the board will enable the study to compare the perceptions of the technology users (students) and assessor/ policy movers (teachers) and determine the areas of similarities and differences between attitude towards AI and academic integrity.

It was assumed that population size is unknown. Thus, to calculate the optimum sample size (n), Cochran formula shown in equation (1) was used.

$$n = \frac{p*(1-p)*z^2}{d^2} \qquad (1)$$

The d is the margin of error (desired level of precision), p = true proportion and z = critical value from the standard normal distribution at 5% level (z =1.96). As p is not known, p was taken as 0.5 which maximizes p*(1-p). The margin of error was taken as 5%. Using these values, it was found that the optimal sample size is 385. However, due to various constraints, sample size was reduced to 350. Of 350, the number of students and number of lectures were taken as 250 and 100 respectively based on the relative population of students to academic staff in Sri Lankan universities. The sampling procedure adopted was simple random sampling.

Research instruments

There were two instruments used. A structured online questionnaire that was created by the researcher and based on already known scales used in Technology Acceptance Model (TAM; Davis, 1989) and academic integrity literature (McCabe et al., 2012) was the main quantitative measure. The questionnaire included five sections that were used to measure: (1) AI awareness and usage (4 items), (2) perceived usefulness (5 items), (3) perceived risk (3 items), (4) academic integrity attitudes (3 items), and (5) AI adoption behaviours (3 items). Everything was rated with 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

The validation of the instrument was done in two phases. To start with, face and content validity were determined by expert review, and three senior academics with expertise in educational technology and research methods were used; their feedback was included in a revised draft. Second, a pilot study was carried out on 30 participants (not part of the main sample) to determine internal consistency and the results (Cronbach alpha) of all scales are 0.858 to 0.947, which indicates high reliability (Table 1). The secondary qualitative tool was a semi-structured interview guide consisting of open-ended questions based on the quantitative constructs and formulated in an iterative manner in response to pilot interview feedback.

Data collection procedure

The quantitative data were gathered using a structured online questionnaire which was implemented using Google Forms over a period of six weeks. The participants were approached by the institutional gatekeepers (heads of departments and faculty coordinators) and were informed about the study and gave their consent. Non-response bias was minimised through two follow up reminders at two-week intervals, with a response rate of 91.2%. Semi-structured interviews and focus group discussions were the means of collecting qualitative data which were conducted in Phase 2 when quantitative analysis was done. Twelve personal interviews (six students, six academic staff) and two focus group discussions were carried out in English and Sinhala, and the answers in Sinhalese were translated and back-translated to convey the exact information. Interviews took about 45 minutes and were tape-recorded with the consent of the participants. The data was collected until thematic saturation.

Quantitative data analysis

Data was analyzed using SPSS software. Statistical techniques such as correlation analysis and multiple linear regression were used. The correlation analysis is useful to understand the strength of linearity and direction between two variables. In this study, the correlation analysis was carried out to test the hypothesis of the existence of significance correlation between academic integrity with AI awareness, perceived usefulness, and perceived risk. The multiple linear regression model was developed to find the joint impact of AI awareness, perceived usefulness, and perceived risk on academic integrity.

Variance Inflation Factor (VIF) was used to determine multicollinearity among explanatory variables. An independent sample t-test was used to determine the differences in gender in academic integrity, and the test of variance was performed using Levene test to ensure the equality of variance before the pooled comparison.

Qualitative data analysis

Reflexive thematic analysis (Braun and Clarke, 2006) was used in the analysis of qualitative data, both manually and via NVivo 14 software. The six stage process included: (1) introduction to data by reading and making notes on the data; (2) systematic generation of initial codes across the entire data; (3) collation of codes into candidate themes; (4) revision of the themes on the coded extracts and the entire dataset; (5) definition and naming of themes; and (6) generation of final thematic analysis. NVivo helped manage the codes effectively and perform inter-rater reliability checks; a second researcher coded 20% of all data independently, and a Cohen Kappa of 0.81 was obtained, which is a high level of agreement.

Integration of quantitative and qualitative data

In accordance with the explanatory sequential design, qualitative data were combined with quantitative data at the interpretation phase with the help of following a thread method (Bazeley, 2018). Findings of quantitative regression on factors that significantly predicted academic integrity were followed by qualitative themes which described the mechanisms, contextual conditions, and experiences of the participants in relation to the statistical associations. As an illustration, the adverse predictive impact of perceived usefulness on academic integrity (quantitative) was put into perspective with qualitative themes about AI as a shortcut and uncertainty regarding institutional boundaries. The Results and Discussion section explicitly detect areas of convergence and divergence between strands of data, which enhances the depth of the analysis and theoretical input of the study.

Results and Discussion

Reliability analysis

Table 1 presents the reliability analysis results. All scales demonstrated strong internal consistency, with Cronbach's alpha values exceeding the recommended threshold of 0.80 (Nunnally, 1978), confirming that the instruments produced reliable measurements suitable for inferential analysis.

Table 1.

Reliability analysis: Cronbach's Alpha coefficients for each scale.

Variable / Scale	Definition	Cronbach's Alpha	Number of Items
AI Awareness	Extent to which students and staff are familiar with various AI tools and their functional capabilities.	0.858	4
Perceived Usefulness	Degree to which users believe AI enhances their academic performance or teaching efficiency.	0.893	5
Perceived Risk	Level of concern regarding potential negative consequences of AI (e.g., loss of critical thinking, data privacy).	0.947	3
Academic Integrity	Individual's moral stance and belief system regarding honesty and ethics in academic work.	0.922	3
AI Adoption	Actual frequency and consistency of integrating AI tools into learning, teaching, or assessment.	0.864	3

Normality assessment

The hypothesis of normality using the Shapiro Wilk test statistic confirmed that all variables in three factors: AI awareness, perceived usefulness, and perceived risk did not significantly deviate from the normal distribution as the corresponding test statistics were significant ($p < 0.05$).

Correlation analysis

The correlation analysis conducted by Pearson considered the bivariate correlation between academic integrity and the three predictors. Findings showed that there is a statistically significant positive relationship between AI awareness and academic integrity ($r = 0.675$, $p < 0.01$), showing that the higher the familiarity with AI tools, the more academic integrity orientations. The given finding can be reconciled with that of Flint et al. (2023), who discovered that AI literacy lowers ethical ambiguity and leads to more responsible AI use, and Cotton et al. (2023), who indicate that the awareness of the AI capabilities is a precondition to navigate its use more ethically.

Academic integrity also showed a positive relationship of moderate significance with perceived risk ($r = 0.469$, $p < 0.01$), implying that the increased perception of the risks posed by AI, such as the threats to critical thinking, authenticity and assessment validity, lead to more ethical academic behaviour. This aligns with the TPB that proposes perceived behavioural consequences influence intentions and behaviour (Ajzen, 1991), and with the result of Ayon and Johns (2023), users of AI tools moderately willing to misuse it are risk-perceiving.

However, despite the initial hypotheses, there was no statistically significant bivariate correlation observed between perceived usefulness and academic integrity ($r = -0.251$, $p = 0.078$), but the negative directionality is theoretically informative and in agreement with Liu (2023), who reported that students who predominantly believe that AI can enhance their efficiency are more prone to ethical boundary violations. This relationship can further be explained in the multivariate regression analysis presented below.

Comparison of academic integrity among genders

To compare the academic integrity of male and female t-test was performed along with 95% confidence intervals. The results are shown in Table 2.

Table 2.
Basic statistics of academic integrity among gender.

Gender	Mean	SE of the mean	95% CI of the mean
Male	3.50	0.112	[3.28 3.72]
Female	3.78	0.153	[3.47 4.09]

Levene's Test of Equality of Variances was carried out to determine whether the variances of two groups are significantly different. As the corresponding test statistic was not significant ($p = 0.346$), it was confirmed that there is no significance difference between variances of males and females. Therefore, under the assumption of equal variance two mean were compared using pooled variance and it was found that the test statistic is not significant (t value = -1.51, $p = 0.137$). Thus, it can be concluded the two means are not significantly different.

Non significance between gender means that gender may not be the strongest predictor of academic integrity in comparison with other factors, e.g., awareness of AI technologies, perceived usefulness, or perceived risk. These outcomes suggest that it is crucial to pay attention to the contextual and psychological aspects instead of demographic ones when elaborating interventions to promote ethical academic behavior.

Impact on explanatory variables on academic integrity

To find the significantly influential factor on academic integrity multiple linear regression analysis was carried out, taking academic integrity as the dependent variable and awareness of AI, Perceived Usefulness and Perceived risk as explanatory variables. The results are shown in Table 3 and Table 4.

Table 3.

ANOVA results for the regression model.

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	15.740	3	5.247	43.796	.000[b]
Residual	5.511	46	.120		
Total	21.251	49			

(R^2 =74.1% and AdjR^2 =72.4%)

Table 4.

Properties of the estimators of the fitted multiple linear regression model.

Estimators	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	SE	B		
Constant	1.996	0.298		6.705	.000
Awareness_AI_Score	0.376	0.049	0.588	7.720	.000
Perceived_Usefulness_Score	-0.312	0.062	-0.400	-5.004	.000
Perceived_Risk_Score	0.421	0.065	0.520	6.457	.000

The results in Table 3 indicate that the F statistic is significant (F value = 43.796, p = 0.00) confirming that the fitted model is significant. It should be noted that all three explanatory variables are significant. In fact, it was found that there is no significance multicollinearity among three variables as the variance inflation factor of all three variables are much less than the critical value of 10. As R^2 is 74.1% it can be concluded that the fitted model is able to explain 74% of the variability of Academic Integrity Scores. All three parameters and the constant term of the fitted model are significantly different from zero (Table 4). Furthermore, the Adjusted R^2 is almost close to R^2. The residual of the models was found to meet the requirement of white noise process It can be concluded with 95% confidence that scores of awareness of AI, perceived usefulness, and perceived risk as a combination generates a meaningful predictor of academic integrity. The fitted model can be written as:

Academic integrity was impacted by the awareness of AI in a positive and significant way ($b = 0.376$, $p < 0.05$). It indicates that one unit increase of awareness AI score would increase academic integrity by 0.376 when other two factors remain the same. The perceived risk was also positively and significantly contributing ($b = 0.421$, $p < 0.05$) to academic integrity which indicates that one unit increase of perceived risk score would increase academic integrity by 0.421 when other two factors remain the same. The coefficient for perceived usefulness was however found to have a significant negative impact ($b = -0.312$, $p < 0.05$). These results indicate that the perception of risk and awareness is likely to enhance ethical behavior, whereas robust perceptions of usefulness can lead to the temptation to utilize AI in a manner that obscures academic integrity. Based on the standardized coefficients it can be concluded that the most influential significant factor to improve academic integrity is awareness of AI when all three factors are considered

$$\text{Academic integrity} = 1.996 + 0421 * \text{Perceived\_risk\_score} + 0.376 * \text{Awareness\_AI\_score} - 0.312 * \text{Perceived\_usefulness\_score} \quad (2)$$

simultaneously. The impact of awareness of AI is 1.13 times higher than the impact of perceived risk. The above result demonstrates that the awareness of AI devices may lead to better ethical decision-making, which is likely because well-informed students and teachers can be aware of the boundaries of AI acceptable use. This proves that AI may be considered of high utility that may lead to the temptation of using AI products in a corrupt way that may pose a threat to ethics. In cases where the students and teachers who know of the resultant ethical issues or chances of detection have greater adherence to academic honesty.

Qualitative Thematic Analysis

Thematic analysis of data through interviews and focus groups revealed five major themes, and the quantitative patterns named above were incorporated and justified.

Theme 1: Academic integrity as a contested value in the AI era

Academic integrity, which is defined as honesty, fairness, originality, and responsibility, was identified by all the participants as a key element of higher education. But overall, there was a lot of disagreement as to whether the use of AI in itself is a violation of integrity. Such findings are consistent with Jamieson and McNeish (2023) who postulate that institutional failure on definitional ambiguity of AI assistance is a systemic issue. Lack of institutional specifications at the Sri Lankan university was also a stable source of ethical confusion, which meets the quantitative evidence that the perceived risk (when operationalised as ethical concern) enhances stronger integrity orientations.

Theme 2: AI as a dual-purpose tool

All participants reported the two-sided character of AI: the facilitator of education (language assistance, feedback, access to literature), and the threat to academic standards (plagiarism, addiction, loss of skills). This is in line with Kasneci et al. (2023) and Bawa (2020) who observe that the educational use of AI depends on institutional direction. The negative regression coefficient of perceived usefulness is motivated by the qualitative ambivalence concerning the usefulness of AI: in the case when AI is promoted as efficiency-enhancing without moral support, the utility of AI becomes a tool to promote misconduct.

Theme 3: Institutional absence and policy gaps

The participants all mentioned lack of proper institutional policies on the use of AI. Employees complained of confusion over incoherent departmental-wide rules; students cited confusion over what AI assistance is allowed. This is in line with UGC (2023) and HEQAC (2022) reports that AI policy in Sri Lankan universities is nascent, and the European Commission (2023) and UNESCO (2021) recommendations regarding institutional AI governance strategies. The policy vacuum was found to be the most critical facilitating factor to AI-assisted misconduct.

Theme 4: Individual, contextual, and cultural factors

Eighty per cent of respondents cited individual factors (workload, language barriers, fear of failure), peer influence, and cultural standards that surround academic assistance as motivators of AI adoption. Language-minority students indicated a specific dependency on AI to assist in writing, which brings up equity issues. The results expand on the works of Chryssafidou (2022) and Gebre-Mariam (2021) by showing that AI use patterns are linguistically and culturally determined by the context of Sri Lanka in a way that is not reflected in the Western literature.

Theme 5: Recommendations for responsible ai integration

The participants suggested some viable interventions such as AI literacy lessons, curriculum-based ethical education, explicit acceptable-use policies, and reformed assessment, with a focus on reflection, oral, and in-class tasks. These recommendations overlap with the quantitative evidence that AI awareness is the most significant predictor of academic integrity, which implies that specific educational activities may be used to directly enhance ethical behaviour.

Conclusions, Recommendations and Suggestions

Conclusions

The paper has demonstrated that the implementation of AI in higher education in Sri Lanka has both positive and negative effects on academic integrity. The TAM-TPB-Academic Integrity conceptual model was a strong explanatory model: AI awareness and perceived risk have a positive influence on ethical academic behaviour, and perceived usefulness (not in combination with ethical guidance) has a negative influence. These findings contribute to the current literature, since they are the first empirical, mixed-method validation of these dynamics in a non-Western, South Asian context, to supplement the extensive Western AI-integrity literature base (Tlili et al., 2023; Cotton et al., 2023).

The theoretical implications of the study are that it demonstrates that academic integrity in AI-intensive environments is not primarily a matter of individual moral character, but rather a determinant of AI literacy, risk awareness, institutional cultures, and policy frameworks. This is beyond descriptive narrations to give theoretical sound explanations which can be applied to other developing-country higher education contexts which grapple with the same predicaments.

Online academic dishonesty is a dynamic and evolving issue. Academic institutions must take charge to balance innovation and ethical responsibility, where AI devices contribute to the learning process rather than eliminate it, and where integrity, creativity, and equity are the key elements of the educational ethos.

Recommendations

In accordance with the findings of the study, the following actionable recommendations can be given to policy makers and institutions. The University Grants Commission (UGC) of Sri Lanka can create and enforce a national AI Acceptable Use Policy framework that applies to all higher education institutions and defines what AI may and may not do, by the nature of the assessment and discipline, with penalties made clear and request to implement such a system by each university. AI literacy modules, including the functioning of AI, its strengths and weaknesses, ethical applications and implications on academic integrity, should become mandatory elements of the university induction programme to all new students, as well as a continuing professional development element of all academic staff. The redesign of assessment should be a priority that cuts across disciplines, promoting the movement to reflective writing, oral assessment, in-class tasks, portfolios, and project-based learning that represents student learning in authentic ways and that cannot be easily replaced by AI.

Suggestions

Long-term longitudinal studies of the effects of AI on academic integrity should be carried out in the future as AI tools develop. The comparative research on disciplines, institutions and countries of South Asia would help in shedding light on the contextual differences. Evidence of scaling successful interventions would be research on the effectiveness of particular policy interventions, including AI literacy programmes and redesigned assessment formats. Research should follow the further challenge of current integrity frameworks by agentic AI systems as they increasingly become widespread (Amrish Solan, 2024).

HEQAC must include AI integrity rule as a formal requirement in its university quality assurance audit, which means that institutions need to show that they are implementing the policies actively, training their staff, and guiding their students as the criteria to qualify as an accredited university.

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