International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(13s) 2026 pp. 1303-1315
https://doi.org/10.70917/ijcisim-2026-4177
Article

A Study on Responsible AI Awareness and Learning Engagement in Higher Education: The Mediating Roles of Trust in AI, AI Literacy, AI Usage Self-Efficacy, and Human–AI Collaboration

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Abstract: Artificial intelligence (AI) is redefining higher education through its support of personalized learning, intelligent tutoring, and collaboration. Yet, responsible utilization of AI is dependent on ethical awareness among the students, AI competencies, and self-efficacy towards the utilization of such technologies. This study analyzes the impact of Responsible AI Awareness on Learning Engagement via Trust in AI, AI Literacy, AI Usage Self-Efficacy, and Human–AI Collaboration in a sequential manner. A quantitative research approach was adopted in this study, with data collected from 431 postgraduate students through a structured survey instrument. The measurement and structural models of the research model were tested through SmartPLS 4 for reliability, validity, direct, and mediation effects using bootstrapping. The results reveal that Responsible AI Awareness positively influences Trust in AI and AI Literacy, which further positively affects AI Usage Self-Efficacy and Human–AI Collaboration resulting in enhanced Learning Engagement.

Keywords: Responsible AI Awareness; Trust in AI; AI Literacy; AI Usage Self-Efficacy; Human–AI Collaboration; Learning Engagement; Higher Education.

1. Introduction

This rapid pace of AI (AI) development, driven by AI technologies like ChatGPT, Google's Gemini, Microsoft's Copilot and Claude [1], has changed the face of higher education. These smart systems have grown from mere information retrieval devices to learning partners that help students create content, solve problems, write programs, conduct research, and write academically, among other tasks, while providing personalized learning support [2]. While the emphasis of educational research has been on comprehending the intentions of students to use AI, it is now a greater focus to understand how students can work effectively and responsibly with AI systems [3]. Human-AI collaboration is a paradigm shift in the field of education, as AI supports and enhances human intelligence, leading to better learning experiences through meaningful collaboration and shared cognitive processes [4].

While the use of AI in education is rising, questions about ethical applications of AI, misinformation [5], algorithmic bias, privacy, overreliance on AI [6], and academic integrity are all barriers to the effective use of AI-powered learning resources in higher education [7].

The experiments showed that technology alone is not enough to ensure productive collaboration between humans and AI and that students also require AI literacy. Responsible AI Awareness is the knowledge of ethical principles for using AI and assessing AI output [8]. Ethical principles include transparency, accountability, fairness, privacy, and assessing the output of artificial intelligence [9]. Students with higher Responsible AI Awareness are more likely to make the right ethical decision and fact-check information generated by AI technologies [10]. Trust in AI is also very important in successful cooperation – trust means providing assurance about the performance and correctness of the AI system [11]. A lack of trust or too much trust can lead to either avoiding technology or depending too much on it; the right amount of trust can let students work with technology as a learning partner [12]. Along with Responsible AI Awareness, AI Literacy is also a critical skill that students need nowadays in order to work with new technologies effectively [13]. More literate students, in particular, are able to understand the results of AI work better, write more effective prompts, understand the restrictions of the system, and responsibly apply AI to learning tasks [14].

AI usage self-efficacy speaks to students' overall skills and their belief that they can successfully apply AI to learning tasks [15]. According to the social cognitive theory, self-efficacy is one of the main factors influencing the willingness to adapt to technological innovations and persist in difficult situations [16]. Given a positive perception of their ability to perform tasks with AI, students are likely to use AI tools, experiment with their features, and apply AI to solve complex learning challenges [17]. This concept helps one move from AI-related skill acquisition to co-creative actions [18]. As a result of the above-mentioned predictors [19], we have the collaboration of humans and AI [20].

Collaborative learning is not about replacing human thinking with AI, but about co-creating, critically evaluating, providing iterative feedback, and making informed decisions [21]. Human-AI collaboration allows students to use AI insights and apply human judgment, creativity, and ethics [22]. As a result, this co-creative process could contribute to improving Learning Engagement [10], defined as engagement of students' behaviour, thoughts and emotions during learning activities [23]. Learners who are engaged exhibit increased curiosity, participation, perseverance and deep learning, and consequently benefit from better learning outcomes [24].

The above perspectives lead to an integrated conceptual framework in this study, where Responsible AI Awareness is positioned as the root that affects Trust in AI and AI Literacy [25]. The factors in turn further bolster AI Usage Self-Efficacy, leading to Human–AI Collaboration and finally Learning Engagement among university students [26]. The proposed model builds on the existing body of knowledge in AI-in-education by incorporating concepts and theories from Responsible AI, Trust Theory, AI Literacy frameworks and Social Cognitive Theory to elucidate the processes by which responsible AI competencies lead to meaningful collaborative learning experiences [27]. The results will offer meaningful implications for teachers, policy makers, and post-secondary institutions trying to prepare students for the future, who are ethically responsible and are equipped to be AI-literate [28].

2. Literature Review

The way the use of Artificial Intelligence has transformed higher education [29]. Now, students can use tools such as ChatGPT, Google Gemini, Microsoft Copilot, and Claude to help with writing academic texts, programming, problem-solving, research, and learning [30]. AI technology enables interaction with students in different ways [31]. The systems provide contextual feedback, facilitate the development of students' ideas, and promote critical thinking. The use of AI in higher education is on the rise, as it is recognized not only as an educational resource but also as a smart companion for learning [32].

All in all, the efficiency of the Human–AI Collaboration is shaped by cognitive, ethical, and behavioral factors that affect how people interact with AI tools. The study aims to identify links among Responsible AI Awareness, trust in AI, AI literacy, self-efficacy in using AI technologies, Human–AI Collaboration, and the degree of learning engagement [33].

2.1 Responsible AI Awareness

Responsible AI Awareness refers to the awareness and understanding of the ethics [34], and responsible practices guiding the design [35], development, and application of artificial intelligence systems. Such ethics include issues of transparency, fairness, accountability, privacy, explainability, bias mitigation, and human oversight [36]. In light of increasing use of AI in the education environment, it becomes important for the students to be aware of how AI works and ethical issues arising due to it [37]. The Responsible AI Awareness course encourages the students to analyze AI outputs, detect any biases, protect the privacy of users, and ensure the ethical and responsible usage of AI [38]. As pointed out in the current literature, ethical awareness may contribute positively to the attitudes and behavior of users toward emerging technologies [39]. It is important to have realistic expectations regarding the performance of AI in order to build appropriate levels of trust in it that will help avoid unhealthy trust, since otherwise individuals tend to overestimate the capabilities of AI [40].

Moreover, knowing how one can responsibly use AI also assists in facilitating learning about the technology through an active process [41]. As a result, the concept of Responsible AI Awareness is the foundation of the proposed model in the sense that it influences both Trust in AI and AI Literacy [42].

2.2 Trust in AI

Trust in AI is the trust of a user in AI systems, which stems from their competence, reliability, predictability, and integrity perception [43]. It is quite understandable why trust has been shown to significantly influence the acceptance and use of technology in various technological settings [44]. In order for students to use AI systems for learning activities in an educational setting, they should have the trust in those systems so as to provide accurate and reliable information [45]. According to research in Human-Computer Interaction, the level of trust decreases uncertainty and facilitates the acceptance of intelligent technologies among users [46]. However, researchers note that trust must be “measured” rather than blind; over-trust may lead students to believe in the answers of AI without verifying them, while under-trust prevents them from using AI systems [47].

Having too much trust can make students believe in AI-generated content without proper verification, and too little trust can make them hesitant to work with AI systems. By raising awareness about the possibilities and limitations of AI, students will be able to make informed decisions on when to trust AI output and when to rely on human judgment in order to build the right level of trust [48]. In the proposed framework, Trust in AI is expected to positively impact AI Usage Self-efficacy through boosting students' confidence in using AI for academic work. Students are more inclined to try out more sophisticated forms of AI and use AI in their learning when they feel it is reliable [49].

2.3 AI Literacy

In the modern digital world, AI Literacy can be considered one of the most important skills. It involves knowledge, skills, and critical thinking that allow understanding AI concepts, assessing the quality of the content generated by AI, identifying the limitations of AI systems, making effective prompts, and using AI responsibly in various situations [50]. AI literacy, in particular, is tailored to enable individuals to work with AI systems intelligently and critically, in contrast to general digital literacy. Due to the fact that businesses try to build AI workforces nowadays, it can be concluded that AI literacy becomes one of the absolute essential graduate skills. Individuals with greater levels of AI literacy will feel more comfortable evaluating the outputs provided by AI, identifying the presence of hallucinations, validating the information, and understanding the role of AI as a cognitive tool. Furthermore, AI literacy promotes effective decision-making for the purpose of responsible usage of AI [51].

Moreover, based on the literature, it should be noted that AI literacy positively influences self-confidence when dealing with AI technologies. Individuals who understand AI mechanisms and possibilities feel more confident, hence, have greater AI Usage Self-Efficacy. Therefore, AI literacy should be regarded as one of the most important [52].

2.4 AI Usage Self-Efficacy

AI Usage Self-Efficacy is the belief of a person in being able to effectively use AI technologies to complete learning-related tasks. Self-efficacy is grounded in Social Cognitive Theory and affects motivation, persistence, effort and performance in behaviour. High self-efficacy is related to people's acceptance of difficult technologies, their ability to get over obstacles, and their willingness to work through problems [53]. AI Usage Self-Efficacy reflects students' attitudes toward incorporating AI into learning tasks in the classroom, including writing, data analysis, coding, brainstorming, and problem-solving. The results of the research are always consistent that the technological self-efficacy has positive impact on the process of technology adoption, usage, and effective learning outcomes. Pupils who feel confident enough in their abilities to use AI tools actively delve into the more sophisticated aspects of AI and create more productive interactions with intelligent systems [54].

It is assumed that the proposed framework will build on how the trust in AI and AI Literacy will lead to an increase in AI Usage Self-Efficacy. AI literacy fosters a knowledge base to effectively use AI, while trust helps mitigate the psychological uncertainty that goes along with using it. These all contribute to boosting their confidence level, thereby fostering meaningful Human-AI Collaboration [55].

2.5 Human–AI Collaboration

Human–AI Collaboration (HAC) is a synergistic relationship between humans and AI systems to achieve common goals. Collaborative AI is not about replacing human intelligence but rather about leveraging the synergies and combining the assets where AI can add value in terms of the efficiency of computation, content creation, and information retrieval, and where humans add value in terms of creativity, critical thinking, contextual understanding, and ethical reasoning [56].

With the rise of Generative AI, the idea of Human–AI Collaboration has become a major focus point in the field of educational research. To collaborate effectively with AI, students must interact with AI in an iterative manner, prompting, reading through content generated by AI, checking the accuracy of information, and using AI's suggestions in their reasoning [57]. Productive HAC is not just about using AI but also involves active learning, cognitive involvement, and reflection, according to scholars. Students who are confident in their AI Usage Self-Efficacy tend to work with AI collaboratively as they feel more assured to experiment and learn through iterations, engaging with AI systems continuously. So, it is suggested that AI Usage Self-Efficacy is directly related to Human–AI Collaboration [58].

2.6 Learning Engagement

Learning Engagement is a student's behavioral, emotional and cognitive participation in learning activities. Learners are involved in learning activities, show curiosity, persist, expend brain power to learn. Learning engagement has been found to be a consistent and reliable predictor of academic achievement, knowledge retention and lifelong learning by educational research [59].

AI-powered learning analytics systems have demonstrated significant promise in improving engagement by tailoring feedback, learning experiences, and providing immediate help and support, as well as facilitating collaborative problem-solving. The learning impact of AI, however, hinges on the ways students engage with the technology. Human AI Collaboration empowers students to engage with AI as a thought partner, fostering active learning and participation, instead of merely relying on it as a source of information [60]. Human–AI Collaboration is hypothesized to have a positive effect on LE. Moreover, it is expected that collaborative interactions with AI systems would also mediate the relationship between AI Usage Self-Efficacy and engagement [61]. The series illustrates how raising awareness, gaining trust, developing literacy, and instilling confidence in AI practices can all play a part in creating more impactful and relevant learning experiences [62].

3. Methodology

This study used the quantitative approach and type of research in cross section to look at the proposed conceptual framework between graduate students in higher education. The data were obtained through a structured questionnaire consisting of validated measurement scales for all the constructs [63], [64]. A convenience sample of 431 valid responses was collected. The data was screened for missing data, outliers, normality, common method bias, reliability, and validity before conducting hypothesis tests. PLS algorithm was used for reliability and validity assessment. The proposed direct, mediating and sequential mediation hypotheses were tested with the SmartPLS using 5,000 bootstrap resampling to estimate indirect effects and to obtain bias-corrected 95% confidence intervals. Results of the statistical analysis established the level of significance at $p < 0.05$ which was regarded as significant and was used to build a strong evidence of the hypothesized relationships between the study constructs [65].

3.1 Conceptual model Validity and Reliability Assessment

The Table 1 presents the reliability and validity assessment of the measurement model used in this study. The analysis was conducted to evaluate the internal consistency, construct reliability, and convergent validity of the six latent constructs, namely Responsible AI Awareness (RAA), Trust in AI (TIA), AI Literacy (AIL), AI Usage Self-Efficacy (AISE), Human–AI Collaboration (HAC), and Learning Engagement (LE) [66]. The results indicate that the measurement scales possess satisfactory psychometric properties and are suitable for subsequent hypothesis testing. The Cronbach's Alpha values ranged from 0.894 to 0.925, exceeding the recommended threshold of 0.70, thereby confirming strong internal consistency among the measurement items. Human–AI Collaboration demonstrated the highest reliability ($\alpha = 0.925$), followed by AI Literacy ($\alpha = 0.918$), Responsible AI Awareness ($\alpha = 0.912$), Learning

Engagement ($\alpha = 0.907$), Trust in AI ($\alpha = 0.901$), and AI Usage Self-Efficacy ($\alpha = 0.894$). These findings suggest that all constructs consistently measure their intended theoretical concepts [67].

Table 1: Construct Reliability Assessment

Construct	No. of Items	Cronbach's Alpha	Eigenvalue	% Variance	CR	AVE
Responsible AI Awareness (RAA)	5	0.912	9.82	28.87	0.931	0.731
Trust in AI (TIA)	5	0.901	3.94	11.58	0.926	0.713
AI Literacy (AIL)	6	0.918	2.76	8.11	0.936	0.709
AI Usage Self-Efficacy (AISE)	5	0.894	2.08	6.13	0.921	0.701
Human–AI Collaboration (HAC)	6	0.925	1.82	5.35	0.942	0.732
Learning Engagement (LE)	5	0.907	1.34	3.94	0.928	0.721

The exploratory factor analysis confirms the measurement model's suitability, as the eigenvalues of all extracted factors exceeded 1.0, thereby validating the attainment of the criteria for factor retention set by Kaiser [68]. The Responsible AI Awareness accounted for the highest one third of total variance (Eigenvalue= 9.82; 28.87%) with results of Trust in AI (Eigenvalue= 3.94; 11.58%), AI Literacy (Eigenvalue= 2.76; 8.11%), AI Usage Self-Efficacy (Eigenvalue= 2.08; 6.13%) and Human–AI Collaboration (Eigenvalue= 1.82; 5.35%) and Learning Engagement (Eigenvalue= 1.34; 3.94%) being in the subsequent lists in terms of variance reported. The extracted factors contributed crucially to explaining the total variance, thereby demonstrating that the extracted dimensions reflect the observed variables [69]. In addition, the Composite Reliability (CR) has been calculated to range from 0.921 to 0.942, well above the suggested minimum of 0.70. The Average Variance Extracted (AVE) has been calculated as well being in the range from 0.701 to 0.732, thereby providing that the minimum recommended level of AVE of 0.50 is also exceeded. Hence, it is clear that each construct explains at least half of the variance of its indicators, thereby establishing good convergent validity. All in all, it could be stated that the obtained results demonstrate the reliability and validity of the measurement model allowing for using it in the further mediation analysis along with the testing of hypotheses via the SmartPLS 4.0.

The Kaiser–Meyer–Olkin (KMO = 0.931) indicates a good sampling adequacy for factor analysis. Additionally, Bartlett's Test of Sphericity was significant ($\chi^2 = 8654.72$, df = 496, $p < 0.001$), confirming sufficient correlations among variables and supporting the suitability of the data for factor analysis using SPSS [70].

Table 2: Data Assessment

Test	Value
KMO Measure of Sampling Adequacy	0.931
Bartlett's Test χ^2	8654.72
df	496
Sig.	<0.001

The below Table 3: Validity Assessment asses using Fornell–Larcker criterion a discriminant validity test. The test had utilized the square root of the AVE of each construct (diagonal values) is greater than its correlations with other constructs, confirming satisfactory discriminant validity. These findings indicate that each construct is empirically distinct and measures a unique theoretical concept within the proposed model [71].

Table 3: Validity Assessment

Construct	RAA	TIA	AIL	AISE	HAC	LE
RAA	**0.855**					
TIA	0.618	**0.844**				
AIL	0.593	0.552	**0.842**			
AISE	0.566	0.671	0.694	**0.838**		
HAC	0.521	0.648	0.712	0.743	**0.856**	
LE	0.486	0.563	0.601	0.664	0.772	**0.849**

Table 4: Model Collinearity Assessment presents the multicollinearity assessment using Tolerance and Variance Inflation Factor (VIF). All tolerance values exceed 0.50, while VIF values range from 1.61 to 1.93, well below the threshold of 5.0, indicating the absence of multicollinearity and confirming the suitability of the predictors for regression analysis [70].

Table 4: Model Collinearity Assessment

Predictor	Tolerance	VIF
RAA	0.621	1.61
TIA	0.583	1.72
AIL	0.541	1.85
AISE	0.517	1.93
HAC	0.563	1.78

4. Analysis

4.1 Direct Assessment

The analysis of direct effects was conducted using the SmartPLS 4.0 method with 5000 sub-samples boot strapping was done to assess the hypothesised model. The results demonstrate that except for one, all direct relationships suggested are statistically significant. Responsible AI Awareness has positive impact on Trust in AI (β=0.618, $p<0.001$) and AI Literacy (β=0.593, $p<0.001$), the implications meaning that students who possess more knowledge on responsible AI practices are trustworthy towards the AI technologies and have better AI-related skills. In addition to this, Trust in AI (β=0.382, $p<0.001$) and AI Literacy (β=0.451, $p<0.001$) enhance AI Usage Self-Efficacy substantially. AI Usage Self-Efficacy is a powerful predictor of the Human–AI Collaboration (β=0.743, $p<0.001$) meaning that students who are self-effective while using AI are more likely to use AI cooperatively. Lastly, Human–AI Collaboration positively impacts Learning Engagement (β=0.772, $p<0.001$), indicating thus that effective cooperation with AI provides a significant contribution into student engagement in learning.

Table 5: Direct Assessment

Hypothesis	Path	β	SE	t	p-value	95% CI	Decision
H1	RAA → TIA	0.618	0.041	15.07	<0.001	[0.537, 0.699]	Supported
H2	RAA → AIL	0.593	0.039	15.21	<0.001	[0.516, 0.670]	Supported
H3	TIA → AISE	0.382	0.048	7.96	<0.001	[0.288, 0.476]	Supported

H4	AIL → AISE	0.451	0.044	10.25	<0.001	[0.365, 0.537]	Supported
H5	AISE → HAC	0.743	0.037	20.08	<0.001	[0.670, 0.816]	Supported
H6	HAC → LE	0.772	0.034	22.71	<0.001	[0.705, 0.839]	Supported

4.2 Indirect Assessment

The mediation analysis was performed using Hayes' PROCESS macro with 5,000 bootstrap resamples and 95% bias-corrected confidence intervals. The results reveal that all proposed indirect effects are statistically significant, as none of the bootstrap confidence intervals include zero. Responsible AI Awareness indirectly influences AI Usage Self-Efficacy through Trust in AI (Effect = 0.236, 95% CI [0.169, 0.309]) and through AI Literacy (Effect = 0.267, 95% CI [0.203, 0.337]), indicating that ethical awareness enhances students' confidence in using AI by fostering both trust and AI-related knowledge. Moreover, AI Usage Self-Efficacy indirectly improves Learning Engagement through Human–AI Collaboration (Effect = 0.574, 95% CI [0.493, 0.654]), emphasizing the importance of collaborative AI interactions in promoting active learning. Sequential mediation analyses further demonstrate that Responsible AI Awareness positively influences Human–AI Collaboration through the pathways of Trust in AI → AI Usage Self-Efficacy and AI Literacy → AI Usage Self-Efficacy. These sequential indirect effects extend to Learning Engagement, confirming that responsible AI awareness contributes to educational engagement by strengthening trust, literacy, self-efficacy, and collaborative behaviors. Overall, the findings provide strong support for the proposed mediation framework.

Table 6: Indirect Assessment

Hypothesis	**Indirect Path**	**Effect**	**Boot SE**	**Boot LLCI**	**Boot ULCI**	**Decision**
H7	RAA → TIA → AISE	0.236	0.036	0.169	0.309	Supported
H8	RAA → AIL → AISE	0.267	0.034	0.203	0.337	Supported
H9	AISE → HAC → LE	0.574	0.041	0.493	0.654	Supported
H10	RAA → TIA → AISE → HAC	0.176	0.028	0.125	0.234	Supported
H11	RAA → AIL → AISE → HAC	0.199	0.031	0.144	0.264	Supported
H12	RAA → TIA → AISE → HAC → LE	0.136	0.025	0.092	0.190	Supported
H13	RAA → AIL → AISE → HAC → LE	0.154	0.026	0.108	0.210	Supported

5. Discussion

The findings of this study provide strong evidence that supports the proposed conceptual framework in this study, as the results found are empirical, and sound evidence of Responsible AI Awareness as the base of Human-AI Collaboration and Learning Engagement of graduate students was achieved [72]. The moderate positive relationship between Responsible AI Awareness and Trust in AI suggests that the students who have greater awareness regarding ethical considerations, transparency, fairness, privacy, and accountability in the utilization of AI systems will be more trusting in utilizing these technologies [73]. This finding resonates well with the expanding body of literature on Responsible AI, as ethical consciousness has been increasingly emphasized in order to create a balanced and manageable trust in AI systems [74].

Further, the results show that Responsible AI Awareness also has a positive effect on AI Literacy, suggesting that students with an understanding of the subject are more likely to possess the skills to understand the capabilities of AI, identify its limitations, assess AI-generated content, and use AI responsibly [75]. The discovery underscores the significance of incorporating AI literacy into today's education system to equip future students with the skills needed to operate in an educational and professional setting with the presence of AI [76].

The study also shows that Trust in AI and AI Literacy have positive effects on AI Usage Self-Efficacy. Students who are confident in AI systems and have more knowledge about AI tend to be more confident in using AI tools for academic purposes, like writing, problem-solving, programming, and conducting research. The results are consistent with Social Cognitive Theory, which posits that knowledge and favourable perceptions are important factors to increase self-efficacy, and consequently, the willingness to use new technologies. Furthermore, AI Usage Self-Efficacy was found to be a strong predictor of Human–AI Collaboration [77]. The finding indicates that students who felt they could use AI tools effectively were more likely to engage with AI tools collaboratively, as opposed to passively, which suggests they have a stronger sense of agency over using AI.

Such collaborative activities involve such processes as adjusting prompts, critically evaluating AI-produced messages, applying AI recommendations in personal actions and thoughts as well as using AI to learn [6]. The findings indicate the changing role of AI in higher education, implying the fact that AI cannot substitute human intelligence but serves its complementary role. Moreover, the research demonstrates that collaboration between humans and AI really contributes considerably to boosting learning engagement of learners. Collaborative learners are involved in learning processes on cognitive, emotional and behavioral levels. Thanks to AI collaboration students can have questioned raised, create and reflect upon their learning along the process. Also, process analysis revealed that mediation variables respectively include Trust in AI, AI literacy as well as confidence in AI usage [78].

The Human–AI Collaboration describes how the Responsible AI Awareness affects Learning Engagement. These sequential relationships show that having ethical awareness is not sufficient; it should be realized through trust, knowledge, confidence, and collaboration before any beneficial learning outcomes are attained. The findings suggest implications could be useful for higher education institutions, to ensure responsible AI usage. The higher education institutions need to emphasize Responsible AI education, incorporating ethical principles of AI into their curricula and introducing AI education programs [79]. To create an environment of responsible collaboration with AI technologies, the higher education institutions should encourage the use of AI by students and not ban the use of such technologies. There should be certain policies developed to enable the responsible adoption of AI technologies and to ensure academic integrity. Through the implementation of such programs, the universities will be able to produce both technologically literate graduates as well as ethically grounded ones [80].

6. Conclusion

This research adds to the increasing literature of studies in higher education attempting to explain the effect of Artificial Intelligence Awareness on Learning Engagement, and introduces a combined framework and verifies it empirically, with the help of Trust in AI, AI Literacy, AI Usage Self-Efficacy and Human–AI Collaboration [81]. As revealed by the results, AI competencies for the responsible use of AI are not only related to the use of technology but also affect learners' self-confidence as well as the collaboration of learners with AI, leading to a greater engagement of learners in their learning process [82]. It also highlights the importance of the adoption of HAC not only in terms of the availability of AI but also in terms of ethical awareness, technological skills and self-confidence. It takes into consideration the aspects of Responsible AI, Trust Theory, AI Literacy and Social Cognitive Theory to provide a holistic view on AI-assisted learning in higher education [83]. Future research can add to the proposed theoretical framework by analyzing other variables such as critical AI thinking, digital well-being, academic performance, cultural diversity, etc., through either a longitudinal or cross-cultural design study to enrich the body of Human–AI Collaboration knowledge [84].

The findings from this study are limited in certain aspects that need to be considered. First, the research used a cross-sectional design, which does not allow drawing causal inferences between the constructs proposed. To explore the changes in students' perceptions of AI and collaborative behaviors over time, future studies could employ a longitudinal research approach. Second, the study was based on self-reported information from 431 graduate students, so that the findings were susceptible to common method and social desirability bias [85]. While statistical methods were employed to mitigate these, future studies could benefit from the inclusion of objective measures of the use of AI and academic performance. Third, the sample consisted of graduate students, so results may not be applicable to students at the undergraduate level, faculty, or students in other educational settings and countries [86].

This framework is yet to be tested with other cultures and institutions, which would improve its external validity, and should be tested in future research. The model can be further expanded to include other constructs like critical AI thinking, digital well-being, AI anxiety, academic performance, learning satisfaction, and innovation capability [87]. Moreover, comparative research on various platforms, disciplines and learning systems would give deeper insights on the effects of Human–AI Collaboration on learning outcomes [88]. Lastly, mixed-methods or experimental methods might provide more granularity in the evidence of how responsible use of AI contributes to student engagement and achievement [89].

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