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A dual-framework analysis of artificial intelligence adoption in cross-cultural higher education

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Abstract

This study proposes a novel dual-framework model integrating the Technology Acceptance Model (TAM) with an AI Ethics Framework, introducing "Ethical Readiness" as a critical mediating construct for AI adoption in higher education. Using 2021 survey data from 47 educators, administrators, and policymakers across 26 countries, the research establishes a pre-generative AI baseline to analyse drivers, barriers, and solutions. Key drivers include data-informed decision-making, pedagogical personalisation, and administrative efficiency, aligning with TAM's perceived usefulness and ease of use. Significant barriers are limited AI literacy, inadequate infrastructure, and unresolved ethical concerns, such as algorithmic bias and data privacy. Proposed solutions focus on ethical policy frameworks, capacity-building, and infrastructural investment. The findings gain urgent relevance in the post-generative AI era, where tools like ChatGPT have accelerated adoption while intensifying ethical and pedagogical challenges. The Ethical Readiness construct, defined as an institution's systemic capacity to ensure transparent, fair, privacy-compliant, and accountable AI deployment, provides a forward-looking framework for navigating this evolving landscape. The study concludes that sustainable AI integration requires not only technological acceptance but also institutional ethical preparedness, bridging behavioural intention with normative accountability. This research offers a theoretically grounded, actionable paradigm for equitable and governance-aware AI implementation in Cross-Cultural higher education contexts.

Keywords Artificial Intelligence in higher education, Drivers and barriers to AI integration, Educational technology adoption, Responsible governance of AI-enabled platforms, Technology Acceptance Model (TAM)

1 Introduction

This study examines the factors that facilitate and hinder the adoption of AI in higher education across diverse cultural contexts. It explores how AI can enhance the administrative effectiveness of higher education and provide personalised instruction. Additionally, it addresses the infrastructure and ethical issues associated with integrating AI. The

study aims to fill a gap in the literature in this manner. This study examines the gaps in the Cross-Cultural application of AI across various educational contexts.

While other technology adoption models exist (e.g., UTAUT, UTAUT2), which incorporate social influence and facilitating conditions, they often lack a structured, integrated ethical dimension. This research is therefore anchored in a novel integration of two key frameworks: the Technology Acceptance Model (TAM) and the AI Ethics Framework. This dual-lens approach specifically addresses the gap between behavioural intention to use AI and the ethical accountability required for its legitimate adoption in educational settings [8, 20].

This research is anchored in two key frameworks: the Technology Acceptance Model (TAM) and the AI Ethics Framework. Developed by Davis [7], the Technology Acceptance Model (TAM) posits that two factors shape users' acceptance of technology. The model has been extensively applied in educational technology research to understand adoption barriers and facilitators [12]. However, its integration with ethical frameworks remains underexplored, particularly in Cross-Cultural higher education contexts. The AI Ethics Framework addresses data privacy, algorithmic bias, and equitable access to AI-driven solutions. Our approach draws on established AI ethics scholarship that identifies core challenges, including transparency, fairness, accountability, and privacy [10, 29]. These principles provide the normative foundation for evaluating institutions' ethical readiness to deploy AI technologies responsibly. Thus, both frameworks provide a structured lens through which to analyse the drivers, barriers, and solutions to the adoption of AI-enhanced systems in higher education.

Recently, AI has evolved from a promising concept in the 1950s to a field with broad applications. AI is transforming traditional practices in higher education [19, 23]. For example, it enables more flexible, personalised learning environments. It also automates administrative tasks such as scheduling and grading. Thus, AI enhances management for both educators and students [44].

Additionally, AI supports admissions, education, and training by optimising resource allocation [53]. Experts argue that AI's ability to disrupt education is significant [27, 34]. However, despite its promise, the adoption of AI in higher education has been slower than expected. Ethical concerns are the primary barriers. These concerns include data privacy, biases in AI algorithms, and institutional readiness [9, 11].

Moreover, AI is now at the forefront of educational innovation, driven by the rapid development of big data and internet technologies [4]. Thus, its integration is critical to improving education systems. For instance, curriculum design and assessment methods may be more efficient when using AI. Cross-Culturally, AI is being integrated into strategic educational plans to improve efficiency and academic integrity [16, 31, 32]. For example, AI is applied to detect academic fraud and manage administrative tasks. Furthermore, AI enhances international competitiveness and supports scientific research.

Recent studies [24, 49] highlight the growing need for AI competency frameworks in higher education. These studies show AI's potential to bridge access and inclusivity gaps. Hence, AI facilitates language translation, cultural preservation, and creativity. They also shed light on its ability to promote transparency and fairness. However, collaboration among experts, scholars, and policymakers is vital to addressing ethical and social issues raised by AI. By doing so, Cross-Cultural competitiveness could improve, demonstrating the benefits of AI across various domains [10, 37, 40].

This study addresses three interrelated objectives:

1. To examine how perceived usefulness and ease of use shape educators' attitudes toward AI (drawing on TAM constructs).
2. To explore how ethical readiness and institutional governance influence actual adoption (drawing on AI Ethics constructs).
3. To identify culturally specific factors that mediate these theoretical dimensions across diverse educational contexts.

It is critical to contextualise this study's empirical findings within the technological moment in which they were collected. The survey data, gathered in 2021, capture institutional readiness and stakeholder perceptions in a *pre-generative AI* era, prior to the disruptive entry of large language models (LLMs) like ChatGPT. Consequently, while the theoretical framework and identified thematic dimensions (e.g., ethical opacity, infrastructure needs) possess enduring relevance, the specific weight and manifestation of drivers and barriers reported herein should be interpreted as a foundational benchmark against which the accelerated evolution of AI in education post-2022 can be measured.

2 Literature review

2.1 The dual trajectories of AI adoption research: a critical disconnect

The scholarly discourse on AI adoption in higher education has progressed along two parallel yet critically disconnected trajectories: one centred on behavioural acceptance and the other on normative governance. This bifurcation reflects a fundamental theoretical gap: while one body of research explains whether and why AI is adopted, the other prescribes how it should be adopted ethically. The integration of the Technology Acceptance Model (TAM) and the AI Ethics Framework is therefore not merely beneficial but crucial for bridging this disconnect and enabling the safe, legitimate application of AI in educational settings. TAM clarifies how perceived usefulness and usability influence technology adoption. This theory offers a critical perspective on the justifications for incorporating AI. It specifically explains why the primary justifications for using AI provided by the research participants were administrative efficiency (13.6%) and personalised learning (24.7%). However, TAM's focus on instrumental utility leaves it structurally blind to the normative conditions that determine whether adoption is ethically defensible and socially sustainable.

2.2 The normative imperative: AI ethics as a governance framework

Conversely, the AI Ethics Framework emphasises fundamental principles, such as transparency, privacy, and equity, all of which are crucial for guiding the ethical application of AI in educational settings. This study supports the applicability of the concept by closely examining the moral conundrums that prevent the adoption of AI-enhanced systems. Concerns raised by participants regarding algorithmic unfairness and data privacy also highlight enduring moral flaws that call into question the acceptability of AI in educational settings [43].

These observations align with broader ethical critiques of AI implementation [10, 29], underscoring the need for robust governance frameworks to ensure responsible AI use in educational settings. The ethical challenges highlighted by participants, particularly those related to algorithmic fairness and data privacy, represent persistent concerns that

question the acceptability of AI in sensitive domains such as education [45]. Nevertheless, this ethical discourse often operates at an abstract level, providing essential principles but limited insight into how these principles interact with and are negotiated within the practical, behavioural drivers of the TAM modelled adoption.

2.3 Drivers for AI use in higher education: the promise and its precariousness

One of the primary motivations for integrating AI into higher education is its proven capacity to enhance both educational outcomes and institutional efficiency [28]. For example, Menkhoff and Teo's (2022) experiential chatbot workshop demonstrates the value of AI in helping non-STEM students acquire essential skills. Their findings confirm that AI aligns with broader educational objectives [15]. Specifically, the role of generative AI in fostering both theoretical and practical skill development is exceptional. Nevertheless, despite AI's advantages, the scalability of such initiatives across a broader range of disciplines and educational contexts is questionable. This directly illustrates the gap between perceived usefulness (a TAM driver) and the institutional, ethical, and infrastructural facilitating conditions required for sustainable implementation.

Moreover, Katsuragi and Tanaka [21] explore the application of AI to improve online student retention. This experiment developed a machine-learning model that accurately predicts dropout rates. This study exemplifies AI's potential to proactively mitigate student disengagement. However, the effectiveness of such data-driven models depends on robust, inclusive data infrastructures, which are often absent in many educational institutions. Furthermore, significant ethical concerns are data privacy and algorithmic biases. Therefore, to prevent current educational disparities, responsible AI management is crucial. Here, the driver (retention) is inextricably linked to ethical barriers (privacy, bias) and infrastructural prerequisites, highlighting the insufficiency of studying drivers in isolation.

Renz and Hilbig, [33] also stress the importance of data-driven business models in the EdTech industry. They emphasise the importance of integrating learning analytics with AI. Doing so would support flexible teaching and learning approaches. Nevertheless, data sovereignty concerns often limit the efficacy of these strategies. However, poor data comprehension could make it more challenging to build and implement AI-driven teaching programmes. This reinforces the critical link between technical potential and the governance of the data that fuels it, a concern central to the AI Ethics Framework but peripheral to TAM.

2.4 Barriers to the adoption of ai-enhanced systems in higher education: the cost of the disconnect

Teuscher, [45] argues that, against its promising potential, AI integration into higher education presents significant challenges. Fields such as deep learning and quantum computing particularly accentuate this issue. The rapid pace of AI advancements outstrips the ability of educational institutions. This rapid pace hinders educational institutions from adapting their curricula accordingly [36]. This could undermine the potential benefits of AI. If this gap is not adequately addressed, it will result in an unprepared workforce [6, 35]. This workforce will be unable to meet the demands of an AI-driven educational environment. This barrier represents a systemic failure of the institutional

readiness concept encompassing both technical capacity (related to PEOU) and adaptive, ethical foresight.

Similarly, Seo [39] asserts that standard curricula are insufficient to meet the diverse needs and abilities of students. Therefore, AI-driven self-diagnostic tools may offer a potential solution by personalising the learning content. Nonetheless, critical concerns regarding the accuracy and fairness of AI-powered assessments are high. There is a risk of perpetuating existing biases [18]. These biases could harm educational equity. This encapsulates the core tension: a tool designed to enhance personalisation (a key driver) may simultaneously exacerbate inequity (a core ethical violation), demonstrating why ethical assessment must be baked into the adoption process, not applied as an afterthought.

Furthermore, Shopland et al. [42] highlight the European Union's initiatives to raise awareness of the necessity of ethically sound AI practices. However, the rapid evolution of the industry calls for a more agile response from academia. Developing courses that address both the technical and ethical dimensions of AI is essential. Moreover, the ethical implications of AI are not merely theoretical; they are also practical. They may have practical consequences for educators, students, and institutions. This calls for an integrated pedagogical response that mirrors the integrated theoretical framework proposed in this study.

Similarly, Xie and Chen [52] emphasise the importance of AI integration in assessments. The authors stress the use of AI in areas such as grading and language processing. They argue that the limitations of AI in automated systems are significant, particularly its inability to assess complex language tasks accurately. Thus, concerns about over-reliance on AI in educational settings are justified. However, excessive reliance on AI could marginalise the roles of human educators [38]. Educators play a crucial role in providing nuanced feedback that AI-driven platforms may not. This barrier underscores the need for a balanced, human-centred approach to adoption, a consideration beyond the scope of TAM but central to responsible integration.

2.5 Viable solutions for potential barriers: implicit calls for integration

Professional collaboration among academia, industry, and policymakers is crucial for addressing the barriers to the adoption of AI-enhanced systems in higher education. For instance, Liwång [25] advocates co-creating a model where higher education institutions work closely with industry and government. According to Liwång [25], socially responsible and relevant AI technologies should be developed and implemented in a socially responsible manner. Moreover, technical challenges must be addressed carefully. Meanwhile, it is essential to incorporate diverse perspectives into AI development. By doing so, AI-driven platforms will inherently embed the ethical, transparent, and equitable aspects needed in higher education [41]. This solution explicitly merges the technical development process (a domain of utility) with social responsibility (a domain of ethics), modelling the integration our theoretical framework seeks to explain.

Likewise, An [1] explores the use of AI-driven facial recognition technology in education. Political and ideological education uses this technology to enhance the emotional aspects of learning. This innovation presents exciting possibilities for personalising education, but it also raises significant ethical concerns. In particular, the potential misuse of AI for surveillance poses a significant threat to privacy. Thus, this study underscores

the need for robust frameworks and ongoing ethical scrutiny to govern the use of AI in sensitive educational contexts. This case is a paradigmatic example of a high-utility driver (engagement, personalisation) clashing directly with a paramount ethical principle (privacy), necessitating governance that can weigh and reconcile these competing imperatives.

Furthermore, Warning et al. [50] argue that AI offers valuable guidance to higher education institutions. They suggest that AI transforms the working environment and prepares students for a workforce increasingly driven by AI. Consequently, AI is likely to influence employee well-being, job security, and flexibility. Thus, these factors are critical to the design of educational programmes that equip students with technical skills and social awareness. This points toward the need for curricula that foster not just AI literacy (skill) but also AI ethics (discernment), again arguing for an integrated approach.

2.6 Synthesis: toward an integrated model of ethical readiness

Additionally, the study supports the growing view of AI as a force for change in education, extending beyond its original function as a technical advancement. Recognising this potential, international organisations like the OECD [30], UNESCO [46], and the United Nations [47] have made strategic calls for the ethical and inclusive use of AI in higher education. These international initiatives support ethical transparency, digital fairness, and sustainable development policies, reaffirming the pressing need for educational systems to embrace AI technologies within a framework of institutional integrity and social responsibility.

The literature, therefore, reveals a consistent pattern: drivers (explained by TAM) are inevitably tempered by barriers (articulated through ethics), and proposed solutions call for the synthesis of technical and normative domains. This persistent interplay demonstrates that the dominant siloed models are inadequate. The path forward requires a framework that treats ethical governance not as an external constraint on adoption, but as an internal, mediating variable.

This study directly addresses this imperative by integrating TAM with the AI Ethics Framework and positing 'Ethical Readiness' as the critical mediating construct. Ethical Readiness operationalises an institution's capacity for transparency, fairness, privacy, and accountability, thereby defining the conditions under which positive behavioural intentions (PU/PEOU) can successfully transition into responsible, sustainable AI adoption. This integrated model provides the necessary theoretical bridge between the two dominant yet disconnected trajectories in the literature.

3 Conceptual framework

This study extends TAM by introducing 'Ethical Readiness' as a mediating construct. We define Ethical Readiness as an institution's systemic capacity to ensure AI deployment is transparent, fair, privacy-compliant, and accountable. This extends the concept of 'facilitating conditions' [48] into the ethical domain, while drawing on organisational readiness literature [51]. By integrating ethical considerations as mediating factors, we bridge the gap between technical adoption and responsible implementation in educational contexts. This construct mediates the pathway between the behavioural intention to use AI (influenced by PU and PEOU) and its actual, responsible adoption.

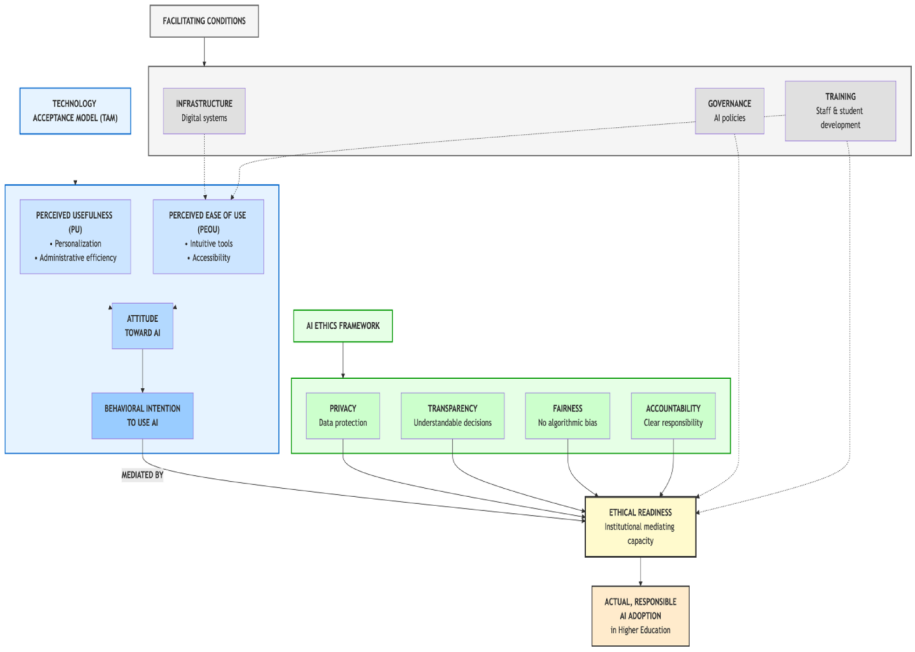

Fig. 1 Integrated TAM–AI Ethics Framework illustrating the mediating role of Ethical Readiness. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) influence Attitude and Intention to Use. Ethical Readiness, composed of Privacy, Transparency, Fairness, and Accountability, mediates the transition from Intention to Actual, Responsible Adoption

Combining TAM with the AI Ethics Framework yields a dual-lens paradigm that links normative accountability to behavioural intention. The synthesis enables the examination of both the cognitive acceptance of AI and the ethical legitimacy of its usage, bridging the gap between functional adoption and moral accountability, in line with Floridi [10] and Henry and Oliver [17].

3.1 Technology Acceptance Model (TAM)

Building on Davis's (1989) Technology Acceptance Model, which posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) shape technology adoption. We introduce 'Ethical Readiness' as a mediating construct. We define Ethical Readiness as an institution's systemic capacity to ensure AI deployment is transparent, fair, privacy-compliant, and accountable. This construct mediates the pathway between behavioural intention to use AI (influenced by PU and PEOU) and its actual, responsible adoption.

3.2 AI ethics filters

'Ethical readiness' refers to an institution's ability to deploy AI-driven platforms that are transparent, fair, and privacy-compliant. Facilitating conditions refer to institutional or policy-level supports that enable or hinder the adoption, including digital infrastructure, governance, and training provisions. These ethical dimensions act as moderating variables between intention and actual adoption:

- Privacy: Protection of student data.
- Transparency: Understanding AI decisions.
- Fairness: Avoidance of algorithmic bias.
- Accountability: Clear responsibility structures in AI deployment.

3.3 Interactions in the framework

$$\text{PU} + \text{PEOU} \rightarrow \text{Attitude} \rightarrow \text{Intention to Use}$$

Ethical Readiness (comprising institutional capacity for privacy, transparency, fairness, and accountability) acts as a critical mediator between Intention to Use and Actual, Responsible Adoption.

Thus, sustainable Adoption of AI-enhanced systems in higher education is conceived as a function of both positive technology acceptance *and* sufficient ethical readiness.

4 Methods

This study employed a qualitative, exploratory survey design complemented by descriptive statistics. We adopted a purposive-convenience sampling strategy to explore factors influencing AI adoption in higher education across diverse contexts. The survey instrument consisted of 15 items: eight closed-ended Likert-scale questions and seven open-ended prompts addressing perceived drivers, barriers, and ethical challenges.

A purposive-convenience sampling strategy was adopted to explore factors influencing the adoption of AI-enhanced systems in higher education across diverse contexts. The survey was distributed through the Office 365 platform. Although randomisation was not feasible, participant diversity across 26 countries ensured theoretical variation and Cross-Cultural representation. The survey was distributed via Office 365 Forms to professional networks across 26 countries. Recruitment faced challenges in Oman due to cultural factors and hesitancy, resulting in a response rate of approximately 18%. The use of an English-only survey may have introduced self-selection bias toward participants with higher digital and English literacy.

While the sample offers valuable Cross-Cultural perspectives, the study's stronger representation of the Gulf region is a deliberate strength. It provides vibrant, in-depth insights into the challenges and drivers in AI-Ed research within an underrepresented, resource-constrained context. This focus helps balance a literature often dominated by perspectives from the Global North and should be considered a specific contribution when interpreting the identified trends.

The respondents represented a wide range of educational and cultural perspectives. Most participants were from the Gulf region and had backgrounds in logistics, transportation, and marine studies. Recruitment challenges were notable, especially in Oman, due to cultural differences and low participation rates. Nevertheless, the diversity of participants ensured rich, meaningful insights.

While the sample offers valuable Cross-Cultural perspectives, its stronger representation of the Gulf region is a deliberate strength, providing in-depth insights into the adoption of AI-enhanced systems within an underrepresented, resource-constrained context.

The survey instrument consisted of 15 items: eight closed-ended Likert-scale questions and seven open-ended prompts that addressed perceived drivers, barriers, and ethical challenges. Reliability was ensured through expert review by two higher education researchers. Despite the modest participant sample (n = 47), the study achieved data saturation and thematic sufficiency, with the 38th respondent stabilising recurring patterns and no new substantive themes emerging thereafter. This approach aligns with established qualitative research standards, in which sample size is determined

by informational needs and the depth of analysis rather than statistical power [3, 13]. The credibility and analytical depth of the findings are thus supported by this saturation point, which ensures comprehensive theme identification within the scope of this exploratory, Cross-Cultural study.

The sample size may seem limited, but its diversity strengthens the findings. The participants' expertise in AI in educational settings adds credibility to the study. However, future research should use larger samples and combine qualitative and quantitative data to yield more profound insights. This will help broaden the understanding of the adoption of AI-enhanced systems across diverse educational contexts. For now, this study provides a valuable snapshot, particularly for regions facing unique academic challenges.

Although the data were collected in 2021, the analysis recontextualises these early, post-pandemic perceptions of AI integration alongside later developments through 2025, thereby offering a temporal comparison. It is important to note that this dataset serves as a historical baseline; the rapid evolution of AI, particularly the rise of generative AI post-2022, is not reflected in the primary survey data but is considered in the discussion of the evolving landscape.

Data were collected in 2021, prior to the widespread adoption of generative AI-driven platforms such as ChatGPT (released late 2022). As such, the findings reflect perceptions and institutional readiness in a pre-generative AI setting. This provides a valuable baseline for understanding how earlier ethical and infrastructural concerns persist or have evolved in the current LLM-dominated educational context [26].

The survey method was ideal for reaching a diverse range of participants, given the geographical and recruitment constraints. Despite the difficulties of in-person recruitment, it enabled authors to gather views from a diverse range of educational backgrounds. To avoid selection bias, random sampling was essential. Furthermore, to ensure all participants could fully engage with the questions, the survey was conducted in English. Therefore, despite the limited sample size, the study's generalisability was enhanced.

The use of an online, English-language survey, while necessary for international reach, may have introduced self-selection bias, favouring participants with higher levels of digital literacy and English proficiency. Furthermore, this qualitative analysis did not statistically control for potential cultural response biases, given the study's Cross-Cultural design. These limitations are acknowledged as inherent to the chosen methodology.

The researchers used a thematic approach to analyse the data. First, researchers review responses to familiarise themselves with the content. Then, they coded the data into categories based on recurring themes related to the adoption of AI-enhanced systems. Researchers ensured that all viewpoints were accurately captured. In brief, investigators confirmed that the analysis remained aligned with the study's objectives. Therefore, participants' complex perspectives will be reflected in the depiction shown in Fig. 2.

The participants represented a broad spectrum. This spectrum encompasses a range of academic, socioeconomic, and cultural backgrounds. To capture varied perspectives on AI in educational settings, this inclusivity was essential. For instance, respondents included academics, administrators, and decision-makers from 26 countries. These contributors covered a wide range of disciplines. Disciplines included education, languages, maritime studies, process engineering, IT, and logistics. This diversity ensured that the findings were well-rounded and robust.

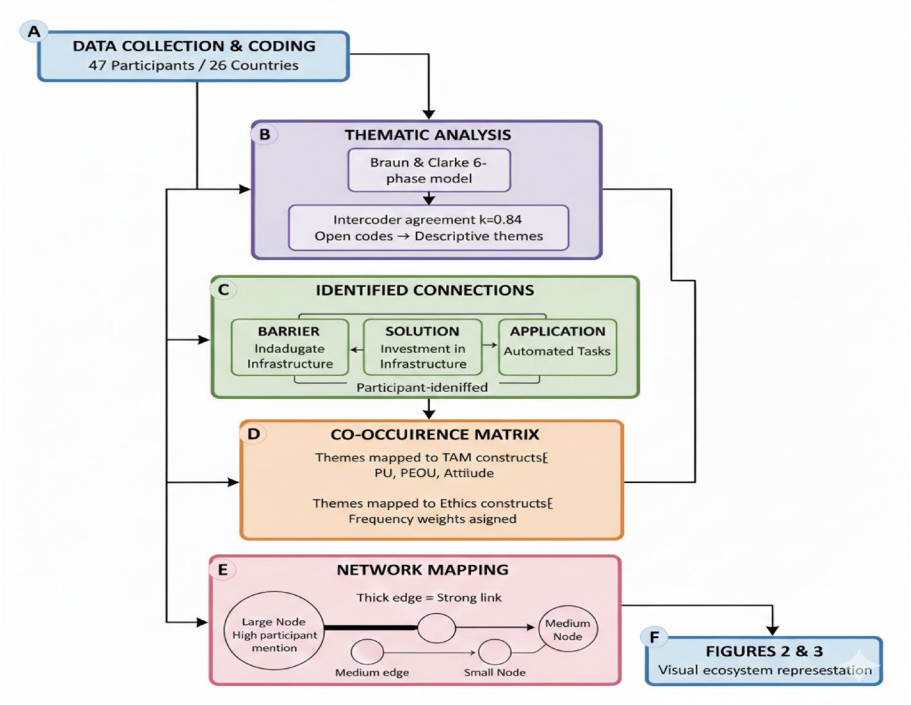

Fig. 2 The systematic progression from qualitative data to network visualisations

4.1 Ethical procedures

Participants were informed of the study's purpose and voluntarily consented to participate, and informed consent was obtained from all participants. Their identities were anonymised, and all data were stored securely. Informed consent was obtained digitally through a secure Office 365 Forms checkbox system before survey submission. Participants were required to acknowledge their understanding of the study's aims, data use, and measures of anonymity. All consent records were stored securely on encrypted university servers accessible only to the principal investigator.

The Research Committee at the National University of Science and Technology, Oman, granted ethical approval. The Research Ethics Committee operates under the auspices of the National University of Science and Technology, which adheres to the Declaration of Helsinki and international ethical research standards. The study received approval from the Research Ethics Committee at the National University of Science and Technology, Oman (Approval ID: REC/NUST/AIED/2021/04).

Data analysis of open-ended responses was conducted using Braun and Clarke's six-step thematic analysis, ensuring a rigorous and transparent coding process. Descriptive statistics were applied to closed responses to support thematic interpretation.

Thematic analysis was conducted using Braun and Clarke's six-phase model. Two coders independently identified initial codes, iteratively refined categories, and achieved intercoder agreement ($\kappa = 0.84$) [22]. Illustrative coding examples showing how textual segments were abstracted into conceptual themes such as 'ethical opacity' and 'pedagogical adaptability'. NVivo 12 supported coding traceability.

Given the qualitative nature of this study and its modest sample size, advanced statistical models, such as structural equation modelling (SEM), were not employed. Therefore, model fit indices (e.g., CFI, RMSEA, SRMR) are not applicable and are not reported.

While this qualitative study provides rich, context-sensitive insights, several limitations should be noted. First, the purposive-convenience sample ($n = 47$) limits statistical generalizability, though it achieves theoretical saturation and provides valuable Cross-Cultural perspectives. Second, the integrated TAM-Ethics framework presented here is theoretically proposed but not statistically validated in this study; it serves as a conceptual model for future quantitative testing. Third, the 2021 data collection provides a valuable pre-generative AI baseline, but the rapid evolution of LLMs post-2022 means the specific quantitative distributions should be interpreted as reflective of that transitional period rather than the current landscape.

Meanwhile, this enriches the analysis of region-specific infrastructural and cultural-readiness challenges; readers should be mindful of this focus when considering the global applicability of the findings. This limits the direct generalisability to all global regions, but usefully highlights regional disparities in the adoption of AI-enhanced systems. Thus, the findings offer a snapshot of AI-enhanced system adoption in higher education. It primarily affects underrepresented regions. Therefore, Future studies should build on this by using larger, more diverse samples.

4.2 Researcher positionality

The authors are based in Omani and Spanish institutions, with research interests in educational technology and equity. This positionality informs our focus on underrepresented regions and may shape the interpretation of findings toward infrastructural and ethical readiness challenges, particularly in resource-constrained contexts.

4.3 From codes to synthesis

The analytical process moved systematically from raw codes to the synthesised representations in the tables and figures. Initial open codes (e.g., "lack of server capacity," "fear of bias") were grouped into descriptive themes (e.g., "inadequate infrastructure," "ethical opacity"). These themes were then mapped onto the theoretical constructs of TAM (PU, PEOU) and the AI Ethics Framework (privacy, fairness, etc.) to create the structured categories presented in the summary table of drivers. For the solutions matrix and network figures, thematic connections and interdependencies identified during analysis were visually mapped. This involved identifying which solutions (e.g., "investment in infrastructure") participants associated with which application areas (e.g., "automated tasks") and which barriers clustered together, thereby creating network diagrams that illustrate the ecosystem's nonlinear dynamics.

4.4 Findings

This study used a thematic analysis. It advocated the systematic categorisation and codification of data derived from participants. This process facilitated the identification of key themes closely tied to the adoption of AI in higher education.

4.5 Analytical process: from codes to network maps

Thematic analysis followed Braun and Clarke's six-phase model. Initial codes (e.g., "lack of server capacity") were grouped into descriptive themes, which were then mapped onto TAM and AI Ethics constructs. Network diagrams (Figs. 2, 3 and 4) were derived through systematic analysis of participant responses using NVivo 12. Node size

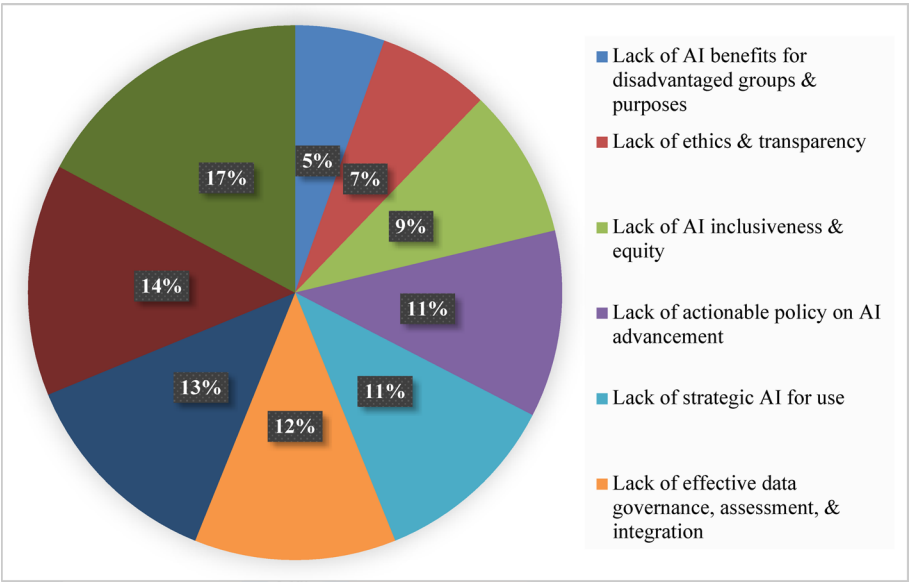

Fig. 3 Barriers to implementing AI in higher education

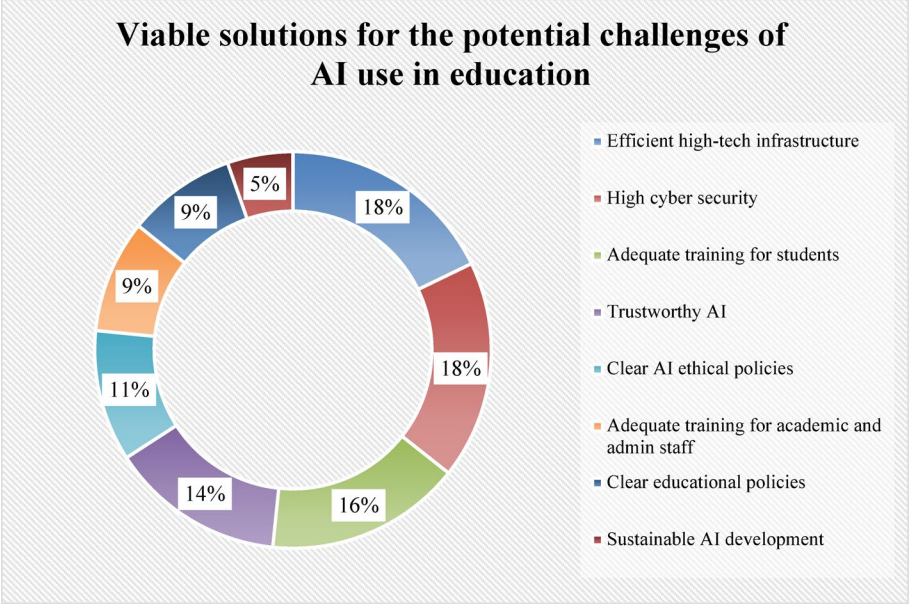

Fig. 4 Viable solutions for the potential challenges of AI use in education

corresponds to the frequency of participant mentions, while edges (connections) were created when participants explicitly linked concepts in their qualitative responses. For instance, when respondents linked 'lack of infrastructure' to 'inability to implement real-time tools,' this relationship was represented as an edge between the nodes. This visualisation approach reveals the ecosystem's nonlinear dynamics and interdependencies.

4.6 Drivers for AI use in higher education

The integration of the Technology Acceptance Model (TAM) and the AI Ethics Framework provides a robust interpretive lens for understanding the drivers of AI-enhanced system adoption in higher education. In this study, the TAM constructs Perceived

Usefulness (PU) and Perceived Ease of Use (PEOU) are evident in participants' emphasis on AI's ability to personalise learning, streamline admissions, and automate educational processes. Simultaneously, the ethical dimensions of privacy, transparency, fairness, and accountability mediate participants' enthusiasm with nuanced concerns regarding the responsible use of AI technologies.

To provide a consolidated overview, Table 1 presents the key drivers identified by participants, categorises them, and maps their relationships to the TAM and AI ethics constructs.

4.6.1 Personalisation and admissions efficiency (PU)

A significant 24.7% of respondents identified personalisation and admissions efficiency as the top motivators for adopting AI-enhanced systems, as shown in Table 1. This finding aligns strongly with TAM's Perceived Usefulness, where AI's ability to improve service quality and administrative responsiveness is viewed as a decisive factor in its adoption. Participants viewed AI as a means of enhancing operational efficiency and tailoring services to individual student needs. However, this operational utility must be considered within the AI Ethics Framework, particularly with respect to fairness and transparency. Without equitable access to AI-enhanced systems, these benefits may be unevenly distributed, reinforcing existing institutional hierarchies.

4.6.2 Strategic enhancement and market positioning (PU + Ethics)

12.8% of participants reported using AI to improve institutional reputation and student recruitment (Table 1). This application also reflects TAM's PU dimension, as institutions perceive strategic gains through AI's data-driven insights. However, when predictive profiling drives marketing practices by potentially favouring demographics aligned with algorithmic biases, ethical concerns arise. This duality highlights the need to integrate ethical governance into AI-enhanced recruitment.

Table 1 Drivers for AI use in higher education, thematically categorised. Source: Authors' analysis (2025). Percentages are derived from survey data

Thematic category	Specific driver	Respondent percentage	Key TAM Construct(s)	Key AI Ethics Construct(s)
Pedagogical & Learning Enhancement	Personalised Learning / Instructional Adaptability	24.7%	PU, PEOU	Privacy, Fairness
	Competency-Based & Lifelong Learning	17.0%	PU	Fairness
	Critical Thinking & Task-Driven Learning	11.0%	PU	Fairness, Accountability
	Engagement & Immersion	12.3%	PU	Transparency
	Innovative teaching & assessment.	17.0%	PU, PEOU	Accountability
Administrative & Operational Efficiency	Admissions & Administrative Efficiency	13.6%	PU, PEOU	Fairness, Transparency
	Retention & Lifecycle Support	10.6%	PU, PEOU	Accountability, Privacy
Strategic & Institutional positions	Strategic Enhancement & Market Positioning	12.8%	PU	Fairness, Transparency
	Teaching Efficacy & Inclusion	18.5%	PU	Transparency, Fairness
	Reducing Administrative Burdens	13.6%	PU, PEOU	(Implied: Accountability)

4.6.3 Retention and lifecycle support (PU + PEOU + Accountability)

The use of AI to improve student retention and issue resolution, cited by 10.6% (Table 1), demonstrates both TAM dimensions: usefulness (early interventions) and ease of use (automated diagnostics). Nonetheless, effective implementation depends on data accountability and privacy safeguards. AI-driven student monitoring tools must operate within ethically grounded frameworks to avoid surveillance or misuse of sensitive data.

4.6.4 Lifelong learning and pedagogical adaptivity (PU + Fairness)

Respondents also emphasised the role of generative AI in promoting continuous and lifelong education (17%) and in developing technological and professional skills (22.6%), as shown in Table 1. These reflect TAM's positive impact on enhancing long-term educational outcomes. However, from an ethical perspective, the accessibility of such adaptive tools warrants scrutiny. Are they available to all learners equally, or do they privilege digitally literate, high-income users? The fairness principle of the AI Ethics Framework is thus critical for ensuring equity in skill-building opportunities.

4.6.5 Engagement and immersion (PU + Transparency)

While 12.3% of respondents valued AI's contribution to entertainment and engagement, and 8.5% referenced immersive learning (Table 1), these applications raise ethical questions regarding transparency. Gamification and immersive technologies must communicate pedagogical intent and algorithmic logic. Without transparency, learners may experience engagement as manipulation rather than empowerment.

4.6.6 Innovative approaches in teaching and assessment include perceived usefulness (PU), perceived ease of use (PEOU), and accountability

Participants also cited AI's potential to support innovative teaching models (17%) and improve grading efficiency (14.9%) (Table 1). These reflect both PU (automated processes) and PEOU (ease of implementing grading tools). However, accountability emerges as a central ethical concern. AI must supplement, not replace, human judgement, especially in formative assessment, where context and nuance are essential.

4.6.7 Competency-based education and accessibility (PU + Fairness)

AI's ability to foster multidisciplinary, competency-based education (10.6%) and improve affordability and accessibility (10.6%) (Table 1) reflects an institutional desire to align education with labour market needs while expanding inclusivity. However, if we design AI platforms with culturally narrow assumptions or inaccessible interfaces, we risk excluding the very learners we aim to support. Thus, fairness and cultural responsiveness must be central to the design and deployment of AI.

4.6.8 Personalised learning and instructional adaptability (PU + PEOU + Privacy)

The reiteration of personalised learning and adaptability by another 24.7% (Table 1) affirms AI's central role in learner-centred education. This directly reflects both PU and PEOU: learners benefit from content tailored to their pace and preferences. However, these affordances are underpinned by data-intensive profiling, which raises significant privacy concerns. To safeguard learners' rights and harness the adaptive power of AI, institutions must implement stringent data governance policies.

4.6.9 Enhancing teaching efficacy and inclusion (PU + Transparency + Fairness)

18.5% of participants cited improvements in teacher effectiveness, while 15.8% emphasised gains in inclusion and accessibility (Table 1). These are clear demonstrations of AI's perceived usefulness for advancing pedagogy. However, achieving genuine inclusivity requires more than tool availability. It demands transparent AI-driven platforms that account for learner diversity and do not replicate biases.

4.6.10 Reducing administrative burdens and enabling higher-order learning (PU + PEOU)

With 13.6% of respondents noting AI's capacity to streamline administrative work, the TAM model's ease-of-use dimension is evident (Table 1). However, this efficiency gain should not come at the cost of relational teaching. Over-reliance on AI for logistical tasks may lead educators to disengage from holistic learner support.

4.6.11 Critical thinking and task-driven learning (PU + Fairness + Accountability)

Finally, 11% of respondents highlighted the role of generative AI in fostering critical thinking and task-driven learning (Table 1), challenging the stereotype that AI stifles creativity. AI can scaffold higher-order thinking by freeing cognitive bandwidth and supporting reflective learning. This is only viable, though, if AI-powered tools are designed to respect epistemic justice and avoid mechanical, drill-based methods that impede metacognitive development.

The interaction between the TAM model and the AI Ethics Framework reveals that ethical concepts, such as privacy, fairness, transparency, and accountability, play a crucial role in mediating the path to responsible adoption, even as perceived utility and ease of use account for a significant portion of adoption intent. When considered as a whole, these frameworks underscore the profound pedagogical and ethical significance of AI in higher education, alongside its technical benefits.

4.7 Barriers to implementing AI in higher education

Participants stated that obstacles offer a stark counterpoint to the positive forces driving AI integration. These limitations cover a wide range of areas, including politics, infrastructure, ethics, and technology. When these results are interpreted using the Technology Acceptance Model (TAM) and the AI Ethics Framework, it becomes clear that there are deeper systemic issues that could impede the equitable and sustainable use of AI in higher education, in addition to the practical barriers to adoption as shown in Fig. 3.

4.7.1 Lack of AI development expertise and infrastructure (TAM–Perceived Ease of Use & Organisational Readiness)

Insufficient technological infrastructure and a lack of appropriate AI competence are the most significant obstacles, as indicated by 17% equally (Fig. 3). Within TAM, these constraints directly undermine Perceived Ease of Use (PEOU), a key predictor of technology acceptance. When institutions lack skilled personnel and foundational infrastructure (e.g., servers, networks, cloud platforms), even the most promising Generative AI applications become impractical or unsustainable. This insight underscores that AI readiness is not merely about acquiring tools but also about fostering human and technical capital.

Critically, this also reflects a geopolitical divide in the adoption of AI-enhanced systems, where under-resourced institutions or regions risk systemic marginalisation from

global AI developments. Without significant investment in upskilling and infrastructure development, AI may exacerbate rather than alleviate educational inequities.

4.7.2 Inadequate data governance and poor-quality data (AI Ethics -- Privacy, Fairness, Accountability)

14% of respondents identified ineffective data governance, assessment, and integration, while 13% cited the lack of high-quality, inclusive datasets as a significant barrier (Fig. 3). These findings directly align with the AI Ethics Framework, which places privacy, fairness, and accountability at its core.

Institutions that lack coherent data strategies are more vulnerable to algorithmic errors, biased outcomes, and breaches of confidentiality. Moreover, the lack of inclusive datasets often results in the exclusion of minority learner groups, undermining the ethical legitimacy of AI-driven platforms. The issue is not simply technical but epistemological: whose knowledge, identity, and needs are encoded in the data systems that drive AI?

Thus, while data may be described as the "fuel" of AI, it is the governance and ethical architecture surrounding that data that determines whether the resulting system is just and responsible.

4.7.3 Absence of ethical governance and regulatory policy (AI Ethics -- Transparency, Regulation, Trust)

A combined 20% of respondents cited a lack of ethical transparency (9%), lack of inclusiveness and equity (11%), and lack of public policy on AI development (11%) as pressing barriers (Fig. 3). These concerns are central to the AI Ethics Framework, particularly regarding transparency and trust.

Higher education institutions must develop isolated, potentially inconsistent standards for AI use in the absence of formal regulatory frameworks. This regulatory vacuum threatens to erode trust among key stakeholders, students, faculty, administrators, and the public. Furthermore, the absence of ethical guidelines heightens the likelihood of adopting AI-powered tools that are opaque, incompatible with educational values, or even exploitative.

These ethical deficits also affect TAM's Attitude Toward Use construct. Even when AI-driven platforms are technically functional, ethical concerns can breed resistance among educators and learners alike, limiting institutional buy-in and long-term integration.

4.7.4 Structural exclusion of vulnerable groups (AI Ethic-Equity and Social Justice)

6% of respondents notably highlighted the lack of Benefits of AI-driven analytics for marginalised and underprivileged groups (Fig. 3). This obstacle highlights a structural problem: vulnerable student populations may not benefit from AI as it is currently developed and implemented, or worse, it may intentionally exclude them. If current educational injustices are not aggressively addressed, the design of AI may exacerbate them, whether through algorithmic bias, socioeconomic disparities, or linguistic barriers.

This highlights the need to develop AI in higher education with a justice-focused approach. Such a strategy would actively prioritise the interests of historically underrepresented students rather than just minimise harm.

4.7.5 Theoretical implications and synthesis

Collectively, these findings reaffirm the relevance of the TAM and AI Ethics Framework as complementary lenses for analysing the adoption of AI-enhanced systems. While TAM explains institutional hesitancy through concepts such as ease of use and infrastructure readiness, the AI Ethics Framework illuminates the moral and regulatory voids that can destabilise or delegitimise AI initiatives.

To achieve the responsible and widespread adoption of AI in higher education, institutions must go beyond merely enabling technical aspects; they must also foster a culture of responsible use. They must build ethical capacity, develop inclusive policies, and reinvest in human expertise. AI readiness, therefore, is not just a technological state. It is a cultural and institutional posture grounded in ethical foresight, critical pedagogy, and sustainable design.

4.8 Viable solutions for the potential challenges of AI use in education

4.8.1 Infrastructure and cybersecurity: foundational enablers for responsible AI integration

According to 21.3% of respondents, the most pressing solutions for the successful Implementation of AI-enhanced systems involve investing in efficient high-tech infrastructure and robust cybersecurity protocols, as shown in Fig. 4 above. These priorities are foundational to both the Technology Acceptance Model's Perceived Ease of Use (PEOU) and the AI Ethics Framework, particularly regarding privacy and security. Participants identified these elements as prerequisites for scaling intelligent systems, including innovative admissions, real-time tools, and automated tasks, as illustrated in Fig. 3. Without a secure and interoperable infrastructure, these applications risk systemic failure and ethical breaches.

4.8.2 Training and trustworthiness: human capacity as a core driver

Approximately 19.1% of participants emphasised the need for student training, while 17% called for enhancing AI trustworthiness (Fig. 4). These responses align with the TAM constructs of attitude and perceived usefulness, as training improves user confidence and engagement with AI technologies. Nodes such as innovative teaching, smart curriculum, and task-driven learning, as illustrated in Fig. 3, demonstrate that the effectiveness of AI-enabled instruction depends on competent implementation and ethical transparency. Moreover, the AI Ethics Framework underscores that trustworthiness in AI must be built through understandable, fair, and auditable systems, a sentiment echoed in the network connections between evaluation, equity education, and innovative presentation.

4.8.3 Policy clarity and sustainable AI: toward long-term alignment

Policy-related solutions were also strongly recommended: 12.8% of participants called for clear AI ethical policies, 11% emphasised the training of academic and administrative staff, and 6.4% prioritised sustainable AI development (Fig. 4). These elements reflect the TAM component of facilitating conditions and the AI ethics principle of accountability. Participants contended that, in the absence of transparent policies, applications such as personalised learning, interactive worksheets, and identity-tailored learning (Fig. 3) risk misuse or underutilisation.

Table 2 AI in higher education ecosystem: cross-cutting solutions and their influenced areas. Source: Authors' analysis (2025), based on network mapping of participant responses

Solution category (from Fig. 3)	Specific solution	Influenced application nodes / areas (from Fig. 2 & Text)
Infrastructure & Security	Investments in High-Tech Infrastructure	Innovative admissions, automated tasks, real-time tools, and deep learning
	Robust Cybersecurity Protocols	Ensuring data privacy, automating tasks securely, and building trustworthy systems are essential.
Human Capacity & Trust	Training for Students & Staff	Innovative teaching, task-driven learning, a smart curriculum, and critical thinking
	Enhancing AI Trustworthiness	Education focused on equity, transparency in ethics, innovative methods of presentation, and fair assessment practices.
Policy & Governance	Clear Ethical AI Policies	Personalised Learning, Identity-Tailored Learning, Interactive Worksheets, Accountability
	Sustainable AI Development	Long-term Institutional Strategy, Environmental & Ethical Responsibility

Furthermore, the limited response rate for sustainable development does not diminish its importance. Instead, it highlights a strategic gap in institutional planning. As AI becomes more embedded, environmental and ethical sustainability will become non-negotiable dimensions of responsible educational practice.

4.8.4 Integrative insight from table 2 (Network analysis)

Table 2 illustrates the interconnected nature of this AI ecosystem by mapping the primary solution categories to the key application areas they influence. This structured overview demonstrates that effective implementation does not occur in isolated domains but rather within a highly interconnected system. The solutions proposed in Fig. 3 (e.g., infrastructure, training, policy) serve as cross-cutting enablers.

Importantly, Table 2 shows that hub applications, such as innovative teaching, task-driven learning, and automated tasks, rely on multiple enabler categories to function effectively. Therefore, solving one issue (e.g., training) without addressing others (e.g., cybersecurity or policy gaps) will result in limited or fragmented success.

The juxtaposition of Fig. 3; Table 2 demonstrates that viable solutions are not standalone interventions but rather part of a cohesive ecosystem strategy. From a theoretical standpoint, the technology acceptance model emphasises ease of use, usefulness, and facilitating conditions as drivers of adoption, whereas the AI Ethics Framework stresses the importance of grounding this adoption in ethical integrity, equity, and sustainability.

Thus, successful AI integration in higher education requires synchronising technical enablers with ethical foresight to ensure that innovation is scalable and socially responsible.

5 Discussion

The findings of this study, anchored in a pre-generative AI (pre-2022) baseline, provide a crucial lens for examining the enduring and emergent challenges of AI integration in higher education. By applying our integrated TAM–AI Ethics framework, the analysis moves beyond cataloguing drivers and barriers to reveal the systemic interdependencies that shape adoption. This discussion interprets these findings through three interrelated themes: (1) the validation and amplification of core challenges in the generative AI era, (2) the critical role of Ethical Readiness as a mediating construct, and (3) the implications for equitable, institutionally-grounded implementation.

5.1 Pre-2022 foundations and post-2022 amplification: ethical and infrastructural constants

Our 2021 data captured institutional readiness at a pivotal juncture, revealing barriers, ethical opacity, infrastructural deficits, and policy gaps that were prescient rather than obsolete. The subsequent rapid proliferation of large language models (LLMs) like ChatGPT has not rendered these concerns obsolete but has dramatically amplified their urgency and complexity [2, 26]. For instance, the pre-generative AI concern over "algorithmic unfairness" [43] has evolved into acute debates about bias and hallucination in LLMs, directly impacting their reliability for assessment and feedback [6, 20]. Similarly, the identified driver of "personalised learning" has been supercharged by generative AI's interactive capabilities, yet this intensifies pre-existing ethical dilemmas around data privacy, intellectual property, and the ethical sourcing of training data [8].

This amplification underscores that the technological context is accelerative, but the underlying socio-technical and ethical prerequisites for responsible adoption are constant. The infrastructural and digital literacy gaps highlighted by participants, particularly in underrepresented regions, have become even more consequential, creating a risk of a "generative AI divide" that exacerbates global educational inequity. Thus, our pre-2022 findings serve not as a historical snapshot but as a diagnostic framework for the core institutional capacities needed to navigate the current, more complex landscape.

5.2 Advancing theory: "ethical readiness" as the crucial mediator

The primary theoretical contribution of this study is the introduction and validation of "Ethical Readiness" as a necessary mediating construct between the intention to use AI and its responsible adoption. This construct directly addresses the critical gap identified in the literature between models of behavioural acceptance (TAM) and frameworks for normative governance (AI Ethics) [10, 29].

Our findings demonstrate that high perceived usefulness (PU) and ease of use (PEOU), such as for personalised learning or administrative automation, do not automatically translate into adoption. Instead, this pathway is actively mediated by an institution's systemic capacity for transparency, fairness, privacy, and accountability. For example, enthusiasm for AI-driven analytics for student retention (PU) was tempered by concerns over surveillance and data misuse, a barrier directly tied to low ethical readiness in privacy and accountability. This evidence allows us to advance TAM by integrating a necessary precondition: positive behavioural intentions (Attitude → Intention to Use) must pass through the filter of institutional Ethical Readiness to result in Actual, Responsible Adoption.

This integrated model provides a more complete and realistic explanation for the "adoption gap" in higher education. It posits that failed or problematic AI integration is often not a failure of perceived utility but a failure of ethical and institutional preparedness. By making this mediating role explicit, the framework offers a diagnostic tool for institutions and a new model for researchers, moving the field beyond the question of "Will they use it?" to the more critical question of "Are they ready to use it well?"

5.3 From diagnosis to action: implications for equitable implementation

The study's Cross-Cultural findings, with deliberate representation from the Gulf region and other contexts, highlight that barriers and solutions are not universally uniform

but are refracted through local infrastructural realities and cultural values. In resource-constrained contexts, the barrier of "inadequate infrastructure" is primary, making even basic adoption a challenge. In contrast, in regions with stronger infrastructure, barriers related to "ethical governance" and "academic integrity" in the face of generative AI dominate the discourse [5, 35]. This disparity necessitates a tiered, context-sensitive approach to implementation, as reflected in our participants' solutions.

Therefore, the prescribed solutions, investment in infrastructure, capacity-building, and ethical policy frameworks, must be understood as interconnected components of building systemic Ethical Readiness. Isolated technical training will fail without concomitant policy development, and top-down ethical guidelines will remain inert without the infrastructural capacity to enact them. The network analysis presented in the findings visually reinforces this ecosystem view, showing how solutions like "staff training" and "cybersecurity protocols" are linked to multiple application nodes (e.g., innovative teaching, automated tasks).

Consequently, for practitioners and policymakers, the imperative is to move from ad-hoc tool adoption to strategic institutional capacity-building. This aligns with international calls for governance-aware AI integration (UNESCO, [30, 46]) but provides a concrete, operational model of the Ethical Readiness construct to guide that process. Future initiatives must be designed not just to demonstrate AI's usefulness but to concurrently build the ethical, pedagogical, and technical foundations that make its use sustainable and just.

6 Implications

The implications of this study can be summarised and categorised into institutional practices, policy development, and future research directions:

6.1 Tiered recommendations for implementation

To bridge the gap between ideal solutions and actionable implementation, especially in under-resourced contexts, we propose a tiered, phased approach:

- Institutional Level: Begin with low-stakes, high-impact initiatives such as AI literacy workshops for staff and pilot projects in administrative tasks (e.g., automated scheduling, feedback systems). This builds foundational capacity without overwhelming infrastructure.
- Policy Level: Develop adaptable ethical guidelines informed by international frameworks (e.g., UNESCO, OECD) but localised to regional legal, cultural, and resource realities. Policy should be iterative, allowing for revision as AI-powered tools evolve.
- Pedagogical Level: Promote AI-human co-teaching models where AI supports rather than replaces educators. This encourages ethical, reflective use of AI in curriculum design, assessment, and personalised learning, ensuring pedagogical values remain central.

This tiered structure acknowledges constraints while providing a scalable pathway toward responsible AI integration.

6.2 Institutional practice

This study demonstrates the potential for AI to improve educational outcomes. AI personalises learning, adapts teaching, and optimises administrative processes. For example, AI can enhance student learning, particularly in curriculum development and student engagement.

Additionally, AI can predict and mitigate student dropout rates. Therefore, it enhances student retention, especially in online education settings where dropout rates are higher. Therefore, institutions should adopt AI-driven tools to enhance their educational offerings.

Furthermore, the rapid advancement of AI in educational settings worldwide necessitates the integration of AI-revised curricula. Particularly in technical fields like the humanities and social sciences, where AI's impact is growing, this integration is vital.

Institutions should establish dedicated AI Ethics Boards, as seen in models emerging in European universities, to oversee implementation. Furthermore, the rapid advancement of AI necessitates the integration of AI-revised curricula, drawing inspiration from national initiatives like Finland's 'Elements of AI' course, which successfully promotes widespread public AI literacy through a free, accessible online platform.

6.3 Policy development

To ensure feasibility, such frameworks should be phased and context-sensitive, prioritising immediate governance needs (e.g., data privacy protocols) while planning for longer-term ethical oversight mechanisms. These frameworks should promote transparency in AI decision-making. They should also guard against biases that could deepen existing inequalities by setting clear rules for data use [20].

Furthermore, this paper emphasises the need for better technological infrastructure to implement AI effectively in higher education. It is essential to prioritise funding and resources to build the infrastructure needed for widespread, successful AI use. Investing in digital infrastructure, such as data management systems and robust cybersecurity measures, will help ensure the safe and effective development of AI applications.

6.4 Future research directions

This study presents many approaches for further research on AI in educational settings. A key topic is how cultural contexts impact the acceptance and effectiveness of AI in diverse educational settings. Long-term studies could help us understand the advantages and disadvantages of AI over time. Tracking its impact on educational results would be valuable.

Future research should explore a broader range of issues beyond the specific focus of this study. This will aid in comprehending the Cross-Cultural application of AI in higher education. The difficulty in recruiting participants in Oman highlights the importance of cultural considerations in the adoption of AI.

In conclusion, cooperation among organisations, decision-makers, and researchers will be necessary to overcome obstacles and capitalise on AI's potential. This study provides a comprehensive understanding of the motivators, obstacles, and potential remedies.

6.5 The policy recommendations are actionable and tiered

Institutional Level: Establish *AI Ethics Boards* in universities and include *AI literacy training* for academic staff.

Policy Level: Propose *national AI education strategies* integrating UNESCO principles but localised for cultural realities.

Pedagogical Level: Suggest *AI-human co-teaching models* to promote ethical, reflective use of generative AI in classrooms.

7 Limitations

A limitation of this paper is its small sample size. The purposive-convenience sample (n = 47) limits global generalisability. Findings are particularly reflective of resource-constrained and Gulf-region contexts and should not be extrapolated to all educational systems without further validation. The sample size may impact its capacity to generalise to a broader population.

The 2021 data collection period, while providing a valuable pre-generative AI baseline, means the specific quantitative findings (e.g., percentage distributions of drivers and barriers) reflect the technological and perceptual landscape of that time. The rapid proliferation of LLMs after 2022 has dynamically altered variables such as perceived ease of use, amplified academic integrity concerns, and reshaped the discourse around personalisation. Therefore, this study offers a snapshot of a pivotal transitional phase; its primary contribution lies in identifying structural and ethical constants that persist, rather than in providing directly transferable statistical metrics for the current LLM-dominated environment.

Future research could benefit from quantitative supplements, such as regression or correlation analysis, to test the statistical significance and predictive strength of identified drivers and barriers, even though this study used a qualitative approach to investigate AI integration in higher education. This would enhance the empirical robustness and generalizability of the findings to larger populations.

The structure and significance of the patterns found align with more recent studies on AI in educational settings, despite the data being gathered in 2021 (e.g., UNESCO, [46]; OECD, 2023). Despite acknowledging this historical gap as a drawback, the results continue to highlight persistent issues and strategic objectives in international AI integration initiatives.

8 Conclusion

In conclusion, AI holds considerable potential for enhancing higher education when used ethically and in a contextually appropriate manner. It can encourage diversity, support learning objectives, and increase administrative effectiveness when implemented within robust governance frameworks.

Transparency, algorithmic bias, and data privacy are additional issues that require proper handling. The incorporation of AI, for example, presents significant ethical problems. If not adequately regulated and monitored, unregulated AI-driven platforms could exacerbate existing disparities, particularly in under-resourced areas.

This study highlights the need for international frameworks that prioritise inclusivity, equity, and transparency. The absence of such frameworks may constrain AI's potential and exacerbate existing disparities. Educational institutions, regardless of their current

resources and capacities, must therefore acquire sufficient training and support to effectively leverage the benefits of AI.

Likewise, the AI Ethics Frameworks and the Technology Acceptance Model (TAM) provide a clearer understanding of the study's conclusions. According to the TAM, the adoption of AI-enhanced systems depends on how beneficial and simple people perceive it to be. Additionally, the AI Ethics Framework highlights key concerns, including fairness, transparency, and privacy. Taken together, these frameworks provide a systematic approach to understanding the factors that both encourage and hinder the adoption of AI-enhanced systems.

The long-term effects of AI in educational settings may remain uneven without a robust theoretical and ethical foundation, particularly in resource-poor contexts. Therefore, it is crucial to create legal frameworks that prioritise ethical AI techniques. Ultimately, to realise AI's potential inclusively and equitably, legislators, educators, and engineers must cooperate.

By combining the AI Ethics Framework and the Technology Acceptance Model (TAM), this study offers a unique dual-framework approach that provides a multifaceted view of AI integration in higher education. This theoretical synthesis enables the analysis of the implementation of AI-enhanced systems from both functional and ethical standpoints, which is uncommon in current research. As a result, the framework offers a reproducible model for further research in other educational settings.

'Ethical Readiness' is the mediating institutional capacity defined above (ensuring AI deployment is transparent, fair, privacy-compliant, and accountable). Facilitating conditions refer to institutional or policy-level supports that enable or hinder the adoption of digital technologies, including digital infrastructure, governance, and training provisions.

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Data availability
All data generated or analysed during this study are available and will be provided based on request.

Declarations

Ethics approval and consent to participate
Ethical approval for this study was granted by the Research Ethics Committee at the National University of Science and Technology, Oman (Approval ID: REC/NUST/AIED/2021/04). The committee operates in accordance with the Declaration of Helsinki and international ethical standards for research involving human participants.

Consent for publication
Not applicable. The manuscript does not contain any person's data in any form (including any individual details, images, or videos).

Informed consent
Informed consent was obtained from all individual participants included in the study. Consent was obtained digitally via the Office 365 Forms platform prior to survey submission, during which participants acknowledged their understanding of the study's aims, data use, and anonymity guarantees.

Competing interests
The authors declare no competing interests.

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