Tuning Journal for Higher Education

Volume 12, Issue No. 2, November 2026
DOI: https://doi.org/10.18543/tjhe1222026

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ARTICLES

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doi: https://doi.org/10.18543/tjhe.2686

Received: 28 March 2023
Accepted: 5 May 2026
E-published: November 2026

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Artificial intelligence in higher education: A foundational analysis of drivers, barriers, and solutions

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doi: https://doi.org/10.18543/tjhe.2686

Received: 28 March 2023
Accepted: 5 May 2026
E-published: November 2026

Abstract: This foundational study provides an empirical baseline for the drivers and barriers influencing the adoption of artificial intelligence (AI) in higher education across diverse cultural contexts. Drawing on 2021 survey data from 47 educators, administrators, and policymakers across 26 countries, the research employs thematic analysis to systematically map adoption dynamics before the generative AI era. The findings identify personalised learning (12.3% of driver mentions), teaching efficacy (9.2%), and innovative teaching models (8.4%) as the most frequently cited drivers for AI adoption. However, significant barriers persist, including a lack of AI expertise (cited by 38 respondents), inadequate technological infrastructure (33 respondents), and unresolved ethical concerns such as data privacy and algorithmic bias. The analysis reveals stark disparities between well-resourced and under-resourced institutions, highlighting infrastructure deficits and limited technical capacity as

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Acknowledgements: The corresponding author acknowledges the collaboration and assistance of his PhD supervisor, Dr Beatriz Villarejo, in preparing the manuscript.

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of interest: The authors declare no conflict of interest regarding the material presented in the manuscript.

particularly acute in developing contexts. Proposed solutions encompass investment in high-tech infrastructure, comprehensive training programmes, robust cybersecurity protocols, and clear ethical governance frameworks aligned with transparency, fairness, and accountability principles. This empirical investigation serves as a baseline study, documenting foundational patterns that subsequently informed the theoretically integrated analysis published by Slimi and Villarejo Carballido (2026), which applies the Technology Acceptance Model and the AI Ethics Framework and introduces "Ethical Readiness" as a novel mediating construct. The study concludes that without targeted investment in infrastructure, capacity-building initiatives, and context-sensitive regulatory frameworks, AI's transformative potential may remain unrealised, particularly in under-resourced regions, exacerbating existing educational inequities and widening the global digital divide.

Keywords: Artificial intelligence; higher education; AI adoption; empirical baseline study; cross-cultural perspectives; infrastructure; digital divide.

I. Introduction

This study provides an empirical mapping of the drivers and barriers influencing the adoption of artificial intelligence (AI) in higher education across diverse cultural contexts.[3] Specifically, it investigates how AI is perceived to enhance personalised learning and administrative efficiency, while also documenting the ethical and infrastructural challenges that accompany its adoption.[4] By capturing these dynamics across 26 countries before the widespread adoption of generative AI tools, this research establishes a foundational baseline dataset against which subsequent developments in AI-enabled education can be measured.

The study addresses a critical gap in the literature. While theoretical discussions of AI in education have proliferated, systematic empirical documentation of cross-cultural adoption patterns, particularly in underrepresented regions, remains limited.[5] This investigation addresses that gap by providing observational data on how educators, administrators, and

[3] For foundational discussions of AI in educational contexts, see Rosemary Luckin et al., *Intelligence Unleashed: An Argument for AI in Education* (London: Pearson, 2016).

[4] On the transformative potential of AI in higher education administration, see I. Roll and R. Wylie, "Evolution and Revolution in Artificial Intelligence in Education," *International Journal of Artificial Intelligence in Education* 26, no. 2 (2016): 582–599.

[5] The underrepresentation of non-Western contexts in AI in education research is noted by Olaf Zawacki-Richter, Victoria I. Marín, Melissa Bond, and Franziska Gouverneur, "Systematic Review of Research on Artificial Intelligence Applications in Higher Education—Where Are the Educators?" *International Journal of Educational Technology in Higher Education* 16 (2019): art. 39.

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doi: https://doi.org/10.18543/tjhe.2686 • http://www.tuningjournal.org/

policymakers across diverse institutional contexts perceive the opportunities and constraints shaping AI adoption.

The findings presented here serve as the empirical foundation for the complementary study by Slimi and Villarejo Carballido, which develops a theoretically integrated analysis applying the Technology Acceptance Model (TAM) and the AI Ethics Framework to explain the psychological and institutional mechanisms underlying these observed patterns.[6] The present study thus functions as the "observational map," systematically documenting the landscape of AI adoption. The complementary study provides the "theoretical compass," offering theoretical synthesis through an "Ethical Readiness" mediating construct.

Since its emergence as a research field in the 1950s, AI has evolved into a field with broad applications, transforming traditional practices in higher education.[7] For example, it enables more flexible and personalised learning environments, automates administrative tasks such as scheduling and grading, and enhances management for educators and students alike.[8] AI also supports admissions, learning, and training services by optimising resource allocation. Scholars argue that AI has considerable potential to transform education.[9] However, despite its promise, AI adoption in higher education has been slower than expected, with major barriers related to ethical concerns, including data privacy, algorithmic bias, and institutional readiness.[10]

This study pursues three interrelated empirical objectives:

1. To identify and categorise the primary drivers shaping AI adoption across diverse higher education contexts.

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[6] Zouhaier Slimi and Beatriz Villarejo Carballido, "A Dual-Framework Analysis of Artificial Intelligence Adoption in Cross-Cultural Higher Education," *Discover Education* 5, no. 1 (2026): art. 406, https://doi.org/10.1007/s44217-026-01415-y.

[7] For historical context on AI development, see Wayne Holmes, Maya Bialik, and Charles Fadel, *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning* (Boston: Center for Curriculum Redesign, 2019); for a philosophical perspective, see Luciano Floridi, *The Logic of Information: A Theory of Philosophy as Conceptual Design* (Oxford: Oxford University Press, 2019).

[8] Anthony Seldon and Oladimeji Abidoye, and Timothy Metcalf, *The Fourth Education Revolution Reconsidered: Will Artificial Intelligence Enrich or Diminish Humanity?* (Buckingham: University of Buckingham Press, 2020).

[9] Luckin et al., *Intelligence Unleashed*.

[10] Víctor González-Calatayud, Paz Prendes-Espinosa, and Rosabel Roig-Vila, "Artificial Intelligence for Student Assessment: A Systematic Review," *Applied Sciences* 11, no. 12 (2021): art. 5467; Wayne Holmes et al., "Ethics of AI in Education: Towards a Community-Wide Framework," *International Journal of Artificial Intelligence in Education* 32, no. 3 (2022): 504–526.

2. To document the structural, infrastructural, and ethical barriers impeding AI adoption; and
3. To map proposed solutions as articulated by educational stakeholders operating across different institutional and cultural settings.

In pursuing these objectives, the study contributes a systematically documented empirical baseline. This baseline captures AI adoption dynamics at a pivotal transitional moment following the initial wave of AI adoption in education but preceding the disruptive entry of large language models in late 2022.[11] As such, these findings provide a valuable historical benchmark for understanding how foundational adoption patterns have subsequently evolved.

II. Literature review: Situating the empirical inquiry

This review briefly contextualises the empirical investigation within existing scholarship on AI in higher education.[12] Rather than reproducing the exhaustive theoretical analysis developed in the complementary study, this section identifies key themes in the literature that inform the present study's empirical focus.

II.1. The emergent role of AI in higher education

Contemporary studies emphasise the increasing role of AI in higher education, stressing its potential to enhance learning outcomes and streamline administrative tasks.[13] Menkhoff and Teo's experiential chatbot workshop, for instance, demonstrates AI's value in helping non-STEM students acquire essential skills, suggesting that AI aligns with broader educational objectives.[14] However, the scalability of such initiatives across disciplines and educational contexts remains empirically under-examined; the present study addresses this gap through cross-cultural data collection.

Katsuragi and Tanaka explore AI applications to improve online student retention, developing a machine-learning model that predicts dropout

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[11] On the significance of the 2022 transition point, see Chung Kwan Lo, "What Is the Impact of ChatGPT on Education? A Rapid Review of the Literature," *Education Sciences* 13, no. 4 (2023): 410.

[12] Holmes, Bialik, and Fadel, *Artificial Intelligence in Education*.

[13] Zawacki-Richter et al., "Systematic Review of Research."

[14] Thomas Menkhoff and Y. Q. L. Teo, "Engaging Undergraduate Students in an Introductory AI Course through a Knowledge-Based Chatbot Workshop," in *ACM International Conference Proceeding Series* (New York: ACM, 2022), 119–125.

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doi: https://doi.org/10.18543/tjhe.2686 • http://www.tuningjournal.org/

rates.[15] This exemplifies AI's potential to proactively mitigate student disengagement. Yet the effectiveness of such data-driven models depends on robust data infrastructures, which many educational institutions lack, particularly in under-resourced contexts. Documenting these infrastructural disparities constitutes a central aim of this investigation.

II.2. Documented barriers to AI adoption

Teuscher argues that, despite its promise, AI adoption presents significant challenges, particularly as the rapid pace of AI advancements outstrips educational institutions' ability to adapt curricula accordingly.[16] Similarly, Seo designs a big data-based platform that recommends software education curricula tailored to individual learners; however, such data-driven personalisation raises concerns about the accuracy and fairness of automated recommendations.[17]

Shopland et al. report initial survey findings on the limited inclusion of students with disabilities in higher education in India and Bangladesh, and propose accessible open educational resources and AI-based personalisation to support learners facing barriers. At the same time, Xie and Chen emphasise AI's limitations in automated assessment systems, particularly for complex language tasks.[18] These documented challenges provide empirical motivation to systematically investigate how stakeholders across diverse institutional contexts perceive and navigate such barriers.

Collectively, these studies show that technical, pedagogical, and ethical barriers are interdependent and cannot be resolved independently. Prior

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[15] M. Katsuragi and K. Tanaka, "Dropout Prediction by an Interpretable Machine Learning Model towards Preventing Student Dropout," in *Advances in Transdisciplinary Engineering*, vol. 28 (Amsterdam: IOS Press, 2022), 678–683.

[16] Christof Teuscher, "A Golden Age for Computing Frontiers, a Dark Age for Computing Education?" in *Proceedings of the 18th ACM International Conference on Computing Frontiers* (New York: ACM, 2021), 140–143.

[17] J. H. Seo, "Big Data-Based SW Education Curriculum Recommendation Platform Design for Learners," *Journal of Theoretical and Applied Information Technology* 100, no. 16 (2022): 4971–4978.

[18] Nicholas Shopland et al., "Improving Accessibility and Personalisation for HE Students with Disabilities in Two Countries in the Indian Subcontinent – Initial Findings," in *Universal Access in Human-Computer Interaction: User and Context Diversity, Lecture Notes in Computer Science*, vol. 13309 (Cham: Springer, 2022), 110–122; B. Xie and L. Chen, "Automatic Scoring Model of Subjective Questions Based on a Text Similarity Fusion Model," in *Lecture Notes in Electrical Engineering*, vol. 942 (Singapore: Springer, 2022), 58–67.

research has examined these barriers in isolation; this study investigates how they manifest differently across contexts.

II.3. The empirical gap

The literature reveals a consistent pattern: while theoretical discussions of AI's potential and risks are well developed, systematic empirical documentation of cross-cultural adoption patterns, particularly those that capture perspectives from underrepresented regions, remains limited.[19] This study directly addresses that gap by providing observational data that maps how drivers, barriers, and solutions manifest across 26 countries, thereby establishing an empirical foundation for subsequent theoretical synthesis.

II.4. Theoretical frameworks guiding this investigation

While this study functions primarily as an empirical baseline investigation, two complementary theoretical frameworks informed the research design and interpretive lens: the Technology Acceptance Model (TAM) and the AI Ethics Framework.

II.4.1. Technology Acceptance Model (TAM)

Developed by Davis,[20] TAM posits that technology adoption is primarily determined by two perceptual factors: perceived usefulness (the degree to which an individual believes technology enhances performance) and perceived ease of use (the degree to which an individual believes technology is effortless to use). TAM has been extensively validated across educational technology contexts and provides a useful lens for understanding how stakeholders' perceptions of AI's utility and complexity shape adoption intentions. In this study, TAM informed the development of open-ended prompts exploring drivers (reflecting perceived usefulness) and barriers (reflecting perceived ease of use and external constraints).

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[19] Neil Selwyn, *Should Robots Replace Teachers? AI and the Future of Education* (Cambridge: Polity Press, 2019); see also Zouhaier Slimi and Beatriz Villarejo Carballido, "Systematic Review: AI's Impact on Higher Education Learning, Teaching, and Career Opportunities," *TEM Journal* 12, no. 3 (2023): 1627–1637.

[20] Fred D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly* 13, no. 3 (1989): 319–340.

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II.4.2. AI Ethics framework

Building on scholarship examining algorithmic fairness, transparency, and accountability,[21] the AI Ethics Framework emphasises that responsible technology adoption requires attention to ethical principles throughout the implementation process.[22] Key dimensions include:

- *Transparency*: clarity about how AI systems make decisions
- *Fairness*: mitigation of algorithmic bias and equitable outcomes
- *Privacy*: protection of stakeholder data
- *Accountability*: clear responsibility for AI-mediated decisions

These ethical dimensions directly informed the study's investigation of barriers and solutions, particularly in probes regarding data governance, ethical concerns, and regulatory frameworks.

The conceptual framework guiding this investigation is illustrated in Figure 1 in the Appendix.

II.4.3. The empirical-theoretical distinction

This study does not *test* these frameworks, which is the purpose of the complementary study by Slimi and Villarejo Carballido. Rather, the frameworks served as *sensitising concepts* that guided data collection and provided an initial interpretive structure.[23] The present study thus provides the empirical observations that enable subsequent theoretical integration and the introduction of an "Ethical Readiness" mediating construct in that complementary analysis.

III. Methods

III.1. Research design

This study employed a qualitative exploratory design complemented by descriptive frequency analysis.[24] The approach was selected to capture

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[21] Holmes et al., "Ethics of AI in Education"; Floridi, *Logic of Information*.

[22] Holmes et al., "Ethics of AI in Education."

[23] Herbert Blumer, "What Is Wrong with Social Theory?" *American Sociological Review* 19, no. 1 (1954): 3–10.

[24] On qualitative research design, see Virginia Braun and Victoria Clarke, "Using Thematic Analysis in Psychology," *Qualitative Research in Psychology* 3, no. 2 (2006): 77–101.

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rich, context-sensitive perspectives on AI adoption while enabling systematic identification of recurring patterns across diverse institutional and cultural settings. Given the study's aim to establish an empirical baseline, qualitative methods were appropriate for surfacing stakeholder perceptions in their own terms. At the same time, frequency analysis provided a structured mechanism for identifying the prevalence of themes. Terminology is standardised throughout: 'drivers/barriers/solutions' denote the three inquiry domains; 'thematic categories' (e.g., Pedagogical Enhancement) group specific items; 'themes' refer solely to analysis-derived patterns.

III.2. Sampling strategy

Participants were recruited through purposive expert sampling targeting academics, institutional administrators, and policy stakeholders engaged in digital transformation initiatives within higher education institutions.[25] Recruitment leveraged professional networks, academic conferences, and institutional partnerships to identify individuals with demonstrated expertise in educational technology or AI applications (minimum five years' higher education experience). Snowball sampling supplemented initial recruitment, with participants invited to nominate qualified colleagues from their professional networks.

The final sample comprised 47 participants (29 male, 18 female) representing diverse professional roles: faculty members (n=24), academic administrators (n=13), and educational policymakers (n=10). Disciplinary backgrounds spanned education, computer science/information technology, engineering, maritime studies, logistics, business administration, and linguistics, ensuring multidisciplinary perspectives.

III.3. Geographical representation

Respondents were drawn from 26 countries across six world regions, including:

- **Middle East and North Africa** (Oman, UAE, Saudi Arabia, Jordan, Egypt, Tunisia, Morocco)

[25] On purposive sampling strategies, see Kate Kelley et al., "Good Practice in the Conduct and Reporting of Survey Research," *International Journal for Quality in Health Care* 15, no. 3 (2003): 261–266.

- **Europe** (Spain, the United Kingdom, Greece, the Netherlands, Italy, and Ireland)
- **Asia** (India, Pakistan, Malaysia, Singapore, Iran)
- **Sub-Saharan Africa** (Nigeria, Ethiopia, South Africa)
- **North America** (United States, Canada)
- **Australasia** (Australia, New Zealand)

The sampling strategy deliberately over-represented the Gulf region (Oman, UAE) to address the underrepresentation of these contexts in AI in education research. At the same time, the broader international sample supports the cross-cultural transferability of the findings.

III.4. Data collection

Data were collected between January and June 2021 using a qualitative survey administered through Office 365 Forms.[26] The survey instrument comprised 15 items: eight closed-ended questions capturing demographic and categorical data, and seven open-ended prompts addressing perceived drivers, barriers, and solutions for AI adoption in higher education. Open-ended prompts included:

- "What do you perceive as the primary drivers for AI adoption in your institutional context?"
- "What barriers have you encountered or anticipate in implementing AI-enabled systems?"
- "What solutions would you recommend addressing these barriers?"

The survey was conducted in English to ensure consistent interpretation across the multinational sample. While this may have introduced self-selection bias towards participants with higher English proficiency, it was necessary given the absence of translation resources and the need for standardised data collection.

Recruitment faced notable challenges, particularly in Oman, due to cultural differences and low interest in participation, resulting in an estimated response rate of approximately 18%. Nevertheless, the diversity of the final participant pool yielded rich and meaningful insights.

[26] For survey methodology, see Kelley et al., "Good Practice."

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III.5. Data analysis

Thematic analysis followed a systematic four-stage process, drawing on established qualitative research frameworks.[27] Frequency analysis employed two metrics: proportion of total mentions (for drivers, capturing discourse intensity) and proportion of participants (for barriers/solutions, capturing concern prevalence).

Stage 1: Open Coding. Two researchers independently reviewed all survey responses to familiarise themselves with the content. Initial codes were generated inductively, capturing specific statements, concerns, and suggestions expressed by participants. Coding was conducted manually with cross-checking to ensure consistency.

Stage 2: Category Development. Initial codes were clustered into conceptual categories based on thematic similarity. For example, codes such as "lack of server capacity," "insufficient bandwidth," and "outdated hardware" were grouped under the category "inadequate technological infrastructure."

Stage 3: Theme Generation. Categories were further synthesised into overarching themes corresponding to the study's three focal areas: drivers, barriers, and solutions. Theme generation involved iterative refinement, with researchers returning to raw data to verify that thematic representations accurately captured participant perspectives.

Stage 4: Frequency Analysis. To assess thematic prevalence, the frequency with which each theme was mentioned across the participant sample was calculated. This provided a structured indication of which drivers and barriers were most salient to respondents, complementing the qualitative depth with descriptive quantification.

Inter-rater reliability was established through independent coding of a 20% subsample, achieving 84% agreement ($\varkappa = 0.78$), indicating substantial consistency.[28] Disagreements were resolved through discussion.

III.6. Ethical considerations

Ethical approval was granted by the Research Ethics Committee at the National University of Science and Technology, Oman (Approval ID: REC/NUST/AIED/2021/04), operating in accordance with the Declaration of

[27] Braun and Clarke, "Using Thematic Analysis," 87–93.

[28] On inter-rater reliability standards, see J. Richard Landis and Gary G. Koch, "The Measurement of Observer Agreement for Categorical Data," *Biometrics* 33, no. 1 (1977): 159–174.

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Helsinki.[29] Informed consent was obtained digitally from all participants before data collection, with participants informed of the study's purpose, data use, and the guarantees of confidentiality. All data were stored securely on encrypted university servers accessible only to the research team.

Cultural variation in ethical norms was acknowledged methodologically. Open-ended prompts allowed respondents to articulate concerns using locally meaningful frameworks; for example, Gulf respondents emphasised community trust and cultural authenticity, while European respondents focused on GDPR compliance and individual privacy rights. This cultural pluralism in interpreting 'ethics' suggests global frameworks must accommodate context-specific norms rather than imposing Western-centric categories.

III.7. Confidentiality

Confidentiality was addressed by assigning each respondent a code number upon completing the survey and using only that code to indicate their responses. This code was entered on each survey, enabling the researcher to link each survey to its respondent. This link allows the survey results to remain confidential without being anonymous to the researcher. The aggregate data reported contain no individually identifiable information, and the coding system masked individual participant identities. Quotations are attributed only by professional role and country; no names, institutions, or other identifying details are reported.

III.8. Methodological limitations

The study's sample size (n=47), while appropriate for qualitative thematic analysis, limits the generalisability of the statistical results.[30] The purposive sampling approach and deliberate over-representation of the Gulf region mean that the findings are particularly reflective of resource-constrained and Middle Eastern contexts; readers should exercise caution when extrapolating to all global regions. Geographic coverage, while broad (26 countries), omits Latin America and most of East and Southeast Asia

[29] World Medical Association, "World Medical Association Declaration of Helsinki: Ethical Principles for Medical Research Involving Human Subjects," *JAMA* 310, no. 20 (2013): 2191–2194.

[30] On sample size in qualitative research, see Greg Guest, Arwen Bunce, and Laura Johnson, "How Many Interviews Are Enough? An Experiment with Data Saturation and Variability," *Field Methods* 18, no. 1 (2006): 59–82.

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(except Malaysia and Singapore). Findings are most reflective of Middle Eastern, European, and Anglophone contexts; transferability to Latin America, East Asia, or Francophone Africa requires further validation.

Additionally, the 2021 data collection period provides a valuable baseline for pre-generative AI. However, the rapid evolution of AI technologies since 2022 means that specific quantitative distributions should be interpreted as reflecting that transitional period rather than the current landscape.

IV. Findings

Thematic analysis of participant responses revealed three overarching categories: drivers facilitating AI adoption, barriers impeding adoption, and solutions proposed by stakeholders. This section presents findings organised by these thematic domains, with descriptive frequencies indicating the prevalence of each theme across the participant sample.

IV.1. Drivers for AI adoption in higher education

Analysis of driver-related responses yielded five thematic categories, with personalised learning emerging as the most frequently cited motivation. Table 1 presents the complete distribution.

The complete distribution of driver categories and frequencies is presented in Table 1 in the Appendix.

IV.1.1. Pedagogical drivers: Personalised learning as primary motivation

Personalised learning emerged as the most frequently cited driver, accounting for 12.3% of all driver mentions. Participants emphasised AI's capacity to adapt educational content to individual learner needs, pacing, and preferences. A faculty member from Spain noted, "The one-size-fits-all model is obsolete. AI enables us to create learning pathways that respond to each student's progress in real time." This perspective was echoed across institutional types, suggesting a broad consensus on AI's pedagogical potential.[31]

Teaching efficacy (9.2%) was the second most frequently cited driver, reflecting expectations that AI would improve teaching effectiveness through real-time feedback. Innovative teaching models (8.4%) and engagement-focused applications (6.0%) were also prominent. Respondents highlighted

[31] Holmes, Bialik, and Fadel, *Artificial Intelligence in Education*.

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AI's ability to support gamification, simulation-based learning, and interactive content delivery. However, several participants cautioned that these applications require substantial faculty development to implement effectively.

IV.1.2. Institutional drivers: Efficiency and strategic positioning

Administrative efficiency (3.9%) and student retention (1.3%) represented key institutional motivations. A UK-based administrator explained: "Our admissions team spends countless hours on routine queries. AI chatbots have dramatically reduced that burden while improving applicant experience." Predictive analytics for retention were similarly valued, though participants noted these applications depend on robust data infrastructures.[32]

Strategic positioning (6.3%) emerged as a distinctive driver among institutions in competitive international markets. An Australian administrator observed, "Students increasingly expect AI-enabled services. Institutions that fail to deliver risk losing market share."

IV.1.3. Competency and equity drivers: Preparing students and expanding access

Technological skill development (6.5%) and lifelong learning (8.4%) reflected concern for student preparedness.[33] An Indian faculty member stated, "If we're not integrating AI into our curriculum, we're failing our students; they'll enter workplaces where AI is ubiquitous." Affordability and accessibility (5.2%) were mentioned primarily by respondents from under-resourced contexts, who viewed AI as potentially democratising access to quality education.

IV.2. Barriers to AI adoption in higher education

Barrier-related responses clustered into four thematic categories, with expertise and infrastructure deficits most frequently cited. Table 2 presents the complete distribution.

Table 2 in the Appendix presents the full distribution of barrier categories.

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[32] Katsuragi and Tanaka, "Dropout Prediction."

[33] Davy Tsz Kit Ng, Jac Ka Lok Leung, Samuel Kai Wah Chu, and Maggie Shen Qiao, "Conceptualizing AI Literacy: An Exploratory Review," *Computers and Education: Artificial Intelligence* 2 (2021): art. 100041.

IV.2.1. Capacity deficits: The expertise and infrastructure gap

The most significant barriers identified were a lack of AI expertise (38 respondents, 80.9%) and inadequate technological infrastructure (33 respondents, 70.2%).[34] These deficits were particularly acute in under-resourced institutions. An Omani administrator explained: "We have the institutional will, but we lack people who can lead AI implementation. Our IT team is skilled in basic systems, not machine learning." A Nigerian faculty member similarly noted: "Before we can talk about AI, we need reliable electricity and internet. Those basics aren't guaranteed."

IV.2.2. Data governance: Quality and integration challenges

Data-related barriers were cited by more than half of respondents, with 28 (59.6%) highlighting poor data governance and integration, and 13 (27.7%) noting a lack of high-quality datasets.[35] A Jordanian administrator described fragmented systems: "Admissions data, academic records, financial aid, they're in separate databases that don't communicate. AI needs integrated data." These governance deficits were linked to concerns about algorithmic bias and the transparency of decision-making.

IV.2.3. Ethical and regulatory gaps

Ethical concerns (53.2%) and lack of public policy (40.4%) represented significant barriers.[36] A Dutch policymaker articulated the transparency problem: "Commercial AI tools are black boxes. We don't know what data they collect or how they reach decisions. In education, that's unacceptable." Respondents from countries without national AI strategies expressed particular concern about ad hoc, inconsistent approaches to AI governance.

IV.2.4. Cross-cultural disparities in AI adoption capacity

Analysis revealed systematic differences between well-resourced and under-resourced institutional contexts.[37] Respondents from high-income

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[34] These findings are consistent with concerns raised in Teuscher, "Golden Age."

[35] On data governance challenges, see Ben Williamson and Rebecca Eynon, "Historical Threads, Missing Links, and Future Directions in AI in Education," *Learning, Media and Technology* 45, no. 3 (2020): 223–235.

[36] These findings echo concerns raised in González-Calatayud, Prendes-Espinosa, and Roig-Vila, "Artificial Intelligence for Student Assessment."

[37] On global disparities, see UNESCO, *AI and Education: Guidance for Policymakers* (Paris: UNESCO, 2021).

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doi: https://doi.org/10.18543/tjhe.2686 • http://www.tuningjournal.org/

countries (e.g., Greece, Canada, Australia) primarily cited ethical and regulatory barriers, while those from lower-income contexts (e.g., Nigeria, Iran, Morocco) emphasised infrastructure deficits and lack of expertise. A South African policymaker observed: "The global conversation about AI ethics assumes basic infrastructure exists. In many contexts, we're still building that foundation. The digital divide isn't closing, it is widening."

IV.3. Proposed solutions to adoption barriers

Participants proposed solutions spanning infrastructure, human capacity, and governance domains. Table 3 in the Appendix presents the distribution.

Participants emphasised that solutions must be integrated rather than siloed.[38] An Australian administrator noted: "Investment in infrastructure without training is wasted. Training without governance is dangerous. We need a holistic approach." A Malaysian policymaker reinforced this perspective: "The solution isn't just buying AI tools; it's building institutional capacity to use them responsibly."

IV.4. Summary of empirical patterns

The findings reveal three overarching patterns:

1. **Drivers are predominantly pedagogical and strategic**, with personalised learning, teaching efficacy, innovative teaching models, and lifelong learning most frequently cited.
2. **Barriers are primarily structural and capacity-related**, with expertise deficits and inadequate infrastructure outpacing ethical concerns in frequency, though ethical considerations were deeply felt.
3. **Proposed solutions emphasise systemic capacity-building**, with infrastructure, training, and governance viewed as interconnected prerequisites for responsible adoption.

These patterns exhibit systematic variation across institutional contexts, with under-resourced settings facing more fundamental capacity constraints while well-resourced institutions grapple with ethical and governance

[38] OECD, *OECD Digital Education Outlook 2021: Pushing the Frontiers with Artificial Intelligence, Blockchain and Robots* (Paris: OECD Publishing, 2021).

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doi: https://doi.org/10.18543/tjhe.2686 • http://www.tuningjournal.org/

challenges.[39] This cross-cultural disparity constitutes a central finding with implications for global AI equity.

V. Discussion

This study provides an empirical baseline mapping of the drivers, barriers, and solutions shaping AI adoption in higher education across 26 countries. The findings illuminate systematic patterns while revealing critical disparities between well-resourced and under-resourced institutional contexts. This discussion interprets these empirical patterns, situates them within the broader literature, and articulates their implications for policy and practice.

V.1. Interpreting the driver landscape

The predominance of personalised learning as a driver (12.3%) aligns with existing scholarship positioning learner-centred education as a central promise of AI adoption.[40] However, the findings extend this understanding by revealing that enthusiasm for personalisation is tempered by infrastructural realities. Respondents from under-resourced institutions expressed concern that personalised learning applications remain aspirational in the absence of foundational investment in digital infrastructure and faculty development.

The emphasis on administrative efficiency (3.9%) and strategic positioning (6.3%) reflects institutional pressures in an increasingly competitive global higher education market.[41] This finding corroborates analyses of data-driven business models in educational technology, while adding cross-cultural specificity: strategic drivers were more pronounced among respondents from institutions actively competing for international students, particularly in Australia, the UK, and the Gulf region.[42]

Notably, technological skill development (6.5%) and lifelong learning (8.4%) emerged as frequently cited drivers, suggesting that stakeholders

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[39] United Nations, *Our Common Agenda: Policy Brief 5 – A Global Digital Compact – An Open, Free and Secure Digital Future for All* (New York: United Nations, 2023).

[40] Luckin et al., *Intelligence Unleashed*; Holmes, Bialik, and Fadel, *Artificial Intelligence in Education*.

[41] André Renz and Romy Hilbig, "Prerequisites for Artificial Intelligence in Further Education: Identification of Drivers, Barriers, and Business Models of Educational Technology Companies," *International Journal of Educational Technology in Higher Education* 17, no. 1 (2020): art. 14.

[42] Renz and Hilbig, "Prerequisites."

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view AI not merely as an operational tool but as integral to graduate preparedness.[43] This finding supports arguments that AI literacy constitutes an emerging core competency, while highlighting a potential equity concern: if AI literacy becomes a graduate attribute, institutions lacking capacity to develop such literacy may further disadvantage their students in the labour market.[44]

V.2. Understanding the barrier structure

The finding that lack of AI expertise (80.9%) and inadequate infrastructure (70.2%) constitute the most frequently cited barriers provides empirical confirmation of concerns raised in the literature.[45] However, the data reveal important nuance: these barriers are not uniformly distributed. For respondents from high-income contexts, ethical and regulatory gaps were primary concerns; for those from lower-income settings, basic infrastructural deficits dominated.

Taken together, these contrasts indicate that the global AI adoption landscape is characterised by multiple, qualitatively different challenges rather than a single hierarchy of barriers. Institutions in Nigeria, Iran, and Ethiopia face preconditions that institutions in Greece, Canada, and Australia have already resolved. The implication is stark: without targeted intervention, AI may exacerbate rather than ameliorate existing educational inequalities.[46]

Ethical concerns (53.2%) and data governance challenges (59.6%) were also widely cited, confirming the salience of transparency, privacy, and fairness considerations documented in prior work.[47] Notably, participants expressed these concerns across institutional types, suggesting they represent enduring challenges that transcend local context. However, the absence of clear public policy (40.4%) was particularly acute in countries without

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[43] Ng et al., "Conceptualizing AI Literacy."

[44] On AI literacy as a core competency, see Ng et al., "Conceptualizing AI Literacy"; on its academic integrity implications in the generative AI era, see Deborah R. E. Cotton, Peter A. Cotton, and J. Reuben Shipway, "Chatting and Cheating: Ensuring Academic Integrity in the Era of ChatGPT," *Innovations in Education and Teaching International* 61, no. 2 (2024): 228–239.

[45] Teuscher, "Golden Age"; Seo, "Big Data-Based SW Education."

[46] On AI and inequality, see Virginia Eubanks, *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor* (New York: St. Martin's Press, 2018).

[47] González-Calatayud, Prendes-Espinosa, and Roig-Vila, "Artificial Intelligence for Student Assessment"; Holmes et al., "Ethics of AI in Education."

national AI strategies, leaving institutions to navigate ethical complexities without regulatory guidance.[48]

V.3. Cross-cultural disparities: The widening digital divide

A central contribution of this study is its systematic documentation of cross-cultural variation in AI adoption capacity.[49] The findings reveal a bifurcated landscape: well-resourced institutions confront challenges of optimisation and governance; under-resourced institutions struggle with foundational capacity.

This pattern has profound implications for global educational equity. As AI-enabled educational tools become increasingly central to teaching, learning, and administration, institutions lacking adoption capacity risk falling further behind. The digital divide, long discussed in terms of internet access and hardware, now encompasses algorithmic literacy, data infrastructure, and AI governance capacity.[50] Without deliberate intervention, AI may accelerate a two-tiered system where technologically advanced institutions capture disproportionate benefits while resource-constrained contexts are left to navigate widening gaps.

V.4. Solutions as systemic capacity-building

Participants' proposed solutions—infrastructure investment (21.3%), training (19.1%), cybersecurity (21.3%), and policy development (12.8%)—reflect an understanding that effective AI adoption requires systemic rather than piecemeal approaches.[51] The emphasis on training across stakeholder groups (students, faculty, administrators) aligns with calls for AI competency frameworks, while the prominence of cybersecurity concerns reflects growing awareness of data protection imperatives.[52]

Notably, only 6.4% of respondents mentioned sustainable AI development, suggesting that environmental and long-term ethical sustainability remain peripheral concerns in current discourse.[53] This

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[48] UNESCO, *AI and Education*.

[49] Slimi and Villarejo Carballido, "Dual-Framework Analysis."

[50] On the evolving digital divide, see Jan A. G. M. van Dijk, *The Digital Divide* (Cambridge: Polity Press, 2020).

[51] UNESCO, *AI and Education*.

[52] On data protection in AI in education, see Williamson and Eynon, "Historical Threads."

[53] On AI sustainability, see Kate Crawford, *Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence* (New Haven: Yale University Press, 2021).

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doi: https://doi.org/10.18543/tjhe.2686 • http://www.tuningjournal.org/

represents a potential gap, as AI systems carry significant environmental footprints and raise questions about long-term institutional commitment.

V.5. The foundational contribution: Establishing an empirical baseline

This study's primary contribution lies in its systematic documentation of AI adoption dynamics at a specific historical moment: following initial AI adoption in education but preceding the generative AI explosion of late 2022.[54] As such, these findings provide a baseline against which subsequent developments can be measured. The patterns identified—the centrality of personalised learning, the primacy of expertise and infrastructure barriers, and the cross-cultural disparities in adoption capacity—provide durable reference points for understanding how foundational dynamics have persisted or transformed in the generative AI era.

Building on this empirical foundation, Slimi and Villarejo Carballido developed a dual-framework model integrating the Technology Acceptance Model with an AI Ethics Framework, introducing "Ethical Readiness" as a mediating construct linking behavioural intention to responsible AI adoption.[55] The present study thus provides the observational data upon which that theoretical synthesis is constructed.

VI. Implications

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

VI.1. Institutional practices

Participants' responses point to the perceived potential of AI to improve educational outcomes.[56] Respondents viewed AI as a way to personalise learning, adapt teaching, and optimise administrative processes. For example, AI was seen as able to enhance student learning, particularly in curriculum development and student engagement.

Additionally, respondents identified predictive analytics to flag at-risk students early, which may support retention, especially in online education settings where dropout rates are higher. Institutions may therefore consider

[54] Lo, "Impact of ChatGPT."

[55] Slimi and Villarejo Carballido, "Dual-Framework Analysis."

[56] Holmes, Bialik, and Fadel, *Artificial Intelligence in Education*.

piloting AI-driven tools, paired with evaluation of their effects on learning and retention.

Furthermore, the rapid advancement of AI in educational settings worldwide necessitates integrating AI-revised curricula.[57] This integration is vital across disciplines, from technical fields to the humanities and social sciences, where AI's impact is growing.

VI.2. Policy development

This study highlights several important ethical issues related to the use of AI. The main concerns are algorithmic bias, data privacy, and the potential for surveillance.[58] To ensure that AI technologies are used ethically and fairly, robust governance frameworks are essential. Such frameworks should promote transparency in AI decision-making and, by setting clear rules for data use, guard against biases that could deepen existing inequalities.

Furthermore, this paper emphasises the need for better technological infrastructure to implement AI effectively in higher education.[59] 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.

VI.3. Future research directions

This study points to several avenues 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.[60] Longitudinal studies could clarify AI's advantages and disadvantages over time, and tracking its impact on educational outcomes would be particularly valuable.

Future research should also explore issues beyond this study's specific focus to deepen understanding of the cross-cultural application of AI in higher

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[57] Seldon and Abidoye, and Metcalf, *Fourth Education Revolution*.

[58] On algorithmic bias, see Cathy O'Neil, *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy* (New York: Crown, 2016); on data privacy, see Williamson and Eynon, "Historical Threads."

[59] OECD, *Digital Education Outlook 2021*.

[60] For cross-cultural research directions, see Geert Hofstede, *Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations*, 2nd ed. (Thousand Oaks, CA: Sage Publications, 2001).

education. The difficulty in recruiting participants in Oman highlights the importance of cultural considerations in the adoption of AI.

More broadly, cooperation among organisations, decision-makers, and researchers will be necessary to overcome obstacles and capitalise on AI's potential. This study offers an empirically grounded account of the motivators, obstacles, and potential remedies.

VI.4. Policy recommendations

For governments:

- Tiered infrastructure investment prioritising under-resourced institutions;
- National AI literacy frameworks for students, faculty, and administrators; and
- Context-sensitive guidelines addressing privacy, transparency, bias, and accountability.

For institutions:

- Cross-functional AI ethics committees overseeing procurement and impact;
- Phased implementation roadmaps (infrastructure → training → tools → governance); and
- Sustained faculty development programmes with incentives.

For international bodies:

- Direct funding for infrastructure and capacity in under-resourced regions; and
- Global AI ethics clearinghouse for policy models and case studies.

For developers:

- Transparency-by-design with explainable algorithms; and
- Contextual adaptability to linguistic and cultural diversity.

These policy recommendations translate the findings into actionable steps for governments, institutions, international bodies, and developers.

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doi: https://doi.org/10.18543/tjhe.2686 • http://www.tuningjournal.org/

VII. Limitations

One limitation of this paper is its sample size. The purposive sample (n=47) limits generalisability to the global population. Findings are particularly reflective of resource-constrained and Gulf-region contexts and should not be extrapolated to all educational systems without further validation.

The 2021 data collection period, while providing a valuable pre-generative AI baseline, means the specific quantitative findings reflect the technological and perceptual landscape of that time.[61] The rapid proliferation of large language models 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 analyses, such as regression or correlation analyses, to assess the statistical significance and predictive power of identified drivers and barriers. This would enhance the empirical robustness and generalisability 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.[62] Although this time lag is acknowledged as a limitation, the results continue to highlight persistent issues and strategic objectives in international AI adoption initiatives.

VIII. Conclusion

To conclude, AI holds considerable potential for enhancing higher education when used ethically and in a contextually appropriate manner.[63] It can encourage diversity, support learning objectives, and increase administrative effectiveness when implemented within robust governance frameworks.

Transparency, algorithmic bias, and data privacy are further issues that require careful management, as the incorporation of AI raises significant ethical challenges. If not adequately regulated and monitored, AI-driven

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[61] Lo, "Impact of ChatGPT."

[62] Lo, "Impact of ChatGPT"; Yogesh K. Dwivedi et al., "So, What If ChatGPT Wrote It? Multidisciplinary Perspectives on Opportunities, Challenges and Implications of Generative Conversational AI for Research, Practice and Policy," *International Journal of Information Management* 71 (2023): 102642.

[63] Floridi, *Logic of Information*.

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doi: https://doi.org/10.18543/tjhe.2686 • http://www.tuningjournal.org/

platforms could exacerbate existing disparities, particularly in under-resourced areas.

This study highlights the need for international frameworks that prioritise inclusivity, equity, and transparency.[64] 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 secure sufficient training and support to leverage the benefits of AI effectively.

This study's primary contributions are threefold. First, the research provides the first systematically documented cross-cultural mapping of AI adoption dynamics prior to the generative AI era. The findings show that personalised learning, teaching efficacy, and innovative teaching models are the most frequently cited drivers, while lack of expertise, inadequate infrastructure, and unresolved ethical concerns are the most significant barriers.

Second, the research reveals stark disparities between well-resourced and under-resourced institutional contexts. Respondents from high-income countries primarily cited ethical and governance challenges, while those from lower-income settings emphasised basic infrastructural deficits. This bifurcation suggests that without targeted intervention, AI may exacerbate, rather than ameliorate, existing educational inequalities, widening rather than narrowing the global digital divide.

Third, the study documents stakeholder-proposed solutions that emphasise systemic capacity-building: investment in infrastructure, comprehensive training programmes, robust cybersecurity protocols, and clear ethical governance frameworks. These proposed interventions, articulated by practitioners operating across diverse contexts, provide empirically grounded guidance for institutional and policy-level action.

The findings carry urgent implications.[65] Without targeted investment in infrastructure, capacity-building initiatives, and context-sensitive regulatory frameworks, AI's transformative potential may remain unrealised particularly in under-resourced regions. Institutions and policymakers must recognise that AI readiness is not merely about acquiring tools but about building the human, technical, and governance capacities that enable responsible adoption.

This study provides the empirical foundation for the complementary study by Slimi and Villarejo Carballido, which extends the present findings by integrating the Technology Acceptance Model and the AI Ethics Framework into a unified explanatory model centred on "Ethical Readiness"

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[64] United Nations, *Our Common Agenda*.

[65] On the urgency of AI governance, see Dwivedi et al., "So, What If ChatGPT Wrote It?"

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doi: https://doi.org/10.18543/tjhe.2686 • http://www.tuningjournal.org/

as a mediating construct between behavioural intention and responsible adoption. Together, the two studies constitute a coherent research programme: the present study provides the observational map; the complementary study offers the theoretical compass.[66]

Ultimately, realising AI's potential to enhance higher education inclusively and equitably will require collaboration among policymakers, educators, and technologists guided by empirical evidence of how adoption dynamics manifest across diverse contexts. This study contributes such evidence, establishing a baseline from which future research and practice can proceed.

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[66] Slimi and Villarejo Carballido, "Dual-Framework Analysis."

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Appendix: tables and figures

Table 1

Drivers for AI Adoption – Thematic Categories and Frequencies

Thematic Category	Specific Driver	n	%	Representative Quote
Admissions & Administration	Personalisation of admissions	11	2.9%	"AI enables personalised communication with prospective students, tailoring information to their interests." – Administrator, UAE
	General administrative efficiency	15	3.9%	"AI streamlines our admissions process and reduces manual workload." – Administrator, UK
	Automation of routine tasks	5	1.3%	"Automating scheduling and routine queries frees staff for higher-value work." – Administrator, Oman
	Efficient grading and assessment	7	1.8%	"AI speeds up grading while maintaining consistency across large cohorts." – Faculty Member, Greece

Thematic Category	Specific Driver	n	%	Representative Quote
Pedagogical Enhancement	Personalised learning and adaptivity	47	12.3%	"AI enables us to tailor content to individual student needs in ways impossible at scale before." – Faculty Member, Spain
	Innovative teaching models	32	8.4%	"We need to rethink pedagogy entirely—AI allows for dynamic, responsive teaching methods." – Administrator, Malaysia
	Critical thinking and task-driven learning	21	5.5%	"Students can focus on higher-order thinking when AI handles routine tasks." – Faculty Member, Canada
	Engagement and immersive learning	23	6.0%	"Gamified AI environments keep students motivated and engaged." – Policymaker, UAE
Institutional Positioning	Strategic enhancement and reputation	24	6.3%	"AI adoption signals innovation and attracts international students." – Administrator, Australia
	Teaching efficacy	35	9.2%	"AI helps us improve teaching effectiveness through real-time feedback." – Faculty Member, Ethiopia
Competency Development	Lifelong and competency-based learning	32	8.4%	"AI supports continuous skill development aligned with industry needs." – Policymaker, Greece
	Technological skill development	25	6.5%	"Students need AI literacy to compete in the modern workforce." – Faculty Member, India
	Tangible learning outcomes	18	4.7%	"AI helps students see real-world applications of theoretical concepts." – Faculty Member, Canada

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Thematic Category	Specific Driver	n	%	Representative Quote
	Multidisciplinary education	5	1.3%	"AI enables integration across disciplines, preparing students for complex problems." – Administrator, Singapore
Access and Equity	Reducing administrative burdens	26	6.8%	"Automating routine tasks frees us for meaningful student interaction." – Administrator, Oman
	Affordability and accessibility	20	5.2%	"AI can democratise access to quality education resources." – Policymaker, Nigeria
	Inclusion and accessibility for diverse learners	31	8.1%	"AI removes barriers for students with disabilities and diverse learning needs." – Faculty Member, UK
	Student retention support	5	1.3%	"Predictive analytics help us identify at-risk students early." – Faculty Member, South Africa

Note: Percentages represent proportion of total driver mentions (N=382 statements across 47 participants). Multiple responses per participant were permitted. Within each thematic category, specific driver percentages reflect their share of total mentions, not percentage of participants.

Table 2

Barriers to AI Adoption – Thematic Categories and Frequencies

Thematic Category	Specific Barrier	n	%	Representative Quote
Capacity Deficits	Lack of AI expertise	38	80.9%	"We simply don't have people who understand AI well enough to implement it." – Administrator, Oman
	Inadequate technological infrastructure	33	70.2%	"Our servers can't handle the data processing AI requires." – Faculty Member, Nigeria

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doi: https://doi.org/10.18543/tjhe.2686 • http://www.tuningjournal.org/

Thematic Category	Specific Barrier	n	%	Representative Quote
Data Governance	Poor data governance and integration	28	59.6%	"Data sits in silos—we can't integrate it effectively for AI." – Administrator, Jordan
	Lack of high-quality datasets	13	27.7%	"Our student data is incomplete and inconsistent." – Faculty Member, Iran
Ethical and Regulatory Gaps	Concerns about ethics and transparency	25	53.2%	"We don't know how algorithms make decisions—that's problematic." – Policymaker, the Netherlands
	Lack of public policy on AI development	19	40.4%	"There's no national framework guiding our AI investments." – Administrator, Ethiopia
	Lack of inclusiveness and equity	11	23.4%	"AI tools don't account for our students' linguistic diversity." – Faculty Member, Morocco
Structural Exclusion	No benefits for marginalised groups	6	12.8%	"AI benefits privileged students; vulnerable populations get left behind." – Policymaker, South Africa

Note: Percentages represent the proportion of participants (N=47) citing each barrier; multiple responses per participant.

Table 3

Proposed Solutions – Thematic Categories and Frequencies

Thematic Category	Specific Solution	n	%	Representative Quote
Infrastructure and Security	Investment in high-tech infrastructure	10	21.3%	"We need government investment in digital infrastructure before AI can work." – Administrator, Ethiopia
	Robust cybersecurity protocols	10	21.3%	"Without security, AI implementation is irresponsible." – Faculty Member, Greece

Thematic Category	Specific Solution	n	%	Representative Quote
Human Capacity Development	Training for students and staff	9	19.1%	"Everyone needs AI literacy – faculty, administrators, students." – Policymaker, UAE
	Enhancing AI trustworthiness	8	17.0%	"We need transparent, explainable AI that users can trust." – Faculty Member, Canada
Policy and Governance	Clear ethical AI policies	6	12.8%	"National frameworks must guide institutional practice." – Administrator, Malaysia
	Mandatory staff training	5	10.6%	"Training shouldn't be optional – it must be required." – Faculty Member, Spain
	Sustainable AI development	3	6.4%	"We need to consider long-term environmental and ethical sustainability." – Policymaker, UK

Note: Percentages represent the proportion of participants (N=47) citing each solution; multiple responses per participant.

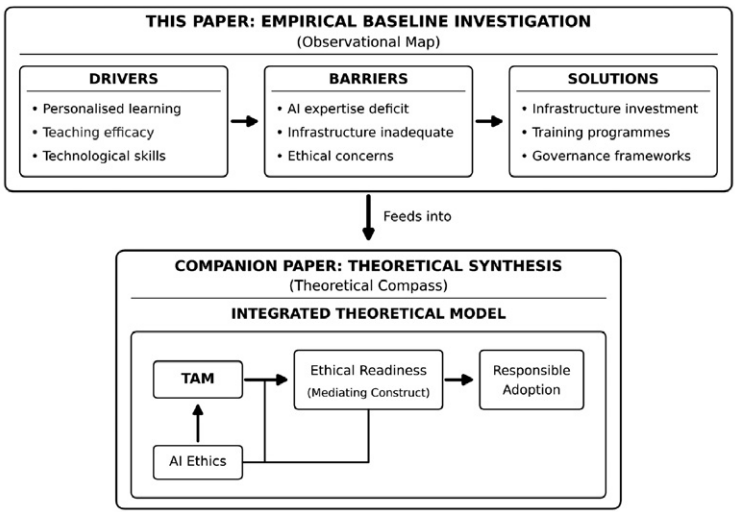


Figure 1

Global AI Adoption Dynamics in Higher Education – A Conceptual Framework

Tuning Journal for Higher Education
© University of Deusto • p-ISSN: 2340-8170 • e-ISSN: 2386-3137 • Volume 12, Issue No. 2, November 2026, 231-261 •
doi: https://doi.org/10.18543/tjhe.2686 • http://www.tuningjournal.org/