Cross-Cultural Adoption of Generative Artificial Intelligence in Higher Education: A Longitudinal Socio-Technical Analysis Using the AI-CLASSIC Framework

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Abstract

Global interest in Artificial Intelligence (AI), and particularly Generative AI (GenAI), has increased sharply over the past decade. While adoption in higher education is accelerating, it remains uneven across countries, institutions, and cultural contexts. Most existing research emphasises automation efficiency, AI literacy, or short-term classroom use, offering limited insight into how GenAI becomes embedded within educational systems over time. This paper introduces AI-CLASSIC (AI Adoption in Classroom Instruction and Cross-Cultural Comparison), a longitudinal, multi-level socio-technical framework integrating classroom practices, institutional readiness, and societal discourse. Drawing on pilot data from Germany, Nigeria, and India, we demonstrate that similar levels of GenAI usage may arise primarily because of different adoption mechanisms. Regression-based analyses identify perceived usefulness as a universal driver, while risk perception, institutional constraints, and cultural expectations shape adoption pathways differently across contexts. By operationalising adoption, the AI-CLASSIC framework proposes the AI Competency Index (ACI), which will be systematically validated in subsequent longitudinal work. This study advances cross-cultural comparability and provides a scalable foundation for predictive modelling and policy-relevant foresight in AI-enhanced higher education.

Keywords: generative AI, artificial intelligence in education, cross-cultural research, socio-technical systems, AI-CLASSIC, higher education

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Introduction

Global interest in generative artificial intelligence (GenAI) has increased sharply over the past decade. There is a substantial growth in both patent activity and reported use among students in higher education (Digital Education Council, 2024; Higher Education Policy Institute, 2025; World Intellectual Property Organization, 2024).Despite this unusual spread, most applications continue to focus on automation and the externalisation of human cognition rather than complementing human intellectual capacity (International Labour Organization, 2023). This situation creates a challenge between efficiency-driven AI and human-centred educational values.

The United Nations Educational, Scientific and Cultural Organization (UNESCO) through ethical guidelines promote responsible GenAI integration. But their impact is undermined by digital divides and uneven national readiness. Also, socio-technical disparities are reinforced through policy fragmentation and media discourse (International Telecommunication Union, 2024; Korneeva et al., 2023). These dynamics present the need to investigate how AI adoption unfolds in different national and cultural settings. While adoption patterns vary widely across countries (Mansoor et al., 2024), existing research remains geographically limited, methodologically fragmented, and largely based on short-term snapshots. The goal of this paper is to advance a longitudinal, cross-cultural, and computationally grounded framework for examining how generative AI is adopted and embedded within higher education.

Why Cross-Cultural AI Research in Higher Education

AI adoption does not happen in a vacuum; it takes shape within the everyday realities of educational systems, institutional practices, and national contexts. Germany, Nigeria, and India offer particularly important contrasts. In Germany, higher education places strong emphasis on critical thinking, academic integrity, and ethical reflection, supported by well-developed infrastructure and relatively stable policy frameworks (Zawacki-Richter et al., 2019). India has rapid uptake of generative AI tools, but this expansion is uneven, limited by gaps in connectivity and insufficient faculty training that affect scalability (Kamble et al., 2024). In Nigeria, growing student demand for AI tools coexists with infrastructural limitations, fragmented policy approaches, and uneven national strategies for AI integration (Adesiji, 2024).

Cultural and educational traditions further influence how generative AI is used in practice. In exam-oriented systems of Nigeria and India, students tend to rely on GenAI for summarisation, rote learning, and exam preparation. But in Western countries, originality and independent thinking are emphasized. Also, GenAI is more often used for brainstorming, drafting support, and idea development (Zawacki-Richter et al., 2019).Recent empirical work confirms that these different educational expectations play a decisive role in influencing patterns of AI use (Ibeh et al., 2025). These contrasts support the need for cross-cultural perspective for understanding AI adoption as a broader, system-level process rather than a uniform or purely technical phenomenon.

Theoretical Foundations

AI-CLASSIC is grounded in a multi-level socio-technical framework integrating organisational theory, educational psychology, and technology adoption research. At the macro level, Cultural–Cognitive Institutional Theory (CCIT) (Scott, 2008) explains how national norms, regulatory regimes, and institutional logics shape AI legitimacy, policy discourse, and adoption attitudes.

At the meso and micro levels, Socio-Technical Systems Theory (Pasmore et al., 2019) and the Technology Acceptance and Use Continuum (Venkatesh et al., 2012) link technological affordances with institutional practices and user perceptions.

At the micro level, constructivist learning theory, self-efficacy theory, and self-regulated learning (SRL) frameworks (Bandura, 1997; Panadero, 2017; Zimmerman, 2002) conceptualise AI use as an active, metacognitive process shaped by learner agency. Evidence on AI-related self-efficacy further underscores the role of cognitive and motivational factors (Liang et al., 2023). These perspectives enable AI adoption to be modelled as a complex adaptive system (Holland, 2006), bridging behavioural logs, attitudinal surveys, and societal discourse.

Limitations of Existing Research

Most studies on AI in education focus on AI literacy, perceptions, or short-term classroom use (Crompton & Burke, 2023; Stöhr et al., 2024). However, findings are inconsistent across disciplines and contexts and often entangled with ethical debates (Korneeva et al., 2023). Existing frameworks such as DigComp 2.2 (Vuorikari et al., 2022) and UNESCO's AI Competency Framework mainly rely heavily on self-report measures and remain context specific.

Snapshot models such as the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), Normalization Process Theory (NPT), and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) are used to explain immediate drivers of AI adoption, but they are limited in terms of how adoption evolves over time. In particular, these approaches struggle to account for changing motivations, longer-term learning processes, and the feedback loops that develop as users interact repeatedly with AI systems (Cukurova, 2025). Although computational methods could help address these gaps, they remain under-used in educational research.

Methodology

Design and Data

Pilot data collection demonstrates feasibility across contexts (refer to Table 1). In Germany, a longitudinal classroom-based cohort (n = 210) is being followed over time. In Nigeria, a national multi-institutional survey (n = 445) demonstrates scalability. In India, a zonal survey (n = 62+) is ongoing with planned expansion.

Table 1
Overview of Preliminary Pilot Studies Across Germany, India, and Nigeria (2025)

Country	Sample Size	Design
Germany	210	Longitudinal (classroom)
India	62+	National (zonal, ongoing)
Nigeria	445	National (multi-institution)

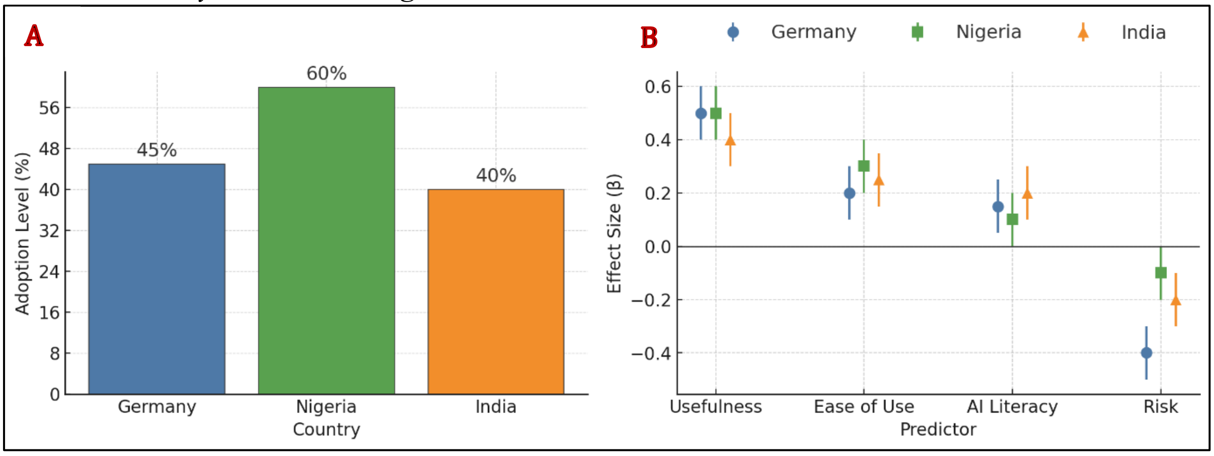
Measures and Analysis

Measures include GenAI usage frequency, perceived usefulness, ease of use, AI literacy, and risk perception. Analyses integrates descriptive comparison and regression modelling, informed by TAM/UTAUT constructs adapted for cross-cultural contexts.

Results and Discussion

Preliminary results show comparable adoption levels across countries, with Nigeria (~60%) slightly higher than Germany (~45%) and India (~40%). However, regression-based analyses (Figure 1) reveal divergent mechanisms. Perceived usefulness resulted as the strongest predictor across all contexts. Risk perception exerts a pronounced negative effect in Germany.

Figure 1
Preliminary Pilot Results on Weekly GenAI Usage (Left) and Adoption Drivers (Right) Across Germany, India, and Nigeria



Results reflect that Germany has more ethical, privacy, and institutional influence on how generative AI is perceived and used. Nigeria and India on the hand, AI adoption is driven primarily by pragmatic considerations. These include exam preparation, and immediate academic utility. Across all the target countries ease of use and AI literacy contribute positively to adoption, but they remain secondary to these broader structural and cultural drivers.

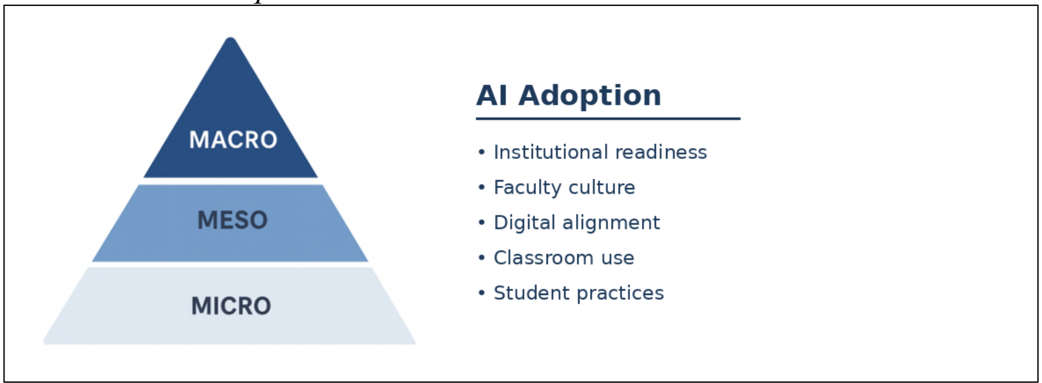
These findings show that similar levels of AI use can result for very different reasons. Apparent convergence in adoption rates therefore masks substantial differences in underlying factors e.g. motivations, constraints, and institutional conditions. This divergence highlights the limits of single-factor or context-neutral explanations of AI adoption and points to the need for a framework that can capture interactions across classroom practices, institutional governance, and wider cultural and policy environments. A multi-level socio-technical perspective is therefore essential for understanding not only whether generative AI is adopted, but how and why adoption pathways differ across educational systems.

The AI-CLASSIC Framework and the Proposed AI Competency Index (ACI)

The AI-CLASSIC (AI Adoption in Classroom Instruction and Cross-Cultural Comparison) addresses persistent gaps in literature by conceptualising generative AI adoption in higher education as a multi-level socio-technical process rather than a single behavioural or attitudinal outcome. The framework integrates behavioural traces, attitudinal measures, institutional indicators, and societal discourse across Germany, Nigeria, and India, enabling systematic comparison across educational and cultural contexts.

As illustrated in Figure 2, AI adoption needs to be modelled as a hierarchically structured but interconnected system comprising three analytical levels.

Figure 2
AI-CLASSIC Conceptual Framework



At the micro level, AI adoption is mainly through classroom practices and learner cognition, including patterns of GenAI use, perceived usefulness, AI literacy, and self-regulated learning. These practices are shaped and constrained at the meso level by institutional capacity and governance, such as curriculum design, assessment regimes, faculty culture, and infrastructural readiness. On the other hand, the AI adoption at macro level involves broader factors such as cultural norms, ethical expectations, regulatory frameworks, and national AI policies provide the structural conditions that legitimise, enable, or restrict institutional and classroom-level adoption.

This multi-level integration forms the proposal of a conceptual foundation of the AI Competency Index (ACI). Rather than relying on self-reported AI literacy alone, the ACI operationalises adoption as a validated composite construct that combines behavioural logs, survey-based perceptions, institutional indicators, and policy discourse.

The AI-CLASSIC framework models generative AI adoption in higher education as a unified, multi-level socio-technical system. This encompasses micro-level classroom practices and learner cognition, meso-level institutional capacity and governance, and macro-level cultural and regulatory environments. The AI-CLASSIC proposes a new framework for understanding the AI adoption through the AI Competency Index (ACI), enabling longitudinal and cross-cultural comparison of AI adoption.

Implications

The findings emerging from AI-CLASSIC underline why uniform or one-size-fits-all approaches to AI governance in higher education are unlikely to be effective. Although overall levels of generative AI use may appear comparable across countries, the underlying drivers of adoption differ substantially. In essence, Institutional responses need to therefore move beyond general statements on AI use and address the specific socio-technical conditions within which students and educators operate. In addition, there should be a careful balancing of perceived usefulness, risk communication, governance structures, and educational culture. In contexts where AI adoption is driven primarily by pragmatic needs—such as exam preparation or workload reduction—policy interventions should focus on supporting responsible use through clear guidelines, assessment redesign, and targeted capacity building. In settings where ethical concerns, data protection, and academic integrity are more prominent, institutions must prioritise transparency, trust-building, and participatory governance mechanisms that involve both staff and students.

For policymakers, the results suggest that global ethical frameworks for artificial intelligence cannot be applied mechanically across national systems. While international guidelines provide important normative direction, their effectiveness depends on how well they are adapted to local regulatory environments, infrastructural realities, and cultural expectations. AI-CLASSIC highlights the importance of aligning ethical principles with institutional practices and classroom realities. There is need to ensure that governance strategies remain both context-sensitive and educationally meaningful.

Limitations and Future Research

This study is subject to several limitations that should be acknowledged. First, the pilot samples are uneven across countries, with behavioural log data currently concentrated in the German longitudinal cohort. While this design reflects differences in data access and institutional partnerships, it limits the extent to which behavioural comparisons can be made across all contexts at this stage. Second, the present analyses focus primarily on associative relationships, and do not yet allow for strong causal inference. These limitations point directly to directions for future research.

Subsequent waves of data collection will extend behavioural logging to additional contexts and strengthen the longitudinal component of the study. This will enable more robust modelling of temporal dynamics. This will require examining dynamics in the motivation, learning strategies as well as institutional responses over time. Future work should develop and validate the AI Competency Index (ACI) by refining its components, testing measurement invariance across cultures, and integrating predictive modelling techniques. These extensions will therefore allow AI-CLASSIC to move beyond descriptive analysis toward forecasting adoption trajectories and identifying leverage points for policy intervention.

Conclusion

AI adoption in higher education should not only be understood as a technological choice or short-term response. Researchers should investigate AI adoption as a longitudinal and socio-technical transformation. There should be focus on how interactions between learners, institutions, and broader cultural and regulatory environments are shaped. The AI-CLASSIC framework provides a structured way to capture these interactions. It also shows how similar levels of AI use can emerge from very different underlying mechanisms.

By combining cross-cultural comparison with longitudinal analysis and computational modelling, AI-CLASSIC offers a rigorous and scalable approach to studying how generative AI moves from novelty to normalised educational infrastructure. This will support evidence-based institutional decision-making. It will aso support more nuanced AI governance, and the development of inclusive policies that recognise the diversity of educational systems worldwide.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The authors declare that generative AI tools were used only for limited language refinement and stylistic clarity. All substantive content, analysis, interpretation, and conclusions are the original work of the authors, who take full responsibility for the manuscript.

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