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Usage Pattern of AI-Driven Adaptive Learning and Analytics: Transforming Higher Education through Intelligent Instructional Systems

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Abstract

The integration of intelligent instructional systems is transforming higher education through the convergence of artificial intelligence (AI), learning analytics and adaptive learning technologies. This review examines their impact on instructional practices, lecturer effectiveness and student outcomes. Evidence shows high and growing prevalence: over 80% of universities deploy learning analytics, about 45% use AI tutoring systems and more than 70% of institutions in developed countries apply AI for personalized learning. Examples include AI-powered learning management systems that track student engagement and predict performance, automated grading and feedback tools that enhance instructional efficiency and adaptive platforms that tailor content and learning pathways in real time. These systems have been associated with improved student engagement, retention and academic achievement. Despite these benefits, adoption remains uneven, particularly in developing regions where usage ranges between 25% and 40%. Key constraints include inadequate digital infrastructure, limited lecturer competencies, data privacy concerns and algorithmic bias. The study concludes that while intelligent instructional systems offer significant potential to enhance teaching and learning, their effectiveness depends on strategic implementation, continuous professional development and supportive institutional policies. It recommends increased investment in infrastructure, targeted capacity building and the development of ethical frameworks to ensure inclusive and sustainable AI integration in higher education.

Keywords: Artificial Intelligence, Learning Analytics, Adaptive Learning and Intelligent Instructional Systems

Introduction

Intelligent Instructional Systems (IIS) are advanced, technology-enhanced learning environments that integrate artificial intelligence (AI), learning analytics and adaptive learning technologies to deliver personalized, data-driven and responsive instruction. These systems simulate elements of human intelligence in teaching by analyzing learner behavior, predicting performance and dynamically adjusting instructional content to meet individual needs (Zawacki-Richter et al., 2023; Holmes et al., 2022). Unlike conventional digital platforms, IIS combine real-time data processing, machine learning algorithms and automated feedback mechanisms to support both lecturers and students in achieving improved learning outcomes. The transformation of higher education through IIS has accelerated markedly in recent years. AI is no longer an emerging innovation but an embedded component of teaching, learning and academic administration. Recent evidence shows that approximately 84% of higher education professionals use AI in academic or administrative tasks, while 45% of universities globally have implemented AI-powered tutoring systems and 83% of leading institutions deploy learning analytics tools (Ellucian, 2024; ZipDo, 2026). These trends highlight the growing prevalence and institutionalization of intelligent instructional systems across higher education. In developed contexts such as the United States and the United Kingdom, adoption rates are particularly high. Over 70% of U.S. colleges reportedly use AI for personalized learning, while more than 90% of students in the UK engage with AI tools in their academic activities, reflecting deep integration into instructional practices. In China, adoption exceeds 80%, supported by strong government investment and strategic policy direction toward AI leadership. Meanwhile, countries such as Japan emphasize human-centered AI integration, focusing on ethical considerations and pedagogical alignment (Xie et al., 2024). Emerging economies are also advancing, with India reporting approximately 39% adoption of AI technologies in higher education despite ongoing infrastructural challenges.

Across Africa, the adoption of AI-driven instructional systems reflects both innovation and constraint, shaped by variations in infrastructure, policy and institutional readiness. Overall adoption remains below 40%, although leading countries are making notable progress (Adeleke & Moodley, 2024; UNESCO, 2023). In South Africa, more than 60% of universities are experimenting with AI and learning analytics to monitor student engagement and develop predictive models for retention and success (Mhlanga, 2023; Ngcobo & Ngoepe, 2024). These systems enable lecturers to identify at-risk students and implement timely interventions, though challenges related to data governance and system transparency persist. Rwanda's AI adoption is largely policy-driven, with national strategies positioning the country as an emerging leader in digital transformation. Over 30% of higher education institutions have begun integrating AI-related programs and digital learning platforms (Uwizeyimana et al., 2024). Similarly, Kenya demonstrates a scalable model through mobile-based adaptive learning platforms such as Eneza Education and M-Shule, which use AI to deliver personalized instruction via SMS and mobile applications, reaching millions of learners and achieving adoption rates exceeding 50% in some regions (Makokha & Mutisya, 2023). In Nigeria, adoption ranges between 25% and 35%, with universities increasingly utilizing AI for virtual learning environments, automated feedback and instructional support, although infrastructural deficits and limited digital competencies among lecturers remain key barriers (Afolabi et al., 2024; Oke & Fernandes, 2023). AI is increasingly applied to personalize learning, automate instructional processes and support data-driven teaching. However, common challenges persist, including unreliable internet connectivity, limited access to digital devices, insufficient lecturer training and concerns regarding data privacy and ethical AI use (Zawacki-Richter et al., 2023; UNESCO, 2023).

Scholarly interest in AI and adaptive learning has grown significantly, with a marked increase in publications since 2020 and peak outputs recorded in 2024, reflecting intensified global research attention. Despite the growing adoption and research interest, a gap remains between technological advancement and institutional readiness, particularly in developing regions where infrastructure and professional development are still evolving. Against this backdrop, this study explores how AI-driven adaptive learning and learning analytics are transforming higher education globally. By synthesizing evidence from both developed and developing contexts, it provides a comprehensive understanding of the prevalence, applications and implications of intelligent instructional systems for lecturers and institutions.

Conceptual Foundations

Intelligent Instructional Systems integrate AI, learning analytics and adaptive technologies to create personalized, data-driven learning in higher education. They shift teaching toward real-time, learner-centered instruction supported by continuous feedback and analysis. The system functions through three layers: data collection, intelligent processing using AI and adaptive delivery of personalized learning content. These layers work together to improve learning outcomes by guiding instructional decisions with evidence from student data. Their effectiveness depends on institutional support, infrastructure, lecturer competence and policy environment.

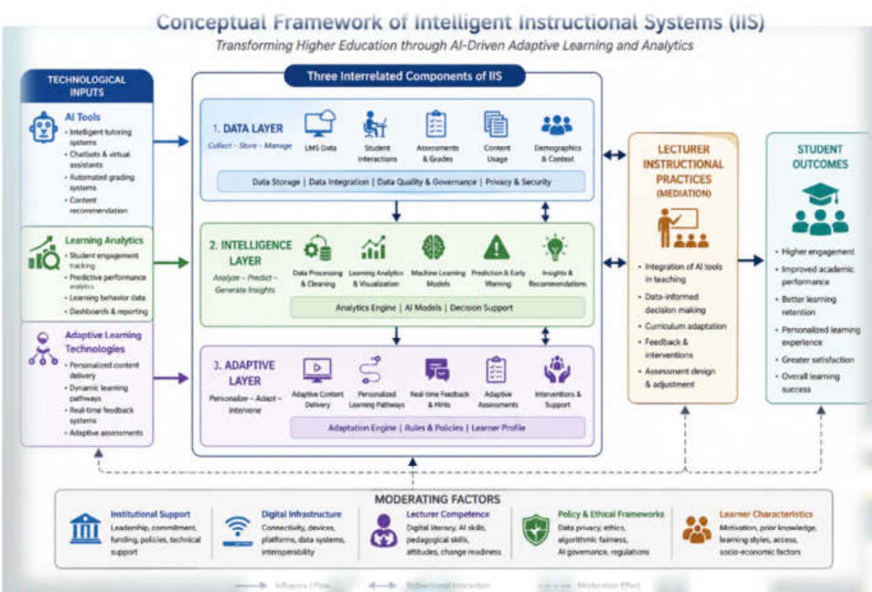


Figure 1: Conceptual Framework of Intelligent Instructional System

Intelligent Instructional Systems

Intelligent instructional systems are advanced digital learning environments that integrate Artificial Intelligence (AI), learning analytics and instructional design frameworks to enhance pedagogical effectiveness and enable personalized learning experiences. These systems operate as interconnected architectures that facilitate continuous interaction among learners, instructional content and educators through automated processes, adaptive feedback loops and real-time data exchange. Within higher education contexts, intelligent instructional systems represent a paradigmatic shift from traditional teacher-centered pedagogies toward digitally mediated, learner-centered instructional models. Empirical studies in the Nigerian context indicate that these systems are progressively influencing instructional delivery by enabling lecturers to monitor learner engagement patterns and adjust pedagogical strategies based on real-time digital feedback (Ifinedo & Oladejo, 2022). Similarly, Akinyemi and Bada (2021) argue that intelligent instructional systems enhance instructional efficiency by automating routine academic tasks, thereby enabling lecturers to concentrate on higher-order cognitive and pedagogical functions such as facilitation, mentoring and curriculum design.

From a structural perspective, these systems typically integrate learning management systems (LMS), AI-powered analytics dashboards and adaptive content delivery mechanisms. In developing higher education systems such as Nigeria, Yusuf and Adeoye (2023) report that adoption levels remain heterogeneous due to infrastructural disparities and varying institutional readiness. However, institutions with higher digital maturity demonstrate significantly improved student engagement outcomes and enhanced academic performance indicators. This evidence suggests that intelligent instructional systems should be conceptualized not merely as technological tools but as comprehensive socio-technical infrastructures that fundamentally reconfigure teaching and learning processes in higher education.

Learning Analytics

Learning analytics refers to the systematic process of collecting, measuring, analyzing and reporting educational data to optimize learning processes and improve instructional decision making. It emphasizes the transformation of large-scale learner data into actionable insights that support academic monitoring, early intervention and evidence-based pedagogical enhancement. In Nigerian higher education institutions, the adoption of learning analytics is increasingly associated with the integration of digital learning platforms such as Moodle and Google Classroom. Olanrewaju and Afolabi (2022) note that learning analytics enables lecturers to systematically track student engagement behaviors, identify at-risk learners and evaluate instructional effectiveness in real time. This capability is particularly critical in large enrollment contexts where individualized monitoring is pedagogically constrained.

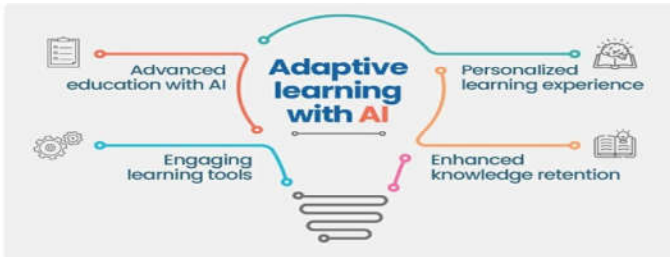
In addition, Eze and Okoye (2021) emphasize that learning analytics supports data-informed pedagogy by providing visual dashboards that present student engagement trends, performance distributions and learning gaps. This facilitates timely instructional adjustments and targeted academic support. Complementing this view, Bolarinwa and Salau (2023) found that lecturers who actively utilize learning analytics tools are more likely to adopt adaptive instructional strategies, which subsequently enhance student retention and academic achievement. However, the effective implementation of learning analytics in Nigerian universities is constrained by factors such as inadequate digital literacy, limited infrastructural support and insufficient institutional capacity (Adesina & Ibrahim, 2022). Despite these limitations, learning analytics remains a core component of intelligent instructional systems due to its critical role in converting raw educational data into meaningful instructional intelligence.

Artificial Intelligence in Higher Education

Artificial Intelligence in higher education refers to the application of machine learning algorithms, natural language processing and predictive analytics to enhance teaching, learning, assessment and administrative processes. AI technologies are increasingly deployed to automate instructional functions, personalize learning experiences and improve institutional efficiency and decision making. In the Nigerian higher education landscape, AI adoption is emerging but steadily expanding. Adeoye and Afolabi (2022) observe that AI-based systems such as automated grading tools and intelligent tutoring platforms have demonstrated potential in reducing lecturers' workload while improving consistency and objectivity in assessment practices. Similarly, Nwankwo and Okeke (2021) highlight the deployment of AI-enabled chatbots in Nigerian universities as a mechanism for providing continuous academic support, particularly in contexts characterized by large student populations and limited academic staff.

Predictive analytics, a key subset of AI applications, is increasingly utilized for forecasting student performance and identifying dropout risks. Salau and Mohammed (2023) report that predictive modeling systems support institutional decision-making by enabling early intervention strategies that enhance student retention and academic success outcomes. Notwithstanding these advancements, several structural and contextual challenges persist. Ezeani (2022) identifies inadequate technological infrastructure, limited technical expertise and ethical concerns surrounding data privacy and algorithmic transparency as major barriers to AI integration in Nigerian higher education. Nevertheless, AI continues to function as a transformative force that is reshaping instructional delivery by enhancing efficiency, personalization and data driven decision making in academic environments.

Adaptive Learning



AI based Adaptive Learning

Adaptive learning refers to technology-enabled instructional systems that dynamically modify learning content, instructional pathways and feedback mechanisms based on individual learner performance, preferences and behavioral data. The primary objective of adaptive learning systems is to deliver personalized educational experiences that align with the cognitive needs and learning trajectories of individual students. In Nigerian universities, adaptive learning technologies are gradually being integrated into digital education ecosystems as a response to challenges such as overcrowded classrooms and heterogeneous learner abilities. Ojo and Akinola (2022) report that adaptive learning systems significantly enhance student engagement by delivering customized learning materials that correspond to learners' cognitive levels and pace of learning. This ensures an optimal balance between instructional difficulty and learner capability. Similarly, Ibrahim and Yusuf (2021) argue that adaptive learning systems improve academic performance by providing continuous formative feedback and enabling learners to progress through content at individualized speeds. This aligns with constructivist pedagogical principles, which emphasize active knowledge construction through interaction with personalized learning environments. Furthermore, Salami and Adebayo (2023) demonstrate that adaptive learning systems contribute to improved retention rates in Nigerian higher education institutions by maintaining sustained learner engagement and reducing knowledge gaps. However, their effectiveness is contingent upon factors such as the lecturer's digital competence, institutional readiness and availability of supporting infrastructure. Generally, adaptive learning represents a significant advancement in instructional design and educational technology. It offers a scalable mechanism for personalization in higher education; however, its successful implementation is highly dependent on systemic factors, including infrastructure development, policy support and educator preparedness for technology integration.

AI-Driven Tools in Intelligent Instructional Systems for Transforming Higher Education

Intelligent Instructional Systems in higher education are powered by several AI-driven tools that work together to improve teaching, learning and academic decision-making. One key tool is Intelligent Tutoring Systems (ITS), which provide step-by-step guidance to learners similar to a human tutor. For example, platforms like Carnegie Learning Math Tutor and ALEKS help students solve problems by giving hints, feedback and adaptive practice based on their performance. Another important tool is AI chatbots and virtual assistants, which support learners through real-time interaction. Examples include ChatGPT-based academic assistants and IBM Watson Assistant used in some universities to answer student questions, provide course guidance and offer administrative support at any time. Learning Management Systems (LMS) such as Moodle, Canvas and Google Classroom serve as central platforms for delivering course content, managing assignments and tracking student participation. These systems allow lecturers to upload materials, conduct assessments and communicate with students efficiently in one digital environment. Learning analytics dashboards are also widely used to monitor student engagement and performance trends. Tools like Power BI integrated with LMS platforms and Blackboard Analytics help lecturers visualize attendance, participation and academic progress to support informed interventions. Automated grading and assessment tools such as Gradescope and Turnitin reduce manual workload **by** marking assignments, detecting plagiarism and providing structured feedback to students. These tools ensure consistency and speed in evaluation processes.

Adaptive learning platforms like Knewton and Smart Sparrow personalize learning experiences by adjusting content difficulty and sequencing based on student performance. This ensures that learners receive tailored instruction that matches their pace and understanding. Predictive analytics tools use machine learning models to forecast student outcomes and identify those at risk of poor performance or dropout. For instance, systems integrated into Canvas and IBM Watson Education can alert lecturers early so they can provide targeted support. Finally, data mining and machine learning tools analyze large educational datasets to uncover patterns in student behavior and learning outcomes. These insights help institutions improve curriculum design and instructional strategies based on evidence rather than assumptions.

Theoretical Framework

The review of intelligent instructional systems in higher education is grounded in a multi-theoretical framework that explains technology adoption, instructional use and institutional integration within academic environments. This study draws on four dominant theoretical models: The Technology Acceptance Model (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), the Diffusion of Innovation Theory (Rogers, 2003) and the Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990). Collectively, these theories provide complementary explanatory lenses for understanding how AI-driven adaptive learning systems and learning analytics are adopted, implemented and sustained in higher education teaching and learning. The transformation of higher education through intelligent instructional systems is best understood through an integrated theoretical lens that connects technology adoption, instructional behavior and learning outcomes. This study is grounded in a synthesis of established educational and technology integration theories, particularly the Technology Acceptance Model (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) and Constructivist Learning Theory (Piaget, 1972; Vygotsky, 1978). These perspectives collectively explain how Artificial Intelligence (AI) tools, learning analytics and adaptive learning systems influence lecturer instructional practices and ultimately shape student learning outcomes in higher education.

Technology Acceptance and Use of AI Tools in Higher Education: The Technology Acceptance Model (TAM) provides a foundational explanation for the adoption of AI-driven instructional systems in universities. TAM posits that perceived usefulness and perceived ease of use determine users' intention to adopt technology (Davis, 1989). In this context, AI tools such as intelligent tutoring systems, chatbots and automated grading systems are more likely to be integrated into instructional practices when lecturers perceive them as enhancing teaching efficiency and simplifying academic tasks.

The Unified Theory of Acceptance and Use of Technology (UTAUT) model: this explanation introduces performance expectancy, effort expectancy, social influence and facilitating conditions as determinants of technology use (Venkatesh et al., 2003). In higher education, lecturers are more likely to adopt AI tools when they believe these systems improve student learning outcomes, reduce workload and are supported by institutional infrastructure and leadership. Together, these theories explain the independent variable layer of the framework, where AI tools function as technological inputs that must be accepted and utilized by lecturers before they can influence instructional processes.

Learning Analytics as a Data Intelligence Mechanism

Data-Driven Decision-Making Theory: Learning analytics is conceptually grounded, which emphasizes the use of empirical evidence to guide instructional improvement (Slade & Prinsloo, 2013). Within this framework, student engagement tracking, predictive performance analytics and behavioral data collection serve as mechanisms for generating actionable insights about learner progress. From a theoretical standpoint, learning analytics aligns with the information processing theory, which suggests that data must be collected, interpreted and transformed into meaningful instructional decisions (Simon, 1978). In higher education, lecturers rely on analytics dashboards to identify learning gaps, monitor student participation and predict academic risk. This positions learning analytics as a critical intermediary layer that bridges raw AI-generated data and pedagogical action.

Adaptive Learning Systems and Constructivist Learning Theory

Constructivist Learning Theory: The Adaptive learning systems are strongly supported by which argues that learners actively construct knowledge based on personalized experiences and interaction with content (Piaget, 1972; Vygotsky, 1978). Personalized content delivery, dynamic learning pathways and real-time feedback systems reflect the constructivist principle that learning should be individualized, flexible and context-responsive. These systems ensure that students are not passive recipients of knowledge but active participants in their learning process. By adjusting instructional content based on learner performance, adaptive systems operationalize differentiated instruction at scale. This theoretical grounding explains why adaptive learning is central to improving engagement, retention and academic performance in digital learning environments.

Integrated Theoretical Perspective: Through these practices, lecturers interpret AI-generated insights, adjust curriculum delivery and provide targeted feedback to students. This mediating role is essential because technology alone does not improve learning outcomes without effective pedagogical application. This study adopts an integrated framework that combines TAM/UTAUT (technology adoption), Constructivism (learning process), Information Processing Theory (data utilization) and TOE (contextual conditions). This integration provides a comprehensive explanation of how intelligent instructional systems function within higher education. However, this process is not linear in isolation. It is shaped by institutional readiness, technological infrastructure, lecturer competence and policy environments, which collectively determine the success of AI integration in higher education.

Challenges in the Implementation of Intelligent Instructional Systems in Higher Education

Despite the increasing integration of intelligent instructional systems, learning analytics, artificial intelligence and adaptive learning technologies in higher education, several systemic, pedagogical and infrastructural constraints continue to limit their effective implementation, particularly in developing contexts such as Nigeria. These challenges are multidimensional, reflecting both structural limitations and human capacity deficiencies that affect sustainable adoption and utilization.

Infrastructural Deficiencies: A major constraint to effective implementation is inadequate digital infrastructure. Intelligent instructional systems depend on stable internet connectivity, functional learning platforms and consistent access to digital devices. However, evidence from Nigerian higher education institutions indicates that unstable power supply, limited broadband access and insufficient ICT facilities significantly hinder the deployment and scalability of AI-enabled instructional systems (Yusuf & Adeoye, 2023; Adesina & Ibrahim, 2022). These infrastructural limitations create unequal access to digital learning opportunities and reduce the overall effectiveness of intelligent learning environments across institutions.

Limited Digital Competence of Lecturers: Another critical challenge is the insufficient level of digital literacy and AI-related competencies among lecturers. The effectiveness of intelligent instructional systems largely depends on lecturers' ability to interpret learning analytics, integrate AI tools into pedagogy and redesign instructional strategies accordingly. However, studies show that many lecturers in Nigerian universities lack adequate training in advanced digital pedagogies and data-driven instructional approaches (Ezeani, 2022; Akinyemi & Bada, 2021). This skills gap often results in underutilization, ineffective application, or superficial adoption of intelligent instructional technologies.

Resistance to Technological Change: Resistance to change also constitutes a significant barrier to adoption. Some lecturers perceive AI-driven instructional systems as overly complex, incompatible with traditional teaching practices, or threatening to established academic roles. Research by Ifinedo and Oladejo (2022) indicates that such resistance is often driven by fear of job displacement, low technological confidence and inadequate institutional support for digital transformation. Consequently, resistance slows the diffusion and normalization of AI-enabled teaching practices in higher education institutions.

Data Privacy, Ethics and Governance Issues: The increasing reliance on student data for learning analytics and AI-driven decision making raises important concerns regarding privacy, ethics and governance. In many Nigerian institutions, weak regulatory frameworks for educational data management exacerbate risks related to unauthorized data access, lack of informed consent and unclear ownership of learner data (Salau & Mohammed, 2023). These issues pose ethical challenges that may undermine trust in intelligent instructional systems and limit their long-term acceptance.

Fragmented Implementation of AI Systems: Another significant gap is the lack of integration among digital learning technologies. In many higher education institutions, AI applications, learning analytics platforms and adaptive learning systems are implemented as isolated tools rather than as interconnected ecosystems. This fragmentation limits the ability of institutions to fully leverage data-driven instructional intelligence. Olanrewaju and Afolabi (2022) note that disconnected systems weaken instructional coherence and reduce the effectiveness of evidence-based decision-making in teaching and learning processes.

Limited Institutional Support and Policy Frameworks: Institutional readiness remains a fundamental determinant of successful technology integration. However, many Nigerian higher education institutions lack comprehensive policies that support AI adoption, continuous staff development and structured digital transformation strategies. According to Adeoye and Afolabi (2022), inadequate funding, weak policy direction and limited leadership commitment significantly constrain the implementation of intelligent instructional systems. In the absence of strong institutional frameworks, technology adoption remains fragmented, inconsistent and unsustainable. Generally, these challenges highlight the complex interplay between technological infrastructure, human capacity, institutional readiness and governance structures. Addressing them is essential for achieving meaningful and sustainable transformation of higher education through intelligent instructional systems.

Conclusion

Intelligent instructional systems driven by artificial intelligence, learning analytics and adaptive learning have the potential to significantly transform higher education by improving teaching effectiveness, personalizing learning and enhancing student outcomes. However, their successful implementation remains constrained by infrastructural deficits, limited digital competence among lecturers, resistance to change, weak data governance, fragmented system integration and inadequate institutional support, particularly in developing contexts such as Nigeria. These challenges show that technological innovation alone is not sufficient for meaningful educational transformation. Effective adoption depends on the alignment of infrastructure, human capacity, institutional readiness and supportive policy frameworks. Therefore, addressing these gaps is essential for the sustainable integration of intelligent instructional systems in higher education.

Recommendations

Based on the findings and challenges identified, the following recommendations are proposed to enhance the effective integration of intelligent instructional systems in higher education:

1. Higher education institutions should invest in reliable internet connectivity, stable electricity and modern ICT infrastructure to support effective deployment of AI-driven instructional systems and learning analytics. Collaboration between the government and institutions is essential for sustainability.

2. Continuous professional development should be provided to improve lecturers' digital literacy and competence in using AI tools, learning analytics and adaptive learning systems, with emphasis on practical application and instructional integration.

3. Institutional leadership should implement awareness and sensitization programmes to reduce resistance to technological change and promote acceptance of AI-driven teaching innovations among academic staff.

4. Clear institutional and national policies should be established to guide data privacy, ethical use of student information, funding and strategic implementation of digital transformation in higher education.

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