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AI-DRIVEN ADAPTIVE LEARNING IN HIGHER EDUCATION: PERSONALIZING UNIVERSITY TEACHING METHODS

Victor Igberaese[1], Zainab Shamsiya Usman
[1,2]Department of Computer Science, American University of Nigeria, Yola, Nigeria[1]
victor.igberaese@aun.edu.ng, zainab.usman@aun.edu.ng

Abstract
Without a doubt there is a transformation in higher education as a result of Artificial intelligence (AI) which is due to adaptive learning systems that is tailored to students needs and even beyond that. The traditional approaches often seem homogenous and leads to a disjointed form of learning within students' populace. In contrast, adaptive learning platforms have real time analyzer which can adjust pace, regulate modality and also temper down the difficulty in content. In recent studies from articles, shows that engagement, knowledge acquisition and motivation especially for students comes with ability for learning to be diverse. (Du Plooy, 2024; Wang et al., 2024; Ipinnaiye et al., 2024). Analysis show that adaptive learning improves outcomes cognitively by at least 10 -15% while this also helps in retention and satisfaction (Hooshyar, D., 2024). There are still challenges that remain such as data risks, faulty workload all of which may hinder institutional adoption of this new approach (Camilleri, 2024). More so, there are varying outcomes such as critical analysis and creativity, which shows reduction in consistent improvements (Chernikova, 2024). In a nutshell, this paper seeks to synthesize an AI-driven adaptive approach towards learning within a multi-layered framework in universities. This analysis shows that AI is here to assist or complement to the already instructor led pedagogy as long as there a form of implementation by the institutions with a robust performance, professional and ethical standards.

Keywords: Artificial intelligence, adaptive learning, personalization, higher education, educational technology

1. Introduction

Higher education has a lot of challenges that faces it ranging from diversification up to falsification. The expansion of access had produced students which are more heterogeneous with different background and culture having exiting knowledges and preference learning styles (Ipinnaiye, 2024). The usual traditional ethics of learning models, however, pace content for delivery and also assume homogeneity. This contributes to a sort of disengagement, contributions are mismatched and rates of attrition are on the high side (Du Plooy, 2024).

During the COVID-19 pandemic, which led to universities to be digitalized at an expedite rate, in turn force institutions to adopt to online learning systems of teaching. This shift no doubt increased flexibility, it also showcased limitations of the usual static content and in some way the need for adaptive learning was underscored (Raza & Khan, 2025). Within this context, AI-driven approach to adaptive learning proffers a paradigm shift which combines scalability as well as personalization in order to meet diverse needs (Wang et al, 2024).

The objectives in these articles are to analyze how AI-driven form to adaptive learning platforms will address the needs of students in diverse spheres, retention, and performance and also propose a model for institutions to adopt a balance towards opportunity as well as governance alongside ethics. Adaptive AI represents not just an upgrade in technology but rather a transformation pedagogically. Studies have suggested an adaptive platform improves performances but in the long run has a way of fostering inclusivity especially with regards to learners who are a disadvantage. (Ayeni et al., 2024; Alrawashdeh et al., 2024).

2. Literature Review

There is a saying that educational psychology is grounded in personalization. The VARK model alongside Gardner's Multiple Intelligences theory emphasizes learner diversity. This theory has been citizen as a result of weak support empirically (Pashler et al., 2008), but it cannot be emphasized of the influence these models have. In modern AI systems today, operational principles help in providing multimodal resources which can adapt dynamically to patterns in performance (Du Plooy; Chernikova et al., 2024).

There has been a notable acceleration in AI adoption as far back as 2019. Periodic reviews have shown that adaptive learning has improved the level of learning and made more induvial knowledgeable (Wang wet al., 2024). An analysis done by Hooshyar et al (2024) showcased that technological enhanced learning is a significant boost in educational achievements especially when there is a form of constant feedback formatively. More so, Ipinnaiye et al., (2024) showed that adaptive methods go hand-in-hand better performances, while Chernikova et al., (2024) stressed the need to find a much-needed balance between the system and learner-driven adaptive approach.

In respect to the design perspective, contributions from ACM shows how learning in systems have integrated adaptive engines with learning management tools which simplifies the process and delivers content in ecosystems. Gautam and Gupta (2024) have proposed frameworks simulations in order to help with evaluating adaptive algorithms before it is fully deployed, this helps to stop the underscoring for rigorous testing. Tan et al. (2025) reports that there is an increase by about 20% in terms of satisfaction, persistence especially amongst students who enrolled for courses that are AI-enabled. On the other hand, Alrawashdeh et al. (2024) the dropout rate by personalized reading platforms reduced, this can be attributed to the alignment of texts with the proficiency of students. Furthermore, Ayeni et al. (2024) recognized that student's inclusivity which the advent of adaptive platforms has improved especially with students with disabilities because resources are tailored to individual needs.

It should be known that algorithms that are poorly designed can ensconce inequalities if the datasets are biased or do not have the needed accessibility features (Mohammadi et al., 2025). The risks that arise with privacy come from multimodal learning analytics (Mohammadi et al., 2025). Additional challenges though not limited include faculty workload and algorithmic bias (Camilleri, 2024; Tan et al., 2024). Analysis gotten from sage put forth arguments that governance frameworks (audits, data minimization) is a must for sustainable and trust integration (Ahmed et al., 2024).

In most researches, there are limitations to short-term pilots in the STEM fields. Little is known when it comes to adaptive learning scales which cuts across the entirety of institutions or the long-term outcomes which include but not limited to employability and retention (Du Plooy, 2024).

3. Proposed AI-Driven Framework

Before adaptive learning can successfully be implemented in higher education, it requires a comprehensive framework that aligns with governance, system architecture and phased integration. Within the main core, is the engine for analytical learning which is where data on students is gathered and interpreted for learning outcomes. There are also trajectories that can be predicted by the algorithm which handles learner modeling (Hooshyar et al., 2024).

Adaptive sequencing adjusts both difficulty and modality which has a way of improving persistence (Chernikova et al., 2024; Ipinnaiye et al., 2024). Teachers are empowered through their dashboards through the maintenance of human-in-the-loop design as well as contextual analytics. Before integration is carried out, the process is in three phases. Firstly, is the readiness phase in terms of infrastructure and policies (Gautam & Gupta, 2024). Next is the pilot phase which deploys a system for adaptiveness especially in courses with high enrollment which gives room for evaluation (Wang et al., 2024). The last stage is the scaling phase which tends to expand the institutions width and this is greatly supported by the faculty's development as well as leadership (Tan et al., 2025). To the very large extent, the need for quality assurance with audits, explainable AI, and data protection compliance standards (Mohammadi et al., 2025), is very much needed. More so, there is the equity demand design for accessibility (AYeni et al., 2024).

Recent literature emphasizes that AI-driven adaptive learning systems must combine robust learner models, explainability, governance, and simulation-led validation to be effective at scale. Several recent reviews and empirical studies show short-term learning gains from personalization but also note risks around algorithmic bias, privacy and limited evidence on long-term outcomes. Accordingly, our proposed framework extends prior work by (1) embedding explainable AI (XAI) modules to provide instructor- and learner-facing rationales, (2) adding a simulation/pilot phase to validate sequencing and adaptation policies before broad deployment, (3) incorporating knowledge-tracing for mastery-based sequencing, and (4) enforcing privacy-first multimodal analytics and an auditable governance layer (Idrizi 2024; Gautam & Gupta 2024; Mohammadi 2024/25).

Table 1: A Critical Analysis of Selected Studies Showcasing AI-Driven Framework

#	**Domain**	**Framework / Method**	**Key strengths**	**Main limitations**	**Relevance / How to incorporate into your AI-driven framework**	**Source**
1	Systematic review/personalized adaptive learning	Aggregated evidence that adaptive learning improves engagement & outcomes; synthesis of effect sizes and contexts.	Good high-level evidence bases for claiming adaptive benefits; helps justify pilot.	Meta-analytic heterogeneity; limited long-term/scale evidence noted.	The literature review established within this paper can be used for foundational justification as well as the introduction which establishes a 10-15% gain in performance claim especially in regards to contextualizing the need for the three-phase implementation within the proposed framework.	du Plooy (2024).
2	Meta-analysis of tech-enhanced personalized learning	Quantitative meta-results showing effect sizes (10–15% gains) and moderators (formative feedback).	Strong empirical numbers to back efficacy claims.	Heterogeneous methods across primary studies; some publication bias.	There is the need for data sensitization especially within the abstract and result sections. This means formative feedback from findings in order to strengthen the	Hooshyar et al. (2024)

					adaptive sequence in terms of the learning component. The need for heterogeneity acknowledgement is much needed especially within the first simulation approach for it to have a meaningful rationale.	
3	Broad SLR on AI in education (scoping review)	Maps applications (tutoring, recommender, analytics) and gaps in governance/ethics.	Useful taxonomy for categorizing components (tutor engine, analytics, UI, governance).	High-level; does not propose integration architecture.	The four components should be adopted which is data layer, (learner model, XAI and the governance architecture), all needed to be the structural backbone of the proposed framework. This can be used to identify gaps and justify quality assurance phase during implementation.	Wang et al. (2024)
4	Framework for simulating adaptive learning systems	Simulation-first approach to test adaptive algorithms before deployment.	Valuable: mitigates rollout risk; permits parameter tuning and A/B testing.	Simulators may not capture real-world noise and user behaviour accurately.	Embedded simulation which is also the pilot phase but more of phase 2 within the 3 phases mentioned earlier which is between	Gautam & Gupta (2024).

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					readiness and scaling. There is the need for adaptive sequencing to be validated alongside knowledge trace algorithms before been deployed fully within the institution. This will help to reduce the untested algorithms.	
5	Equity & inclusivity studies (disability focus)	Case studies showing adaptive systems can support learners with disabilities.	Evidence that personalization improves accessibility and inclusion.	Requires careful design (alt formats, multimodal input), risk of algorithmic bias if not designed carefully.	There is to make accessibility mandatory in the designing of the architectural framework. This helps to tackle audits and bias detection especially when it comes to quality assurance. This will also align with framework emphasis in address inclusivity and performance gaps especially for students with special needs.	Ayeni et al. (2024).

6	Governance & organizational readiness	Discusses ethics, governance, organizational change for AI adoption in education.	Emphasizes need for audits, consent, staff training and leadership buy-in.	Mostly prescriptive (few operational templates).	This needs to be operationalized as the framework for governance with detailed mechanisms such as audit logs, faculty development, workflows and leadership engagement. All of this is essential for the readiness phase (phase 1) and also the ongoing quality assurance which deals with the matter of institutional readiness and also factors determinants for success.	Ahmed (2024); Camilleri (2024).
7	Meta-analysis on personalization (critique)	Finds mixed effects on higher-order skills; warns personalization can reduce practice on difficult tasks.	Important caution: personalization must preserve rigor & challenge.	Risk of optimizing for short-term gains at cost of deeper learning.	Curriculum integration constraint is needed into the adaptive sequence engine which is needed to prevent over-simplification as the case maybe. There is the need to ensure that the challenge with exposure of content challenging is taken care of and	Chernikova et al. (2024).

					also handled in high thinking tasks that maybe assigned. This helps to address the thinking challenge especially in higher-order thinking as mention in the paper. That is, creating a balance with the human-in-loop design within the pedagogical rigor.	
8	XAI for adaptive learning (2024)	Argues for explainable AI layers to increase trust and pedagogical transparency for AL systems.	Proposes concrete XAI patterns (global + local explanations) that help instructors trust recommendations.	XAI adds computational cost; explanations must be pedagogically meaningful, not technical.	Embedded XAI module that has a dual-level of explanations namely: student-facing which deals with justification for recommendations for content; and also, the instructor dashboard: which will handle counterfactual explanations and importance of the features.	Idrizi (2024).
9	Multimodal Learning Analytics SLR (2024–25)	Reviews use of audio/video/biometric + interaction logs with AI to model learners.	Shows potential for richer learner models (engagement, emotion) and	Privacy, data governance and sensor reliability are major barriers.	Multimodal data needs to be added for the capturing of learning analytics but will have a privacy -	Mohammadi et al. (2024/25).

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			robust personalization.		by-deign principal setup which will have data minimization, explicit consent. this will enhance the learner module and also at the same time address privacy risks that has been emphasized in the earlier discussions. This can be seen as an optional module for institutional governance.	
10	Knowledge-tracing + XAI approach (2025)	Combines student knowledge tracing with explainability to guide interventions.	Strong at modeling mastery over time; better for sequencing & spacing decisions.	Requires fine-grained assessment data (not always available) and complexity to implement.	There needs to be an integration with deals with knowledge-based algorithms into adaptive sequence algorithms for a well-rounded mastery-based operation. This supports the framework emphasis especially in real-time analytics and trajectories predication. What this means is that high enrollment courses will be started with because data	Muthangi (2025).

					assessment is abundant.	
11	Adaptive Algorithms & practice (2025)	Adaptive algorithm designs that integrate pedagogical models and reinforcement learning.	Demonstrates RL for long-horizon sequencing and adaptive pacing.	RL needs large interaction data; cold-start problem for new courses.	The need to use adaptive algorithms that are RL-based which can handle traffic which is very likely to be very high especially as a result of courses especially after the pilot scheme. For smaller courses a warm start with a system that is rule-based and that will align with passed scaling approach will help to address the challenges of untested algorithms that have been deployed.	Endla (2025).
12	Empirical study: adaptive platforms in practice (2024 ACM/IEEE)	Evaluations showing improved satisfaction/persistence when AL is combined with faculty support.	Empirical support for coupling tech + instructor scaffolding.	Institutional readiness mediates outcomes strongly.	There has to be priority dashboards for instructors and faculty for development programs and also the reinforcement for human-in-the-loop principle of design which	ACM/IEEE 2024 proceedings (exploration & practice).

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					handles and addressed the unpreparedness of faculty which was raised as a discussion. Also, there is the need to make professional development a much-needed requirement in the first phase which is an on-going process throughout all phases.	
13	APT: Adaptive Personalization Theory (2024)	Proposes theoretical model (APT) for personalization using real-time signals & curriculum constraints.	Provides theoretical grounding for design choices (what to personalize, when).	Still early-stage; needs empirical validation.	APT can be used as foundation for conceptual learning model and policy for personalization. This also provides justification for the real-time analytics and components for adaptive sequence learning in real-time analysis, as moted within the literature review of this paper.	"Adaptive Personalization Theory" (2024).
14	Adaptive AI prototypes (recent applied paper 2024–25)	Demonstrations of end-to-end adaptive systems (data pipeline → models → dashboards).	Useful implementation patterns and open-source tools.	Many are domain-specific; limited general-purpose frameworks.	With Technical architecture patterns, event streaming for real data, LMS modules integration and also dashboard	Adaptive AI-based systems (2024–25 sample papers).

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					templates. This accelerates to phase 2 which is the pilot implementation that leverages on technical components and efficiently reduces time and risk development.	
15	Reviews on AI governance & ethics (2024–25)	Summarizes governance recommendations (audits, impact assessments, standards alignment).	Provides policy language and governance checklist items you can include.	Broad and high-level; may require contextualization for universities.	Institutional governance can be created with a checklist for the much-needed framework with include but not limited to audit logs, bias assessments, audit logs, data protection compliance and also data protection as stated earlier. The quality assurance operationalizes ethical standards emphasized throughout this paper which deals with sustainable and trustworthy adoption	Papagiannidis et al. (2025) & UN recommendations (2024).

4. Results and Discussion

5. Implications and Future Research

There are opportunities as well as responsibilities when it comes to adaptive learning. Universities should be able to prioritize development of their faculty, thereby equipping instructors with the ability to read, interpret and redesign pedagogy as the case study (Wei et al., 2025). More so, the framework for government must have regulated consent, audits and a detailed form of transparency (Camilleri, 2024). Within a resource-constrained setting, it should be noted that infrastructure investments are very vital (Ahmed et al., 2024).

Research has its limitation which is bounded by disciplinary scope and timeframes. Work done in the future should try to examine impacts on retention and graduate success and if possible, some form of cross-cultural adoption (Du Plooy, 2024). A very critical frontier is explainable AI which has enabled trust and transparency (Mohammadi et al., 2025). If these gaps can be successfully addressed, it will ensure that adaptive learning will evolve into an effective and equitable tool in educational advancement.

6. Conclusion

Without a doubt AI-driven adaptive form of learning has a promise to improving academic performance and can be maintained at a very substantial level as long as there is inclusivity. From studies, we can see benefits across multiple users, however, there is the need for privacy to be addressed, algorithm bias and to a very large extent the institutional readiness. Having that said, adaptive AI should complement rather than replace (Raza & Khan, 2025). With the right support from faculty, governance and also inclusive design, universities can leverage on the model of adaptive learning in order to be able to deliver education for the future without fear of the old learning styles being faded out.

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