

The Application and Challenges of Artificial Intelligence in Personalized Learning for Higher Education

Sichen Wang

Tianjin Foreign Studies University, Tianjin, China
13821817458@163.com

Abstract. Universities worldwide are rapidly advancing artificial intelligence (AI) to reconcile the perennial tension between educational quality, scalability, and personalization. This paper analyzes 13 studies and case analyses, focusing on AI applications in higher education: (1) adaptive learning systems, (2) real-time instructional tools, and (3) automated assessment feedback. These technologies improve course completion, reduce instructor preparation time, and enhance student writing. Nonetheless, they also introduce fresh risks related to academic integrity, data privacy, shifting teacher–student roles, and equity in resource distribution. This paper proposes a two-tier, triadic governance framework to address the intertwined challenges of educational ethics and quality, user adaptation, and the digital divide posed by generative AI. Universities should adopt honor codes, AI evaluation guidelines, secure data sandboxes, and AI-literacy curricula. Governments and industry must provide regulatory standards, resources, and multilingual large-language-model infrastructure. AI can significantly drive equity and excellence in higher education when internal self-regulation aligns with external policies.

Keywords: Artificial intelligence, Higher education, Personalized learning, Educational equity and quality

1. Introduction

AI is catalyzing a profound transformation within higher education. Intelligent question banks, automated scoring, and learning analytics are transforming education from a one-size-fits-all model to personalized learning [1]. Defined as a technology-driven approach that both recognizes and nurtures individual differences, personalized learning in AI-supported environments exhibits three salient features [2]: (1) high adaptability, whereby the system autonomously adjusts task difficulty in real time; (2) rich human machine interaction, achieved through intelligent tutoring, conversational agents, and related tools; and (3) fine-grained precision, in which data-driven algorithms analyze learning behaviors and deliver targeted recommendations. Collectively, these features delineate the technical architecture of AI-enabled education.

Empirical research confirms AI's considerable promise for higher education. By mining students' behavioral data, AI can generate individualized learning trajectories that enhance motivation and achievement. It can also perform automatic grading, compile data dashboards, and provide evidence-based teaching recommendations, reducing instructors' workloads. Nevertheless, extant

scholarship often examines these functions in isolation and rarely integrates the complete learning–teaching–assessment cycle; many studies also foreground the risks and ethical challenges of AI-mediated personalization [3].

This study investigates AI's application in personalized higher education via systematic review and cross-case analysis. It details use cases, identifies challenges, and suggests mitigation strategies, providing actionable guidelines for universities, policymakers, and educators to promote equitable and effective AI-driven learning.

2. Application of artificial intelligence in higher education

2.1. Student learning path

The essence of personalized education is discovering a learning trajectory that fits each student. In conventional classrooms, every learner follows the same instructional sequence and problem set: weaker students struggle to keep up, whereas advanced students are seldom pushed to their limits [4]. To bridge educational gaps, universities are adopting AI learning platforms using machine learning and deep-learning analytics. These platforms customize resources and pacing based on individual needs and adjust learning paths with real-time feedback. For instance, Arizona State University's AdaptiveMath project, utilizing the Knewton engine, increased course-completion rates compared to traditional methods, as reported by the Teaching Innovation Center in 2022.

AI transforms education by enabling flexible learning across devices and locations. Students can engage with content on mobile devices during commutes or on library computers, with progress automatically synchronized. The system adapts to individual learning preferences, offering visual content or audio alternatives. Tsinghua University's "Xuetang & Rain" Classroom exemplifies this approach, combining WeChat integration with analytics that dynamically adjust difficulty and provide targeted remediation. This multichannel delivery increases student autonomy while generating valuable data for AI-driven educational planning.

AI systems create personalized materials and schedules based on student goals, monitoring progress and adjusting workload automatically. The Open University's OUAlyse extracts data from Moodle to generate real-time analytics, with risk-prediction algorithms forecasting failure probabilities and sending targeted nudges that improve submission rates. Instructors access comprehensive dashboards to identify intervention needs. A Canadian distance-education provider's engagement model predicts drop-out risk with 82% accuracy, enabling evidence-based early intervention.

2.2. Teacher support pathways

As artificial intelligence becomes embedded in higher education, the teacher's role is evolving across all stages of instruction—pre-class planning, in-class facilitation, and post-class assessment and reflection. Purpose-built AI tools now support each stage, allowing instructors to work more efficiently while delivering greater precision in teaching [5].

Pre-class preparation can be streamlined using large language models (ChatGPT, DeepSeek) that efficiently compile research, case studies, and lesson plans. Knowledge graph platforms (Google Course Builder, Superstar Knowledge Graph) visualize concept relationships and prerequisites, allowing instructors to quickly assess content structure and design targeted instruction.

In-class facilitation. Smart-classroom systems collect interaction data, such as click streams, quiz responses, and real-time questions, and translate them into attention heat maps and mastery

dashboards. These analytics let instructors adjust pacing and focus instantly. The same systems push adaptive mini-quizzes, supplemental resources, and extension readings tailored to individual feedback. An AI teaching assistant can answer routine questions or supply detailed examples on demand for students who struggle, mitigating conventional instruction's "one-size-fits-all" limitations. As a result, every learner can follow a personalized trajectory within the shared classroom, and teachers can concentrate on fostering critical thinking and addressing higher-order misconceptions rather than repeating basic explanations.

Post-class, automated grading and AI writing evaluation provide instant scores and revision advice, maintaining student engagement. Detailed learning logs (concept mastery, retry counts, collaboration metrics) aid instructors in diagnosing content or instructional issues. This enables rapid intervention for at-risk students, preventing performance decline.

As summarized in Table 1, numerous validated use cases demonstrate that AI, whether serving as a digital tutor or analytic assistant, can enhance the effectiveness and the efficiency of university teaching.

Table 1. Representative initiatives targeting teacher support

Region	Institution / Project	AI-Enabled Support for Instructors	Reported Impact	Source
United Kingdom	David Game College, "Hummingbird Project"	An AI tutor delivers mathematics and English lessons, while human assistants monitor progress and logistics.	The system pinpoints individual weaknesses and offers targeted guidance, leading to measurable gains in STEM proficiency.	Daily Mail, 10 Aug 2024
United States	Los Angeles Unified School District	A conversational agent fields student queries about attendance, grades, and related matters; teachers mine the dashboard data to refine instruction.	The bot achieves an answer accuracy of 93%, outperforming ChatGPT's reported 85-87 % range.	AIGC Daily, 2024
China	Northeast Forestry University, Chaoxing AI Teaching Assistant	Generates learning analytics, adaptive lesson plans, and automated grading.	When leveraging the assistant's complete feature set, instructors report higher efficiency and reduced administrative load.	Undergraduate Portal, 20 Sep 2024

2.3. Completion and evaluation of assignments

Completing, evaluating, and diagnosing assignments is inherently slow in traditional settings. AI, however, enables a real-time feedback loop that operates on two fronts: it delivers immediate support to students and streamlines instructors' assessment workflows [6]. With AI-assisted assignments, learners receive instant scores, diagnostics on error types, and actionable revision advice, allowing them to correct misunderstandings on the spot. The platform aggregates error patterns on the back end, giving teachers rapid insight into instructional effectiveness.

Monash's Learning Analytics Center assesses group contributions via multimodal data mining. In Germany, an automated-essay platform uses NLP (Natural Language Processing) for objective grading. East China Normal University's system offers real-time English writing feedback, aiding weaker students. Closed-loop systems like ASU's Adaptive Math and OU Analyse enhance learning efficiency by overcoming teacher grading speed limits in iterative cycles.

The main issue in assignment workflows is that full reliance on AI by students can undermine independent reasoning, while instructors must still evaluate AI-generated work [7]. Most Chinese universities lack formal detection methods, leaving instructors to rely on personal judgment. In

contrast, some Australian and UK institutions address this by requiring students to orally present or defend their work.

To uphold fairness, a pragmatic approach combines automated screening with human validation. In this two-stage model, an AI system conducts an initial review, grading the work and classifying error types, after which instructors audit submissions flagged as high-risk or anomalous. Final marks and justifications remain the instructor's responsibility; AI outputs function solely as advisory input.

3. Challenges of generative AI in higher education

3.1. Quality and ethical challenges in education

Adopting generative AI in higher education has raised serious concerns about academic quality and ethics. A multi-university survey in the United States found that roughly 90 % of students admit to using AI tools in coursework, with many cases constituting academic misconduct. UK institutions likewise report that AI-generated essays often appear rigorous on the surface yet contain fabricated content, jeopardizing the integrity of assessment.

Policy on AI use is preliminary. Universities need precise definitions to differentiate acceptable AI assistance from plagiarism. Instructors must increase efforts to verify AI-generated submissions. Data security is at risk because training LLMs (Large Language Models) needs extensive student data logs, but anonymization and encryption are uncommon. Data transfer to third parties increases leak risks. Efficiency is reduced by reliability issues. LLMs can reproduce bias from training data and fabricate citations, which undermines academic integrity.

3.2. Adaptability of teachers and students

AI is transforming education, necessitating updated skills for both teachers and students. Faculty concerns about automation's impact on their roles have led to resistance. Many educators are ill-equipped to handle students' use of AI for learning, which challenges conventional teaching authority. Instructors are unable to adapt to risk marginalization [8].

Students, in turn, may lean so heavily on AI that independent reasoning atrophies. Although undergraduates readily embrace new tools, excessive reliance can erode critical thinking and academic writing skills, making authentic mastery harder to gauge. Few students verify AI outputs, treating the technology as a shortcut rather than a fallible assistant.

Traditional teacher-student dynamics are shifting in modern education. Educators evolve from knowledge gatekeepers to learning collaborators or advanced-concept facilitators, while students negotiate the blurred boundary between human instruction and machine support.

3.3. Educational equity and resource allocation

In its early stages, AI risks widening existing inequities. Han & Kumwenda report that institutions in less-developed regions lack the network infrastructure and computing resources needed to deploy AI tools, deepening the digital divide [9]. Higher education could bifurcate into an "AI elite" and an "AI-disadvantaged" cohort without a broad-based infrastructure and faculty training. Nations with robust AI ecosystems will accelerate, leaving others further behind.

Language and culture exacerbate disparities, as foundation models, trained mainly on English corpora, exhibit Anglocentric bias. This leads to misinterpretation of linguistic nuances and lower-quality output for non-English speakers, disadvantaging them academically. An inequity mirroring the Matthew effect emerges: well-funded universities license bespoke platforms like GPT-4

Enterprise, while under-resourced schools use free, feature-limited tools, widening the personalized-learning divide.

4. Response strategies and suggestions

4.1. Citation strategies of higher education institutions

This paper posits that universities should establish ethical and behavioral guidelines for AI applications, alongside explicit usage rules and academic standards. It advocates for regulations on AI use in student assignments, noting that approximately 51% of U.S. universities delegate ChatGPT usage decisions to instructors, mandating citation and prohibiting direct submission of AI-generated content as original work. The paper also calls for corresponding supervision and penalties to reinforce academic integrity by detecting and sanctioning academic misconduct. To address the challenges in the previous section, this paper proposes actionable strategies around three dimensions [10].

Challenges in educational quality and ethics. This paper suggests starting from institutional, technical, and review aspects to avoid the two major problems of ambiguous academic-integrity boundaries and a lack of data-security standards [11].

(1) Adopt a dual-document system: students must include a unified AI usage statement in their assignments, and an AI Review Manual is issued to assist teachers in "AI preliminary review + manual sampling + random oral examination."

(2) Carry out privatized deployment: prioritise on-campus large models or local API gateways, desensitize student data and use encrypted inference to lower leakage risks.

(3) Establish an AI ethics group: faculty, students, and the IT office jointly examine new tools for bias and security, issuing a risk bulletin each semester.

Improving teacher and student adaptability to AI. Measures should be considered separately for students and teachers [12]. Design a university-wide compulsory "1 + X" general education course centered on AI literacy, emphasizing generative AI and academic integrity. Additionally, universities should introduce AI micro-courses and emphasize educators' crucial role by retraining them through a tiered system. This system advances from basic AI literacy to advanced smart-education innovations, transforming teachers into architects of learning experiences.

Challenges in educational equity and resource allocation. Infrastructure sharing, adaptive teaching reform, and institutional safeguards should be strengthened [13].

(1) Universities should jointly build computing-power platforms that under-resourced universities can use during off-peak hours.

(2) Encourage students to annotate minority-language corpora to provide data for on-campus fine-tuning models, alleviating the English-centric tendency and adapting to contextual deviations in different languages.

(3) Establish tiered teaching schemes: course syllabi should also provide a "non-AI alternative pathway" to guarantee every student's minimum learning right.

4.2. Government and social support measures

Effective AI governance in higher education requires coordinated action by government and civil society in three domains: regulation, funding, and shared resources: regulation and standards. Governments should swiftly issue guidelines for generative AI in educational settings that mandate robust data-governance procedures, human oversight, and algorithmic transparency. Third-party

vendors would need a "Trusted Education AI" certification-granted only after stringent audits of security and openness-before their products may be deployed on campus [14].

To equalize AI education access, we need funding and capacity-building. A national "Faculty AI Training Fund" for teachers and "bandwidth-plus-GPU" subsidies for universities are essential [15]. Tech firms should donate education-edition API quotas to students and sponsor open-source models in minority languages. With proper governance, safeguards, and contributions, AI can enhance personalized learning and reduce inequities.

5. Conclusion

This study uses an "applications-challenges-strategies" framework to analyze AI-driven personalized learning in higher education. Addressing generative AI's challenges, it suggests a university-government-society solution. AI already facilitates large-scale differentiated instruction through adaptive recommendation, real-time diagnostics, automated feedback across learning pathways, faculty support, and assessment. Yet, these gains are accompanied by heightened risks to academic integrity, data security, role stability, and resource equity. If institutions implement internal safeguards like honor pledges, review manuals, and data sandboxes, alongside external support via regulation, funding, and multilingual models, personalized learning benefits are achievable. This analysis, based on literature and illustrative cases, addresses algorithmic transparency and bias conceptually. Future studies should employ longitudinal, cross-cultural, large-sample methods to assess AI personalization's long-term effects on learner motivation and cognition.

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