

ADAPTIVE DISTANCE LEARNING FRAMEWORKS IN EMERGING MARKETS: LEVERAGING GENERATIVE AI AND INTERNATIONAL DIGITAL ECONOMY STANDARDS

Yakhshiboev Rustam Erkinboy ugli

Independent researcher, Tashkent State University of Economics

+998 99 890 96 23

r.yaxshiboyev@tsue.uz

Abstract – *The rapid expansion of higher education in emerging markets has outpaced the growth of teaching capacity, while generative artificial intelligence (GenAI) offers a potential way to scale personalised tutoring in distance learning. This article aims to design an adaptive distance learning framework for emerging markets that combines GenAI-based tutoring with international digital economy standards. The study used a design science approach that combined three methods: secondary statistical analysis of higher education in Uzbekistan for 2020/21–2024/25, a structured synthesis of randomised controlled trials and meta-analyses on AI tutoring, and a document analysis mapping eight international standards and regulatory instruments onto framework layers. The results show that student enrolment in Uzbekistan grew 2.5 times over four years, correspondence (part-time) enrolment grew 5.7 times and reached 47.0% of all students, whereas full-time teaching staff grew only 1.55 times; the student–teacher ratio rose from 17.8 to 28.9. Restoring the 2020/21 ratio would require about 30.9 thousand additional teachers. The evidence synthesis indicates that GenAI tutoring improves learning when it is pedagogically scaffolded and supervised, but unrestricted access can reduce independent performance. Based on these findings, the article proposes the ADAPT-EM framework, consisting of five layers (access, interoperable content, adaptive AI engine, assessment and learning analytics, governance) aligned with WCAG 2.2, LTI 1.3, xAPI, ISO/IEC 42001, the EU AI Act, UNESCO and OECD instruments and national data protection law. The framework includes a set of performance indicators and addresses data localisation requirements. It can support universities and policymakers in emerging markets in introducing GenAI into distance learning responsibly.*

Keywords: *adaptive learning, distance education, generative artificial intelligence, intelligent tutoring, emerging markets, digital economy standards, interoperability, AI governance, learning analytics, higher education.*

INTRODUCTION

Distance learning has moved from the periphery of higher education to its core. In many emerging markets the move has been driven less by pedagogical choice than by demand: young populations, rising returns to tertiary education and limited campus capacity push universities to enrol more students in part-time and remote formats. At the same time, digital divides remain wide. According to the International Telecommunication Union (ITU), 94% of people in high-income countries used the Internet in 2025 compared with 23% in low-income countries, and 96% of the 2.2 billion people who remain offline live in low- and middle-income countries [12].

Distance learning in emerging markets therefore has to deliver more with fewer teachers and less reliable infrastructure.

Generative artificial intelligence (GenAI) has created a new possibility for addressing this problem. Personalised one-to-one tutoring has long been regarded as the most effective form of instruction: B. Bloom reported that tutored students performed about two standard deviations better than students in conventional classes [3], and later meta-analyses confirmed large effects for intelligent tutoring systems [16; 27]. Large language models make it technically possible to offer tutoring-like interaction at very low marginal cost. However, early experimental evidence shows that the effect depends strongly on design: well-scaffolded AI tutors can improve learning [15], whereas unrestricted access can undermine it [2].

Uzbekistan illustrates both the opportunity and the challenge. The number of students in higher education rose from 571.5 thousand in 2020/21 to 1,432.8 thousand in 2024/25 [19], and the government has adopted the Strategy for the Development of Artificial Intelligence Technologies until 2030 [23]. Yet a UNESCO survey found that fewer than 10% of schools and universities worldwide had formal guidance on GenAI [26], and national institutions in emerging markets rarely have the capacity to translate international standards on accessibility, interoperability, AI management and data protection into operational requirements.

The scientific problem addressed in this study is the absence of an integrated framework that links the pedagogical evidence on GenAI tutoring with the international standards of the digital economy and with the specific constraints of emerging markets. The aim of the study is to design and justify an adaptive distance learning framework for emerging markets that uses GenAI and is aligned with international digital economy standards. The objectives are: (1) to quantify the capacity gap in distance-oriented higher education using Uzbekistan as a case; (2) to synthesise rigorous evidence on the effects of AI tutoring and derive design principles; (3) to map relevant international standards and regulations onto framework components; and (4) to propose a framework with measurable performance indicators.

The object of the research is distance and part-time higher education in emerging markets; the subject is the organisational, technological and regulatory mechanisms for integrating GenAI into adaptive distance learning. The study tests the hypothesis that the benefits of GenAI for distance learning in emerging markets depend less on access to the technology itself than on pedagogical guardrails and standards-based governance. The scientific novelty lies in combining a quantified capacity-gap analysis, an evidence-derived set of design principles and a standards-alignment matrix into one framework (ADAPT-EM) tailored to emerging-market conditions.

LITERATURE REVIEW

The literature relevant to this study can be grouped into three streams: research on adaptive and intelligent tutoring systems, emerging experimental evidence on GenAI in education, and policy and standards literature on AI governance in education.

Adaptive and intelligent tutoring. B. Bloom’s “2 sigma problem” framed the search for group instruction methods that could approach the effectiveness of one-to-

one tutoring [3]. K. VanLehn’s review challenged the assumption that human tutoring is vastly superior, showing that step-based intelligent tutoring systems achieved an effect size of about 0.76, close to the 0.79 found for human tutoring, while simpler answer-based systems achieved about 0.31 [27]. J. Kulik and J. Fletcher reported a median effect size of 0.66 across 50 controlled evaluations of intelligent tutoring systems [16]. These studies share an important conclusion: effectiveness comes from the granularity of feedback and scaffolding, not from automation as such. At the same time, O. Zawacki-Richter and co-authors, in a systematic review of AI in higher education, noted weak connections between AI applications and pedagogical theory and a limited role of educators in the research [29]. W. Holmes, M. Bialik and C. Fadel similarly argued that AI in education should be evaluated through its effect on learning rather than technical capability [9].

Generative AI in education. E. Kasneci and colleagues outlined the opportunities of large language models for personalised learning while warning about bias, over-reliance and assessment integrity [14]. Experimental evidence has since begun to accumulate. G. Kestin and co-authors conducted a randomised controlled trial at Harvard University and found that students using a pedagogically designed AI tutor learned significantly more in less time than students in an active-learning class [15]. M. De Simone and co-authors evaluated a six-week programme in Nigeria in which secondary students used Microsoft Copilot under teacher supervision and found an improvement of 0.31 standard deviations, equivalent to 1.5–2 years of typical schooling [5]. In contrast, H. Bastani and co-authors showed in a field experiment with nearly a thousand high school students that unrestricted GPT-4 access improved practice performance but reduced subsequent exam performance by 17%, while a version with teacher-designed guardrails largely eliminated this harm [2]. Y. Fan and co-authors described a related risk of “metacognitive laziness”, in which learners delegate thinking to the AI [7].

The evidence base is still young and uneven in quality. A widely cited 2025 meta-analysis reporting a large positive effect of ChatGPT on learning performance was retracted in 2026 because of discrepancies in the analysis [10]. This case shows that policy decisions in emerging markets should rely on well-designed randomised trials and transparent syntheses rather than on headline effect sizes.

Governance and standards. UNESCO’s Recommendation on the Ethics of Artificial Intelligence established human rights, transparency and accountability as baseline principles [25], and its Guidance for Generative AI in Education and Research called on governments to regulate GenAI, protect data privacy and set an age limit of 13 for classroom use [17]. The OECD Digital Education Outlook 2023 emphasised the need for an effective digital education ecosystem that combines infrastructure, interoperability and governance [21], and the OECD AI Principles set out intergovernmental standards for trustworthy AI [22]. The EU Artificial Intelligence Act classifies AI systems used for admission, evaluation of learning outcomes and proctoring as high-risk [6]. Technical standards address complementary layers: WCAG 2.2 defines accessibility requirements [28], LTI 1.3 enables secure integration of external tools into learning platforms [1], the IEEE xAPI standard defines how learning

experience data are recorded [11], and ISO/IEC 42001 specifies requirements for an AI management system [13].

Taken together, the literature provides strong evidence on what makes tutoring effective and a growing body of guidance on AI governance. However, these streams rarely meet. Pedagogical studies seldom address interoperability, data protection or accessibility, while policy documents stay at the level of principles. Furthermore, most evidence comes from high-income countries, and research specific to emerging markets, especially Central Asia, remains scarce. This study fills this gap by linking evidence-based design principles to specific standards and by grounding the framework in quantified capacity constraints of an emerging-market higher education system.

METHODOLOGY

The study followed a design science research approach, in which an artefact (in this case, a framework) is built to solve an identified problem and justified by existing knowledge [8]. This approach was chosen because the aim was to produce a usable framework rather than to test a single causal relationship, and because primary experimental data on GenAI tutoring in Uzbekistan were not available. The research was carried out in four stages.

Stage 1: problem quantification. Official data of the National Statistics Committee of the Republic of Uzbekistan for the academic years 2020/21–2024/25 were collected on total enrolment, correspondence (part-time) enrolment and full-time teaching staff [18; 19; 20]. Uzbekistan was selected as a case because it combines rapid enrolment growth, a large part-time segment and an explicit national AI strategy. The following indicators were calculated: the share of correspondence students, the student–teacher ratio ($STR = \text{students} / \text{teachers}$), growth indices with 2020/21 as the base year, and the compound annual growth rate ($CAGR = (X_n / X_0)^{(1/n)} - 1$). The teacher gap was estimated as the number of additional teachers needed to restore the 2020/21 student–teacher ratio at 2024/25 enrolment. Connectivity conditions were described using ITU [12] and DataReportal [4] data.

Stage 2: evidence synthesis. Studies were included if they were randomised controlled trials or meta-analyses of controlled studies, reported learning outcomes rather than only perceptions, and were published in peer-reviewed journals or by major international organisations. Two classic meta-analyses on intelligent tutoring [16; 27] and three recent trials on GenAI tutoring [2; 5; 15] met these criteria. Retracted studies were excluded [10]. For each study, the context, design, sample, AI configuration and main effect were extracted, and recurring design features associated with positive or negative effects were identified.

Stage 3: standards mapping. Eight international and national instruments were selected on the basis of their relevance to accessibility, interoperability, AI management, risk regulation, ethics and data protection [1; 6; 11; 13; 17; 22; 24; 28]. Their requirements were coded against five framework layers, with each cell marked as a primary or secondary area of coverage.

Stage 4: framework construction. The results of the first three stages were integrated into a layered framework, and performance indicators were defined for each

layer. Calculations were carried out in Python and checked manually. Because the framework has not yet been implemented, its evaluation in this article is analytical rather than empirical.

ANALYSIS AND RESULTS

Capacity gap in Uzbekistan’s higher education. Between 2020/21 and 2024/25, total enrolment grew 2.5 times, correspondence enrolment 5.7 times and full-time teaching staff 1.55 times (Table 1, Figure 1).

Table 1.
 Students, teaching staff and student–teacher ratio in higher education of
 Uzbekistan

Academic year	All students, thousand	Correspondence students, thousand	Share of corresp., %	Teaching staff, thousand	Students per teacher
2020/21	571.5	118.1	20.7	32.1	17.8
2021/22	808.4	228.0	28.2	37.4	21.6
2022/23	1,042.1	381.8	36.6	41.7	25.0
2023/24	1,314.5	607.6	46.2	45.2	29.1
2024/25	1,432.8	673.4	47.0	49.6	28.9

The compound annual growth rate was 25.8% for total enrolment, 54.5% for correspondence enrolment and 11.5% for teaching staff. As a result, the student–teacher ratio increased from 17.8 to 28.9, and the number of correspondence students per full-time teacher rose from 3.7 to 13.6. To restore the 2020/21 ratio at 2024/25 enrolment, about 80.5 thousand teachers would be needed, which is 30.9 thousand (62.3%) more than the actual number. Almost half of all students (47.0%) now study in the correspondence format, in which contact with teachers is limited by design.

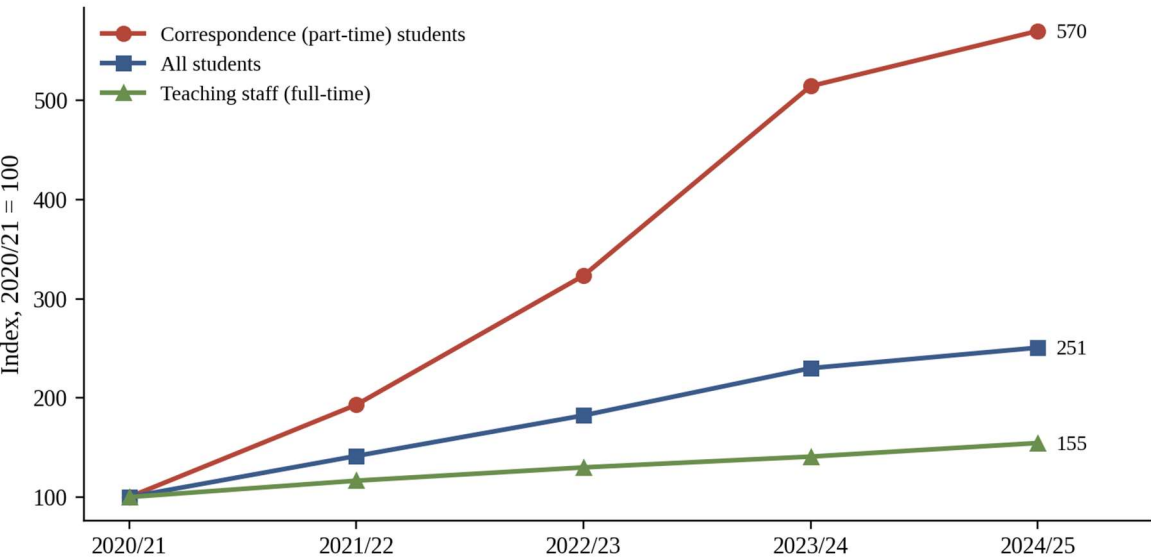


Figure 1. Growth indices of students and teaching staff, 2020/21 = 100

Connectivity conditions are favourable compared with many emerging markets: about 33.1 million people, or 89% of the population, used the Internet in Uzbekistan at

the end of 2025 [4]. Globally, however, Internet use is 85% in urban areas and 58% in rural areas [12], which indicates that distance learning designs must account for uneven bandwidth.

Evidence on AI tutoring. Table 2 summarises the studies included in the synthesis.

Table 2.

Synthesis of evidence on AI-based tutoring			
Study	Context and design	AI configuration	Main result
VanLehn (2011) [27]	Meta-analysis of tutoring studies	Step-based intelligent tutoring systems	Effect size ≈ 0.76 , close to human tutoring (≈ 0.79)
Kulik & Fletcher (2016) [16]	Meta-analysis, 50 controlled evaluations	Intelligent tutoring systems	Median effect size 0.66
Kestin et al. (2025) [15]	USA, university physics, RCT (crossover), 194 students	GenAI tutor built on research-based pedagogy with structured prompts	Significantly higher learning gains in less time than active-learning class
De Simone et al. (2025) [5]	Nigeria, secondary school, RCT, 6 weeks	Copilot (GPT-4), teacher-supervised sessions with guided prompts	+0.31 SD overall; +0.23 SD in English; 1.5–2 years of schooling equivalent
Bastani et al. (2025) [2]	High school mathematics, field experiment, $\approx 1,000$ students	GPT Base (unrestricted) vs GPT Tutor (teacher-designed guardrails)	Practice +48% / +127%; unassisted exam –17% for GPT Base, harm largely mitigated with guardrails

Three design features recur in studies with positive effects: (a) the AI guides the learner step by step instead of providing final answers; (b) prompts and content are aligned with the curriculum and designed by educators; (c) a teacher or structured course design frames AI use. The only study with a negative effect on independent performance involved an unrestricted chat interface [2].

Standards alignment. The results of mapping international and national instruments onto the five layers of the proposed framework are presented in Table 3.

Table 3.

Alignment of standards and regulations with framework layers					
Instrument	L1 Access	L2 Content	L3 AI engine	L4 Assessment	L5 Governance
WCAG 2.2 (W3C, 2023) [28]	●	●	○	○	
LTI 1.3 (1EdTech) [1]		●	●	○	
IEEE 9274.1.1-2023 xAPI [11]		○	●	●	○
ISO/IEC 42001:2023 [13]			●	○	●
EU AI Act 2024/1689 [6]			○	●	●
UNESCO Guidance	○	○	●	○	●

2023 & Ethics 2021 [17; 25]					
OECD AI Principles [22]			○	○	●
Law of Uzbekistan “On personal data” [24]			●	●	●

No single instrument covers all layers. Technical standards (WCAG, LTI, xAPI) concentrate on access, content and data flows, while governance instruments (EU AI Act, UNESCO, OECD) concentrate on assessment and accountability. The AI engine layer is the only layer addressed by all eight instruments, five of them as a primary area of coverage. National data protection law affects the three most data-intensive layers, which is particularly important because Uzbek legislation requires personal data of citizens to be processed on servers located in the country [24].

The ADAPT-EM framework. Integrating the three sets of results produced a five-layer framework (Table 4).

Table 4.

ADAPT-EM framework: layers, functions, design rules and indicators

Layer	Function	Design rules derived from results	Performance indicator
L1 Access	Delivery to learners with uneven connectivity	Mobile-first, low-bandwidth and offline modes; WCAG 2.2 conformance	Share of learners completing modules on mobile / low bandwidth
L2 Interoperable content	Curriculum-aligned materials and tools	LTI 1.3 integration; content co-designed by faculty; local-language versions	Share of courses with AI-ready structured content
L3 Adaptive AI engine	Personalised tutoring and feedback	Scaffolded hints instead of answers; teacher-authored prompts; locally hosted or compliant models	Learning gain on unassisted tests vs. control group
L4 Assessment and analytics	Measuring progress and adapting pathways	xAPI data model; human review of high-stakes decisions; no emotion recognition	Time to feedback; proportion of AI decisions reviewed by humans
L5 Governance	Accountability, ethics and data protection	ISO/IEC 42001 management system; institutional GenAI policy; data localisation compliance	Existence of audited AI policy; number of incidents

The framework treats the teacher gap identified in Stage 1 as the main problem to be solved and uses the AI engine to extend, rather than replace, teacher capacity. For example, if the AI layer handles routine explanations and practice feedback for correspondence students, teachers can concentrate on synchronous sessions, assessment review and supervision of AI use.

DISCUSSION

The results support the hypothesis of the study. In Uzbekistan, the demand for flexible higher education has grown much faster than teaching capacity, and the gap is concentrated in the correspondence format, where students have the least contact with teachers. This is exactly the situation in which personalised tutoring would have the

highest value and in which traditional solutions, such as hiring about 31 thousand additional qualified teachers, are least feasible in the short term. GenAI therefore addresses a real structural problem, not merely a technological opportunity.

At the same time, the evidence synthesis shows that access to GenAI is not sufficient. The contrast between the positive results of G. Kestin and co-authors [15] and M. De Simone and co-authors [5] and the negative effect of unrestricted access found by H. Bastani and co-authors [2] suggests that the pedagogical design of the AI system is the decisive variable. This finding is consistent with the older literature on intelligent tutoring, which attributed effectiveness to step-level scaffolding [27], and with concerns about metacognitive laziness [7]. For correspondence students who study largely alone, the risk of using AI as a “crutch” may be even higher than in supervised settings, which is why the framework places scaffolding rules and unassisted assessment at the centre of the AI engine and assessment layers.

The Nigerian trial is particularly relevant for emerging markets, because it showed large and cost-effective gains in a low-resource setting when AI use was supervised by teachers [5]. It also found that the largest effects were among female students and students with higher initial performance, which indicates that GenAI can both reduce and widen inequalities depending on how it is deployed. For this reason, the framework includes indicators that measure effects on unassisted performance and on access through low-bandwidth channels, rather than only overall usage.

The standards mapping reveals a practical tension that is rarely discussed in the literature. The most capable GenAI models are generally offered as cloud services hosted abroad, whereas Uzbek legislation requires citizens’ personal data to be processed domestically [24]. Institutions therefore face a choice between locally hosted models, anonymisation before data are transferred, or waiting for national infrastructure. The national AI strategy, which foresees the development of domestic computing capacity and AI solutions in education [23], can help resolve this tension, but in the meantime the governance layer must include explicit data-flow rules. Similarly, although the EU AI Act does not apply directly in Uzbekistan, its classification of AI-based assessment and proctoring as high-risk [6] offers a useful reference for universities that participate in international partnerships or joint degree programmes.

Compared with policy documents such as the UNESCO guidance [17] and the OECD Digital Education Outlook [21], the proposed framework is more operational: it translates principles into design rules and measurable indicators. Compared with experimental studies, it is broader but less tested. The retraction of a highly cited meta-analysis in 2026 [10] is a reminder that the field is still developing and that the framework should be updated as new evidence emerges.

Limitations. First, the study relies on secondary data, and the framework has not yet been empirically validated in Uzbek universities. Second, the correspondence format in Uzbekistan is not identical to fully online distance learning; it is used here as the closest official proxy. Third, the teacher gap is estimated using full-time staff only and assumes that the 2020/21 ratio is a meaningful benchmark. Fourth, the experimental evidence comes from different countries, levels of education and subjects

and covers short periods, so long-term effects remain unknown. Fifth, the standards mapping is based on the author's expert coding and would benefit from independent validation.

CONCLUSION

The study shows that emerging-market higher education systems such as Uzbekistan's face a structural teaching capacity gap: enrolment grew 2.5 times in four years, almost half of students study in the correspondence format, and about 30.9 thousand additional teachers would be needed to return to the 2020/21 student-teacher ratio. GenAI-based tutoring can help close this gap, but only when it is pedagogically scaffolded, aligned with the curriculum and embedded in a governance system; unrestricted access can reduce independent learning.

The main contribution of the article is the ADAPT-EM framework, which links evidence-based design principles to eight international and national instruments across five layers (access, interoperable content, adaptive AI engine, assessment and analytics, governance) and provides performance indicators for each layer. For universities, the practical recommendations are to adopt an institutional GenAI policy, to deploy AI tutors with scaffolding rules and teacher-authored prompts, to measure learning on unassisted tests, and to use interoperability standards to avoid dependence on a single vendor. For policymakers, the priorities are to clarify data localisation rules for educational AI, to support domestic computing capacity and to fund rigorous pilot evaluations.

Future research should test the framework in randomised or quasi-experimental pilots in correspondence programmes of Uzbek universities, measure long-term effects on unassisted performance and equity, and estimate the cost-effectiveness of different hosting models for GenAI in emerging markets.

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