HSR (LONDON),
HOUGHTON STREET REVIEW JOURNAL
ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

# AI-DRIVEN ONLINE ADAPTIVE LEARNING SYSTEMS IN HIGHER EDUCATION: AN INTEGRATIVE REVIEW OF LEARNER MODELLING, ADAPTATION MECHANISMS AND EVIDENCE OF EFFECTIVENESS

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doi:https://doi.org/10.5281/zenodo.23385110

**Abstract.** Background. The rapid expansion of online and blended learning in higher education has exposed a persistent limitation of conventional online courses: content is delivered to all students in the same sequence and at the same pace, regardless of differences in prior knowledge, learning progress and needs. Online adaptive learning systems, increasingly powered by artificial intelligence (AI), aim to overcome this limitation by continuously diagnosing the learner and personalising content, sequence, difficulty and feedback. Aim. This article reviews the theoretical foundations, learner-modelling techniques, adaptation mechanisms and empirical evidence on the effectiveness of AI-driven online adaptive learning systems, and derives implications for higher education systems undergoing digital transformation, with particular reference to Uzbekistan. Methods. An integrative literature review was conducted following the framework of Whittemore and Knafl. Seminal works and peer-reviewed publications indexed in Scopus, Web of Science, ERIC and Google Scholar, together with international policy documents, were analysed using reflexive thematic synthesis. Results. Six themes were identified: (1) pedagogical and psychological foundations; (2) learner modelling, from Bayesian knowledge tracing to deep learning; (3) adaptation targets and mechanisms; (4) evidence of effectiveness from meta-analyses; (5) the emerging role of generative AI; and (6) ethical, pedagogical and infrastructural challenges. Meta-analytic evidence shows moderate to large positive effects of intelligent and adaptive tutoring on learning outcomes, while gaps remain regarding teacher involvement, transparency and applicability to low-resource language contexts. Conclusion. Effective adaptive learning requires the integration of validated learner models, pedagogically grounded adaptation rules, interoperable learning platforms and a teacher-in-the-loop approach. A set of requirements for national adaptive learning systems is proposed.

**Keywords:** adaptive learning; artificial intelligence in education; learner modelling; knowledge tracing; personalised learning; online learning; higher education; learning analytics

**Introduction.** Digital transformation has made online and blended learning an integral part of higher education. Learning management systems (LMS), massive open online courses (MOOCs) and video-based lectures have widened access to education and made it possible to study at any time and place. However, most online courses still follow a "one-size-fits-all" model in which all students receive the same materials in the same order and at the same pace. Such an approach ignores substantial differences between learners in prior knowledge, learning speed, motivation and difficulties encountered, and is associated with low completion rates and uneven learning outcomes.

The pedagogical value of individualisation has long been recognised. Bloom (1984) reported that students tutored one-to-one using mastery learning techniques performed about two standard

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ISSN: 2058-5519|Impact factor-15.9
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deviations better than students taught in conventional classes — the so-called "2 sigma problem" — and challenged researchers to find methods of group instruction that could approach this effect. Providing a human tutor for every student is economically impossible; adaptive learning technologies represent an attempt to approximate the benefits of individual tutoring at scale.

An adaptive learning system can be defined as a technology-enhanced learning environment that collects data on a learner's interactions, builds and continuously updates a model of the learner, and uses this model to adjust the learning content, its sequence, difficulty, presentation or feedback to the individual learner (Brusilovsky, 2001; Martin et al., 2020). Advances in artificial intelligence (AI), machine learning and learning analytics have considerably extended these capabilities: modern systems can estimate a learner's mastery of individual skills, predict future performance and recommend optimal next activities (Kabudi et al., 2021; Pelánek, 2017). More recently, large language models (LLMs) have opened new possibilities for generating explanations, hints and practice items on demand (Kasneci et al., 2023).

Interest in AI in education is also reflected in national and international policy. UNESCO has issued guidance for policy-makers on AI and education and on generative AI in education and research (Miao et al., 2021; Miao & Holmes, 2023). In Uzbekistan, the Concept for the Development of the Higher Education System until 2030, the "Digital Uzbekistan – 2030" strategy and the Strategy for the Development of Artificial Intelligence Technologies until 2030 set the goals of digitalising education and introducing AI solutions. Nevertheless, online platforms in national universities are used mainly to distribute materials and administer tests, while their adaptive capabilities remain limited, and adaptive solutions designed for Uzbek-language content are scarce.

Although several systematic reviews of adaptive and personalised learning exist (Xie et al., 2019; Martin et al., 2020; Kabudi et al., 2021), they tend to focus either on technological aspects or on research designs, and few connect learner-modelling techniques, adaptation mechanisms, evidence of effectiveness and implementation conditions in a single framework. Moreover, the rapid emergence of generative AI requires these findings to be revisited. The aim of this article is therefore to provide an integrative review of AI-driven online adaptive learning systems in higher education and to derive requirements for their development in national contexts. The review addresses four research questions:

RQ1. What pedagogical and psychological foundations underpin adaptive learning?

RQ2. Which learner-modelling and adaptation techniques are used in AI-driven adaptive learning systems?

RQ3. What does empirical research reveal about their effectiveness?

RQ4. What challenges and requirements should be considered when developing such systems for higher education in contexts such as Uzbekistan?

## Materials and Methods.

### 2.1. Review design

An integrative review design was chosen because it allows the combination of theoretical, empirical and methodological literature, including experimental and quasi-experimental studies, meta-analyses and conceptual papers, to produce a comprehensive understanding of a phenomenon (Whittemore & Knafl, 2005). The review followed the five stages proposed by Whittemore and Knafl: problem identification, literature search, data evaluation, data analysis and presentation. Reporting was informed by the relevant items of the PRISMA 2020 statement (Page et al., 2021).

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### 2.2. Literature search

The literature search covered the Scopus, Web of Science Core Collection and ERIC databases, supplemented by Google Scholar and backward citation searching of key reviews. The following search string was adapted to each database: ("adaptive learning" OR "adaptive e-learning" OR "personalised learning" OR "personalized learning" OR "intelligent tutoring system*") AND ("artificial intelligence" OR "machine learning" OR "knowledge tracing" OR "learner model*" OR "learning analytics") AND ("higher education" OR university OR online). The main search focused on publications from 2015 to 2025; seminal earlier works that define the field were included through citation tracking. Policy documents of UNESCO and national strategic documents of Uzbekistan were added to address RQ4.

### 2.3. Inclusion and exclusion criteria

Publications were included if they (a) were peer-reviewed journal articles, conference papers from established venues, scholarly books or official policy documents; (b) were published in English, Russian or Uzbek; and (c) addressed adaptive or personalised learning systems, learner-modelling or adaptation techniques, or empirical evaluation of such systems. Publications were excluded if they dealt exclusively with K-12 classroom practice without a technological component, described commercial products without empirical or conceptual analysis, or were not available in full text.

### 2.4. Data evaluation and analysis

Sources were appraised for relevance, methodological rigour and contribution to the research questions; meta-analyses and systematic reviews were given priority as sources of evidence on effectiveness. Data were extracted into a matrix recording publication type, context, the learner model, the adaptation target and mechanism, outcome measures and main findings. Reflexive thematic analysis (Braun & Clarke, 2006) was then applied: codes were generated inductively, grouped into candidate themes, reviewed against the data and refined into six final themes, which structure the Results section.

## 3. Results

### 3.1. Pedagogical and psychological foundations

Adaptive learning draws on several complementary theories. Mastery learning (Bloom, 1984) holds that most students can achieve a high level of mastery if instruction is adjusted to their needs and they are given sufficient time and corrective feedback before moving on. Vygotsky's (1978) concept of the zone of proximal development suggests that learning is most productive when tasks are slightly above the learner's current independent level and are supported by appropriate scaffolding; adaptive systems operationalise this idea by selecting tasks of suitable difficulty and adjusting the amount of help. Cognitive load theory (Sweller, 1988) explains why adaptation of presentation and difficulty matters: tasks that exceed working-memory capacity hinder learning, especially for novices. Together, these theories justify the three core functions of adaptive systems: continuous diagnosis, individualised selection of tasks and timely feedback.

The literature also warns against weakly supported constructs. Adaptation to so-called "learning styles" remains popular in adaptive e-learning research (Truong, 2016), yet controlled studies have not provided convincing evidence that matching instruction to self-reported learning styles improves outcomes (Pashler et al., 2008). Current evidence therefore favours adaptation based on measured knowledge, performance and behaviour rather than on learning-style labels.

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ISSN: 2058-5519|Impact factor-15.9
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### 3.2. Learner modelling: from Bayesian knowledge tracing to deep learning

The learner model is the core component of any adaptive system. The most influential approach, Bayesian knowledge tracing (BKT), represents each skill or knowledge component as a binary latent variable (mastered or not mastered) and updates the probability of mastery after each observed response using four parameters: initial knowledge, probability of learning, probability of a slip and probability of a guess (Corbett & Anderson, 1994). BKT is interpretable and computationally simple, which explains its continued use in intelligent tutoring systems.

Logistic and item response theory (IRT) based models estimate the probability of a correct answer as a function of learner ability and item difficulty and can incorporate practice history; they often perform comparably to or better than BKT while remaining interpretable (Pelánek, 2017). Deep knowledge tracing (DKT) applies recurrent neural networks to sequences of learner interactions and can capture complex dependencies between skills (Piech et al., 2015). Subsequent work has introduced memory-augmented, attention-based and graph-based models; a recent survey shows that deep models frequently improve predictive accuracy but at the cost of interpretability, larger data requirements and sensitivity to data quality (Abdelrahman et al., 2023). For higher-education contexts with limited historical data, these findings suggest a pragmatic strategy: interpretable models (BKT or IRT-based) at the initial stage, with deep models introduced as interaction data accumulate.

Beyond cognitive state, many systems model behavioural indicators (time on task, number of attempts, help-seeking, login regularity) and, less often, affective and motivational states. Learning analytics provides methods for collecting and interpreting such data at scale (Siemens & Long, 2011).

### 3.3. Adaptation targets and mechanisms

Brusilovsky (2001) distinguished two broad classes of adaptation: adaptive presentation (changing what is shown on a page, e.g., additional explanations or examples) and adaptive navigation support (guiding the learner's path through content, e.g., direct guidance, link sorting, hiding or annotation). Later reviews show that modern systems adapt a wider range of targets — content, sequence, difficulty, pace, feedback and assessment — and use increasingly data-driven mechanisms (Xie et al., 2019; Martin et al., 2020). The main mechanisms identified in the literature are summarised in Table 1.

**Table 1. Main approaches to learner modelling and adaptation in online adaptive learning systems**

| Approach | Principle | Strengths | Limitations | Key sources |
|---|---|---|---|---|
| Rule-based adaptation | Expert-defined if–then rules linking learner state to actions | Transparent; easy for teachers to understand and edit | Labour-intensive; poorly scalable; limited personalisation | Brusilovsky (2001) |
| Bayesian knowledge tracing | Hidden Markov model of mastery per knowledge component | Interpretable; works with little data | Binary mastery; assumes independent skills | Corbett & Anderson (1994) |
| IRT / logistic models | Probability of success as a function of ability | Psychometrically grounded; supports difficulty targeting | Requires item calibration | Pelánek (2017) |

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| | | | | |
|---|---|---|---|---|
| | and item difficulty | | | |
| Deep knowledge tracing | Recurrent or attention-based neural networks over interaction sequences | High predictive accuracy; models skill relations | Low interpretability; data-hungry | Piech et al. (2015); Abdelrahman et al. (2023) |
| Recommender systems and reinforcement learning | Selection of next activity to optimise expected learning | Optimises sequences dynamically | Complex evaluation; risk of opaque decisions | Kabudi et al. (2021) |
| Generative AI (LLMs) | On-demand generation of explanations, hints and items | Flexible natural-language support | Accuracy, bias and academic integrity risks | Kasneci et al. (2023) |

**3.4. Evidence of effectiveness**

Several meta-analyses provide robust evidence on the effectiveness of intelligent and adaptive tutoring. VanLehn (2011) compared human tutoring, step-based intelligent tutoring systems and answer-based systems with no tutoring; step-based tutoring systems produced an effect size of about d = 0.76, close to that of human tutoring (d = 0.79), whereas answer-based systems produced a smaller effect (d = 0.31). Ma et al. (2014) found that the use of intelligent tutoring systems was associated with higher achievement in comparison with teacher-led large-group instruction, non-ITS computer-based instruction and textbooks, with a moderate overall effect ($g \approx 0.41$). Kulik and Fletcher (2016), analysing 50 controlled evaluations, reported a median effect size of 0.66, while noting that effects were larger on locally developed tests than on standardised tests.

Systematic reviews of adaptive learning confirm generally positive findings but also reveal methodological weaknesses. Martin et al. (2020) found that many studies relied on small samples, short interventions and self-reported satisfaction, and called for more rigorous experimental designs and long-term outcome measures. Xie et al. (2019) observed that research had concentrated on a limited number of learning parameters and subject areas, with computer science and mathematics dominating.

**3.5. The emerging role of generative AI**

Large language models offer new forms of adaptivity: they can generate explanations at different levels of complexity, produce practice questions, provide formative feedback on open-ended answers and act as conversational tutors. At the same time, they may produce inaccurate or biased content, encourage over-reliance and raise questions of academic integrity and data protection (Kasneci et al., 2023). UNESCO guidance recommends a human-centred approach, age-appropriate use, validation of tools and the development of AI competencies among teachers and learners (Miao & Holmes, 2023). The literature therefore positions generative AI as a complement to, rather than a replacement for, validated learner models and pedagogically designed adaptation rules.

**3.6. Ethical, pedagogical and infrastructural challenges**

Four groups of challenges recur in the literature. First, the role of teachers is often neglected: in a systematic review of AI applications in higher education, Zawacki-Richter et al. (2019) found few

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ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

studies that critically reflected on pedagogical aspects, and asked "where are the educators?". Second, adaptive systems collect detailed behavioural data, raising concerns about privacy, informed consent, algorithmic bias and the transparency of automated decisions (Holmes et al., 2019). Third, the development of adaptive courses requires fine-grained knowledge-component mapping, large item banks and high-quality metadata, which are costly to produce. Fourth, most tools, datasets and language models are designed for widely spoken languages, which limits their direct transfer to low-resource language contexts such as Uzbek.

**Discussion.** This integrative review indicates that AI-driven adaptive learning rests on a well-established pedagogical basis — mastery learning, the zone of proximal development and cognitive load theory — and that the technical means for diagnosing learners and personalising instruction have matured considerably, from interpretable Bayesian and IRT-based models to deep learning and generative AI (RQ1, RQ2). The meta-analytic evidence is consistent with Bloom's (1984) original argument: well-designed adaptive tutoring can substantially improve learning compared with conventional instruction, although the effects reported in the literature are smaller than the two-sigma benchmark and depend strongly on design quality and outcome measures (VanLehn, 2011; Kulik & Fletcher, 2016) (RQ3).

Three implications emerge for the design of national adaptive learning systems (RQ4). First, the choice of learner model should match data availability and the need for transparency: interpretable models allow teachers and students to understand why a recommendation is made, which is essential for trust and for pedagogical control. Second, adaptivity should be built on a carefully structured domain model — a map of knowledge components linked to learning objects and assessment items — because the quality of adaptation cannot exceed the quality of the domain model. Third, adaptive systems should be integrated into the LMS infrastructure that universities already use, through interoperability standards, rather than deployed as isolated platforms.

On this basis, the following requirements for AI-driven online adaptive learning systems in higher education are proposed: (1) a domain model organised around knowledge components and learning outcomes; (2) a multidimensional learner model combining cognitive, behavioural and motivational indicators; (3) transparent, pedagogically grounded adaptation rules, complemented by data-driven recommendations; (4) teacher-in-the-loop functions, including dashboards and the ability to override automated decisions; (5) interoperability with existing LMS through open standards; (6) support for national-language content and metadata; and (7) built-in mechanisms for privacy protection, informed consent and the evaluation of effectiveness.

The review has limitations. As an integrative rather than a systematic review, it does not provide a quantitative synthesis of effect sizes, and the selection of sources may reflect the author's interpretive choices despite the structured search. Only publications in three languages were considered, and the rapidly evolving field of generative AI may outpace the available peer-reviewed evidence. Future research should include rigorous controlled studies of adaptive learning in Central Asian universities, the development of open Uzbek-language item banks and domain models, and the evaluation of hybrid systems that combine interpretable learner models with generative AI.

**Conclusion.** AI-driven online adaptive learning systems offer a realistic way to bring the benefits of individual tutoring to large numbers of students in higher education. Their effectiveness depends not on the sophistication of algorithms alone, but on the integration of a sound pedagogical foundation, validated learner models, transparent adaptation mechanisms, interoperable infrastructure

HSR (LONDON),
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and an active role for teachers. For higher education systems undergoing digital transformation, such as that of Uzbekistan, the priorities are the development of national-language domain models and item banks, the integration of adaptive services into existing LMS and the preparation of teachers to work in data-rich adaptive environments. The requirements proposed in this article can serve as a framework for the design and evaluation of such systems.

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