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DESIGNING AN AI-BASED ONLINE ADAPTIVE LEARNING SYSTEM FOR HIGHER EDUCATION: A CONCEPTUAL MODEL INTEGRATING MULTIDIMENSIONAL LEARNER MODELLING, KNOWLEDGE TRACING AND LMS INTEROPERABILITY

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Abstract. Background. Universities increasingly rely on learning management systems (LMS) for online and blended learning, yet these platforms rarely adapt instruction to the individual learner. Existing adaptive solutions are often proprietary, isolated from the institutional LMS, opaque to teachers and unavailable for national-language content. Aim. The article presents a conceptual model of an AI-based online adaptive learning system for higher education that integrates a multidimensional learner model, an interpretable adaptation engine and standards-based interoperability with existing LMS. Methods. The study follows the design science research methodology (Peffers et al., 2007). Design requirements were derived from a review of research on adaptive learning, learner modelling and AI in education, and from strategic documents on the digitalisation of higher education in Uzbekistan. The artefact was then designed and specified, and a plan for its demonstration and evaluation was developed. Results. The model comprises five design principles; a domain model structured around knowledge components; a multidimensional learner model combining cognitive (Bayesian knowledge tracing), behavioural and motivational indicators; an adaptation engine that selects learning activities within the learner's zone of proximal development using item response theory; a layered architecture integrated with the LMS via IMS LTI 1.3 and the Experience API (xAPI); and a teacher dashboard that supports human oversight. An evaluation framework with measurable criteria is proposed. Conclusion. The model offers a transparent and technically feasible basis for introducing adaptive learning into national higher education platforms. Its effectiveness will be tested empirically in a quasi-experimental study.

Keywords: adaptive learning system; conceptual model; learner model; Bayesian knowledge tracing; item response theory; LTI; xAPI; design science research; higher education

Introduction

The digital transformation of higher education has made learning management systems such as Moodle the backbone of online and blended learning in many universities. These platforms are effective for distributing content, organising assignments and administering tests, but in their standard configuration they offer the same learning path to every student. As a result, well-prepared students spend time on material they have already mastered, while students with gaps in prior knowledge move on before they are ready. Research on mastery learning and tutoring has long shown that adjusting instruction to the individual learner can produce substantial gains in achievement (Bloom, 1984; VanLehn, 2011).

Adaptive learning systems address this problem by building a model of each learner from interaction data and using it to personalise learning activities, their sequence, difficulty and feedback (Brusilovsky, 2001; Martin et al., 2020). Advances in artificial intelligence (AI) — knowledge tracing, recommender systems and, most recently, large language models — have

expanded the possibilities for such personalisation (Kabudi et al., 2021; Kasneci et al., 2023). Meta-analyses report moderate to large positive effects of intelligent and adaptive tutoring on learning outcomes (Ma et al., 2014; Kulik & Fletcher, 2016).

However, several barriers limit the use of adaptive learning in universities. Many adaptive platforms are proprietary and operate separately from the institutional LMS, which fragments the learning environment and the data. Deep-learning-based learner models can be accurate but are difficult for teachers to interpret (Abdelrahman et al., 2023), while systematic reviews have pointed to the limited involvement of educators in the design of AI-based educational tools (Zawacki-Richter et al., 2019). In addition, most adaptive solutions and content repositories are designed for widely spoken languages. In Uzbekistan, national strategies on higher education, the digital economy and artificial intelligence prioritise the digitalisation of education, yet adaptive solutions integrated with university LMS and designed for Uzbek-language content are still lacking.

The aim of this study is to design a conceptual model of an AI-based online adaptive learning system for higher education that (a) relies on interpretable learner modelling, (b) adapts learning activities on a sound pedagogical basis, (c) integrates with existing LMS through open standards and (d) keeps the teacher in the loop. The study addresses the following research question: What components, principles and mechanisms should an AI-based online adaptive learning system include in order to be pedagogically sound, transparent and technically feasible for integration into higher education platforms?

Materials and Methods

2.1. Research design

The study follows design science research (DSR), a paradigm aimed at creating and evaluating innovative artefacts that solve identified problems (Hevner et al., 2004). The six-activity process model of Peffers et al. (2007) was applied: (1) problem identification and motivation; (2) definition of the objectives of a solution; (3) design and development; (4) demonstration; (5) evaluation; and (6) communication. This article reports activities 1–3 and specifies the plan for activities 4–5, which will be carried out in subsequent stages of the doctoral research.

2.2. Derivation of requirements

Requirements were derived from two sources. First, research on adaptive learning, learner modelling, intelligent tutoring and AI in education was analysed, with priority given to meta-analyses and systematic reviews (e.g., VanLehn, 2011; Pelánek, 2017; Xie et al., 2019; Martin et al., 2020; Kabudi et al., 2021). Second, national strategic documents on the development of higher education, the digital economy and AI technologies in Uzbekistan, as well as UNESCO guidance on AI in education (Miao et al., 2021; Miao & Holmes, 2023), were examined to identify contextual and ethical requirements. Requirements were formulated as design objectives and traced to the components of the model.

2.3. Design and specification

The domain model was specified using the knowledge component concept of the Knowledge-Learning-Instruction framework (Koedinger et al., 2012). The cognitive part of the learner model was specified using Bayesian knowledge tracing (Corbett & Anderson, 1994), and item difficulty targeting was specified using the one-parameter (Rasch) item response model. Interoperability was specified using the IMS Learning Tools Interoperability (LTI) 1.3 standard for launching the adaptive service from the LMS and exchanging grades, and the Experience API (xAPI) for recording learning events in a learning record store (LRS). The architecture was described as a layered model and represented graphically.

2.4. Evaluation planning

An evaluation framework was developed in line with DSR guidance that artefacts should be evaluated for utility, quality and efficacy (Hevner et al., 2004). Evaluation criteria, indicators and instruments were selected from established measures in educational research and human–computer interaction, including normalised learning gain (Hake, 1998) and the System Usability Scale (Brooke, 1996).

Results

3.1. Design requirements and principles

Analysis of the literature and policy documents produced seven requirements, which were consolidated into five design principles (Table 1).

Table 1. Design principles of the AI-based online adaptive learning system

Principle	Content	Grounding
P1. Knowledge-component orientation	All content and assessment items are linked to explicit knowledge components and learning outcomes	Koedinger et al. (2012)
P2. Continuous diagnosis	The learner model is updated after every meaningful interaction	Corbett & Anderson (1994); Pelánek (2017)
P3. Adaptation within the zone of proximal development	Activities are selected so that they are challenging but achievable, with scaffolding when needed	Vygotsky (1978); Sweller (1988)
P4. Transparency and teacher-in-the-loop	Decisions are explainable; teachers can view, adjust and override recommendations	Zawacki-Richter et al. (2019); Miao & Holmes (2023)
P5. Interoperability and national-language support	Integration with existing LMS via open standards; Uzbek-language content and metadata	IMS LTI 1.3; xAPI; national digitalisation strategies

3.2. Domain model

The domain model represents a course as a directed acyclic graph of knowledge components (KCs), where an edge from KC_i to KC_j indicates that KC_i is a prerequisite of KC_j. Each KC is linked to learning objects (texts, videos, worked examples, simulations) and to a bank of assessment items. Items are annotated with metadata in Uzbek and, where available, in other languages: the KCs assessed, item type, estimated difficulty b, expected time and the type of feedback provided. This structure allows the adaptation engine to reason about what the learner has mastered and what should come next.

3.3. Multidimensional learner model

The learner model consists of three dimensions. The cognitive dimension stores, for each KC, the probability that the learner has mastered it, P(L), and a global ability estimate θ. The behavioural dimension aggregates learning-analytics indicators recorded via xAPI: time on task, number of attempts, hint use, regularity of activity and completion of assigned activities. The motivational dimension captures short self-reports of confidence and interest collected at the end of learning units. The cognitive dimension drives the selection of content, while the behavioural and motivational dimensions are used to adjust pacing, trigger supportive messages and alert the teacher.

The probability of mastery is updated with Bayesian knowledge tracing. Given the parameters P(T) (probability of learning at each opportunity), P(S) (slip) and P(G) (guess), the posterior after a correct response is:

$$P(L \mid \text{correct}) = P(L)\cdot(1 - P(S)) / [P(L)\cdot(1 - P(S)) + (1 - P(L))\cdot P(G)]$$

and after an incorrect response:

$$P(L \mid \text{incorrect}) = P(L)\cdot P(S) / [P(L)\cdot P(S) + (1 - P(L))\cdot(1 - P(G))]$$

The probability of mastery at the next opportunity accounts for learning:

$$P(L_{t+1}) = P(L \mid \text{obs}) + (1 - P(L \mid \text{obs}))\cdot P(T)$$

A KC is considered mastered when $P(L) \geq 0.95$, a threshold commonly used in mastery-based tutoring systems. Initial parameter values are set from expert judgement and a diagnostic pre-test, and are re-estimated from accumulated data at the end of each semester.

3.4. Adaptation engine

The adaptation engine performs three functions: selecting the next KC, selecting the next activity for that KC and providing feedback. A KC is eligible if it is not yet mastered and all its prerequisites are mastered. Among eligible KCs, priority is given to those required by the current course module and those with the lowest mastery. Within the selected KC, an assessment item is chosen so that the predicted probability of success is close to a target value p^* within the zone of proximal development. Under the Rasch model, the probability that a learner of ability θ answers an item of difficulty b correctly is:

$$P(\text{correct} \mid \theta, b) = 1 / (1 + \exp(-(\theta - b)))$$

so the target difficulty for a success probability of $p^* = 0.70$ is $b^* = \theta - \ln(p^*/(1 - p^*)) \approx \theta - 0.85$. If repeated errors occur on a KC, the engine switches from practice items to explanatory learning objects or worked examples (adaptive presentation); if behavioural indicators show disengagement, the pace is reduced and a notification is sent to the teacher. Generative AI may be used to produce additional explanations or hints, but only from teacher-approved templates and with clear labelling. The adaptation cycle is summarised in Algorithm 1.

Algorithm 1. Adaptation cycle

Input: domain graph G, learner model M, item bank I, threshold $\tau = 0.95$, target $p^* = 0.70$

1. Eligible ← {KC ∈ G : P_M(KC) < τ and all prerequisites of KC have P_M ≥ τ}
2. If Eligible = ∅ : mark module as mastered; recommend enrichment or next module; stop
3. KC* ← argmin over Eligible of P_M(KC), weighted by module priority
4. If errors on KC* in last 3 attempts ≥ 2: present worked example / explanation for KC*
5. Else: b* ← θ_M − ln(p*/(1 − p*)); choose item i ∈ I(KC*) with |b_i − b*| minimal, not seen recently
6. Observe response; update P_M(KC*) by BKT and θ_M by IRT; record xAPI statement
7. Provide feedback (correctness + explanation or hint)
8. If behavioural indicators below threshold: adjust pace; notify teacher dashboard
9. Return to step 1

3.5. System architecture and LMS integration

The system is organised in five layers (Figure 1). The presentation layer delivers adaptive activities inside the LMS course page. The integration layer launches the adaptive service from the LMS through LTI 1.3 and returns grades to the LMS gradebook, so that students do not need a separate account and teachers continue to work in a familiar environment. The data layer records every learning event as an xAPI statement in a learning record store, ensuring a standardised and

portable record of learning activity. The intelligence layer contains the learner model, the adaptation engine and analytics services. The content layer stores the domain model, learning objects and the item bank with Uzbek-language metadata. A teacher dashboard visualises the mastery of each student and of the group, highlights students at risk and allows the teacher to adjust or override recommendations.

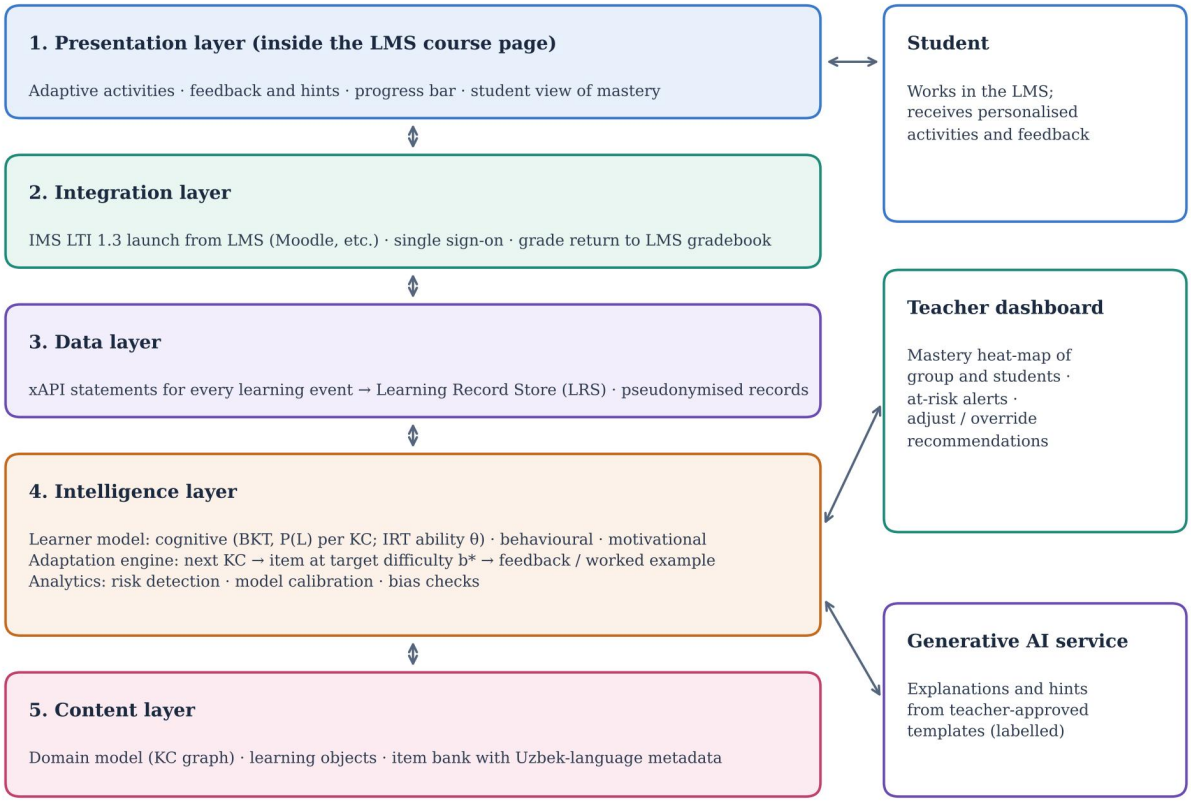


Figure 1. Layered architecture of the AI-based online adaptive learning system integrated with the institutional LMS

3.6. Ethical safeguards

In line with UNESCO guidance (Miao et al., 2021; Miao & Holmes, 2023), the model includes the following safeguards: informed consent for data processing; data minimisation and pseudonymisation of learner records; storage of data within the institution's infrastructure in accordance with national legislation on personal data; explanations of recommendations visible to students and teachers; the right of the teacher to override automated decisions; and regular checks of model performance across student groups to detect bias.

3.7. Evaluation framework

The planned evaluation combines technical, pedagogical and user-centred criteria (Table 2). The pedagogical efficacy of the system will be assessed in a quasi-experimental study with experimental and control groups in several universities, using pre-tests and post-tests on the course learning outcomes.

Table 2. Evaluation framework for the adaptive learning system

Criterion	Indicator	Instrument / method
Predictive validity of the learner model	Accuracy of predicting next-response correctness (AUC, RMSE)	Cross-validation on interaction logs
Learning effectiveness	Normalised learning gain; effect size between groups	Pre-/post-tests; Hake (1998); Student's t-test
Mastery efficiency	Time and number of items needed to reach mastery	xAPI analytics
Engagement	Regularity of activity; completion rate	xAPI analytics
Usability and acceptance	SUS score; perceived usefulness and ease of use	System Usability Scale (Brooke, 1996); questionnaire
Teacher perspective	Perceived usefulness of dashboard; frequency of overrides	Interviews; system logs

Discussion

The proposed model responds to the research question by specifying the components, principles and mechanisms that an AI-based online adaptive learning system should include to be pedagogically sound, transparent and feasible for integration into university platforms. Compared with many existing solutions, it has three distinctive features. First, it deliberately combines interpretable models — Bayesian knowledge tracing and the Rasch model — rather than relying solely on deep learning. Reviews show that interpretable models perform competitively in many settings and are easier to calibrate with limited data (Pelánek, 2017), whereas deep models require large datasets and are harder to explain (Abdelrahman et al., 2023). The architecture nevertheless allows more complex models to be introduced later as data accumulate.

Second, the model operationalises established pedagogical theories. Mastery thresholds implement the logic of mastery learning (Bloom, 1984); difficulty targeting implements the zone of proximal development (Vygotsky, 1978); and the switch to worked examples after repeated errors reflects cognitive load theory (Sweller, 1988). This addresses the criticism that AI in education research often lacks pedagogical grounding (Zawacki-Richter et al., 2019) and avoids weakly supported constructs such as adaptation to learning styles (Pashler et al., 2008).

Third, integration through LTI 1.3 and xAPI allows adaptivity to be added to the LMS that universities already use, rather than replacing it. This reduces implementation costs, preserves institutional data ownership and keeps teachers in their familiar environment, while the teacher dashboard and override functions keep pedagogical decisions under human control. Support for Uzbek-language content and metadata addresses a gap noted for low-resource language contexts.

The study has limitations. The model has been designed and specified, but not yet implemented and empirically evaluated; its effectiveness therefore remains to be demonstrated. The parameters of the learner model and the thresholds used in the adaptation engine are initial values that will require calibration on real data. The quality of adaptation will also depend on the quality of the domain model and item bank, the development of which requires substantial effort from subject experts. The next stages of the research will include the development of a prototype, its

integration with a university LMS, expert validation of the domain model and a quasi-experimental evaluation according to the framework in Table 2.

Conclusion

This article has presented a conceptual model of an AI-based online adaptive learning system for higher education, developed using the design science research methodology. The model integrates five design principles, a knowledge-component-based domain model, a multidimensional learner model, an interpretable adaptation engine based on Bayesian knowledge tracing and item response theory, a layered architecture integrated with existing LMS through LTI 1.3 and xAPI, and a set of ethical safeguards. It provides a transparent and technically feasible foundation for introducing adaptive learning into national higher education platforms, including those using Uzbek-language content. Its practical value will be established through the prototype development and empirical evaluation planned in the next stages of the research.

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