

AI-DRIVEN ADAPTIVE LEARNING FOR FORMING INDIVIDUAL LEARNING TRAJECTORIES OF ARCHITECTURE STUDENTS IN ESP COURSES

Shokirov Bahodir Ismoilovich

Independent Researcher, Uzbekistan State World Languages University

Email: baxashok@gmail.com, ORCID: 0009-0006-4161-7519

Annotatsiya. Maqolada arxitektura yoʻnalishi talabalarining kasbiy ingliz tili (ESP) kurslarida sunʼiy intellekt asosidagi adaptiv taʼlim tizimlaridan foydalanib individual oʻquv trayektoriyasini shakllantirish masalasi koʻrib chiqiladi. Tadqiqot nazariy-tahliliy yondashuvga asoslanib, 2020–2025 yillardagi Scopus, Web of Science va Google Scholar maʼlumotlar bazalaridagi 28 ta ilmiy manba tizimli tahlil qilingan. Adaptiv algoritmlarning talabalar ehtiyojlariga moslashish mexanizmlari oʻrganilgan va uch qatlamli kontseptual model — diagnostik qatlam, adaptiv mexanizm va taʼlim kontentini yetkazish qatlami — taklif etiladi. Natijalar shuni koʻrsatadiki, bunday tizimlar mustaqil oʻrganish layoqatini, kasbiy lugʻat boyligini va muloqot kompetensiyasini sezilarli darajada oshirishga xizmat qilishi mumkin. Shu bilan birga, kontent bazasini yaratish, maʼlumotlar yetishmasligi va axloqiy masalalar kabi cheklovlar ham muhokama qilinadi.

Kalit soʻzlar: adaptiv taʼlim, sunʼiy intellekt, ESP, arxitektura taʼlimi, individual oʻquv trayektoriyasi, shaxsiylashtirilgan taʼlim, til oʻrganish.

Аннотация. Статья посвящена исследованию адаптивных систем обучения на основе искусственного интеллекта для формирования индивидуальных учебных траекторий студентов-архитекторов в курсах профессионального английского языка (ESP). Исследование основано на теоретико-аналитическом подходе: систематический обзор 28 публикаций 2020–2025 годов из баз Scopus, Web of Science и Google Scholar. Анализируются механизмы адаптации алгоритмов, предлагается трёхуровневая концептуальная модель персонализированных маршрутов — диагностический уровень, адаптивный механизм и уровень доставки учебного контента. Результаты показывают эффективность таких систем в развитии автономии обучающихся, профессионального вокабуляра и коммуникативной компетенции, однако отмечаются ограничения, связанные с разработкой контента, нехваткой данных и этическими вопросами.

Ключевые слова: адаптивное обучение, искусственный интеллект, ESP, архитектурное

образование, индивидуальная учебная траектория, персонализированное обучение, усвоение языка.

Abstract. This paper explores how AI-driven adaptive learning systems can shape individual learning trajectories for architecture students in ESP courses. The study employs a theoretical-analytical approach, systematically reviewing 28 publications from 2020–2025 indexed in Scopus, Web of Science, and Google Scholar. It analyses how adaptive algorithms respond to differences in proficiency, learning style, and professional need, and proposes a three-tier conceptual model — comprising a Diagnostic Layer, an Adaptive Engine, and an Instructional Delivery Layer — for personalized learning pathways. The findings suggest that such systems can strengthen autonomous learning, broaden professional vocabulary, and improve communicative competence. At the same time, the paper identifies limitations related to content development costs, data scarcity in niche domains, and ethical concerns that must be addressed before practical implementation.

Keywords: adaptive learning, artificial intelligence, ESP, architecture education, individual learning trajectory, personalized learning, language acquisition.

Introduction

Artificial intelligence has begun to reshape language teaching in higher education. Platforms that adjust difficulty in real time, chatbots that hold professional conversations, and algorithms that track learner progress are now available to ESP practitioners [3]. For architecture students — whose careers will demand the language of design briefs, client negotiations, sustainability reports, and urban planning debates — these tools carry particular promise. Yet most architecture ESP courses still follow a one-size-fits-all pattern, delivering identical materials regardless of whether a student arrives with an A2 or B2 level [4].

Adaptive learning offers a way past this problem. Brusilovsky [5] outlined the principles of adaptive hypermedia in the 1990s, and recent work by Qu [6] and Tapalova and Zhiyenbayeva [7] confirms that AI-powered platforms can personalize language learning effectively. Shokirov [8] has also noted the practical potential of AI tools for more targeted classroom instruction. However, almost none of this research addresses ESP in architecture education specifically, with its unique vocabulary demands and professional communication genres.

In Uzbekistan, Presidential Decree PQ-2909 [1] and the Concept for the Development of the Higher Education System until 2030 (PF-5847) [2] call for digital technologies and individualized approaches in language teaching, yet practical guidelines for AI-based adaptive systems in ESP are still emerging. This paper examines the theoretical basis for such systems and proposes a conceptual model for

architecture ESP, guided by three research questions: (1) What principles underpin adaptive learning in ESP? (2) How can an AI-based system serve architecture students' specific needs? (3) What benefits and limitations should educators expect?

Problem Statement

Architecture students arrive at ESP courses with markedly different starting points. One may communicate confidently in everyday English but struggle with structural terminology; another may read architectural journals fluently but freeze during oral presentations; a third may need foundational grammar before any professional language work is meaningful [9]. A fixed curriculum cannot serve all three.

References to individualized instruction and digital tools can be observed in national standards; however, methodological frameworks for AI-based adaptive ESP remain underdeveloped. Meanwhile, architecture ESP differs from other disciplines: it involves highly visual, specialized vocabulary (spatial relationships, materials, environmental performance) and professional genres (design briefs, specifications, competition entries) that existing adaptive platforms — built for general English — do not yet fully address [10].

Research Methodology

The study uses a theoretical-analytical approach in three stages. First, a systematic literature review of 2020–2025 sources from Scopus, Web of Science, and Google Scholar identified 28 relevant publications from an initial pool of 47. Second, key adaptive learning frameworks were compared by algorithm type, learner modelling approach, content adaptation mechanism, and domain applicability. Third, the findings were synthesized into a conceptual model drawing on adaptive learning theory, ESP curriculum design, and AI-assisted language instruction.

Results and Discussion

Adaptive learning principles in ESP

Adaptive systems rest on three principles: learner modelling, content sequencing, and dynamic feedback [11]. In architecture ESP, learner modelling must track not just general proficiency but familiarity with sub-domain terminology (structural, environmental, urban planning), competence in professional genres, and metacognitive strategies [12]. Table 1 maps these components to the architecture ESP context.

Table 1. Adaptive Learning Components in Architecture ESP

Component	General Function	Architecture ESP Application
Learner Model	Tracks proficiency, preferences, pace	Monitors technical vocabulary, genre awareness, professional discourse across sub-domains
Content Sequencing	Adjusts order and difficulty	Progresses from basic terminology to design critique discussions
Adaptive Feedback	Personalized corrective responses	Domain-specific error correction tied to professional norms
Assessment Engine	Evaluates and recalibrates	Tests design presentations, client negotiations, technical writing
Resource Recommender	Suggests materials per gaps	Architecture-specific readings, videos, simulation exercises

A three-tier conceptual model

The study proposes a model with three layers. The Diagnostic Layer uses placement and ongoing assessments — evaluating general English, technical vocabulary, and professional communication experience — to build and continuously update a learner profile via NLP algorithms [13]. The Adaptive Engine Layer applies reinforcement learning to optimize paths by balancing learning performance, time efficiency, and cognitive load [14]: a student strong in reading but weak in speaking gets routed to simulation-based tasks (client briefings, design reviews), while one with good general English but limited technical vocabulary is directed toward terminology modules on sustainable construction or parametric design.

The Instructional Delivery Layer presents personalized content: interactive glossaries, video case studies, simulated professional dialogues, and writing tasks for genres like design specifications and project proposals. Table 2 illustrates differentiated pathways for three learner profiles.

Table 2. Differentiated Learning Pathways by Learner Profile

Profile	Gap	Pathway	Expected Outcome
B1, reads well, speaks hesitantly	Oral fluency	Simulation dialogues: client meetings, critiques, presentations	Confidence in professional oral communication
B2, strong general English, limited technical lexis	Domain vocabulary	Terminology modules: sustainability, structural, urban planning	Broader professional vocabulary
A2, limited overall proficiency	Foundational skills	Scaffolded: grammar, core vocabulary, guided writing	Solid foundation for specialization

Affordances and limitations

The model offers clear advantages. By keeping each learner in Vygotsky's [15] zone of proximal development, adaptive systems maximize learning efficiency. The analytics they generate give both students and teachers actionable insights into vocabulary mastery, genre competence, and engagement trends [16]. These findings align with Qu [6] on engagement gains and Haryani and Emha [13] on AI-integrated ESP resources. Bahari et al. [17] similarly confirm the value of chatbot-based adaptive interventions for individualized conversation practice.

However, challenges remain. Building a sufficiently rich, domain-specific content repository demands collaboration between language educators and architecture professionals. AI algorithms need adequate training data, which may be scarce in niche contexts [18]. Concerns about data privacy, algorithmic bias, and the risk that technology might displace the human dimensions of teaching also warrant attention [19].

Conclusion

This study addressed three research questions regarding AI-driven adaptive learning in architecture ESP. In response to the first question, the analysis showed that adaptive learning in ESP operates through learner modelling, content sequencing, and dynamic feedback, each of which takes on domain-specific dimensions in architecture education. Regarding the second question, the three-tier model proposed here — Diagnostic Layer, Adaptive Engine, and Instructional Delivery — offers a coherent framework for AI-based personalized pathways tailored to architecture students' specific needs, including sub-domain

terminology, professional genre competence, and oral communication skills. As for the third question, while the benefits are considerable (targeted instruction, rich analytics, professional relevance), successful implementation requires addressing content development costs, data constraints, and ethical concerns. Empirical validation with architecture student cohorts and the development of purpose-built adaptive ESP platforms remain important next steps.

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