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Pedagogical and Methodological Foundations for Designing Artificial-Intelligence-Based Adaptive Learning Systems in Higher Education

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Abstract: Artificial-intelligence-based adaptive learning systems (AI-ALS) are increasingly promoted as a means of personalizing instruction at scale, yet their design in higher education continues to be driven predominantly by technical and algorithmic considerations rather than by explicit pedagogical reasoning. This gap between technological capability and pedagogical grounding limits the instructional effectiveness of many implemented systems and complicates their adoption by teaching staff. The purpose of this study is to substantiate the pedagogical and methodological foundations that should underpin the design of AI-based adaptive learning systems for university students. The study employed a theoretical-analytical design based on a comparative-pedagogical analysis of ten peer-reviewed and internationally recognized sources spanning foundational learning-science research, systematic literature reviews, practitioner design frameworks, and recent empirical interventions. The analysis identifies four interdependent architectural-pedagogical components that any AI-ALS must integrate - the learner model, the domain model, the pedagogical model, and the adaptive engine and interface - and specifies the didactic principles that should govern each component, including the sequencing of scaffolded support, the calibration of adaptivity to a learner's zone of proximal development, and the maintenance of teacher agency within algorithmically mediated instruction. The findings show that systems designed around an explicit pedagogical model, rather than around algorithmic capability alone, produce more consistent gains in engagement, motivation, and academic performance. The study concludes with a structural-methodological model and a set of design recommendations intended to guide instructional designers, educational technologists, and university administrators in the pedagogically sound implementation of AI-based adaptive learning systems.

Keywords: Artificial intelligence, adaptive learning, personalized instruction, instructional design, higher education, intelligent tutoring systems, learner model, pedagogical model.

Introduction: The idea that instruction can be individualized to the specific needs, pace, and prior knowledge of each learner is one of the oldest aspirations of pedagogy, and one of the most persistently unmet at scale. In a classic analysis, Bloom demonstrated that students who received one-to-one tutoring combined with mastery-learning techniques performed, on average, two standard deviations better than students taught in conventional group instruction, and posed the resulting "two-sigma problem" as a challenge to identify methods of group instruction capable of approximating the effectiveness of individual tutoring [8]. For four decades, this problem remained largely unresolved at the level of everyday classroom practice, since one-to-one human tutoring for every learner in every course is economically unfeasible for most higher education systems. The recent maturation of artificial intelligence (AI) technologies - machine learning, natural language processing, and large-scale learner-data analytics - has reopened the two-sigma problem as a practically addressable design challenge, giving rise to a new generation of AI-based adaptive learning systems (AI-ALS) capable of dynamically tailoring content, pacing, and feedback to individual learners at institutional scale.

However, the growth of AI-ALS research and implementation has substantially outpaced the development of a coherent pedagogical foundation for their design. A systematic review of 146 studies on AI applications in higher education published between 2007 and 2018 found that the dominant strands of research concerned profiling and prediction, automated assessment and evaluation, adaptive systems and personalization, and intelligent tutoring systems, but that the reviewed literature showed only a weak connection to established pedagogical theory and an almost complete absence of critical reflection on the challenges and risks associated with AI in education [1]. This finding indicates that AI-ALS are frequently engineered as technical artifacts optimized for algorithmic performance metrics, such as prediction accuracy or content-recommendation efficiency, rather than as didactic instruments explicitly grounded in theories of learning, motivation, and instructional design.

This disconnection between technological sophistication and pedagogical grounding is not merely a theoretical concern; it has measurable consequences for learning outcomes. A meta-analytic review comparing the effectiveness of human tutoring, intelligent tutoring systems, and other forms of computer-based tutoring found that well-designed intelligent tutoring systems can approach the effectiveness of expert human tutors, with effect sizes of 0.76 and 0.79 respectively, but also showed that the systems achieving such results shared specific pedagogical design features - particularly step-based rather than purely answer-based interaction granularity and structured, dialogue-like feedback - rather than relying on adaptivity or personalization mechanisms alone [5]. This suggests that the pedagogical architecture of an AI-ALS, and not merely the sophistication of its underlying algorithms, is the decisive factor in its instructional effectiveness.

The relevance of the problem is further underscored by the rapid institutional uptake of AI-ALS. A systematic mapping of 147 studies on AI-enabled adaptive learning systems published between 2014 and 2020 found that adaptive learning systems, intelligent mechanisms, and adaptive learning platforms were the most frequently proposed interventions for addressing challenges faced by students and teachers, and that the practical importance of such systems increased markedly during the period of large-scale remote and blended instruction, even though most of the reviewed systems and frameworks remained in experimental or pilot phases rather than being fully embedded in institutional practice [2]. This combination of rapid technological uptake and limited pedagogical maturity creates an urgent need for a systematic articulation of the didactic principles that should guide the design of AI-ALS, so that pedagogical soundness keeps pace with technological capability.

Accordingly, the purpose of this article is to substantiate the pedagogical and methodological foundations that should underpin the design of AI-based adaptive learning systems for university students, and to propose a structural-methodological model integrating the learner-centred, content-related, instructional, and technological dimensions of such systems. The objectives of the study were: (1) to analyse and systematize theoretical and empirical approaches to the pedagogical design of AI-ALS; (2) to identify the architectural components and didactic conditions associated with stronger, more consistent learning outcomes in the reviewed empirical literature; (3) to construct a structural-methodological model expressing the interrelationships among these components; and (4) to formulate design-oriented recommendations for instructional designers, educational technologists, and university faculty responsible for implementing AI-ALS in the educational process.

The theoretical significance of the study lies in reframing AI-ALS design as fundamentally a pedagogical, rather than a purely technical, problem, and in demonstrating that internationally recognized competency frameworks - in particular the UNESCO AI Competency Framework for Teachers - can serve as a bridge between algorithmic system design and the pedagogical judgment that must remain central to instructional decision-making [7]. The practical significance lies in providing university instructional designers and educational-technology developers with an explicit, empirically grounded model for embedding pedagogical principles into the architecture of AI-ALS from the earliest stages of design, rather than retrofitting pedagogy onto an already-built technical system.

The problem also carries specific relevance for institutions in the process of digitalizing their educational infrastructure, where AI-ALS are frequently procured as ready-made commercial platforms rather than developed in-house. In such circumstances, faculty and instructional designers typically lack influence over the system's underlying algorithms but retain substantial influence over how the domain model is populated with course content, how the pedagogical model's recommendations are contextualized within actual teaching practice, and how teacher oversight is exercised over system-generated decisions. A structural-methodological model that clearly separates these components allows institutions adopting externally developed AI-ALS to identify precisely which pedagogical responsibilities remain theirs to fulfil, rather than assuming that purchasing a technically sophisticated platform is sufficient to guarantee pedagogically sound personalized instruction.

METHODS

The study employed a theoretical-analytical design based on a systematic, comparative-pedagogical analysis of scientific literature and international policy documents concerning the design, implementation, and pedagogical evaluation of AI-based adaptive learning systems in higher education. The literature search was conducted across Web of Science, Scopus, ScienceDirect, and MDPI databases, as well as the UNESCO digital library, using combinations of the keywords "adaptive learning system," "artificial intelligence in education," "intelligent tutoring system," "personalized learning," "instructional design," and "pedagogical framework." The inclusion criteria were: (a) publication in a peer-reviewed journal, a recognized international policy report, or a foundational, widely cited scholarly work; (b) explicit focus on the pedagogical, instructional, or architectural design of adaptive or AI-enabled learning systems; (c) availability of a described framework, systematic review methodology, or empirical evaluation; and (d) relevance to higher-education or generalizable adult-learner contexts.

Ten sources meeting these criteria were selected for in-depth analysis: one foundational psychological study establishing the theoretical rationale for individualized instruction [8]; one classic meta-analytic review of tutoring-system effectiveness [5]; three systematic literature reviews mapping the state of research on AI applications, AI-enabled adaptive learning systems, and adaptive learning research more broadly [1, 2, 3]; one systematic review specifically addressing learner-modelling and personal-trait identification techniques [9]; one practitioner-oriented design-framework study [4]; one recent empirical pilot study evaluating a game-mechanics-and-AI-personalization framework [10]; and one international policy framework specifying the AI-related competencies required of teachers who work with such systems [7], complemented by a comprehensive research-and-practice synthesis on the promises and implications of AI in education [6].

The analytical procedure comprised four stages. In the first stage, each source was coded according to the architectural component(s) of adaptive systems it addressed (learner model, domain model, pedagogical/instructional model, adaptive engine and interface), the pedagogical principles or theories invoked, and the empirical outcome measures reported, where applicable. In the second stage, a comparative-content analysis was conducted to identify convergences and divergences in the pedagogical conditions associated with successful AI-ALS implementation across different technological architectures and educational contexts. In the third stage, the coded data were synthesized into a structural-methodological model expressing the interdependencies among the four architectural components and the didactic principles that should govern each. In the fourth stage, the model was translated into concrete, design-oriented recommendations addressed to instructional designers, educational-technology developers, and university faculty.

Given the theoretical-analytical nature of the study, no primary human-subject data were collected; the analysis relies exclusively on previously published, peer-reviewed, and policy-level sources, several of which themselves report primary empirical or quasi-experimental evidence (for example, a controlled pilot study involving 250 university students [10], and a meta-analysis aggregating effect sizes across dozens of primary tutoring-system evaluations [5]). The reliability of the synthesis was strengthened by cross-referencing findings across independent research traditions - cognitive and educational psychology, computer science and learning analytics, instructional design, and international education policy - which allowed conclusions to be verified against convergent rather than isolated evidence, and by explicitly distinguishing foundational, still-authoritative studies (such as Bloom's 1984 analysis) from more recent empirical work, so that the resulting model reflects both the enduring theoretical rationale for adaptive instruction and its contemporary technological realization.

RESULTS

The comparative analysis of the selected sources allowed four interdependent architectural-pedagogical components of AI-based adaptive learning systems to be identified: the learner model, the domain model, the pedagogical (instructional) model, and the adaptive engine and interface. Although this four-component architecture is most explicitly described in the systematic literature on personal-trait identification in adaptive learning environments [9], its constituent elements recur, in varying terminology, across virtually all of the analysed sources, indicating that it reflects a structurally necessary rather than incidental organization of AI-ALS design.

The learner model constitutes the component responsible for representing the individual characteristics of each student that the system uses as a basis for adaptation. A systematic review of personal-trait identification techniques found that cognitive variables serve as the basis for adaptation in more than half of the reviewed studies on adaptive learning environments, with behavioural and psychomotor traits, such as help-seeking behaviour, considered far less frequently, and identified nine finer-grained categories of learner characteristics - including learning style, prior and background knowledge, metacognitive knowledge, learner preference, behaviour, profile, ability, and interest - that can meaningfully guide adaptive decision-making [9]. This finding indicates that AI-ALS design decisions concerning which learner characteristics to model are not merely technical choices but substantive pedagogical judgments about which dimensions of individual difference are instructionally relevant.

The domain model represents the structure of the subject-matter content to be taught, including its decomposition into instructional units, prerequisite relationships, and difficulty gradations. A practitioner-oriented design-framework study conducted at a large public university found that successful adaptive-learning implementations required close, iterative collaboration between instructional designers and subject-matter experts to decompose course content into granular, prerequisite-linked learning objects, and that adaptive pathways functioned effectively only when the underlying domain model reflected an explicit, pedagogically validated sequencing of concepts rather than an arbitrary partition of existing course materials [4]. This underscores that the domain model cannot be adequately constructed through automated content analysis alone; it requires deliberate pedagogical design grounded in disciplinary expertise.

The pedagogical (instructional) model determines how the system selects, sequences, and delivers instructional interventions - explanations, practice items, hints, and feedback - based on the learner and domain models. The meta-analytic comparison of tutoring-system effectiveness found that systems using step-based or substep-based interaction granularity, in which the system monitors and responds to each individual step of a learner's problem-solving process, produced markedly stronger learning outcomes than systems using coarser, answer-based interaction, with effect sizes for intelligent tutoring systems ($d = 0.76$) approaching those of expert human tutors ($d = 0.79$) specifically when this fine-grained, dialogue-like pedagogical interaction was present [5]. This result provides strong evidence that the instructional-interaction design embedded in the pedagogical model, rather than the general presence of "adaptivity," is the primary driver of AI-ALS effectiveness.

The adaptive engine and interface constitute the technical component that implements real-time decision-making - selecting content, adjusting difficulty, and triggering feedback - based on continuous inference from the learner and domain models, and presents these decisions to the learner through a usable interface. A recent controlled pilot study involving 250 university students, randomly assigned to an AI-personalized adaptive platform or a non-adaptive control condition, found that the experimental group integrating AI-driven personalization with structured game mechanics - levelling systems, badges, and timely feedback - showed significant gains in engagement, motivation, and learning outcomes over an eight-week period compared with the non-adaptive control group [10]. This finding demonstrates that the adaptive engine's effectiveness depends on its integration with motivationally supportive interface design, not solely on the sophistication of its underlying personalization algorithm.

Beyond these four architectural components, the analysis identified a set of cross-cutting pedagogical conditions recurring across the reviewed sources as prerequisites for the effective design of AI-ALS:

1. Explicit grounding of system design in established learning theory - particularly mastery learning and the calibration of task difficulty to a learner's current level of competence - rather than in algorithmic capability alone, since the very rationale for adaptive instruction originates in mastery-learning research demonstrating the superiority of individualized, criterion-referenced pacing over uniform group instruction [8]. 2. Fine-grained, step-based pedagogical interaction design, allowing the system to monitor and respond to intermediate stages of a learner's reasoning process rather than only to final answers [5]. 3. Deliberate, expert-validated construction of the domain model's content sequencing, rather than automated or arbitrary content segmentation [4]. 4. Selection of learner-model variables based on pedagogical relevance - cognitive, motivational, and behavioural - rather than on data availability or ease of algorithmic processing alone [9]. 5. Integration of motivationally supportive design elements (feedback timing, gamified progress indicators) with the adaptive engine, since personalization mechanisms alone do not reliably produce engagement or performance gains without such integration [10]. 6. Preservation of teacher agency and pedagogical oversight within AI-mediated instruction, in line with international competency frameworks specifying that educators must retain the professional judgment to interpret, override, and pedagogically contextualize system-generated recommendations [7]. 7. Sustained attention to ethical and equity considerations - including algorithmic bias, data privacy, and unequal access to adaptive technologies - which the broader research and policy literature identifies as still critically underdeveloped relative to the pace of technical implementation [1, 6].

Table 1 summarizes the four architectural-pedagogical components, their defining pedagogical function, and the empirically supported design principles associated with each, according to the analysed sources.

Table 1. Architectural-pedagogical components of AI-based adaptive learning systems

Component	Pedagogical function	Empirically supported design principle	Key sources
Learner model	Represents cognitive, motivational, and behavioural characteristics used as a basis for adaptation	Select variables by pedagogical relevance (prior knowledge, metacognition, interest), not data convenience	[9]
Domain model	Structures subject-matter content into prerequisite-linked, difficulty-graded instructional units	Construct through expert-validated instructional design, not automated content segmentation	[4]
Pedagogical model	Determines selection, sequencing, and delivery of explanations, practice,	Use fine-grained, step-based interaction and dialogue-like feedback rather than	[5, 8]

	and feedback	answer-based checking	
Adaptive engine and interface	Implements real-time adaptive decisions and presents them through a usable, motivating interface	Integrate personalization algorithms with motivational design (gamification, timely feedback)	[2, 10]

The analysis further revealed that the four components are bound together by a directional dependency structure rather than functioning as parallel, independent modules. The domain model must be constructed prior to, and independently of, individual learner data, since it represents the stable structure of the subject matter that all learners will traverse; the learner model is then populated dynamically as the system gathers evidence of each student's characteristics and performance in relation to that domain structure [4, 9]. The pedagogical model operates as the mediating layer that interprets the joint state of the learner and domain models to select an appropriate instructional action, and the empirical evidence indicates that the granularity and dialogic quality of this mediating layer - rather than the statistical sophistication of the learner-modelling algorithm - is what most strongly predicts learning gains [5]. Finally, the adaptive engine and interface operationalize the pedagogical model's decisions in real time and are the component most directly experienced by the learner, which explains why motivational and interface-design features exert an influence on outcomes that is at least as strong as the underlying personalization logic itself [10].

This dependency structure carries an important methodological implication for system design: attempts to build the adaptive engine and learner-modelling algorithms before an explicit pedagogical model has been articulated risk producing technically capable systems that lack a coherent instructional rationale, a pattern that the systematic review of AI applications in higher education explicitly identified as a weak connection to established pedagogical theory across the majority of reviewed studies [1]. The structural-methodological model proposed in this study therefore recommends that AI-ALS design begin with an explicit statement of the pedagogical model - the instructional theory and interaction design the system is meant to instantiate - before the domain model, learner model, and adaptive engine are engineered around it, reversing the sequence in which many current systems appear to have been developed.

DISCUSSION

The results obtained both confirm and substantially extend Bloom's original formulation of the two-sigma problem. Bloom's analysis demonstrated that one-to-one tutoring combined with mastery-learning techniques could raise the average tutored student's performance to a level exceeding that of 98 per cent of students in a conventional class, and framed the central challenge as finding scalable methods of group instruction that approximate this effect [8]. The meta-analytic evidence reviewed in this study shows that intelligent tutoring systems, when properly designed with step-based pedagogical interaction, can achieve effect sizes closely approaching those of expert human tutoring [5], suggesting that AI-ALS represent a technologically scalable, though not yet fully equivalent, response to Bloom's original challenge. However, the magnitude of this effect is contingent on specific pedagogical design choices - fine-grained interaction granularity and dialogue-like feedback - rather than being an automatic consequence of introducing AI or adaptivity into a learning system, which reframes the two-sigma problem as a pedagogical design challenge rather than a purely technological one.

A particularly important finding concerns the systemic gap between technological capability and pedagogical grounding identified across multiple independent reviews. The observation that most AI-in-education research shows only weak connections to established pedagogical theory [1], together with the finding that most AI-enabled adaptive learning systems and frameworks remain in experimental rather than institutionally embedded phases [2], and the broader systematic finding that adaptive-learning research over the preceding decade concentrated heavily in computer-science disciplines with comparatively limited representation from educational-research perspectives [3], jointly indicate that the field has developed a strong technical infrastructure without a correspondingly mature pedagogical infrastructure. This asymmetry helps explain why so many AI-ALS implementations remain confined to pilot projects: a system that is technically functional but pedagogically under-specified is unlikely to gain the sustained confidence of teaching staff or to demonstrate the consistent learning gains needed to justify institution-wide adoption.

The comparative analysis also clarifies the specific mechanism through which pedagogically well-designed AI-ALS translate technical adaptivity into learning gains. The recent pilot study demonstrating that AI-driven personalization combined with structured game mechanics produced significant engagement and performance gains over a non-adaptive control condition [10] is consistent with, and extends, the practitioner-based design-framework literature emphasizing that successful adaptive-learning implementation depends on the deliberate, collaborative construction of a pedagogically coherent domain model [4]. Taken together, these findings suggest that the "personalization" achieved by an AI-ALS is only as pedagogically meaningful as the instructional design decisions embedded in its domain and pedagogical models; an algorithmically sophisticated system built on a pedagogically thin domain model is unlikely to produce the gains attributed to adaptivity in principle.

The analysis of learner-modelling research adds a further layer of nuance to this picture. The finding that cognitive variables dominate current learner models, while behavioural, motivational, and socio-cultural variables remain comparatively underused [9], suggests that many existing AI-ALS may be adapting primarily to what a learner knows, while paying insufficient attention to how a learner engages, self-regulates, or responds motivationally to feedback. Given that the pilot evidence on game-mechanics integration shows sizeable engagement effects attributable specifically to motivational design features [10], this points to a concrete and currently underexploited opportunity: enriching learner models with motivational and self-regulatory variables, rather than relying predominantly on cognitive-performance data, to make adaptive decision-making pedagogically more comprehensive.

The role of the teacher within AI-mediated adaptive instruction also emerges as a decisive, though frequently underspecified, design consideration. The UNESCO AI Competency Framework for Teachers explicitly positions educators as retaining professional judgment and pedagogical oversight over AI-generated recommendations, situating teacher AI competence within a human-centred mindset, an understanding of AI ethics, and the capacity to critically evaluate and pedagogically contextualize AI outputs rather than defer to them automatically [7]. This framing is consistent with the broader synthesis of promises and implications of AI in education, which cautions that the effective and equitable use of AI in classrooms depends fundamentally on how well teachers are prepared to interpret, adapt, and, where necessary, override algorithmically generated instructional decisions [6]. A structural-methodological model for AI-ALS design that omits an explicit mechanism for teacher oversight and intervention therefore risks producing systems that are pedagogically incomplete regardless of their algorithmic sophistication.

It is necessary to acknowledge the limitations of the present analysis. First, because the study is theoretical-analytical rather than empirical, the structural-methodological model proposed here synthesizes converging evidence from independently conducted studies rather than reporting original primary data collected by the author; its validity should be understood as a synthesis of the best currently available evidence rather than as an experimentally validated design. Second, several of the most influential sources analysed - including the foundational tutoring-effectiveness meta-analysis [5] and the original mastery-learning research [8] - predate the current generation of large-language-model-based educational tools, so the applicability of their specific effect-size estimates to contemporary generative-AI-enabled adaptive systems should be treated as an informed extrapolation rather than a directly established fact; this is an important direction for future empirical replication. Third, the reviewed empirical intervention studies, while methodologically rigorous, were conducted in a limited number of institutional and national contexts, which constrains the extent to which specific quantitative findings can be generalized without contextual adaptation, including to Central Asian higher-education settings where infrastructural and curricular conditions may differ substantially from those of the reviewed studies.

Notwithstanding these limitations, the convergence of evidence across foundational learning-science research, systematic literature reviews spanning multiple disciplinary traditions, practitioner design frameworks, and a recent controlled pilot study lends considerable weight to the four-component structural-methodological model proposed in this article, and to the broader claim that pedagogical grounding, not algorithmic sophistication alone, is the decisive determinant of AI-ALS effectiveness in higher education.

This conclusion also has implications for how institutions should interpret vendor claims about AI-ALS effectiveness. Because commercial adaptive-learning platforms are frequently marketed on the basis of their algorithmic capabilities - the size of their training data, the sophistication of their machine-learning models, or the granularity of their analytics dashboards - institutions evaluating such platforms risk over-weighting technical specifications that the evidence reviewed here suggests are not, by themselves, reliable predictors of instructional effectiveness. A more defensible evaluation approach, consistent with the structural-methodological model proposed in this study, would require vendors and adopting institutions alike to specify explicitly which learning theory underlies the platform's pedagogical model, how its domain model was validated by subject-matter experts, which learner-model variables it captures beyond raw performance data, and what mechanisms exist for instructors to interpret, adjust, or override its recommendations. Institutions able to answer these four questions clearly are considerably better positioned to judge whether a given AI-ALS is likely to produce genuine pedagogical benefit, as opposed to a superficially personalized but instructionally shallow experience.

Based on this discussion, the following design-oriented recommendations can be formulated for the pedagogically sound implementation of AI-based adaptive learning systems in higher education:

1. Begin system design with an explicit pedagogical model - grounded in mastery-learning and scaffolding principles - before engineering the technical learner-modelling and adaptive-engine components [5, 8]. 2. Construct the domain model through sustained, iterative collaboration between instructional designers and subject-matter experts, ensuring pedagogically validated content sequencing rather than automated segmentation [4]. 3. Design learner models to capture motivational, behavioural, and self-regulatory variables alongside cognitive-performance data, rather than relying predominantly on the latter [9]. 4. Prioritize fine-grained, step-based pedagogical interaction and dialogue-like feedback over coarse, answer-based adaptivity mechanisms [5]. 5. Integrate the adaptive engine with motivationally supportive interface elements, such as structured feedback timing and progress-visualization features, rather than treating personalization as a purely content-selection function [10]. 6. Embed explicit mechanisms for teacher oversight, interpretation, and override of system-generated recommendations, consistent with international AI-competency frameworks for educators [7]. 7. Establish institutional protocols for monitoring algorithmic bias, data privacy, and equitable access as a mandatory, ongoing component of AI-ALS governance rather than a one-time compliance check [1, 6].

CONCLUSION

The analysis conducted in this article confirms that the effective design of artificial-intelligence-based adaptive learning systems for higher education is fundamentally a pedagogical undertaking, in which algorithmic sophistication functions as a necessary but insufficient condition for instructional effectiveness. Four interdependent architectural-pedagogical components were identified - the learner model, the domain model, the pedagogical model, and the adaptive engine and interface - bound together by a directional dependency in which the pedagogical model must be explicitly articulated before the remaining technical components are engineered around it. The comparative analysis of foundational learning-science research, systematic literature reviews, practitioner design frameworks, and recent empirical interventions demonstrates that the strongest and most consistent learning gains are associated not with adaptivity or personalization as such, but with specific, empirically identifiable pedagogical design choices: fine-grained, step-based instructional interaction; pedagogically validated content sequencing; learner models enriched with motivational and behavioural, not only cognitive, variables; and the deliberate preservation of teacher agency within algorithmically mediated instruction.

The proposed structural-methodological model offers instructional designers, educational-technology developers, and university administrators a coherent, empirically grounded basis for sequencing the design of AI-based adaptive learning systems around pedagogical rather than purely technical priorities, and for evaluating existing or prospective systems against a clear set of pedagogically justified design criteria. Future research should focus on the direct empirical replication of classic tutoring-effectiveness findings within contemporary large-language-model-enabled adaptive systems, on the development of learner-modelling techniques that more fully integrate motivational and self-regulatory variables alongside cognitive ones, and on the design and evaluation of institutional governance frameworks capable of safeguarding pedagogical oversight, equity, and data ethics as AI-based adaptive learning systems move from pilot implementation toward institution-wide adoption.

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