Development and Integration of Multimodal and Context-Sensitive Recommendation System Methodology for Enhancing Learning Adaptivity

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Abstract

Digital education environments face growing learner diversity, widening student performance gaps and an increasing workload on educators. This research proposes the development and empirical validation of a multimodal, context-aware recommendation system (RS) methodology integrating behavioral data, cognitive indicators, and contextual dimensions to enable real-time personalization of learning content. The methodology addresses key gaps in the literature – lack of multimodal data integration, weak pedagogical grounding, and absence of real-time context sensitivity – by establishing evidence-based design principles grounded in constructivist learning and cognitive load theory for translating heterogeneous learner data into pedagogically meaningful recommendations, advancing beyond existing approaches that address these dimensions in isolation. The novelty lies not in any single component but in their systematic, pedagogically grounded integration. The research adopts Design Science Research (DSR) as its methodological framework that is structured across four phases: a systematic literature review (SLR), scalable data architecture design, deep learning-based algorithm development and empirical prototype validation in a real digital learning environment. The expected contribution operates at theoretical, methodological, and technological levels – establishing transferable design principles for multimodal RS integration in digital education. Primary outcomes target measurable learning gains and knowledge gap closure; secondary outcomes address learner engagement and educator workload reduction.

Keywords

Recommendation system, adaptive learning, learning management system, multimodal data, context-aware systems, education

1. Introduction

Digital education environments have dramatically transformed over the past decade, expanding educational reach and resource efficiency [36]. Rapid expansion has created an overwhelming volume of learning content and vast repositories of materials raise a question: how to ensure that learning content reaches the right learner, at the right moment, in a form that supports individual learning? Yet despite the growing academic interest, most deployed systems continue to rely on unidimensional behavioral models while overlooking the cognitive states of a learner, contextual conditions as well as pedagogical trajectories that fundamentally shape the learning experience and outcomes. The ability to meaningfully personalize learning content to learners' individual needs as well as cognitive capacities remains a largely unsolved challenge.

Given the variability in learning processes, personalization tools like recommendation systems have been proposed as a potential solution. Evidence suggests RSs can improve engagement [2, 19, 25], academic outcomes [22, 23], and socio-emotional benefits such as peer learning, sense of institutional belonging [8] and adaptability [14] while indirectly mitigating dropout risks [4, 18]. RSs also aid educators in resource management [15] enabling them to focus on more targeted learner support, fostering equitable academic growth [2, 25]. However, most of deployed systems remain limited – built around clickstream logs or session duration, capturing how a learner behaves without accounting for how a learner thinks or in what conditions they are learning.

These limitations are reflected in data. In an open online learning environment, completion rates vary between 5% and 15% regardless of content quality, signaling a systemic failure to sustain learner

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engagement [9]. Organisation for Economic Co-operation and Development (OECD) data from 2022 place Latvia among the highest dropout rates in Europe – 52% in first-cycle and 42% in short-cycle programmes [38]. State Audit report published in 2026, examining the period 2021–2024 of the Latvian education system identified performance gaps of 20–25% between learners in primary education level across regions and social groups [37]. Data outlines future challenges – structurally unequal entry-level knowledge creates uneven admission and further learning opportunities. Vast differences in students' knowledge levels increase the workload on teachers aiming to adapt and differentiate content delivery to bridge performance gaps. The 2025 OECD TALIS (Teaching and Learning International Survey) report confirms this statement – time allocated to grading increased from 5.0 to 5.4 hours per week between 2017 and 2025, with Latvia consistently exceeding OECD averages across all measured categories – total hours, lesson preparation, and assessment [35]. More than a third of educators cite high psychological burden and insufficient institutional support as primary reasons for leaving the profession and deepening already critical educator shortage [35]. This deterioration is inseparable from the broader context of inclusive education policies and the growing institutional expectations in differentiation, individualization, and personalization of both teaching methods and learning content. Data underlines a need for scalable, intelligent systems that can reduce educator workload while simultaneously delivering individualized learning experiences.

Closing this gap requires a fundamentally different approach to learner modeling – one that integrates behavioral, cognitive, and contextual data into a unified, real-time recommendation framework. The novelty of this research lies not in any single component but in their systematic integration: combining a pedagogically grounded theoretical framework with a scalable multimodal architecture and empirically validated design principles that extend beyond the specific deployment context. The work builds directly on prior research, in which a pedagogically grounded RS methodology using an S-matrix – mapping learning materials to specific skills – a Q-matrix – mapping assessment questions to skills – and a Markov Decision Process (MDP), a framework modelling relevant learning material suggestions based on the learner's current knowledge state, demonstrated measurable gains in knowledge gap identification and academic outcome improvement. Current research advances this foundation toward a combined, empirically validated, context-sensitive methodology.

2. Research questions and objectives

The aim of this research is to advance adaptive learning in digital education environments by designing, developing and empirically validating a multimodal, context-aware recommendation system methodology that systematically integrates behavioral, cognitive, and contextual learner data to enable real-time personalization of learning content and sequencing. The research seeks to establish evidence-based design principles for multimodal RS integration that reduce learning fragmentation, address knowledge gaps, and are transferable beyond a single platform or institutional context.

To address this aim the central question driving research is stated as follows:

1. How can a multimodal and context-aware recommendation system methodology improve adaptive learning effectiveness and learner engagement in digital education environments?

The research question is defined from identified gap in literature. Studies consistently show that RSs improve personalization outcomes [19, 21], yet most reviewed systems rely on a single data modality and treat context as either a filter or an afterthought [6, 32]. The step from demonstrating RS benefits in controlled conditions to building systems that function dynamically across learner populations – with all their variability in device, location, cognitive load, and prior knowledge, remains largely unaddressed.

Research is structured by the following objectives:

1. To conduct an SLR to map specifically what is known about multimodal data integration, context-aware personalization, and cognitive signal processing in learning systems.
2. To design a data engineering architecture capable of handling heterogeneous, continuous data streams – behavioral, cognitive, and contextual – in a scalable way.
3. To develop recommendation algorithms that use deep learning methods to model the relationships between these data streams and generate adaptive content sequences in real time.

4. To integrate and validate the resulting prototype into a digital learning environment measuring its effect on engagement and academic outcomes through controlled experimentation.

The research **object** is adaptive learning processes in digital education environments.
The research **subject** is the multimodal and context-aware RS methodology for personalizing adaptive learning. Combined, these elements define research boundaries including theoretical, methodological, and technological aspects grounded in a practical problem in digital education ecosystem that have not yet been solved.

3. State of the art

Research on RSs in education has grown considerably since 2019, with most of the peer-reviewed output concentrated in the period 2021–2023, partly due to the COVID-19 pandemic [39]. To identify the research gap, an SLR was conducted across ScienceDirect and SpringerLink repositories – selected based on the following reasons: interdisciplinary coverage of educational technology and adjacent fields, academic credibility and full-text accessibility via the university's scientific database. Using defined keywords and relevant synonyms (*recommendation systems, education, and adaptive learning)* and the following filtering attributes (article type, subject areas and CiteScore top 10% by Scopus) 451 records were identified – 50 from ScienceDirect and 401 from SpringerLink. Papers were further evaluated using the criteria summarized in Table 1, guided by the PRISMA (*Preferred Reporting Items for Systematic Reviews and Meta-Analyses*) framework, resulting in 34 studies in total for further review.

Table 1
Research selection criteria

Criteria	Inclusion	Exclusion
Language	Published in English	Non-English publications
Accessibility	Full-text availability	Full text not available
Publication type	Peer-reviewed articles, research articles, book chapters, conference papers	Non-research outputs (e.g., letters to editors, opinion pieces, reviews)
Research field	Focus on computer science and/or education	Studies outside computer science and education (e.g., medicine)
Relevance	Relevant keywords are mentioned in abstract that aligns with research objectives	Abstract indicates irrelevance or specialization in unrelated sectors

The review addresses the central research question: *What are the current research trends, innovations, and limitations in the application of recommendation systems in education?* The conducted review provides the empirical basis for situating this research within the existing landscape [6, 19]. Analysed studies span 2015–2025 and are categorized into four groups: systematic literature reviews, trends and innovations in RSs, challenges and limitations in RS deployment, and MOOC platforms (Table 2).

Studies consistently report improvements in learner engagement, content relevance, and academic performance when RSs are deployed [2, 19, 21] with broader benefits of reduced dropout risk [4, 18], stronger peer learning dynamics [4], improved learner satisfaction and institutional reputation [8] and support for educators – reducing the cognitive load of resource management and pedagogical planning [15] enabling educators to focus on the learners who need additional assistance [2,25]. Hybrid approaches combining collaborative filtering, content-based methods, and AI-driven components have emerged as a dominant design pattern to compensate for the weaknesses of a single technique [6, 21]. Knowledge graph-based systems represent one of the more promising directions, enabling richer semantic representations [13, 31], while natural language processing supports more nuanced content analysis and learner profiling [28].

Table 2
Summary of literature review

	Key insights	Representative studies
Systematic literature review	Adaptive systems improve student engagement and academic outcomes by personalizing learning content delivery	6,17, 19, 20, 21, 26, 32, 34
Trends and innovations in RSs	RS advancements are driven by AI, knowledge graphs, and hybrid approaches.	1, 2, 5, 10, 11, 12,14, 15, 16, 22, 23, 25, 27, 30
Challenges and limitations in RSs deployment	Cold-start issues, scalability, and ethical concerns hinder RS deployment.	3, 7, 8, 24, 28, 29
MOOC platforms	RSs for personalized learning in MOOCs, addressing challenges like learner diversity.	4, 9, 13, 18, 31, 33

Despite this progress, persistent and unresolved limitations remain. Most systems capture only behavioral signals – clickstream data, time-on-task, quiz scores, while overlooking the cognitive and contextual dimensions that shape meaningful learning experiences [2, 6]. Cognitive load theory establishes that learning outcomes are directly shaped by the conditions under which information is processed. A learner accessing course material on a mobile device during a commute is in a fundamentally different cognitive and contextual situation than the same learner at a desk with two hours available – yet current solutions treat these situations as equivalent.

Alignment with pedagogical theory remains limited across the field. While constructivism, cognitive load theory, and self-regulated learning concepts are frequently cited as motivating frameworks, they rarely are integrated into concrete system design decision making [6, 19, 32]. This results in technically functional systems that are pedagogically shallow – optimizing for engagement signals without modeling whether genuine learning is occurring. Furthermore, systems typically identify dropout risk only when intervention is no longer effective [36].

Cold-start problems persist across nearly all reviewed systems, particularly in multimodal or knowledge graph-based designs where sparse data undermines early recommendations [21, 32]. Scalability is a related concern: architectures that perform well in controlled experiments often struggle when deployed across diverse learner populations with heterogeneous data [6]. Ethical dimensions – algorithmic bias in content selection, data privacy in learner profiling – are acknowledged in the literature but remain largely unaddressed in implementations [6, 32].

The gap this research addresses sits at the intersection of three under-explored areas: multimodal data integration, real-time context sensitivity, and pedagogical grounding. Current systems pick at most one or two of these – a system might be pedagogically informed but context-blind, or context-sensitive but behaviorally shallow. No reviewed study demonstrates a methodology that brings all three together in an empirically validated, scalable architecture.

The prior research established that a pedagogically grounded RS using Q-matrix and S-matrix and MDP for dynamic sequencing can identify knowledge gaps early and generate relevant content recommendations in a real learning environment. Prior work operated on a single data modality. The research asks what becomes possible when behavioral signals are combined with cognitive indicators and contextual variables, and whether that combination can be operationalized in a system that works at scale, in real time, and in alignment with how learning occurs in digital environment.

4. Research methodology

Developing a multimodal, context-aware recommendation system is not solely a technical task – it is equally a question of what pedagogical and contextual dimensions should be integrated, how knowledge about such a system should be produced, validated, and made scalable to be transferable beyond the specific context in which it was built.

Research adopts Design Science Research (DSR) as its main methodological framework as the primary goal is to construct theoretically grounded artifact – a methodology and a prototype that can be integrated in a real learning environment. Design decisions across all phases will be justified against the theoretical framework established in Phase 1, grounding architectural and algorithmic choices in constructivist learning theory and cognitive load theory rather than optimizing for performance metrics alone.

The research is organized into four phases, each corresponding to a defined objective.

Phase 1 – to conduct an extended SLR. A PRISMA-guided SLR conducted at the prior research stage reviewed 34 peer-reviewed studies on RS deployment in education broadly. The extended research targets three areas that the existing SLR has left underexplored: multimodal data integration in learning analytics, cognitive signal capturing and its processing in digital environments and context-aware personalization architectures. The extended review will map current research done in domain and identify where methodological and empirical gaps remain, forming the theoretical background of the proposed contribution.

Phase 2 – to design data engineering architecture. A scalable architecture will be designed for continuously collecting and processing heterogeneous learner data across three streams: behavioral indicators collected from LMS (Learning Management System) interaction logs such as clickstream patterns, session dynamics, task completion rates, and navigation sequences; cognitive signals derived as proxies from learner interaction data – response latency, error frequency, and task-switching patterns as indicators of cognitive load and attentional state [2, 6]; contextual variables – device type, time of day, and session location will be collected through LMS metadata and browser-level signals. Data minimization, anonymization, and informed consent mechanisms will be embedded to address ethical concerns [6, 32].

Phase 3 – algorithm development. Context-aware recommendation algorithms will be developed incorporating all three data streams, extending the Q-matrix and S-matrix outcome mapping and MDP baseline from the author's prior research toward a multimodal setting. Deep learning methods will be explored for optimal content sequencing, with proposed algorithm design grounded in pedagogical principles: recommendations must align with defined learning outcomes directly addressing the identified pedagogical limitations.

Phase 4 – to integrate and empirically validate the prototype. The methodology will be operationalized as a functioning prototype in a real learning environment. Validation will follow a controlled experimental design comparing learner engagement and academic outcomes between control and experimental groups. Quantitative analysis will extend beyond group mean comparisons – T-tests for initial outcome comparison, with mixed-effects models considered to capture individual learner variation and temporal dynamics. Qualitative feedback from learners and educators will be collected to capture perceived usability, relevance of recommendations, and cognitive experience alongside quantitative measures.

The four phases are sequential but not rigid — consistent with DSR's iterative logic, findings from any phase may trigger revisiting earlier design decisions.

5. Proposed contribution

The research proposes a contribution that operates on three levels – theoretical, methodological, and technological. Existing research addresses these dimensions in isolation without combining them into a unified framework [6, 19, 32].

The *theoretical contribution* synthesizes and structures knowledge across these three dimensions, producing a theoretically grounded framework that maps the relationships between learner behavioral signals, cognitive indicators, and contextual variables in adaptive learning. The framework establishes design principles for how multimodal data should be interpreted and translated into meaningful recommendations. While context-awareness and multimodal data have been studied individually, the novelty lies in the systematic articulation of their combination that produces effects that no single dimension achieves alone – reducing cognitive overload while simultaneously improving content relevance and sequencing alignment with individual learning trajectories.

The core of *methodological contribution* is a multimodal, context-aware RS methodology designed specifically for adaptive learning environments. Building on the prior research findings the methodology extends findings in two directions. Firstly, it expands the data modality from behavioral signals alone to an integrated model incorporating cognitive and contextual streams. Second, it introduces real-time adaptivity – moving from static or session-level recommendations toward dynamic sequencing that responds to a learner's current state as it changes within a learning session. The methodology will include explicit design principles for integration into existing digital learning environments, making it applicable beyond the specific platform used for validation.

The methodology will be operationalized as a functioning prototype in a real learning environment to achieve *technological contribution* – a scalable data engineering architecture combined with context-aware recommendation algorithms built on deep learning methods for sequence modeling. Three heterogeneous data streams – behavioral, cognitive, and contextual – are continuously collected and processed through a scalable data engineering architecture (see Figure 1). A context-aware RS engine combining deep learning with Q-matrix, S-matrix mapping and MDP generates dynamically personalized content sequences in real time, with a learner feedback loop enabling continuous improvement. Together, these three levels reflect a qualitatively different conception of what an adaptive learning system should know about its learners and how it should act on that knowledge.

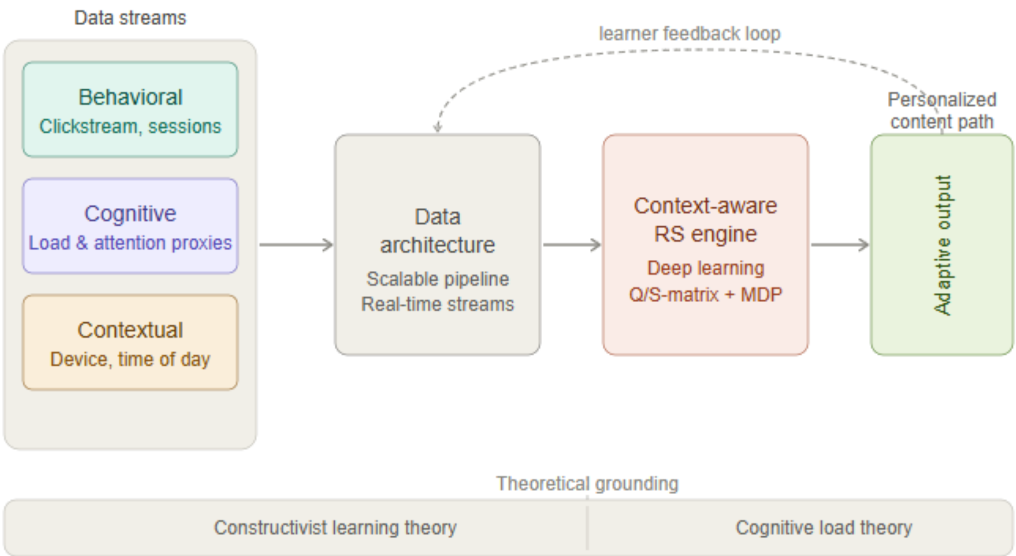

Figure 1: Conceptual model of the proposed multimodal, context-aware recommendation system methodology.

6. Current progress and further research

The research is in its early stages with foundational work providing a validated methodological baseline. Prior research developed and validated a pedagogically grounded RS methodology that integrated Q-matrix and S-matrix outcome and learning material mapping with an MDP for personalized learning content management, demonstrating measurable gains in knowledge gap identification. The methodology was validated in a controlled experimental design using T-test group comparison between learners with and without the system active. A PRISMA-guided SLR of 34 peer-reviewed studies (2015–2025) was conducted to map current trends, innovations and limitations in RS deployment within the education domain.

Currently, the research question, objectives, research object and subject have been defined. The extended SLR targeting multimodal data integration, cognitive signal processing, and context-aware personalization architectures is in progress. Conceptual work on data engineering architecture design has been initiated. The research is currently progressing in parallel with Phase 1 and Phase 2 of the proposed DSR framework. The theoretical foundation is established, and the methodological design phase is steadily advancing.

Several methodological and technical questions remain open. The fundamental concerns are linked to the operationalization of cognitive signals in real learning environments and processing them to provide meaningful and sequential recommendations. Cognitive load, motivational patterns and attention are well-established theoretical constructs; however, measuring these attributes in naturalistic digital settings remains methodologically challenging. In further work indicators such as response latency, error patterns, and interaction rhythm will be explored and validated before incorporation into a recommendation pipeline. Effectiveness will be operationalized across two levels: primary outcomes – knowledge gap closure and learning gain, measured through pre/post assessment comparison between control and experimental groups, and secondary outcomes – learner engagement, session completion, and reported relevance of recommendations.

A related challenge is the cold-start problem in a multimodal context. Extending to three data streams increases data requirements for generating reliable recommendations, particularly for new learners with no prior interaction history. Strategies for managing sparse data in early stages of learner profiling need to be designed and tested. The ethical dimensions of multimodal learner data collection also require explicit resolution – informed consent, data minimization and storage, as well as algorithmic bias risk will be addressed through the Phase 2 architecture design, but specific mechanisms require further development. Partial empirical results are expected by the end of Phase 3, with preliminary validation data from a pilot deployment in Phase 4. Full empirical results are planned for the final year of the doctoral timeline.

Finally, prototype integration introduces practical constraints that are difficult to anticipate at the design stage – LMS compatibility, institutional data governance requirements and maintaining experimental validity within a live educational setting.

The immediate next steps are to complete the extended SLR, finalize the conceptual data architecture, and begin algorithm prototyping. The expected outcome is a scientifically grounded and empirically validated methodology that advances personalization of learning experiences in digital education, reducing burden on educators while meaningfully improving engagement and outcomes for learners.

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Declaration on Generative AI

During the preparation of this work, the author used Claude in order to: translation, grammar and spelling check. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the publication’s content.

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