Adaptive Cognitive Recommendation Systems and Learning Optimization in the age of AI (a survey)

Hind Ben Rahmoun, Aneliya Ivanova, Noura Aknin, Souhaib Aammou

Abstract:
The rise of digital learning environments over the last two decades has been accompanied by an explosion of pedagogical data, which, combined with recent AI advances, opens new perspectives on adaptive learning management systems (LMS). Most existing LMS rely on static recommendations or observable behavior alone, systematically ignoring the learner's real cognitive state, cognitive load, attentional engagement, and motivational orientation. This absence of cognitive awareness frequently leads to information overload or, conversely, to disengagement and boredom, both of which erode motivation and compromise learning effectiveness. This survey examines the challenges in designing an intelligent adaptive recommendation system capable of understanding and anticipating the learner's cognitive needs in order to adapt content and educational pathways in real-time. The theoretical lens is grounded in Cognitive Load Theory, Attention Theory, and Self-Determination Theory.

Keywords: Adaptive LMS; Cognitive Load Theory; Attention Theory; Self-Determination Theory; Personalized Learning; Real-Time Adaptation

For contacts: Hind Ben Rahmoun, PhD Student, Abdelmalek Essaadi University, Morocco, hind.benrahmoun@etu.uae.ac.ma

INTRODUCTION

The rapid digital transformation of education has generated vast amounts of educational data [1]. The convergence of this data with advancements in artificial intelligence offers promising prospects for rethinking how learning systems support ach learner, shifting the paradigm from a standardized distribution of content to systems tailored to individual cognitive abilities [2].

Significant research progress has been made, however, most adaptive learning platforms still rely on indirect behavioral indicators such as task time, click patterns, and assignment scores to assess learners' needs [3]. These indicators are available but they fail to capture the learner's internal cognitive state, which results ecommendations that are not aligned with their actual processing capacity at any given moment [4].

The consequences are concrete: overly dense content leads to cognitive overload (CL), while unstimulating content breeds boredom and a gradual disengagement from learning. Both situations weaken intrinsic motivation and the long-term effectiveness of learning [5]. This paper explores the main challenges related to designing a system that, beyond simple behavioral observation, allows us to understand and predict cognitive needs in real time, in order to recommend content based on learners' instant state, drawing on cognitive load theory (CLT) , attention theory (AT), and self-determination theory (SDT) [6].

LAYOUT

1. Theoretical Framework

Cognitive Load Theory: This theory, developed by Sweller [7], posits that working memory has a limited capacity for simultaneous processing. It distinguishes between internal load (content complexity), external load (inadequacies of instructional design), and relevant load (construction of cognitive schemas). In adaptive systems design, cognitive load theory provides a theoretical framework for dynamically calibrating content difficulty to conserve cognitive resources for efficient learning rather than surface level processing.

Attention Theory: In digital environments, sustained and selective attention is a key factor in effective learning. Attention is highly dynamic and fluctuates according to content importance, task duration, and accumulated cognitive fatigue. A system sensitive to attentional states can intervene proactively by modifying the presentation or introducing short pauses before the level of engagement falls below an acceptable productivity threshold.

Self-Determination Theory: Deci and Ryan [8] propose that sustained motivation is based on three psychological needs: autonomy, competence, and relatedness. Adaptive systems inspired by self-determination theory (SDT) must go beyond simply improving performance, actively creating conditions in which learners feel autonomous, achieve progressive mastery, and feel a sense of belonging to their learning environment.

2. State of the Art in Adaptive Learning Systems

Two fundamental pillars are rested upon by the development of adaptive learning systems (ALS), illustrated in Figure 1: the development of adaptive learning systems, and development of learner modeling.

Adaptive learning systems (ALS) has evolved from rule-based intelligent tutoring systems to machine learning systems leveraging collaborative filtering and Bayesian knowledge tracing [9]. Simultaneously, learner modeling has evolved toward richer, multi-state representations that integrate the behavioral, emotional, and cognitive dimensions of the learner profile [10].

3. Key Challenges in Cognitive-Aware Adaptive Systems

Figure 1 illustrates the four main technical and theoretical challenges to be addressed when designing a cognitive aware adaptive recommendation system that takes cognitive states into consideration. Each challenge has a theoretical and technical impact on the core system.

Multi-Dimensional Knowledge State Modelling. Representing a learner's knowledge across multiple cognitive dimensions simultaneously is a major challenge [10]. Traditional unidimensional knowledge tracking models fail to capture the complex and interconnected structure of competence in real situations. Multidimensional approaches must reconcile accurate representation, computational ease, and the scarcity of classified training data in real educational contexts [11].

Measurable Cognitive State Modelling. Cognitive load, attention, and motivational state are latent concepts that are difficult to observe directly. Transforming these concepts into applicable and measurable representations, requires the development of proven inference models capable of detecting real-time changes in cognitive state from readily available signal sources, without imposing undue cognitive load on learners [3].

Real-Time Multimodal Learner State Fusion. Effective inference of learner cognitive state requires the systematic integration of multiple data streams such as behavioral recordings, physiological signals, interaction chronology, and semantic content features, into a coherent, time-bound representation of that state [4]. Achieving robust integration across heterogeneous modalities with low latency, a necessary condition for real-time adaptation, is one of the most technically complex open problems in this field [11].

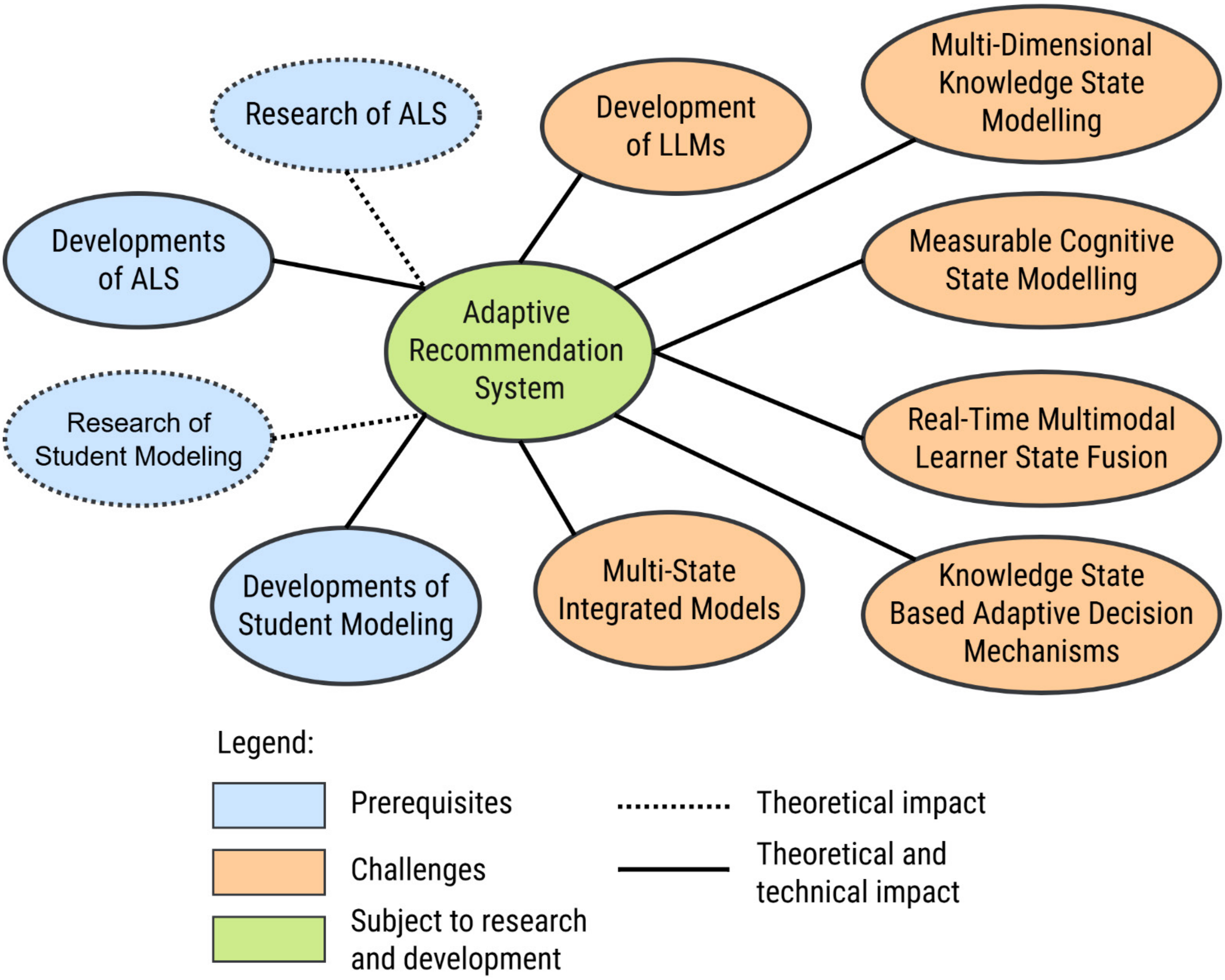

Fig. 1. Key challenges and prerequisites of the Adaptive Recommendation System.

Knowledge State Based Adaptive Decision Mechanisms. Translating inferred, multidimensional knowledge into actionable and pedagogically relevant content recommendations requires adaptive, responsive, and explanatory decision-making mechanisms that remain consistent with the curriculum [12]. Self-determination theory principles must be integrated at this level to ensure that adjustments not only improve cognitive load but also actively support learner autonomy, competence awareness, and engagement over time [13].

4. Discussion and Future Directions

The review of challenges illustrated in Figure 1 reveals an area where theoretical aspirations have largely outpaced practical application.

Four key challenges remain largely unresolved, both individually and collectively. Bridging this gap requires sustained, multidisciplinary collaboration among artificial intelligence, educational psychology, cognitive neuroscience, and human-computer interaction [14].

Designing, developing, and implementing an integrated, responsive, and cognitive aware adaptive recommendation system is a crucial direction for future work. This system should integrate real-time cognitive state inference, multimodal integration of learner states, and multidimensional knowledge modeling [15].

Longitudinal deployments in real learning environments will be essential to verify whether the theoretical promise of responsive adaptive learning translates into tangible gains in learning outcomes and sustained engagement [16].

CONCLUSION

This paper identified and examined the main challenges associated with designing intelligent and cognitive aware adaptive recommendation systems capable of taking into consideration the learner's actual cognitive state. Drawing on cognitive load theory, attention theory, and self-determination theory, and based on the challenge map presented in Figure 1, the analysis revealed a fundamental gap in current adaptive learning systems: the inability to perceive, model, and respond to the internal cognitive and motivational dynamics of learning, which ultimately determine its effectiveness. Addressing this gap requires cutting-edge technological innovations including knowledge state modeling, cognitive dimensions inference, and adaptive decision-making mechanisms as well as a firm commitment to placing the learner's cognitive experience at the heart of the system design.

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