



A Comparative Evaluation of Adaptive Learning Recommendation Models for Improved Student Learning Performance

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Abstract- Adaptive learning models utilise interaction data from learners to recommend study resources, practice activities and learning pathways. This paper provides a comparative evaluation of the three main categories of models; knowledge tracing, reinforcement learning and language model assisted. These models were evaluated in terms of how they conceptualise knowledge, choose the next activity, provide explanations for recommendations and overcome cold start and fairness issues. A standardised experiment protocol was developed and includes data processing, time based split of training, validation and testing data sets, leakage control, prediction accuracy and ranking metrics and learning performance metrics. As there was no original dataset, implementation, sample of participants or experiment carried out for this manuscript, the results section details the validation plan. The aim is to give an open and replicable design for evaluating adaptive recommendation models. This paper also outlines the requirements for keeping track of assumptions, model choices, learner feedback and ethical considerations for implementation in an educational setting.

Keywords- Adaptive Learning, Knowledge Tracing, Reinforcement Learning, Educational Recommender Systems, Personalisation, Deep Learning, Student Performance.



I. INTRODUCTION

1. Background

The move from traditional one-size-fits-all computer aided instruction (CAI) to adaptive personalisation systems is a large change in pedagogical theory [1]. Adaptive Learning Systems (ALS) can adapt content, pacing and difficulty of material to suit individual learner needs [13], [15]. This is achieved through the recommendation models within these systems that must accurately understand the learner's knowledge state and recommend the best next steps [16], [34].

While there are many AI enabled learning tools available, there are some challenges that need to be addressed. Traditional recommendation algorithms focus on static preferences however recommendations in education must consider the changing cognitive state of the learner (Knowledge Tracing - KT) [25]. In addition, the complexities of learning have led to models being developed to ensure long term learning goals are met while also maintaining engagement. This has led to an increase in the use of Reinforcement Learning (RL) [3], [6], [26]. More recently Large Language Models (LLMs) and Multi Agent Systems have been developed which allow for real time diagnostics [2], [16], [18].

This paper provides a comparison of the different models. We look at the different model architectures from Attention enhanced LSTMs to Concept Graph Aware GNNs and compare the results across different educational datasets (ASSISTments, Junyi and real university datasets) [1], [28], [32]. We aim to answer the following questions by looking at recent high impact research:

- What modelling paradigms are the most effective at improving learning performance?
- How do the different models overcome the issues with diversity, accuracy and engagement?
- What are the limitations and gaps in the current adaptive recommendation models when it comes to explainability and fairness?



The remainder of this paper is organized as follows: Section 2 reviews related work and categorizes existing paradigms. Section 3 describes the comparative methodology and system architectures found in the literature. Section 4 outlines the experimental setups and evaluation metrics used in these studies. Section 5 presents a comparative analysis of the results. Section 6 discusses the implications, limitations, and ethical considerations. Section 7 concludes with future research directions.

II. RELATED WORK / LITERATURE REVIEW

1. Knowledge Tracing and Student Modeling

Knowledge Tracing (KT) is the task of modeling a student's knowledge over time based on their past interactions with learning objects [25]. Deep Knowledge Tracing (DKT), which utilizes Recurrent Neural Networks (RNNs) to capture complex learning patterns, serves as the foundation for many modern systems [25], [36]. Some studies augment deep knowledge-tracing models with behavioral priors and tuning rules to infer adaptive paths [27]. The specific settings are implementation choices and should be reported only after source and experiment verification.

Recent developments have seen the introduction of Attentive Knowledge Tracing (AKT), a method that makes use of self-attention mechanisms—including an encoder for exercises and one for knowledge acquisition—in order to assess the relevance of previous exercises to the student's present state of knowledge [6], [28]. The Dynamic Key-Value Memory Network (DKVMN) has also been combined with learning-behavior modules in order to achieve a more detailed tracing of individual concepts. Furthermore, auxiliary-concept representations have been suggested as a way to improve student modelling, but the extent and generalizability of any such improvement must be verified by referring to the original source and replicated using a standard protocol [4], [5], [6].

2. Reinforcement Learning and Educational Sequencing

In Reinforcement Learning (RL), learning is modeled as a Markov Decision Process (MDP), with the 'agent' (ALS) taking actions (learning materials) to maximise rewards (student learning gains) [10, 26].



Research has identified the Entropy-enhanced Proximal Policy Optimization (EPPO) algorithm is effective for optimising learning material recommendations [6]. This algorithm uses an actor-critic framework with a replay buffer and clipped surrogate objectives to ensure stable learning [28].

Other research has looked at the convergence of RL and KT (RL-KT). This considers education as a dynamic conversation between human and artificial intelligence [24]. PPO-LSTM architectures have been found to be promising. Using aux-KCs in conjunction with the LSTM outputs being passed to individual fully connected policy (actor) and value (critic) networks for optimisation [5]. These systems reflect a novel ontology of adaptive intelligence; self organising, goal driven and epistemologically aware [24].

3. LLM and Multi-Agent Frameworks

The integration of LLMs (e.g., GPT-4o) and Retrieval-Augmented Generation (RAG) into educational recommendation marks a shift toward more explainable and contextually aware systems [2], [16], [18]. The ALIGNAgent framework employs a multi-agent architecture in which specialized agents identify skill gaps using concept-level diagnostic reasoning and retrieve preference-aware materials. Its reported evaluation should be checked against the original source before any precision value is quoted as evidence [16]. Similarly, Bayesian estimation and fine-tuned BERT models are used to offer personalized improvement suggestions and adaptive content delivery in higher education [30]. LLM-powered virtual teaching assistants are also being evaluated for their role in formative assessment and adaptive learning in data-science education [39].

4. Comparative Analysis

From the literature, there is an emerging trend to consider hybrid models. Hybrid models combine deep learning techniques for predicting performance and genetic algorithms for recommending content [30] or use NLP techniques from machine learning to offer personal feedback and social encouragement [33] [35]. Knowledge enhanced hybrid models are being developed to create adaptive and intelligent learning systems to overcome the shortcomings of traditional recommendations [38].



III. PROPOSED METHODOLOGY

To compare models we need a common framework. The existing ALS models can be divided into three main components:

1. Learner Modeling

- Learner modelling: has developed over the years to include more complex analysis. Sequence based modelling Attention mechanisms have been implemented with LSTM networks to model learners actions. These networks use multi-level embeddings to make use of the different elements of learning such as text, knowledge concepts and meta data [1] [17].

- Graph based modelling: Ontology based models have been implemented using Semantic Web technologies (RDF and SPARQL). Courses and lessons can be structured using a

two layered concept graph. Pathways are often created using Depth First Search (DFS) or A algorithms. [8] [14]

- Physiological modelling: More advanced models include physiological anomalies and fatigue levels in real time into the learner modelling. This creates a session based model to adapt the difficulty of learning. Difficulty adaptation policies can be rule based or use AI strategies [29].

2. Decision-Making

The recommendation strategy is the main component of an ALS.

- Policy Gradient Methods: EPPO and PPO-LSTM architectures optimize recommendation policies by maximizing normalized gains and rewards. Some studies report gains in simulated environments when auxiliary concepts are included, but the original evaluation conditions and effect sizes must be verified before comparison [5], [6].

- Formative Assessment Agents: Multi-agent architectures integrate learning-style identification and formative-assessment agents. These agents may use Upper-Confidence Bound (UCB) or Elo-Bandit strategies for test-item selection and knowledge-gap estimation; reported precision should be compared only after the source definitions and evaluation settings are verified [7], [8].



- LLM-Driven Feedback Loops: GPT-4o-based agents deliver personalized learning through continuous feedback loops, aligning diagnosed deficiencies with preference-aware learning materials [16].

3. Decision Criteria for Selecting Learning Paths

The proposed system selects a learning path by considering three main factors: expected learning improvement, coverage of the required topics, and the time needed to complete the activities.

A good learning path should help students improve their knowledge and cover the concepts they need to learn. At the same time, the path should avoid unnecessary activities that require excessive time. The system therefore gives higher priority to learning paths that provide greater educational benefit in a reasonable amount of time.

For reinforcement-learning-based recommendation, the system first estimates the learner's current condition using information such as previous answers, knowledge level, completed activities, and recent learning behavior. Based on this information, the system recommends the next suitable learning resource, such as a video, exercise, quiz, or revision activity.

After the learner completes the recommended activity, the system observes the outcome. For example, the learner may answer an assessment correctly, demonstrate improved knowledge, or complete the activity successfully. This outcome is treated as feedback for the recommendation system.

The system uses this feedback to improve future recommendations. It does not focus only on the immediate result of one activity. Instead, it attempts to select learning activities that can produce better long-term learning performance and knowledge retention.

The importance assigned to learning improvement, topic coverage, completion time, and long-term performance can be adjusted according to the educational objectives of the course. These criteria should be tested experimentally using real student interaction data before making conclusions about their effectiveness.



IV. EXPERIMENTAL SETUP / IMPLEMENTATION

1. Study Design

The proposed study will use a retrospective, time-ordered evaluation of learner--resource interactions. A dataset may be selected from a public educational interaction repository after checking its license, documentation, population, and available fields. The dataset must contain, at minimum, learner identifiers, instructional-item identifiers, timestamps, response or completion outcomes, and a mapping to skills or concepts where available. If an appropriate public dataset is not available, the study should be described as a simulation and must not be presented as evidence from real students.

2. Preprocessing and Leakage Control

Interaction records will be sorted by learner and timestamp. Duplicate events, impossible timestamps, and records with missing outcome values will be handled using rules documented before model training. The split will be chronological rather than random whenever future behavior is being predicted. Information from a learner's future interactions must not be used to construct features for an earlier recommendation. Concept labels, resource metadata, and learner histories will be checked separately for leakage.

3. Models and Baselines

The comparison will include a non-adaptive baseline, a knowledge-tracing baseline, a deep knowledge-tracing model, a sequence-recommendation model, and a reinforcement-learning or policy-optimization model. A language-model-assisted condition may be included only if its prompts, retrieved materials, model version, access date, and safety controls are recorded. All models must receive comparable information and be evaluated on the same temporal test period. The model family names describe proposed comparison conditions; they are not evidence that any condition has already been implemented.



4. Implementation Requirements

The final implementation record must specify the software versions, preprocessing code, hyperparameters, random seeds, hardware, training budget, early-stopping rule, and treatment of failed runs. A recommendation must be logged with the learner state used, candidate resources considered, selected resource, explanation shown to the learner, and subsequent outcome. These records are needed to distinguish predictive accuracy from actual educational benefit.

V. RESULTS

No original experimental results are available for this manuscript. Accordingly, this section defines the results that should be reported after implementation rather than presenting fabricated values.

1. Predictive and Recommendation Metrics

The study should report knowledge-prediction metrics such as AUC, accuracy, log loss, and calibration, when their assumptions are appropriate. Recommendation quality should be reported with ranking metrics such as Recall@K, NDCG@K, and MRR, together with coverage and diversity. Metrics must be calculated on the same held-out temporal test set and accompanied by confidence intervals or an appropriate uncertainty analysis.

2. Learning and Process Outcomes

If the dataset contains valid outcome measures, the analysis may examine post-activity performance, delayed retention, completion, time-on-task, and unnecessary repetition. Offline recommendation metrics must not be described as proof of learning improvement. Claims about causal learning gains require a suitable experimental or quasi-experimental design, clearly defined comparison groups, and a prespecified analysis.

3. Fairness, Explainability, and Robustness

The evaluation should examine performance and recommendation exposure across relevant learner groups only when those group attributes are lawfully available and ethically appropriate to use. It should



also document explanation fidelity, explanation usefulness, cold-start performance, sensitivity to sparse histories, and robustness to changes in course or cohort. Results should identify trade-offs rather than selecting a single model using accuracy alone.

VI. DISCUSSION

The proposed framework treats adaptive recommendation as a combination of learner-state estimation and instructional decision-making. Knowledge-tracing models are suited to estimating changing mastery, while sequential or reinforcement-learning models can represent the consequences of selecting one activity rather than another. Language-model-assisted systems may provide more flexible explanations or resource synthesis, but they introduce additional requirements for grounding, privacy, reproducibility, and output safety. These are evaluation hypotheses, not conclusions from completed experiments in this manuscript.

The plain-language criteria in Section 3.3 are intentionally modest. A recommended path should support learning improvement, cover the required concepts, and avoid unnecessary time or activity burden. The importance of each criterion depends on the course objective and must be chosen before evaluation or tuned using validation data rather than the test set.

Important limitations remain. Offline logs record observed behavior rather than the learning that would have occurred under a different recommendation. Datasets may omit instructional quality, learner context, teacher intervention, delayed retention, and subgroup information. Cold-start learners have little history, and changes in course design can make a model trained in one setting unreliable in another. Fairness and explainability also require human and educational judgment in addition to numerical metrics.



VII. Conclusion and Future Work

This manuscript presents a proposed, reproducible plan for comparing adaptive learning recommendation models. It does not claim that any model family is superior because no new experiment was executed. The central methodological requirement is to compare models under the same temporal splits, information constraints, outcome definitions, and reporting standards. Section 3.3 now states the path-selection criteria in accessible prose so that the design can be understood without relying on unexplained equations.

Future work should implement the protocol on a documented dataset, preregister the evaluation where feasible, conduct sensitivity and subgroup analyses, and validate offline findings with a prospective study. Future implementations should also report the source and limits of learner data, provide meaningful explanations, test cold-start behavior, and include safeguards for privacy, fairness, and human oversight.

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