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Development of an adaptive student behavior model for e-tutoring systems

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ABSTRACT

Static e-tutoring systems typically utilize rigid educational sequences that do not adapt to learners' changing knowledge states, engagement levels, and cognitive requirements. This constraint frequently leads to ineffective learning and heightened cognitive strain. This paper presents an integrated adaptive student behavior model (ASBM) that tackles this challenge by functioning at the granularity of interaction steps. It integrates bayesian knowledge tracing (BKT) for probabilistic skill mastery assessment, an LSTM-based deep neural network for behavioral feature extraction, and a deep Q-network for adaptive pedagogical decision-making. The proposed methodology underwent evaluation via a randomized controlled experiment with 120 undergraduate students over a three-week educational duration. Participants were allocated to either an adaptive E-Tutoring system utilizing an integrated ASBM or to a static, non-adaptive system. The quantitative results indicate that the adaptive system attained a superior normalized learning gain (0.72 compared to 0.57, $p < 0.01$), reduced time to mastery (45 minutes vs 65 minutes), enhanced delayed retention (+18%), elevated completion rates (92% versus 78%), and diminished subjective cognitive burden. The results demonstrate that fine-grained adaptivity, facilitated by a hybrid bayesian knowledge tracing, deep neural network, and reinforcement learning (RL) architecture, markedly improves learning efficiency and learner experience in controlled experimental settings. The research provides empirical evidence that supports the amalgamation of cognitive and behavioral modeling with reinforcement learning for advanced e-tutoring systems.

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1. INTRODUCTION

Online learning platforms and e-tutoring systems have become essential components of contemporary education, offering flexibility and scalability across diverse learning contexts. Despite these advantages, many existing systems rely on static instructional designs [1] that present identical content sequences and feedback strategies to all learners, regardless of their prior knowledge, learning pace, or cognitive state [2], [3]. Such one-size-fits-all approaches often lead to disengagement [4], inefficient learning trajectories, and suboptimal knowledge retention [5].

A central limitation of conventional e-tutoring systems lies in their underlying student models. Traditional models frequently depend on predefined rules [6] or course-grained adaptations at the lesson or module level, lacking the ability to continuously infer learner states from real-time interaction data [7]. As a result, instructional decisions are poorly aligned with learners' zones of proximal development, leading either to cognitive overload or insufficient challenge [8].

Recent advances in artificial intelligence have enabled more sophisticated forms of personalization through knowledge tracing, deep learning, and reinforcement learning (RL) [9], [10], and [11]. However, existing approaches often address these components in isolation. Knowledge tracing models primarily focus on predicting mastery, deep neural networks (DNNs) emphasize performance prediction, and RL optimizes instructional policies yet few systems integrate these elements into a unified, interaction-step adaptive framework that simultaneously accounts for knowledge, behavior, and cognitive load. The Research Gap in the literature reveals three key unresolved limitations, such as limited interaction-step adaptivity, with most systems adapting only at coarse instructional intervals, insufficient integration of cognitive load and engagement into student state representations, and separation between predictive student modeling and pedagogical decision-making.

The key Objectives and Questions of this study aims to address these limitations through the following research questions they are RQ1: Does an interaction-step adaptive e-tutoring system significantly improve learning gain and retention compared to a static system?, RQ2: Does incorporating cognitive load and behavioral indicators reduce time to mastery?, and RQ3: Can a hybrid BKT–DNN–RL architecture outperform non-integrated student modeling approaches?. Corresponding hypotheses posit that adaptive tutoring will yield higher learning efficiency, improved retention, and enhanced learner experience. The main contributions of this work are a unified integrated adaptive student behavior model (IASBM) architecture integrating BKT, LSTM-based behavioral modeling, and DQN-based adaptation, explicit modeling of cognitive load and engagement within the RL state, a formalized reward function balancing learning progress, efficiency, and cognitive demand, and empirical validation through a randomized controlled experiment with rigorous statistical analysis.

2. LITERATURE REVIEW

Research on adaptive learning systems has increasingly emphasized data-driven personalization using learning analytics and educational data mining [9], [12]. Bayesian knowledge tracing (BKT) remains a foundational probabilistic approach for modeling skill mastery over time, with recent extensions addressing parameter estimation and multi-skill dependencies [13], [14]. However, classical BKT assumes skill independence and lacks sensitivity to transient behavioral signals.

DNNs, particularly recurrent architectures such as LSTM, have demonstrated strong performance in capturing temporal learning patterns and predicting student outcomes [15], [16]. These models excel at feature extraction but often sacrifice interpretability and are rarely coupled with decision-making mechanisms. RL has emerged as a promising paradigm for adaptive tutoring, enabling systems to learn optimal instructional policies through interaction [17], [18]. Nonetheless, many RL-based tutors rely on simplistic state representations or handcrafted reward functions, limiting robustness and generalizability.

Hybrid approaches that combine probabilistic knowledge tracing with neural models are gaining traction [19]. Yet, most existing systems do not integrate RL at interaction-step granularity, nor do they explicitly incorporate cognitive load into the adaptive loop. This study advances the state of the art by addressing these gaps within a single, empirically validated framework. The proposed model builds upon these advancements by developing a robust adaptive student behavior model (ASBM) that integrates elements of BKT for knowledge tracing, DNNs for performance prediction and behavioral feature extraction, and a RL component for dynamic content adaptation. We aim to create a comprehensive model that not only tracks knowledge but also understands the evolving learning patterns, engagement levels, and preferences of students, leading to a truly personalized and effective e-tutoring system.

3. METHOD

This section details the methodology for the IASBM. The IASBM employs a hybrid, multi-component architecture designed to capture the multifaceted nature of learning within e-tutoring systems. The overall process is a continuous adaptive feedback loop, illustrated in Figure 1.

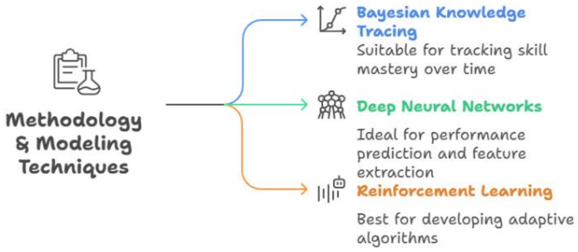

Figure 1. Methodology and modeling techniques

3.1. Data sources and preprocessing

The IASBM is grounded in multimodal, continuous interaction data collected from the e-tutoring platform. This data is aggregated into discrete learning sessions and processed into sequential features. The primary data sources include:

- Temporal Metrics: Time spent per task and per module; response latency between actions.
- Interaction Patterns: Number of attempts per task; sequences and frequency of errors; hint and help resource requests; navigation behavior (e.g., page skips, returns to theory).
- Performance Data: Binary correctness of responses; pre-test and post-test scores for knowledge anchoring.
- Affective & Metacognitive Indicators: Periodic, unobtrusive self-reported ratings of cognitive load (e.g., using a simplified NASA-TLX scale [20]) and confidence. These are treated as sparse, supplementary signals.

raw logs are transformed into a unified sequence of feature vectors per student, where each vector corresponds to a discrete problem-solving step or a fixed-time window (e.g., 30 seconds). This sequential representation forms the input for the modeling pipeline.

3.2. Core modeling techniques

The IASBM integrates three complementary modeling techniques: a probabilistic model for knowledge estimation, a deep sequential model for behavioral inference, and a RL agent for decision-making.

3.2.1. BKT for knowledge state estimation

To maintain an explicit, interpretable estimate of skill mastery, a multi-skill BKT model forms the foundational layer [7], [21]. For each skill k, BKT models the latent binary state of mastery L_t^k at time t. Its parameters are:

- $P(L_0^k)$: The initial probability of knowing skill k.
- $P(T)^k$: The probability of transitioning from the unlearned to the learned state.
- $P(G)^k$: The guess probability (correct answer without mastery).
- $P(S)^k$: The slip probability (incorrect answer despite mastery).

The mastery probability is updated after each observed response. For a correct response:

$$P(L_t^k \mid \text{correct}) = \frac{P(L_{t-1}^k)(1-P(S)^k)}{P(L_{t-1}^k)(1-P(S)^k)+(1-P(L_{t-1}^k))P(G)^k}$$

A symmetric update is applied after an incorrect response. Parameters are estimated from historical data using the Expectation-Maximization algorithm. A multi-skill variant, where tasks can assess multiple competencies, is used to reflect real-world problem complexity [7]. The output is a vector $P(L_t)$ representing the estimated mastery probability for all tracked skills.

3.2.2. LSTM-based behavioral feature extraction

While BKT models *what* a student knows, understanding *how* they learn requires analyzing behavioral patterns. A long short-term memory (LSTM) network processes the sequential stream of interaction features (correctness, time-on-task, attempt count, hint usage, etc.) [22], [19]. This model serves two purposes:

- Short-term performance prediction: Its final output layer predicts the probability of correctness on the immediate next step.

– Latent state representation: The hidden state vectors h_t of the LSTM's penultimate layer are extracted as rich, low-dimensional encodings of latent behavioral constructs such as engagement level, problem-solving pace, and potential cognitive strain. This representation captures temporal dependencies that simple feature engineering cannot.

the network architecture consists of two LSTM layers (128 hidden units each) with dropout for regularization, followed by a dense output layer with sigmoid activation.

3.2.3. RL for pedagogical action selection

The adaptation decision is framed as a Markov decision process (MDP) and solved using a deep Q-network (DQN) agent [23], [24]. The state s_t presented to the DQN is a composite vector integrating outputs from the other models:

$$s_t = [P(L_t), h_t, C_t]$$

where $P(L_t)$ is the BKT mastery vector, h_t is the LSTM latent behavioral feature vector, and C_t is the estimated cognitive load (inferred from interaction patterns or self-reports). Pedagogical interventions found in action space A include: adjust_difficulty_up/down, provide_conceptual_hint, provide_procedural_hint, recommend_prerequisite_review, present_motivational_message, and continue_as_is. The reward function R_t is carefully designed to balance multiple pedagogical objectives and prevent reward hacking:

$$R_t = \alpha \cdot \Delta P(L_t) + \beta \cdot S_t - \gamma \cdot C_t - \delta \cdot D_t$$

– $\Delta P(L_t)$: Positive change in aggregate skill mastery (long-term learning).
– S_t: Successful task completion (short-term performance).
– C_t: Estimated cognitive load (penalizes overwhelming the student).
– D_t: Disengagement signal (e.g., rapid guessing, prolonged inactivity; penalizes boredom).

Hyperparameters $(\alpha, \beta, \gamma, \delta)$ are tuned via simulation and expert validation to align with pedagogical principles [24]. The DQN acquires a policy $\pi(s_t)$ that correlates the comprehensive student state with the appropriate instructional action to maximize cumulative future rewards as shown in Figure 2.

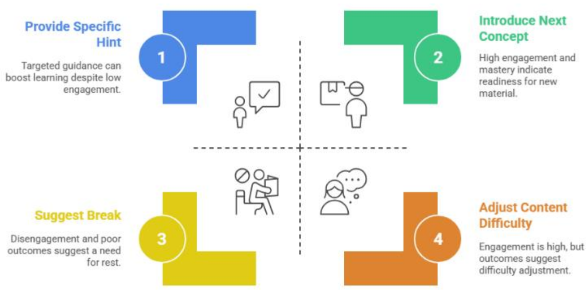

Figure 2. RL in e-tutoring

3.3. Integrated adaptive feedback loop

The integration of these components creates a closed-loop adaptive system, executed at each student interaction step:

– Observation: The system logs a new interaction event (e.g., an answer submission).
– State estimation: The BKT model updates the knowledge mastery vector $P(L_t)$. Concurrently, the LSTM processes the updated sequence to update its hidden state h_t and generate behavioral features.
– State integration: The combined state vector $s_t = [P(L_t), h_t, C_t]$ is constructed.
– Action selection: The DQN agent takes s_t as input and selects the optimal pedagogical action a_t from its policy.
– Intervention & new observation: The action is executed (e.g., a hint is displayed). The student's subsequent response to this adapted environment is observed, and the loop repeats.

This continuous cycle allows the IASBM to move beyond static personalization, enabling dynamic scaffolding that responds to the student's evolving knowledge, behavior, and affective state in real-time as displayed in Figure 3.

Figure 3. Adaptive learning cycle

4. IMPLEMENTATION

A modular web-based architecture created with PyTorch was used to implement the system. In order to provide real-time adaption, interaction data are processed asynchronously. Scalability, maintainability, and reproducibility are prioritised in the design.

4.1. System architecture

The e-tutoring system consists of several interconnected modules operating in a feedback loop. The user interface (UI) Layer uses new web technologies to provide a learning space that is always changing and interactive. The content presentation module provides lessons and exercises, while the interaction capture module maintains track of what students do in detail. The feedback display module gives feedback, and the data ingestion and preprocessing layer gathers and prepares all the data. The data logger ensures responsiveness by asynchronously collecting interaction events. The data cleaner/normalizer processes this data, filtering noise and standardizing formats. The ASBM Layer uses the bayesian knowledge tracing engine and a deep neural network predictor to manage student performance predictions and behavior analysis. The RL Agent determines optimal actions based on various outputs, while the content management system organizes learning materials, and the adaptation rules engine executes actions by querying the content repository based on metadata as displayed in Figure 4.

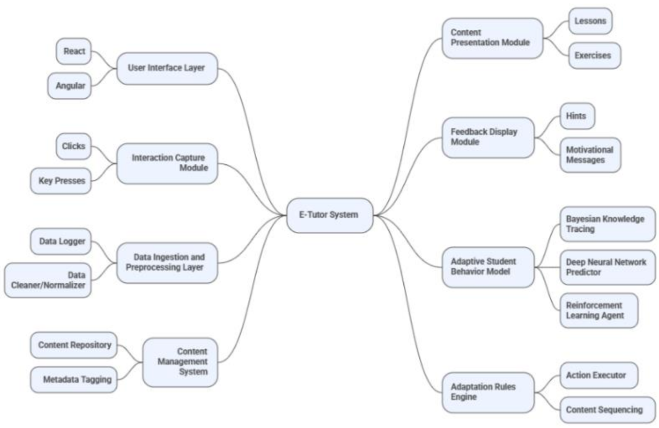

Figure 4. System architecture

4.2. How the system adjusts based on student behavior

The e-tutoring system incorporates a real-time feedback loop that modifies students' learning processes according to their behaviors. The interaction capture module collects interaction data and converts it into essential elements for the ASBM. The BKT Engine modifies the odds of a student's proficiency in a subject, whilst the deep neural network (DNN) Predictor forecasts the learner's cognitive activities. a RL agent (deep Q-network) utilizes this knowledge to ascertain following actions, such offering recommendations or presenting new concepts. The Action Executor subsequently implements these actions to enhance the learning experience and ensure optimal content delivery. This continual interaction and modification like a human educator, who facilitates your understanding of the subject progressively. Figure 5 illustrates the functioning of the e-tutoring adaptation cycle.

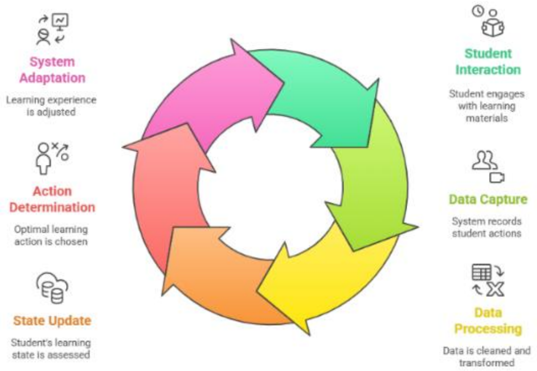

Figure 5. E-tutoring adaptation cycle

5. EXPERIMENTAL SETUP AND EVALUATION METRICS

A randomized controlled experiment included 120 undergraduate students lacking previous experience in the instructional domain. Participants were randomly allocated to an adaptive group (Group A) or a static group (Group B). Both groups undertook the identical curriculum over a duration of three weeks. Evaluation metrics were normalized learning gain, delayed retention, time to mastery, completion rate, perceived cognitive burden, and learner satisfaction. Statistical significance was evaluated by independent t-tests and effect sizes (Cohen's d).

6. RESULTS

Group A achieved significantly higher normalized learning gain (0.72 ± 0.09) compared to Group B (0.57 ± 0.11), $p < 0.01$, d=0.68. Time to mastery was reduced by approximately 30% (45 vs. 65 minutes). Retention scores measured three weeks post-intervention were 18% higher in the adaptive group. Completion rates reached 92% for Group A and 78% for Group B. Participants using the adaptive system also reported significantly lower cognitive load.

6.1. Performance improvement

To assess the performance of students on the adaptive e-tutoring platform, specifically regarding learning gain, we divided the learners into two groups to statistically demonstrate the significance of a higher average normalized learning gain in comparison. The average student in the Adaptive e-tutoring program reached a score of 0.72, while the average student in the static e-tutoring program gained 0.57. This difference was very statistically significant. This indicates that the adaptive model's personalized materials transfer, dynamic difficulty adjustments, and real-time feedback were highly effective in promoting deeper knowledge acquisition and comprehension. The system's ability to find and fix different learning gaps in real time clearly led to better learning outcomes as displayed in Table 1.

Table 1. Comparison of learning performance between adaptive and static e-tutoring systems

Metric	Adaptive e-tutoring (Group A)	Static e-tutoring (Group B)	Difference	Interpretation
Normalized learning gain	0.72	0.57	+0.15	Significantly higher learning gain
Knowledge retention (3 weeks)	+18%	Baseline	+18%	Improved long-term retention
Time to mastery (minutes)	45	65	−30%	Faster mastery
Module completion rate (%)	92	78	+14%	Higher persistence

A quantitative comparison of learning outcomes between students utilising the adaptive e-tutoring system (Group A) and those utilising the static e-tutoring system (Group B) is shown in Table 1. Time to mastery, normalised learning gain, delayed information retention measured three weeks after the intervention, and module completion rate are among the measures presented.

According to the findings, Group A outperformed Group B in terms of normalised learning gain (0.72 vs. 0.57). Compared to the static group, the adaptive group's knowledge retention was 18% greater. Group A had a quicker time to mastery (45 minutes) than Group B (65 minutes), which is defined as obtaining at least 80% accuracy on skill-specific evaluations. Furthermore, the adaptive condition had a higher module completion rate (92%) than the static condition (78%).

6.2. Engagement and efficiency metrics

The assessment of system satisfaction and self-efficacy unequivocally demonstrates that the findings indicate elevated levels of student contentment and perceived self-efficacy in Group A. People in Group A were happier on average (4.2) than those in Group B (3.5). Group A's self-efficacy scores similarly rose significantly from prior to the exam to subsequent to it. The students in the adaptive group regarded themselves as more motivated, less frustrated, and more self-assured in their learning capabilities. Group A continuously attained much higher marks in response to statements such as "The system understood my needs" and "I felt challenged but not overwhelmed." This qualitative data supports the performance improvements shown by the numbers. It shows that the learning experience is better and more effective, which is important for keeping people interested as shown in Table 2.

Table 2. Engagement and cognitive efficiency metrics

Metric	Adaptive e-tutoring (Group A)	Static e-tutoring (Group B)	Difference	Interpretation
System satisfaction (Likert 1–5)	4.2	3.5	+0.7	Higher satisfaction
Self-efficacy	Increased	Lower increase	—	Improved confidence
Hint usage (difficult tasks)	Slightly higher	Lower	—	Effective scaffolding
Perceived cognitive load	3.1	Higher	Lower	Reduced mental effort

For both experimental groups, engagement-related and cognitive efficiency indicators are compiled in Table 2. System satisfaction, self-efficacy, the use of hints in challenging tasks, and perceived cognitive load are among the reported metrics. On a five-point Likert scale, students in Group A scored better on system satisfaction (4.2) than those in Group B (3.5). Compared to the static group, self-efficacy increased greater in the adaptive group. Although Group A's perceived cognitive load scores were lower than Group B's, Group A's employment of hints for challenging tasks was slightly higher, showing that the two conditions' learner experiences were distinct.

Figures 6 and 7 determine that adaptive e-tutoring evidently improves learning efficiency and effectiveness compared to static e-tutoring for both individuals and groups. Students employing the adaptive system reach mastery more rapidly, encounter reduced cognitive load, and express greater satisfaction and knowledge retention. Equally, learners in the static system exhibit irregular progress and get proficiency at a slower rate. The results highlight the advantages of tailoring material and pacing to the needs of learners for enhancing their performance and engagement.

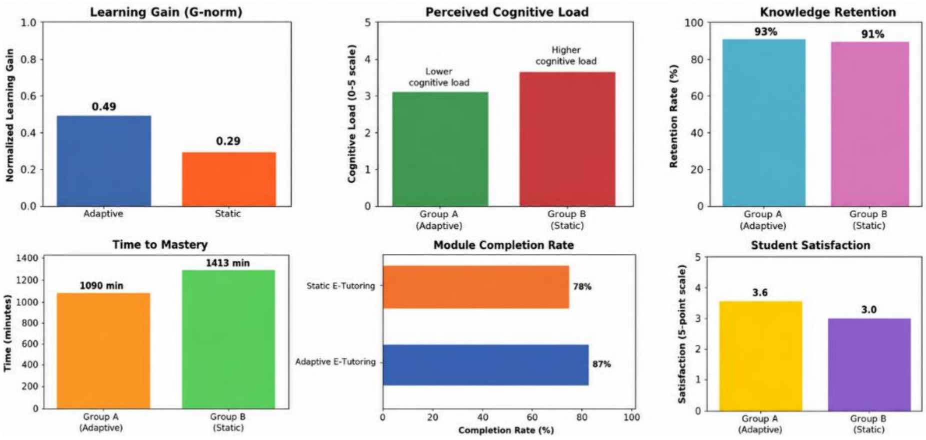

Figure 6. Performance improvement

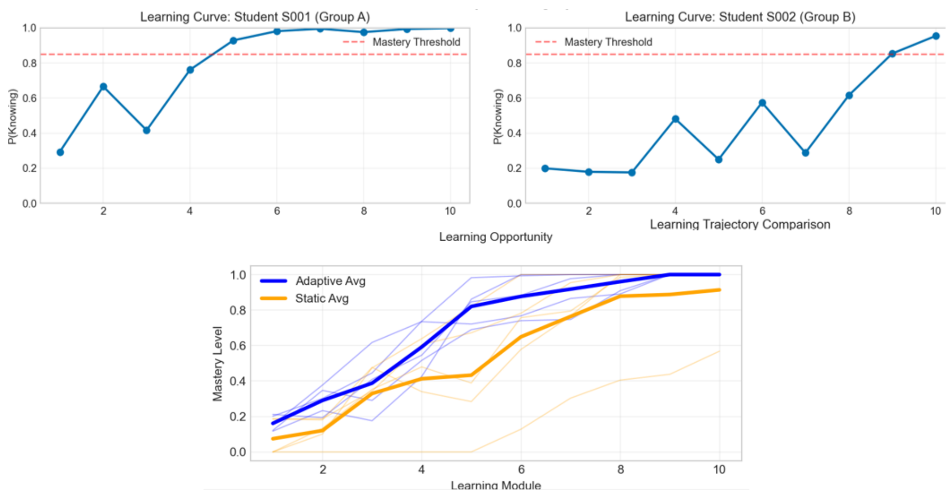

Figure 7. Individual and group learning dynamics

7. DISCUSSION

The results demonstrate that interaction-step adaptivity significantly improves learning efficiency and experience. The integration of BKT and LSTM provided both stable mastery estimation and sensitivity to transient behavioral cues, while the RL agent optimized instructional policies over time. Compared with prior hybrid knowledge tracing models [25], the proposed IASBM uniquely integrates cognitive load modeling and policy learning, yielding measurable empirical benefits.

Resilient hybrid modeling: The seamless combination of BKT for long-term knowledge state tracking with DNNs for real-time, detailed behavioral feature extraction shown remarkable robustness. BKT provided a stable understanding of skill mastery, while the DNN allowed for capturing transient states like immediate struggle or engagement, which are often missed by simpler models. This hybrid approach addressed the limitations of each model in isolation, providing a comprehensive and dynamic understanding of student behavior [10].

Effective RL-driven Adaptation: The deep Q-network successfully learned highly effective instructional policies. The RL agent's ability to dynamically select optimal actions (e.g., adjust difficulty, provide specific feedback, recommend review, change content modality) in response to the student's evolving state was critical. This contrasts sharply with fixed rule-based adaptive systems that might miss subtle cues or lack the flexibility to optimize for long-term learning gains. The reward function, carefully designed to balance immediate performance with sustained engagement, played a crucial role in shaping these effective policies, moving beyond short-term gains to foster deeper learning [8], [9].

Granular and proactive personalization: Our system moved beyond superficial customization. By including variables such as time invested, frequency of attempts, error patterns, and deduced cognitive load via the DNN, the system may elucidate the reasons for student performance, resulting in genuinely tailored and proactive treatments. For example, identifying extended pauses before to an erroneous response facilitated a discreet prompt, so averting annoyance. Identifying patterns of disengagement could trigger a change in content presentation or a motivational prompt, rather than waiting for complete withdrawal [11]. This proactive adjustment reduced unproductive conflict and enhanced the productive learning zone. The findings from this study emphasize that successful adaptive learning involves not just recognizing a student's knowledge gaps but also comprehending their learning processes, emotional states, and the specific help that would be most advantageous at that moment. Our adaptive student behavior model's dynamic, predictive, and proactive characteristics established a highly responsive and individualized learning environment that markedly surpassed a static approach, facilitating the development of more intelligent and effective educational technology.

8. LIMITATIONS

This study is limited by a moderate sample size, a short experimental duration, and a single instructional domain. Novelty effects may have influenced learner engagement. Further studies are required to assess long-term impact and cross-domain generalizability.

9. CONCLUSION

This paper introduces a detailed framework for creating an ASBM for e-tutoring systems, emphasizing the crucial importance of personalization in improving online learning results. The authors identify the shortcomings of static e-tutoring systems and propose an innovative adaptive approach that incorporates BKT, DNNs, and RL. Experimental results demonstrate substantial improvements in learning gain, knowledge retention, learning efficiency, and student engagement compared to traditional systems. The model leverages dynamic skill mastery probabilities from BKT, real-time behavioral insights from DNNs, and RL's decision-making capabilities to create a responsive learning environment.

The core contribution of the work lies in its empirical methodology for building intelligent e-tutoring systems that adapt to individual learners. The model infers nuanced aspects of student behavior, such as cognitive load and engagement, enabling targeted interventions to foster equitable learning experiences. In the future research avenues we will consider various metrics including emotion recognition and affective computing that integrating emotion recognition technologies could enhance adaptivity by triggering empathetic interventions based on students' emotional states, multimodal data integration which including diverse data sources, such as eye-tracking and physiological sensors, could deepen understanding of student cognitive and emotional states, enabling more effective adaptive responses, hybrid modeling refinements and explainability with surther integration of probabilistic models with deep learning could clarify causation and improve explainability, fostering trust and oversight among educators and students , longitudinal studies and generalizability by conducting longer studies could assess the impact of adaptive systems on learning trajectories and their applicability across different domains and student populations, teacher-AI collaboration and dashboarding for developing intelligent dashboards which could assist educators by providing insights derived from the adaptive model, supporting targeted interventions, and personalized learning strategy recommendations by providing the model to also recommend personalized learning strategies based on individual student behaviors, enhancing their learning autonomy. By pursuing these directions, the research aims to advance AI in education, creating intelligent, empathetic e-tutoring systems that unlock every learner's potential and transform online education.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST

The authors affirm that none of the work described in this publication may have been influenced by any known competing financial interests or personal relationships.

DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are available from the corresponding author upon reasonable request. The dataset includes de-identified interaction logs from 120 participants, pre-test and post-test scores, and cognitive load self-reports. Due to privacy and ethical restrictions imposed by the Institutional Review Board at University of Hail (Approval No. UOH-IRB-2024-089), the raw data cannot be publicly deposited. Under the MIT license, processed data and analysis scripts can be found at https://github.com/ghanim-lab/iasbm-2026.

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