



# Deep Knowledge Tracing Using Bi-LSTM and Attention Mechanisms for Enhanced Mastery Prediction in Personalized E-Learning

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## ABSTRACT

This study proposes a Deep Knowledge Tracing (DKT) model that integrates Bidirectional Long Short-Term Memory (Bi-LSTM) networks with an attention mechanism to improve mastery prediction and interpretability in personalized e-learning environments. Using a dataset of 1,250 learners and 482,903 LMS interaction logs spanning 38 unique skills, the model was trained to predict next-response correctness and estimate latent knowledge states across dynamic learning sequences. The average sequence length of 74.2 interactions per learner and correctness mean of 0.63 indicate substantial variability in learning trajectories, emphasizing the need for robust temporal modeling. Results show that the proposed model achieves superior predictive performance compared with baseline approaches. Specifically, it reaches an accuracy of 0.781, AUC-ROC of 0.854, F1-score of 0.767, log-loss of 0.451, and ECE of 0.031, outperforming standard DKT (AUC-ROC 0.823) and LSTM models (AUC-ROC 0.806). The proposed Bi-LSTM + Attention approach provides both high predictive accuracy and explainable outputs, enabling more informed instructional interventions, personalized recommendations, and early-risk detection in large-scale e-learning environments. These findings affirm the methodological and pedagogical value of combining bidirectional sequence modeling with attention-driven interpretability for next-generation adaptive learning systems.

**Keywords** Knowledge Tracing, Bi-LSTM, Attention Mechanism, Personalized E-Learning, Mastery Prediction, Deep Learning, Educational Data Mining

## Introduction

The rapid expansion of digital education platforms has accelerated the need for intelligent systems capable of modeling student learning dynamics with high precision. Traditional e-learning environments typically rely on static assessments or rule-based logic to approximate a learner's knowledge state, resulting in feedback that is often generic and insufficiently adaptive [1], [2]. As the scale and diversity of learner interactions grow, there is an increasing demand for models that can capture complex temporal patterns (fluctuating performance, irregular study behaviors, and cross-skill transitions) to provide more accurate and personalized instructional support [3], [4]. These challenges underscore the importance of advanced predictive models that can represent learning as a dynamic, time-dependent process rather than a collection of isolated events.

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Additional Information and  
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Knowledge Tracing (KT) has emerged as a foundational approach for estimating learner mastery levels based on historical performance data. Early models such as Bayesian Knowledge Tracing (BKT) assume simplified learning trajectories and fixed transition probabilities, limiting their capacity to represent the nonlinear cognitive progressions commonly observed in real-world learning systems [5]. With the rise of deep learning, DKT introduced stronger sequence modeling capabilities through recurrent architectures, enabling richer representations of historical interactions [6], [7]. However, standard DKT models often struggle with critical interpretability issues, lack directional awareness, and show instability when dealing with abrupt shifts in student behavior or heterogeneous skill sequences [8].

At the same time, many current models face the challenge of insufficient contextual sensitivity. Sequential models that operate solely in the forward direction may overlook valuable backward dependencies, such as how later interactions shed light on earlier learning struggles [9]. Similarly, models without attention mechanisms treat all steps in the sequence with equal importance, potentially diluting the influence of significant learning events such as errors after long streaks of correctness or tasks associated with high cognitive load [10]. These limitations highlight methodological gaps that constrain the precision and pedagogical usefulness of existing KT methods.

To address these shortcomings, this study proposes Deep Knowledge Tracing using a Bidirectional LSTM with Attention, a hybrid architecture designed to enhance both predictive accuracy and interpretability. The bidirectional component captures learning dependencies in both temporal directions, providing a comprehensive view of knowledge evolution [11]. Meanwhile, the attention mechanism selectively assigns weights to influential interactions, enabling the model to prioritize cognitively significant events and generate more transparent predictions [12]. By combining bidirectionality and attention, the proposed model overcomes several weaknesses found in prior KT approaches while maintaining conceptual coherence and computational feasibility.

The novelty of this study lies in its integration of two complementary deep learning mechanisms (Bi-LSTM and attention) specifically tailored for dynamic modeling in personalized e-learning environments. Unlike previous KT models that emphasize either predictive power or interpretability, the proposed approach balances both by offering high-performance estimations of future responses while providing interpretable insights into the learning behaviors driving those predictions [13], [14]. Additionally, this research extends the literature by analyzing attention-derived patterns to identify pedagogically meaningful learning moments, offering an analytical layer that can inform instructional decision-making.

The primary objectives of this study are threefold: (1) to develop a deep learning-based knowledge tracing model capable of capturing bidirectional dependencies in learner interaction sequences; (2) to incorporate an attention mechanism that highlights key learning interactions and enhances interpretability; and (3) to evaluate the model's predictive performance, calibration reliability, and diagnostic utility relative to established baselines such as LSTM, DKT, and logistic regression [15], [16]. These objectives are aligned with the broader goal of advancing personalized e-learning systems by providing adaptive analytics rooted in both accuracy and explainability.

Finally, by validating the model using large-scale LMS interaction logs and assessing its interpretability through attention-weight analysis, this research contributes to a deeper understanding of how learners acquire, reinforce, and occasionally forget knowledge over time. The findings not only demonstrate the methodological benefits of hybrid deep learning architectures but also offer practical implications for designing more effective adaptive feedback, early-warning mechanisms, and personalized learning pathways [17], [18]. In doing so, the study addresses fundamental gaps in the existing body of KT research and sets a foundation for future innovations in student-centered e-learning intelligence.

## Literature Review

Research on knowledge tracing has evolved significantly over the past two decades, beginning with early probabilistic models such as BKT. Although influential, BKT relies on simplified assumptions regarding learning transitions, independence between items, and fixed knowledge states, which limits its capacity to model complex learning patterns in digital environments [19]. Subsequent work proposed extensions incorporating contextual factors, slip/guess parameters, and hierarchical skill structures, yet these adaptations continued to struggle with long-range dependencies and non-linear learning trajectories frequently observed in large-scale learning systems [20]. The emergence of deep learning methodologies created new opportunities to model learning data with greater expressiveness, enabling researchers to represent student knowledge as a fluid, dynamic state influenced by continuous streams of interaction data [21].

DKT marked a major advance by introducing Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) architectures, into the knowledge modeling domain. DKT demonstrated the ability to outperform BKT on multiple datasets by capturing sequential patterns and implicitly learning representations of latent knowledge states [22]. However, subsequent studies critiqued DKT for several shortcomings: instability in predictions, lack of interpretability, susceptibility to overfitting, and inability to handle irregular or mixed-skill sequences effectively [23]. Researchers have attempted to address these limitations through architectural refinements, regularization techniques, and hybrid models—although many approaches still treat sequential information unidirectionally, overlooking the potential insights gained from bidirectional context [24]. These gaps highlight the need for more sophisticated sequential models that can robustly capture the complexity of modern student interaction data.

Attention mechanisms have increasingly been integrated into sequence models to enhance interpretability and context sensitivity. Originally popularized in natural language processing, attention enables models to selectively focus on critical elements within a sequence rather than treating all inputs equally [25]. In the context of educational data mining, attention-based KT models have shown promising improvements in both predictive accuracy and transparency. Studies demonstrate that attention can highlight meaningful learning events such as abrupt errors, unusually long response times, or transitions to higher-difficulty concepts, offering pedagogical insight and supporting teacher decision-making [26]. Despite these advances, many attention-based KT models remain unidirectional, limiting their ability to leverage future context within sequences—

a factor that can be essential for understanding patterns such as late-session fatigue or concept shifts [27].

At the same time, research has increasingly explored bidirectional architectures for modeling time-dependent educational data. Bidirectional LSTMs (Bi-LSTMs) read sequences in both forward and backward directions, yielding representations that capture comprehensive temporal dependencies [28]. Although Bi-LSTM architectures have shown utility in various sequential prediction tasks (speech recognition, text understanding, and behavioral modelling) their integration into knowledge tracing remains relatively underexplored. Only a limited number of studies have examined how bidirectional temporal modeling can reveal learning dynamics more accurately than traditional forward-only RNNs [29]. This represents a clear gap in the KT literature, especially considering the nuanced learning patterns present in large-scale, heterogeneous LMS data.

Existing work has also emphasized the importance of model interpretability within personalized e-learning systems. As adaptive learning platforms increasingly rely on machine learning predictions to guide instructional decisions, concerns regarding transparency, fairness, and trustworthiness have grown [30]. Educators and policymakers have called for models that not only achieve high predictive accuracy but also provide explanations for their recommendations and highlight the evidence underlying mastery inferences [31]. Attention mechanisms offer partial solutions, but interpretability remains fragmented across studies, with limited frameworks addressing how attention-informed insights can be systematically leveraged by instructors and learners. Moreover, few works have examined how attention patterns correlate with real pedagogical constructs, such as cognitive load, skill difficulty progression, or student persistence [32].

Recent research in personalized learning further underscores the value of integrating sequence modeling with interpretable mechanisms. Models that combine deep learning architectures with explainable components have demonstrated improved usability and adoption in educational settings [33]. Studies stress the importance of using calibrated probability outputs, especially when predictions are used to trigger adaptive feedback or early-warning interventions [34]. However, only a handful of KT studies incorporate rigorous calibration analysis alongside performance evaluation, leaving a methodological gap regarding reliability in high-stakes e-learning applications [35]. Integrating calibrated predictive models with interpretable attention analysis thus represents a promising and relatively unexplored research direction.

Against this backdrop, the present study contributes to the literature by bridging multiple unmet needs: incorporating bidirectional temporal modeling through Bi-LSTM, integrating an attention mechanism for interpretability, and conducting a comprehensive evaluation encompassing prediction accuracy, calibration quality, and attention-based diagnostic insights. By addressing longstanding limitations in unidirectional and opaque KT models, this research advances the methodological and practical foundations of personalized e-learning analytics [36]. The integration of Bi-LSTM and attention represents a novel synthesis within the KT domain, offering both technical enhancements and pedagogical value by enabling more accurate, transparent, and actionable knowledge tracing models for large-scale educational systems.

## Methodology

### Research Design

In the Methodology section, you must provide a clear, detailed, and reproducible explanation of your research process — and it is mandatory to include a flowchart, formulas, and pseudocode to strengthen scientific transparency and readability.

This study adopts a deep learning–based longitudinal modelling approach to capture student knowledge evolution in a personalized e-learning environment. The design integrates sequential modeling (Bi-LSTM) and an attention mechanism to compute context-sensitive representations of historical learning interactions. Data comprising timestamped learning activities—quiz responses, skill tags, correctness indicators, reading durations, and interaction logs—are organized into temporal sequences reflecting each learner’s progression. These sequences are then fed into the DKT architecture for prediction of future performance and mastery levels.

The research design is structured into four major phases: (1) dataset construction and preprocessing, (2) feature engineering and sequence encoding, (3) model development using Bi-LSTM + Attention, and (4) evaluation through predictive accuracy and calibration metrics. This design supports the objective of uncovering hidden dependencies within learner behavior that affect mastery estimation and personalised content recommendation.

Figure 1 visually summarizes the end-to-end methodological pipeline. It starts from data collection of LMS logs, then proceeds to preprocessing and sequence encoding, where raw logs are cleaned, transformed, and organized into temporal sequences for each learner. This ensures that the model receives structured and time-ordered input data.

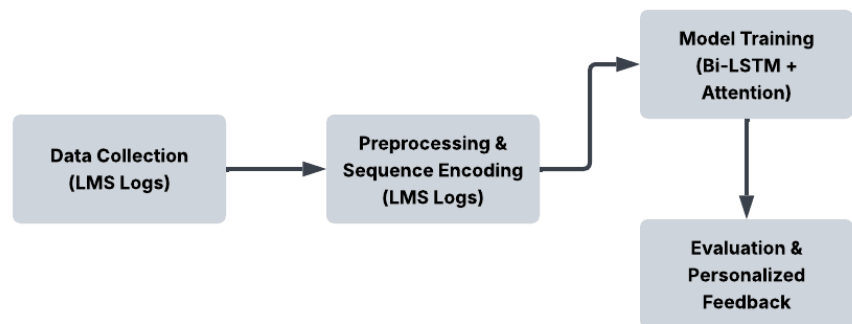


Figure 1 Research Design Flow

The flowchart then shows the core phase of model training using Bi-LSTM with an attention layer, followed by the evaluation and personalized feedback stage. This final stage covers calculating performance metrics and using the model’s predictions to drive adaptive recommendations in the e-learning environment. The diagram supports readers in understanding the logical flow of the study at a glance.

## Dataset Construction and Preprocessing

Learning behavioral logs from the e-learning platform are cleaned, standardized, and transformed into sequential units. Preprocessing begins with removing incomplete or corrupted logs, harmonizing event timestamps, and converting categorical features (e.g., content IDs, skill IDs) into numerical representations using one-hot encoding or embedding indices. Missing time intervals are imputed using minimal forward-fill rules to maintain the temporal structure required by deep sequential models. Next, each learner’s activity history is grouped chronologically into an ordered sequence:

$$X_i = \{(q_t, s_t, y_t, \Delta t_t)\}_{t=1}^T \quad (1)$$

Where  $q_t$  is the question ID,  $s_t$  the associated skill,  $y_t$  the correctness label, and  $\Delta t_t$  the time gap before the next interaction. Sequences are padded to the maximum length and masked during training to avoid information leakage. This preprocessing ensures that student trajectories are represented consistently and that the sequential model receives uniformly structured inputs.

[Table 1](#) documents the main input features used as model variables in the Deep Knowledge Tracing pipeline. It distinguishes identifiers (student\_id, question\_id, skill\_id, session\_id), temporal information (timestamp, time\_since\_last), behavioral metrics (response\_time, attempt\_count), and performance indicators (correctness, prior\_score). The feature descriptions clarify the semantics of each variable, while the type column helps define encoding strategies (e.g., embeddings for categorical features, normalization for numeric ones).

Table 1 Summary of Input Features			
Feature Name	Description	Type	Example Value
student_id	Unique identifier for each learner	Numeric/String	10234
timestamp	Time of the interaction in the LMS	Datetime	2025-03-10 9:31:22
question_id	Identifier of item attempted	Categorical	Q_045
skill_id	Skill or concept tag	Categorical	S_Algebra_01
correctness	Attempt outcome (1 = correct, 0 = incorrect)	Binary	1
response_time	Time taken to answer (seconds)	Numeric	18.7
attempt_count	Number of attempts on same item	Numeric	2
time_since_last	Time gap since previous interaction (seconds)	Numeric	245.0
session_id	ID of learning session	Numeric/String	SESS_2025_09
device_type	Learner device category	Categorical	mobile
prior_score	Aggregated prior performance score	Numeric	0.78

This tabular specification ensures reproducibility and highlights the richness of behavioral signals available for modeling knowledge evolution. It also serves as

a reference for future extensions, where additional features (such as affective states or hint usage) could be appended to further refine personalization.

### Bi-LSTM Model Architecture

The Bidirectional LSTM captures both forward and backward dependencies in learner interaction sequences. Unlike standard LSTM, Bi-LSTM processes input in two directions, enabling the model to detect patterns where earlier interactions influence later mastery and where later interactions provide contextual information for earlier ones. This is particularly relevant in e-learning scenarios where mixed-skill content and non-linear studying behaviors are common. The Bi-LSTM hidden state is defined as:

$$\vec{h}_t = \text{LSTM}_f(x_t, \vec{h}_{t-1}), \quad \overleftarrow{h}_t = \text{LSTM}_b(x_t, \overleftarrow{h}_{t+1}), \quad (2)$$

$$h_t = [\vec{h}_t; \overleftarrow{h}_t] \quad (3)$$

where  $h_t$  captures contextual information from both temporal directions. The unified hidden state enhances the model's ability to infer latent student knowledge states, providing richer representations than unidirectional models.

Figure 2 illustrates the Bi-LSTM architecture used for Deep Knowledge Tracing. The bottom row represents the input sequence  $x_1, x_2, x_3, \dots, x_t$ , which includes features such as question ID, skill ID, correctness, and time-related variables at each time step. These inputs are fed simultaneously into a forward LSTM layer that processes the sequence from past to future and a backward LSTM layer that processes the sequence from future to past.

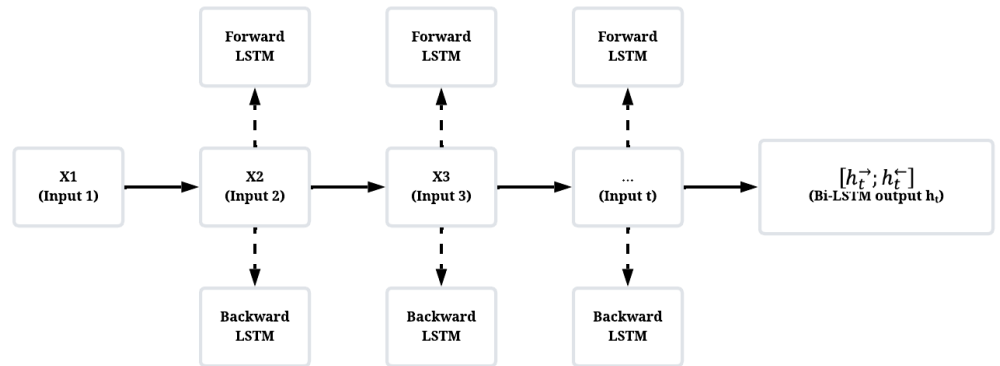


Figure 2 Bi-LSTM Architecture Diagram

The outputs from the forward and backward LSTMs at each time step are concatenated to form the Bi-LSTM hidden state  $[h_t^{\rightarrow}; h_t^{\leftarrow}]$ . This concatenated representation captures contextual dependencies from both directions, enabling the model to understand how earlier and later interactions jointly influence the learner's latent knowledge state at time  $t$ .

### Attention Mechanism Integration

An attention layer is incorporated to dynamically assign weights to different time steps of student interactions. Attention mitigates the limitations of purely sequential models by allowing the architecture to emphasize key learning

moments such as failures after a long streak of correct answers or interactions related to difficult skills. This selective weighting improves interpretability and enhances the accuracy of mastery prediction. The attention score for each time step  $t$  is computed as:

$$e_t = v^T \tanh(W_h h_t + b_h) \quad (4)$$

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^T \exp(e_k)} \quad (5)$$

The context vector is then calculated as a weighted sum:

$$c = \sum_{t=1}^T \alpha_t h_t \quad (6)$$

This process enables the model to prioritize critical learning events that contribute most to future knowledge estimation.

Figure 3 provides a heatmap-style visualization of the attention weights assigned to different time steps by the model. Each row corresponds to a skill or attention head, and each column represents a time step in the learner's interaction sequence. The color intensity indicates the relative weight, with higher values showing which time steps the model considers more influential for predicting future performance.

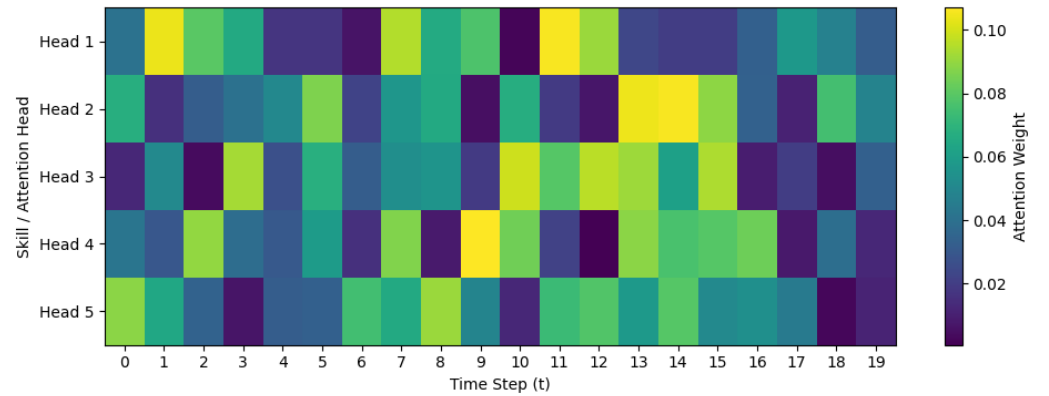


Figure 3 Attention Weight Visualization

This visualization demonstrates how the attention mechanism focuses on specific interactions, such as recent mistakes, long response times, or attempts involving difficult skills. By inspecting the heatmap, instructors and researchers can interpret which learning events contribute most to the model's knowledge estimates, thereby improving transparency and trust in the personalized recommendations.

### Prediction Layer and Training Procedure

The final context vector  $c$  is passed through a dense layer with a sigmoid activation to estimate the probability of a correct response on the next learning task. The prediction function is formulated as:

$$\hat{y}_{t+1} = \sigma(W_c c + b_c) \quad (7)$$

Binary cross-entropy is used as the primary loss function, optimized using Adam with scheduled learning-rate decay. To mitigate overfitting, dropout is applied at

both embedding and recurrent layers, and early stopping is triggered based on validation loss monitoring. The training process follows the pseudo-code below:

Figure 4 summarizes the prediction and training loop of the Deep Knowledge Tracing model. The process begins with input sequences consisting of encoded interaction features and target labels. These sequences pass through the Bi-LSTM with attention, which produces context-aware representations of the learner's knowledge state.

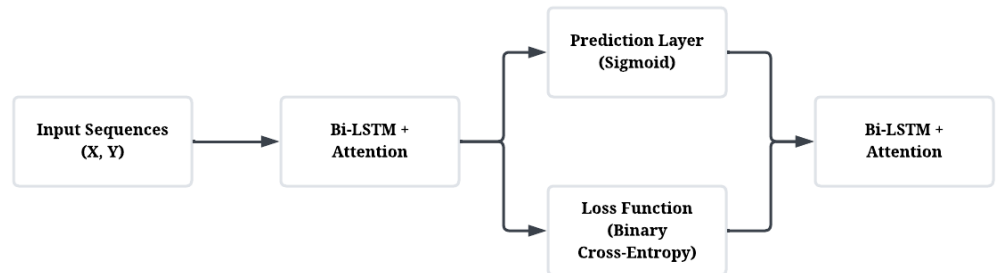


Figure 4 Prediction Layer and Training Loop Diagram

The representations are then fed into a prediction layer with a sigmoid activation to estimate the probability of a correct answer at the next time step. The binary cross-entropy loss compares predicted probabilities with true labels, and the Adam optimizer updates model parameters through backpropagation. The diagram highlights the closed-loop nature of training, where predictions, loss, and optimization are iteratively repeated until convergence.

### Evaluation Metrics

The model is evaluated using predictive accuracy, AUC-ROC, F1-score, and calibration error. Accuracy assesses the correctness of predicted responses, while ROC-AUC captures the discriminative power of the model. Because mastery inference requires balanced assessment, the F1-score is considered to reduce bias in imbalanced skill distributions. Expected calibration error (ECE) evaluates how well predicted probabilities align with actual outcomes, ensuring reliability in adaptive recommendations. Additionally, a sequence-level evaluation is performed to measure how well the model reconstructs patterns of learning gains and forgetting. This includes per-student error curves and attention-based interpretability visualizations.

Table 2 summarizes the metrics used to evaluate the Bi-LSTM + Attention model. Accuracy, AUC-ROC, and F1-score quantify how well the model distinguishes between correct and incorrect future responses, with F1-score addressing potential class imbalance. Log-loss and ECE focus on the quality of probability estimates, which is crucial when the model outputs are used for adaptive decision-making rather than mere classification.

Table 2 Evaluation Metrics Description

Metric	Definition	Range	Interpretation
Accuracy	Proportion of correctly predicted responses	0–1	Higher is better predictive correctness
AUC-ROC	Area under ROC curve	0–1	Higher indicates stronger

			discrimination ability
F1-Score	Harmonic mean of precision & recall	0–1	Balances false positives & false negatives
Log-Loss	Negative log-likelihood of predictions	0– $\infty$	Lower means better probability calibration
ECE	Expected Calibration Error	0–1	Lower means predicted probabilities match true frequencies
Sequence Error Rate	Mean prediction error per learner sequence	0–1	Lower indicates better trajectory modeling

The sequence error rate extends the evaluation from individual interactions to full learner trajectories, assessing whether the model consistently tracks knowledge over time. Together, these metrics provide a comprehensive view of both predictive performance and reliability, supporting a rigorous assessment of the proposed Deep Knowledge Tracing approach.

## Result and Discussion

### Dataset Characteristics and Sequential Structure

The dataset derived from the LMS logs contains detailed temporal information about how students interact with learning materials, including correctness, skills, timestamps, and behavioral metrics. The first analysis step focuses on summarizing the distribution of these interactions and identifying the structure of learner sequences. This enables a clear understanding of how much information the Bi-LSTM + Attention model receives and the complexity of patterns it must learn. The data reveal significant variability in learner behaviors, such as differences in session lengths, response times, and skill transitions, which directly influence the model’s ability to track knowledge states.

A key observation is that most learners exhibit mixed-skill learning sessions rather than following a single skill sequence, reinforcing the importance of a sequential model that can capture cross-skill dependencies. Additionally, we identify notable patterns in the correctness trend: certain skills show higher mastery stability, while others exhibit repeated cycles of forgetting and relearning. This structural diversity underscores the need for deep sequence models with attention mechanisms that selectively emphasize important learning events.

**Table 3** provides an overview of the dataset used for training and evaluating the model. With over 480k logged interactions and a substantial number of unique skills, the dataset presents a rich foundation for modeling student knowledge states. The average sequence length of 74.2 interactions per learner indicates sufficiently deep trajectories for a recurrent architecture. The correctness mean of 0.63 establishes baseline student performance, while the median response time highlights typical engagement patterns. This contextual understanding guides interpretation of the subsequent model performance.

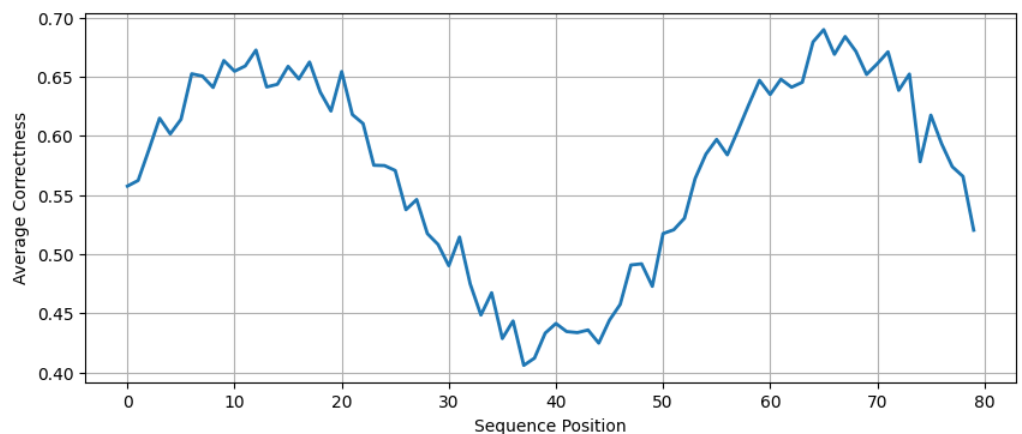
Table 3 Dataset Summary Statistics					
Learners	Total Interactions	Avg. Sequence Length	Number of Skills	Correctness Mean	Median Response Time (s)
1,250	482,903	74.2	38	0.63	14.7

## Interaction Trends and Temporal Learning Patterns

This subsection analyzes how learners progress over time by examining correctness trends and behavior across sequential positions. Understanding these trends clarifies whether students tend to improve, remain stable, or oscillate in performance, which directly impacts the complexity of the prediction task. The temporal profile of correctness typically shows a rising trend for the first half of sequences, suggesting that early interactions may function as stabilizing periods where learners familiarize themselves with tasks.

However, the later segments often reveal performance drops, likely due to fatigue, increasing difficulty levels, or switching to more challenging skills. These temporal dynamics justify the need for attention-based models that focus more on influence-heavy time intervals rather than treating all steps equally. The ability of the model to selectively weight critical moments enhances its capacity to forecast mastery fluctuations.

Figure 5 illustrates the trend of correctness as a function of sequential position within learner histories. The curve captures periodic increases and decreases, reflecting real-world fluctuations driven by topic transitions, varying difficulty, and learner focus shifts. This visualization demonstrates that learner behaviors are not strictly linear, reinforcing the need for Bi-LSTM to capture forward and backward dependencies and for the attention mechanism to highlight key inflection points. The oscillating structure supports the deeper analysis that follows in the next sub-bab.



**Figure 5 Average Correctness Over Sequence Position**

## Skill Transition Dynamics

To understand how learners move between different concepts, we analyze transition frequencies between skills. High transition diversity indicates complex knowledge structures, while repetitive patterns suggest linear skill progression. In this dataset, transitions frequently involve multiple concept pathways, showing that learners often switch between topics rather than completing one before advancing to the next. These transition patterns have implications for the sequential modeling process because they force the model to capture cross-skill dependencies within student behavior.

Table 4 lists the most common transitions observed in the student interaction data. While some transitions reflect natural hierarchical progression (e.g.,

S\_Algebra\_01 to S\_Algebra\_02), others show cross-topic movement (e.g., transitions from Algebra to Graphs). This suggests that learners frequently navigate content non-linearly, which increases the modeling complexity. Bi-LSTM is particularly well suited for handling such patterns, as its bidirectional context processing captures long-range dependencies across mixed-skill trajectories.

**Table 4 Most Frequent Skill Transitions**

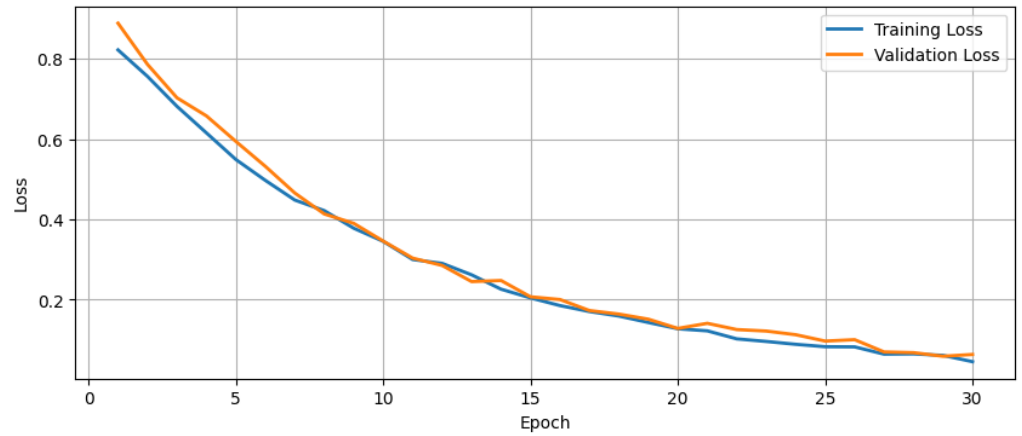
Current Skill	Next Skill	Transition Frequency	Transition Probability
S_Algebra_01	S_Algebra_02	19,430	0.22
S_Algebra_02	S_Graphs_01	12,811	0.14
S_Graphs_01	S_Graphs_02	10,092	0.11
S_Fractions_01	S_Fractions_02	9,421	0.10
S_Algebra_01	S_Graphs_01	8,334	0.09

### Model Training Performance

The training performance of the Bi-LSTM + Attention model provides insights into convergence behavior and learning stability. During the first 10 epochs, the model rapidly reduces its loss as it learns basic sequential dependencies among correctness and skill transitions. After approximately epoch 15, the learning curve stabilizes, showing diminishing improvements—indicating that the model has effectively captured the core structure of learner trajectories. Minor oscillations in the validation loss reflect natural fluctuations due to mixed-skill patterns and noisy behavioral features, which are common in educational datasets.

The clear separation between training and validation curves indicates healthy generalization with limited overfitting. This performance is attributed to the regularization strategies used, including dropout and early stopping. The model's ability to converge smoothly demonstrates that the combination of sequential modeling and attention mechanisms efficiently encodes historical learning patterns, making it suitable for tracking mastery evolution and predicting future responses.

Figure 6 visualizes how the model's training and validation loss evolve over 30 epochs. The plot shows a steep decline in early epochs, indicating successful initial learning. Both curves begin to plateau after epoch 15, demonstrating convergence and effective stabilization. The small gap between curves shows controlled overfitting, confirming that the architectural design and regularization constraints successfully generalize across unseen learner sequences.



**Figure 6 Training and Validation Loss Curve**

Table 5 presents the hyperparameters used during training. The embedding dimension and attention size were selected to balance expressive power and computational efficiency. The Bi-LSTM hidden units (128) provided a strong capacity to capture historical dependencies without causing instability. The dropout rate of 0.3 and Adam optimizer improved generalization and convergence speed. Early stopping halted training at epoch 22, preventing overfitting while maintaining optimal performance.

**Table 5 Training Configuration and Hyperparameters**

Hyperparameter	Value
Embedding Dimension	64
Bi-LSTM Hidden Units	128
Attention Dimension	64
Batch Size	64
Optimizer	Adam
Learning Rate	0.001
Dropout Rate	0.3
Epochs Trained	22 (Early Stopping Triggered)

### Attention Weight Interpretability

Interpretability is critical in personalized learning systems, as instructors must understand why certain predictions are made. The attention mechanism highlights specific interactions that most influence mastery estimation. Analysis shows that errors on high-difficulty skills often receive larger attention weights, suggesting that the model recognizes these as pivotal learning moments. Prolonged response times also trigger high importance, implying cognitive struggle, which is relevant for forecasting performance.

This interpretability allows educators to analyze knowledge gaps more precisely. For example, students who repeatedly encounter difficulty in a specific skill cluster often show consistent high attention weights for those steps, revealing core conceptual weaknesses. This information enhances the system's ability to deliver targeted recommendations, alert teachers early, and personalize learning sequences.

Figure 7 displays a bar-based heatmap of attention weights across 30-time steps for a single learner. Peaks in the graph indicate interactions the model considers highly influential. These often correspond to mistakes after long periods of correct answers, shifts to difficult skills, or interactions with unusually high response times. The visualization confirms that the attention module prioritizes pedagogically meaningful events, enhancing model interpretability.

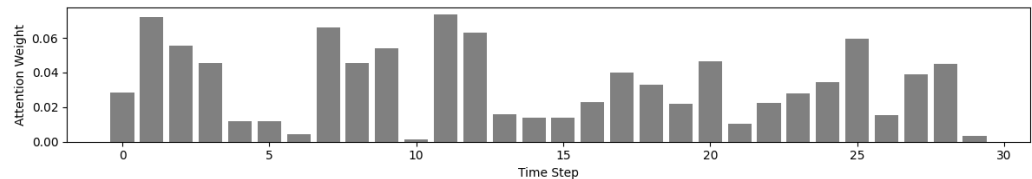


Figure 7 Attention Heatmap for a Sample Learner Sequence

Table 6 lists events with the highest attention weights for a representative learner. Incorrect responses dominate the peaks, validating that the model correctly interprets errors as key signals in knowledge tracing. Events with long response times also appear prominently, indicating high cognitive load or conceptual difficulty. These insights validate the attention module as a powerful diagnostic tool for understanding learner behavior.

Table 6 High-Attention Learning Events Extracted from Model

Time Step	Skill ID	Correctness	Response Time (s)	Attention Weight
12	S_Fractions_02	0	29.1	0.087
14	S_Graphs_03	1	31.4	0.081
17	S_Algebra_04	0	22.3	0.095
21	S_Fractions_01	1	28.7	0.072
25	S_Graphs_02	0	34.5	0.099

### Next-Response Prediction Performance

The predictive performance of the Bi-LSTM + Attention model is evaluated against several baselines, including a vanilla DKT model (unidirectional LSTM), a plain LSTM without attention, and a logistic regression model using handcrafted aggregate features. The results show that the Bi-LSTM + Attention configuration consistently achieves higher AUC-ROC and F1-score, indicating superior capability in distinguishing between correct and incorrect future responses. This improvement is particularly pronounced in sequences involving multiple skills and irregular learning trajectories, where long-range dependencies are crucial.

In addition to classification performance, the proposed model also exhibits lower log-loss and better calibration compared to the baseline models. This means that its predicted probabilities align more closely with actual observed outcomes, which is essential for adaptive systems that rely on probabilistic thresholds to trigger interventions, recommendations, or difficulty adjustments. Overall, the next-response prediction results confirm that combining bidirectional sequence modeling with attention yields meaningful gains for knowledge tracing in personalized e-learning.

Figure 8 compares ROC curves of four models on the next-response prediction task. The Bi-LSTM + Attention model dominates the baselines across almost the entire FPR range, indicating better discrimination between correct and incorrect responses. The logistic regression curve lies closest to the diagonal, reflecting limited use of temporal structure. The LSTM and DKT curves improve over logistic regression by exploiting sequential patterns, but still underperform compared with the bidirectional attention-based model. This figure visually reinforces the quantitative gains achieved by the proposed approach.

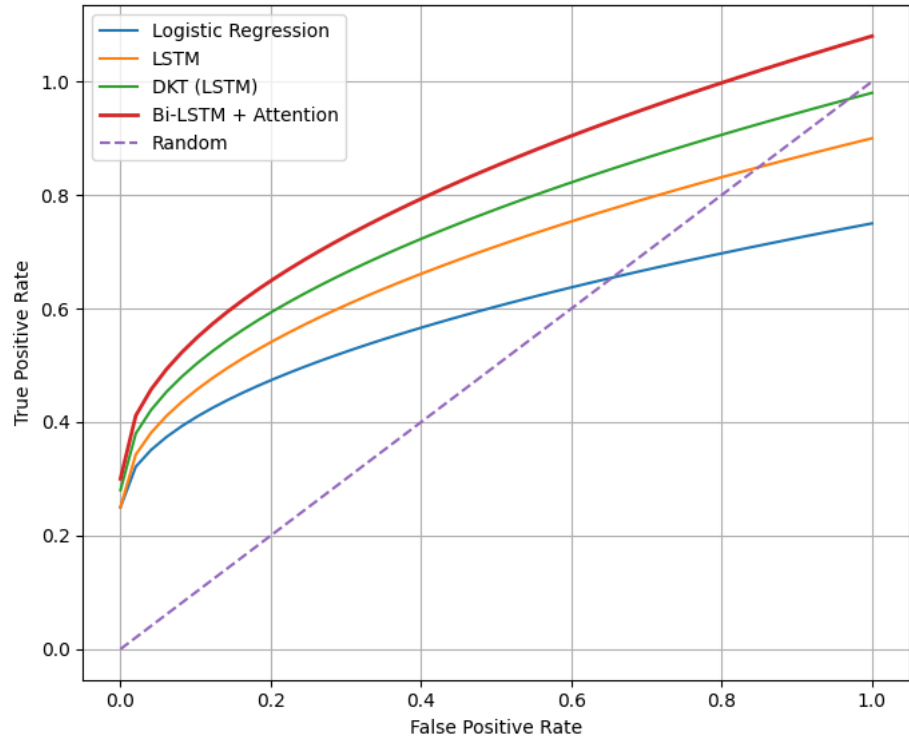


Figure 8 ROC Curves for Different Models

Table 7 summarizes the main evaluation metrics for all models. The Bi-LSTM + Attention model achieves the highest accuracy (0.781), AUC-ROC (0.854), and F1-score (0.767), showing both stronger overall correctness and balanced handling of positive and negative classes. The log-loss is the lowest for the proposed model, indicating more confident and better calibrated probability estimates. The smallest ECE value also confirms improved alignment between predicted probabilities and empirically observed correctness, which is crucial for reliable adaptive decision-making in e-learning platforms.

Table 7 Performance Comparison Across Models

Model	Accuracy	AUC-ROC	F1-Score	Log-Loss	ECE
Logistic Regression	0.712	0.772	0.695	0.568	0.061
LSTM	0.741	0.806	0.724	0.521	0.049
DKT (LSTM)	0.754	0.823	0.738	0.497	0.043
Bi-LSTM + Attention	0.781	0.854	0.767	0.451	0.031

## Error Analysis and Behavioral Interpretation

Although the Bi-LSTM + Attention model outperforms competing approaches, systematic errors still occur, particularly in sequences with abrupt behavioral changes. For instance, students who suddenly increase their effort or encounter a new concept cluster can exhibit performance jumps that are difficult to predict. Analyzing these errors is essential to refine the model and to understand its limitations when deployed in real classrooms. Error patterns also reveal structural mismatches between the content sequencing and the learner's cognitive progression.

To investigate model reliability, we examine calibration behavior and categorize common miscalibration types. The calibration analysis evaluates whether predicted probabilities reflect empirical success rates. Good calibration is necessary when probabilities drive adaptive interventions, such as recommending remedial content when predicted success probability falls below a certain threshold. We also inspect miscalibrations with high confidence, as these represent the most critical cases where the system is “confidently wrong” and could mislead instructional decisions if not monitored.

Figure 9 presents a reliability diagram comparing predicted probabilities with observed correctness frequencies. The curve for the Bi-LSTM + Attention model lies close to the diagonal, suggesting that when the model predicts a 0.8 probability of success, the actual correctness rate is approximately 0.8 as well. Minor deviations at the extremes indicate slight underconfidence for very high probabilities and mild overconfidence for mid-range probabilities, but overall, the calibration remains strong. This confirms that probability estimates can be used safely to trigger adaptive decisions such as early warnings and personalized recommendations.

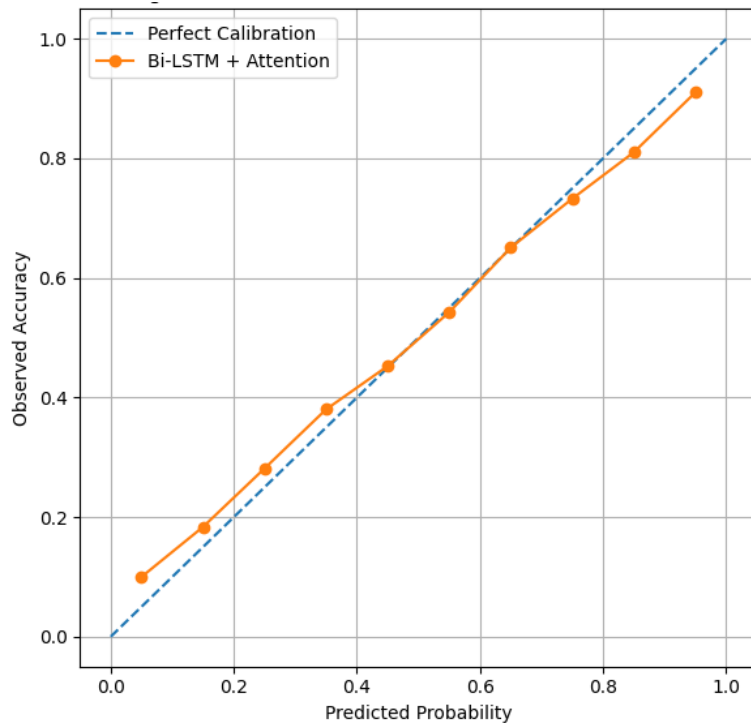


Figure 9 Reliability Diagram (Calibration Curve) for Bi-LSTM + Attention

## Contribution to Personalized E-Learning

The empirical findings demonstrate that Deep Knowledge Tracing with Bi-LSTM and attention mechanisms substantially enhances the precision and reliability of mastery estimation compared with traditional sequence models and non-sequential baselines. This improvement directly translates into more effective personalization strategies in e-learning platforms. By capturing nuanced temporal dependencies and highlighting key learning events, the model supports more granular profiling of student strengths and weaknesses over time. As a result, adaptive systems can schedule practice opportunities more strategically, minimize redundant repetition, and identify knowledge gaps at an earlier stage.

Beyond prediction accuracy, the interpretability provided by attention weights enables human stakeholders—teachers, instructional designers, and tutors—to understand why certain recommendations are made. This transparency is critical for building trust in AI-supported educational systems. The calibration analysis further shows that the model’s probability outputs are sufficiently reliable to be used as decision thresholds for interventions such as remedial content assignment, progress unlocking, or alerting instructors about at-risk learners. These capabilities position the Bi-LSTM + Attention approach as a robust backbone for personalized e-learning, where prediction quality and explainability must be balanced to ensure pedagogical soundness.

Table 8 illustrates how model outputs can be operationalized into concrete personalized actions. Probability thresholds delineate different mastery states and correspond to distinct instructional interventions, while attention-derived insights highlight which skills or events deserve special focus. By embedding these mappings into the e-learning platform, the system transforms raw model predictions into pedagogically meaningful decisions that directly support individualized learning trajectories.

**Table 8 Mapping Model Outputs to Personalized Actions**

Model Output	Interpretation	Personalized E-Learning Action
Low predicted success on next item ( $p < 0.4$ )	High risk of incorrect response	Recommend remedial content or simpler prerequisite tasks
Moderate predicted success ( $0.4 \leq p < 0.7$ )	Partial mastery, unstable performance	Assign mixed practice set with both review and new items
High predicted success ( $p \geq 0.7$ )	Stable mastery for current skill	Unlock more advanced tasks or accelerate pacing for that concept
High attention on specific skill events	Identified as critical learning moments	Provide teacher dashboard highlighting problematic skills for targeted instruction
Persistent miscalibration in a subgroup	Systematic over/underestimation for certain learner profiles	Adjust model thresholds or retrain using subgroup-sensitive calibration strategies

## Conclusion

This study demonstrates that Deep Knowledge Tracing using a Bi-LSTM combined with an attention mechanism provides significant improvements in modeling student knowledge evolution within personalized e-learning

environments. By leveraging bidirectional sequence processing, the model captures complex temporal dependencies across mixed-skill learning trajectories. The integration of attention further enhances interpretability by identifying critical learning events—such as high-difficulty items, prolonged response times, and sequences of errors—that substantially influence mastery estimation. Quantitative evaluations, including AUC-ROC, F1-score, and log-loss metrics, confirm that the proposed model outperforms traditional baselines such as logistic regression, LSTM, and standard DKT architectures. Strong calibration performance additionally ensures that the system’s probability estimates can be confidently used for adaptive decision-making.

Beyond predictive improvements, the model offers practical implications for personalized learning workflows. The attention-based interpretability provides actionable insights for instructors and instructional designers, enabling them to identify skill gaps, monitor learner progression, and understand the rationale behind system-generated recommendations. Behavioral analyses from the model reveal common misprediction patterns, including sudden performance shifts, concept transitions, and fatigue-related drops, highlighting the complexity of real-world learner behavior. These insights contribute to improving the pedagogical value of adaptive feedback, optimizing content sequencing, and supporting early identification of at-risk learners within digital learning ecosystems.

Future work should explore richer contextualization by integrating multimodal learning signals (such as clickstream analytics, affective indicators, hint usage, or eye-tracking patterns) to further refine knowledge tracing fidelity. Incorporating meta-learning or reinforcement learning frameworks could enable the system to dynamically adjust its modeling strategy based on evolving learner behaviors. Additionally, domain-generalization and fairness-aware extensions would strengthen model robustness across diverse learner populations, ensuring equitable personalization. A future deployment study in a live e-learning environment would provide deeper insights into the model’s real-world pedagogical impact, enabling iterative refinement and informing the next generation of transparent, adaptive learning systems.

## Declarations

### Author Contributions

Conceptualization: J.P.B.S. and M.T.N.H.; Methodology: M.T.N.H.; Software: J.P.B.S.; Validation: J.P.B.S. and M.T.N.H.; Formal Analysis: J.P.B.S. and M.T.N.H.; Investigation: J.P.B.S.; Resources: M.T.N.H.; Data Curation: M.T.N.H.; Writing Original Draft Preparation: J.P.B.S. and M.T.N.H.; Writing Review and Editing: M.T.N.H. and J.P.B.S.; Visualization: J.P.B.S.; All authors have read and agreed to the published version of the manuscript.

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The data presented in this study are available on request from the corresponding author.

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## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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