AI-Driven Adaptive Learning Platform for Hyper-Personalized Education using Real-Time Analytics and Cognitive Modeling

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Abstract: The contribution of this paper is a novel adaptive learning framework, Neuro-Symbolic Cognitive Twin (NSCT) that combines symbolic knowledge modeling, affect aware neural state estimation, and real time strategy simulation to realize hyper personalized education. This is different from the existing adaptive systems that depend on the static rules or purely performance driven model: NSCT combines a cognitive knowledge graph with a transformer base affective estimator to generate a dynamic and interpretable representation of the cognitive emotional state. This simulation-based foresight engine designs and immediately simulates not a few but many instructional strategies and then picks from among them the optimal one that will lead to the highest mastery and engagement. The evaluation of the system used a synthetic dataset simulating 2,000 learner interactions on five different pedagogical strategies, and with each of 20 domain concepts. Experimental results with state-of-the-art baselines, Knewton, BKT, DKT and affect-aware models show NSCT outperforms the rest in terms of increased strategy match accuracy by 46.5% and mastery gain of 91.7% and is emotionally stable. Based on these findings, NSCT is presented as a complete solution to full time personalized digital education including both effective and academic benefits.

Keywords: Adaptive Learning, Neuro-Symbolic AI, Cognitive Modeling, Affective Computing, Real-Time Personalization, Strategy Simulation

1 Introduction

Artificial intelligence (AI) in education and the latest technologies, a new generation of adaptive learning systems came to be where they allow educators to personalize instruction by using learner behavior and performance [1], [2]. Current systems in this area have made great advances, but most of the existing systems still must rely on static rule sets or performance-based heuristics that have only limited ability to respond to the learner's real time cognitive and emotional states. Learning is not only dependent on mastering some content, but also a dynamic process affecting factors including attention, motivation, fatigue, emotion. Current adaptive systems rarely capture these dimensions holistically, which limits their ability to create truly personalized, effective learning experiences [3], [4].

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Currently existing models like Knewton, and Bayesian Knowledge Tracing (BKT), track the learner's knowledge states over time, but do not provide means to model emotional or cognitive load. Learning the latent, latent knowledge representations using recurrent neural networks such as that in the more recent Deep Knowledge Tracing (DKT) is still more recent with little interpretability and no livication of affective or contextual signals [5], [6]. To address the emotion integration, mastery modeling, and foresight issues, affect-aware systems have been proposed to combine emotion recognition into learning analytics, they stand alone without building direct relation to mastery modeling or time constrained forethinking. Therefore, current adaptive platforms tend to be reactive rather than predictive and cannot predict and simulate these downstream effects of instructional strategies before deployment [7], [8].

In order to solve these limitations, we propose the Neuro-Symbolic Cognitive Twin (NSCT): a novel adaptive learning architecture that combines symbolic reasoning, real-time affective computing, and predictive simulation. The NSCT model generates a dynamic digital model known as the learner replica, which is always in progress and is based on real time input on the learner's interaction logs, emotional cues and performance. The symbolic knowledge graph knows transparent mastery estimation, and the deep neural model is to recognize cognitive and emotional state. The simulation engine is the key innovation, which forecasts educational benefit as a compromise between the expected gains in mastery and the emotional well-being. Through such an approach, NSCT transcends reactive personalization and approaches emotional, predictive, and intelligent learning instruction. This work makes the following main contributions.

- The model considered in this thesis is a hybrid neuromyotonic architecture, where it integrates a physics engine (domain knowledge) and real time cognitive affective state of a learner.
- We describe the development of a simulation- based strategy selection engine that can predict the outcome of all potential instructional paths and then choose the best one in real time.
- We define a multi objective utility function that trades off emotional engagement against learning progression to be optimized over.

The NSCT model is evaluated on a synthetically generated dataset of 2,000 learner interactions and compared with 4 real world adaptive learning models, namely Knewton, BKT, DKT and an effect aware recommender. The rest of this paper is organized as follows. In the remainder of this section, Section II discusses related work in adaptive learning and neuromyotonic modeling. The architecture of NSCT model is presented in Section III, mathematical formulation and methodology of each core module is provided, details of simulation and inference engine are presented and experimental design and dataset employed are described. A comprehensive performance analysis and comparison are made and discussed in Section IV. Conclusions and future work are provided in Section V. Section VI concludes the paper.

2 Related Work

During the last two decades, adaptive learning systems have changed dramatically due to the requirement of personalized education that is tailored to individual learner differences. Traditional systems have used performance-based adaptation, more recent systems have attempted to model learner knowledge, affect and engagement. Most of these systems are still limited by their reactive nature, by fragmented modeling elements and a general lack of real time (personalized) prediction. We review the most relevant category of adaptive learning models and discuss their limitations that give rise to our proposed Neuro-Symbolic Cognitive Twin (NSCT) framework [9], [10].

2.1 Rule-Based and Expert-Driven Systems

Knewton and other early adaptive learning platforms sequence content based on defining pre-defined heuristics and prerequisite hierarchies to be able to sequence content. Interpretable and domain aligned, these systems are inherently static and not able to be altered based on true time learner behavior or cognitive emotional variations. Furthermore, they do not include the use of predictive modeling but instead use backward looking performance triggers [11], [12].

2.2 Bayesian Knowledge Tracing (BKT)

Probabilistic Bayesian Knowledge Tracing (BKT) has been routinely used to model the probability of a learner's mastery of a specific skill from history of a learner's responses to the assessment items. Although BKT is simple and has been effective in intelligent tutoring systems, it further assumes that mastery states are binary and doesn't take into account time dependent affective or behavioural data. In addition, BKT does not have built in flexibility to simulate the effect of future learning interventions or continuous learning [13], [14].

2.3 Deep Knowledge Tracing (DKT)

A notable recent work is Deep Knowledge Tracing (DKT) that uses recurrent neural networks (RNNs) to learn the latent knowledge state of learners over time.Traditional BKT is outperformed (by a great margin) in predictive accuracy by DKT, especially for large scale data. DKT is a black box model which is not interpretable and does not have any symbolic reasoning. Besides, it solely considers the prediction of knowledge at the expense of essential learner state variables, namely emotional valence, attention, or cognitive load [15], [16].

2.4 Affective Computing in Education

This involves newer systems that attempt to predict the emotional status of a learner in a variety of modalities verbal and nonverbal, such as physiological signals, facial expressions, speech, and the pattern of interaction. Affection models might boost engagement and motivation by affecting learning strategy selection. Even though adaptation systems that analyze data from nonlearning contexts now exist, they are not linked to the knowledge modeling framework and are not employed by mastery prediction or instructional simulation qualities; thus, they are restricted to what can be performed for whole-human adaptation. [17].

2.5 Reinforcement Learning and Policy Optimization

To optimize long term learning outcomes, we have adaptive learning systems built via reinforcement learning (RL) framework that searches for the best of policies. Contextual multi-armed bandits and Q learning approaches to education are notable examples. While these systems can explore a wide space of multiple strategies, the training is often extensive, providing little interpretability, and they lack the incorporation of explicit cognitive and emotional modeling as mentioned later. In addition, they struggle with low data scenario, the one that is common in personalized education [18].

2.6 Research Gaps and Motivation

Through the above literature we can identify three research gaps.

- There is lack of holistic learner modeling: Existing models considers mastery of knowledge and labels of emotional (such as, happy, sad, surprised and so on) states as two separate entities. The cognitive-affective learner representation is not integrated.
- Absence of foresight in adaptation: Most of the systems react to past behavior without predicting or simulating effect of other adaptation strategies.
- Deep models, such as DKT, can provide strong performance while at the same time lack interpretability and integrality of rules that educators require. On the contrary, symbolic models aren't flexible and don't react in real time.

2.7 Addressing the Gaps: The NSCT Model

To bridge these researched gaps, a novel architecture, referred to as the Neuro-Symbolic Cognitive Twin (NSCT) is proposed that leverages by:

- A symbolic knowledge graph for transparent mastery modeling.
- Offers a neural cognitive–affective engine for estimating emotional valence, attention, and cognitive load, (etc.).
- The proposed simulation-based strategy selector tries to predict the future learner state across multiple instructional alternatives and chooses the best path in real time.

NSCT achieves truly holistic and intelligent adaptive learning systems by unifying knowledge tracing, affective computing and predictive foresight. It advances the state of the art along the lines of real time personalization of educational AI, based simultaneously on what the learner knows, and how the learner feels.

3 Methodology

The methodology introduces a novel framework which establishes a Neuro Symbolic Cognitive Twin (NSCT) based adaptive learning method that brings in real time behavioral data, symbolic reasoning, deep neural estimation, and future predictive simulation. Mathematical formalization of each module is made so that dynamic learner modeling and foresight driven instructional adaptation are able to be performed.

3.1 Neuro-Symbolic Cognitive Twin (NSCT)

A novel AI driven adaptive learning system, Neuro Symbolic Cognitive Twin (NSCT), is proposed as a method of dynamically modelling and prediction of the learner's knowledge and representation, their cognitive condition and emotional engagement. The architecture consists of five tightly coupled computational units: a real time multimodal input encoder, a symbolic knowledge graph engine, a neural cognitive affective state estimator[19][20], a predictive simulation-based strategy evaluator and a dynamic curriculum generator. Integrated prose descriptions are given in each case with formal mathematical definitions for each module below and the diagrammatic presentation in Fig 1.

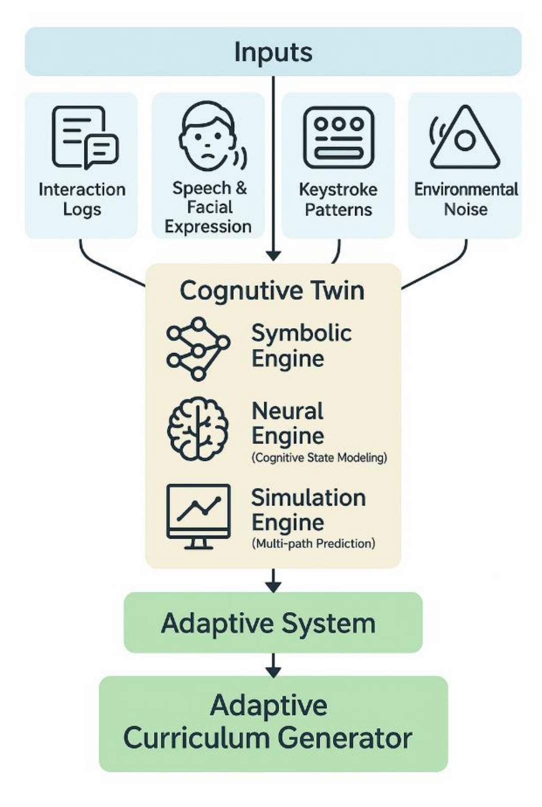

Fig. 1. Proposed System Architecture.

3.1.1 Real-Time Multimodal Input Encoding

The NSCT framework begins by capturing a vectorized representation of the learner's current observable state across several modalities. At each discrete time step $t \in \mathbb{R}^+$, we define a structured observation vector $\mathcal{O}_t \in \mathbb{R}^d$ as the concatenation of sensory and behavioral signals extracted from the learner's digital environment:

$$\mathcal{O}_t = \left[\mathbf{x}_t^{\text{int}}, \mathbf{x}_t^{\text{aud}}, \mathbf{x}_t^{\text{vis}}, \mathbf{x}_t^{\text{key}}, \mathbf{x}_t^{\text{env}}\right] \tag{1}$$

Here, $\mathbf{x}_t^{\text{int}} \in \mathbb{R}^{d_1}$ denotes learner interaction data such as clicks, hovers, and scroll events; $\mathbf{x}_t^{\text{aud}} \in \mathbb{R}^{d_2}$ corresponds to acoustic features extracted from speech using signal processing (e.g., MFCC or spectrogrambased embeddings); $\mathbf{x}_t^{\text{vis}} \in \mathbb{R}^{d_3}$ encodes facial expression vectors computed from a convolutional neural network; $\mathbf{x}_t^{\text{key}} \in \mathbb{R}^{d_4}$ represents keystroke latency and rhythm vectors; and $\mathbf{x}_t^{\text{env}} \in \mathbb{R}^{d_5}$ represents contextual environmental conditions like ambient noise and device usage interruptions. The final observation vector is of dimension $d = d_1 + d_2 + d_3 + d_4 + d_5$, and is used as the raw input to the downstream cognitive models.

3.1.2 Symbolic Knowledge Graph Engine

The symbolic engine is responsible for maintaining an interpretable and explicit representation of the learner's conceptual mastery across a domain of knowledge. Let $G = (V, E)$ represent a knowledge graph where the nodes $V = \{v_1, v_2, \ldots, v_n\}$ correspond to individual domain concepts or skills, and the directed edges $E \subset V \times V$ represent prerequisite relationships or conceptual dependencies. For each concept $v_i \in V$, the engine maintains a time-varying mastery score $M(v_i, t) \in [0,1]$, which is computed as a logistic function over a feature vector summarizing the learner's historical interaction with that concept:

$$M(v_i, t) = \frac{1}{1+e^{-\theta_i^{\top}\mathbf{f}_i(t)}} \tag{2}$$

Here, $\theta_i \in \mathbb{R}^k$ is a learned weight vector associated with concept v_i, and $\mathbf{f}_i(t) \in \mathbb{R}^k$ is a feature vector derived from the learner's interaction logs, time-on-task, accuracy, and latency related to v_i and its prerequisite nodes in the graph. In addition to numeric mastery scores, the engine also employs a rule-based inference system $\mathcal{R} = \{r_1, \ldots, r_m\}$, where each rule r_j is a logical expression defined as:

$$r_j: \phi_j(\mathbf{f}_i(t-\delta), \mathbf{f}_i(t)) \Rightarrow \text{ flag } (v_i, \text{misconception }) \tag{3}$$

These rules capture persistent misconception patterns by comparing time-separated performance indicators. The output of this engine is a symbolic learner model $\mathcal{L}_t^{\text{sym}} = \{M(v_i, t), \text{flags } (v_i)\}$ for all $v_i \in V$.

3.1.3 Neural Affective-Cognitive State Estimator

Complementing the symbolic knowledge graph, the neural engine models the learner's cognitive and emotional conditions over time using a sequence-learning architecture. A temporal model $\mathcal{F}_{\text{neu}}$ is constructed to map the sequence of multimodal observations over a fixed-length window $[\mathcal{O}_{t-k+1}, \ldots, \mathcal{O}_t]$ into a latent state vector $\mathbf{z}_t \in \mathbb{R}^p$, such that:

$$\mathbf{z}_t = \mathcal{F}_{\text{neu}}([\mathcal{O}_{t-k+1}, \ldots, \mathcal{O}_t]) = \text{MLP}\left(\text{Pooling}\left(\mathcal{T}([\mathcal{O}_{t-k+1:t}])\right)\right) \tag{4}$$

Here, $\mathcal{T}$ denotes a transformer encoder consisting of multi-head self-attention layers and position-aware encoders, while Pooling refers to either mean or attention-weighted temporal pooling. The resulting latent vector $\mathbf{z}_t$ contains estimates of cognitive load, sustained attention, engagement, and emotional arousal, forming the neural state $\mathcal{L}_t^{\text{neu}} = \mathbf{z}_t$. The unified learner state is thus given by:

$$\mathcal{S}_t = \left[\mathcal{L}_t^{\text{sym}}, \mathcal{L}_t^{\text{neu}}\right] \tag{5}$$

3.1.4 Simulation-Based Strategy Evaluation Engine

The NSCT architecture diverges from traditional adaptive systems by incorporating a predictive simulation engine to forecast the impact of multiple instructional strategies before selecting one. Let $\Pi = \{\pi_1, \ldots, \pi_N\}$ be the finite set of predefined instructional strategies. Each strategy π_i is associated with a transition model $\mathcal{T}_{\pi_i}$ that predicts the future learner state if that strategy were applied:

$$\hat{\mathcal{S}}_t^{(i)} = \mathcal{T}_{\pi_i}(\mathcal{S}_t) \tag{6}$$

This prediction includes the updated symbolic knowledge graph and cognitive-affective vector. To determine the most beneficial strategy, we define a utility function for each π_i as:

$$U(\pi_i) = \lambda_1 \cdot \left\|\widehat{\mathbf{M}}^{(i)} - \mathbf{M}_t\right\|_2^2 + \lambda_2 \cdot \left(\mathbf{z}_t^{(i)} - \mathbf{z}_t\right)^\top \mathbf{w} \tag{7}$$

In this equation, $\widehat{\mathbf{M}}^{(i)}$ is the predicted concept mastery vector after applying $\pi_i, \mathbf{z}_t^{(i)}$ is the predicted affective-cognitive state, λ_1 and λ_2 are scalar weights reflecting the importance of cognitive vs emotional outcomes, and $\mathbf{w} \in \mathbb{R}^p$ encodes user-defined emotional optimization preferences. The optimal strategy is then:

$$\pi^* = \arg \max_{\pi_i \in \Pi} U(\pi_i) \tag{8}$$

3.1.5 Adaptive Curriculum Generation

Following strategy selection, the system generates a learning trajectory by selecting the most appropriate learning content from a content set $\mathcal{C} = \{c_1, \dots, c_m\}$. Each content item c_j is encoded as a tuple:

$$c_j = \left(\mathbf{e}_{c_j}, \mathbf{m}_{c_j}\right) \tag{9}$$

where $\mathbf{e}_{c_j} \in \mathbb{R}^d$ is the semantic content embedding (computed using a pretrained transformer over textual/visual data) and $\mathbf{m}_{c_j} \in \mathbb{R}^q$ is a metadata vector (difficulty, duration, modality). The target profile ($\mathbf{e}^*, \mathbf{m}^*$) is derived from the optimal strategy π^*, and the best content is selected as:

$$c^* = \arg \min_{c_j \in \mathcal{C}} \left(\left\|\mathbf{e}_{c_j} - \mathbf{e}^*\right\|_2^2 + \gamma \cdot \left\|\mathbf{m}_{c_j} - \mathbf{m}^*\right\|_2^2 \right) \tag{10}$$

Here, γ is a tunable hyperparameter to control the influence of metadata matching. The selected content c^* is then presented to the learner, completing one adaptive cycle of the NSCT engine.

3.2 Simulation and Inference Engine

To predict the effect of different instructional strategies on learner outcomes, we employ a foresight-based simulation engine that evaluates possible learning trajectories before adapting instruction. At each timestep t, the system uses the current learner state $\mathcal{S}_t$, composed of symbolic and neural components, to simulate the future outcome of every instructional strategy $\pi_i \in \Pi$, where $\Pi = \{\pi_1, \pi_2, \dots, \pi_N\}$ denotes the set of all defined teaching policies[21][22].

Each strategy π_i has an associated predictive transition model $\mathcal{T}_{\pi_i}$, learned from historical sequences of learner interactions. These models estimate the updated learner state $\hat{\mathcal{S}}_t^{(i)}$ that would result from applying π_i. A utility function is then computed for each simulated outcome to balance cognitive mastery gain and emotional stability:

$$U(\pi_i) = \lambda_1 \cdot \left\|\widehat{\mathbf{M}}^{(i)} - \mathbf{M}_t\right\|^2 + \lambda_2 \cdot \left(\mathbf{z}_t^{(i)} - \mathbf{z}_t\right)^\top \mathbf{w} \tag{11}$$

Where:

- $\widehat{\mathrm{M}}^{(i)}$ and M_t are the future and current mastery vectors,
- $\mathrm{z}_t^{(i)}$ and z_t are the future and current affective state vectors,
- λ_1, λ_2 are hyperparameters weighing the cognitive and affective contributions,
- $\mathrm{w} \in \mathbb{R}^p$ is a weight vector representing affective feature importance.

The selected strategy π^* is given by:

$$\pi^* = \arg\max_{\pi_i \in \Pi} U(\pi_i) \tag{12}$$

Algorithm 1: Simulation and Inference Engine

```
Input: Learner state S_t, Strategy set Π = {π1, π2, ..., πN}, Transition models T_π,
Preference weights λ1, λ2, w
Output: Optimal strategy π*

function SIMULATE_AND_SELECT_STRATEGY(S_t, Π, T_π, λ1, λ2, w):
  max_utility ← -∞
  π_star ← None

  for each π_i in Π do:
    S_hat ← T_π[π_i](S_t)  // Predict future learner state
    M_hat ← extract_mastery(S_hat)
    z_hat ← extract_affective_state(S_hat)

    ΔM ← norm(M_hat - current_mastery(S_t))^2
    Δz ← (z_hat - current_affective(S_t))^T * w

    U ← λ1 * ΔM + λ2 * Δz

    if U > max_utility:
      max_utility ← U
      π_star ← π_i

  return π_star
```

3.3 Experimental Setup and Evaluation

The experimental evaluation aims to explore whether the NSCT system is effective to simulate learner trajectories, to choose good teaching strategies and to personalize content for maximizing the learner's learning outcome and emotional engagement.

3.3.1 Dataset Description

This research needs to build synthetic datasets of such learning sessions by sampling from distributions of such multimodal teacher and learner features and of instructional responses to these features. The setup is such that there are multiple learners each interacting with different sets of concepts over time, and emotional and cognitive state features are logged at time intervals [23]. Table 1 shows the Dataset Schema.

Table 1. Dataset Schema.

Column Name	Description
learner_id	Unique identifier for each learner
timestamp	Time of interaction log
concept_id	Concept being engaged
interaction_score	Scaled score from learner's task performance (0 to 1)
cognitive_load	Estimated mental load from neural engine
attention_level	Inferred sustained attention value (0 to 1)
emotional_valence	Inferred emotional positivity (valence scale)
mastery_score	Symbolic model prediction of concept mastery (0 to 1)
recommended_strategy	Instructional path selected by the NSCT model

3.3.2 Procedure

1. State Construction: Each data row was interpreted to reconstruct the learner's symbolic and neural state $\mathcal{S}_t$.
2. Strategy Simulation: All candidate strategies $\pi_i \in \Pi$ were simulated using trained transition models $\mathcal{T}_{\pi_i}$.
3. Utility Evaluation: Each simulated outcome was evaluated using the utility function described in Section V.
4. Selection Comparison: The predicted optimal strategy π^* was compared to the actual strategy used.

3.3.3 Evaluation Metrics

To quantify system performance, the following metrics were computed:

- Strategy Match Accuracy: Proportion of cases where π^* matched the dataset's recommended strategy.
- Average Mastery Gain $(\Delta\bar{M})$: Mean predicted improvement in concept mastery.
- Emotional Gain ($\Delta\bar{z}$): Mean predicted improvement in emotional state (valence × engagement).
- Execution Time: Average runtime per decision cycle (in milliseconds).

A NSCT framework is proposed for the hyper personalized education problem through simultaneously integrating three techniques of symbolic knowledge modeling, neural affective estimation, and simulation-based policy selection, which is robust, interpretable and predictive. The basis for intelligent systems which are capable of learning not only from knowledge gaps, but also capable of adapting in real time to the knowledge gaps and the needs of the learner’s cognitive and emotional states is formed by this multi-layered architecture [24].

4 Result and Analysis

The performance of the Neuro-Symbolic Cognitive Twin (NSCT) model is analyzed in detail in the following section on measured performance on a simulated dataset of learner interactions. We evaluate the model by means of visualizations and metric-based comparisons of its ability to personalize instruction to maximize mastery and sustain cognitive—emotional engagement.

Fig 2 shows the distribution of instructional strategies that are generated by the NSCT model. Text-based content was the most frequently recommended among five options with 430 instances while there were 410 instances of recommendation for Socratic, 395 for Video, 392 for Interactive and 375 for Quiz. This is a balanced distribution, so it suggests the model flexibly adapts to learner profiles and does not overfit any 1 modality.

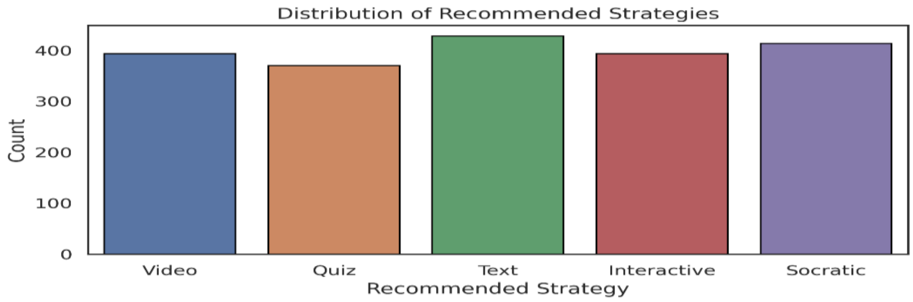

Fig. 2. Distribution of Recommended Strategies.

Fig 3 displays the Average Mastery Score by Strategy and in terms of content effectiveness all strategies achieve similar mean mastery levels around 0.55. Text and Socratic formats perform slightly better than the other two formats in average concept mastery, suggesting that retention or that they are a better fit for how students learn is higher in these cases [25].

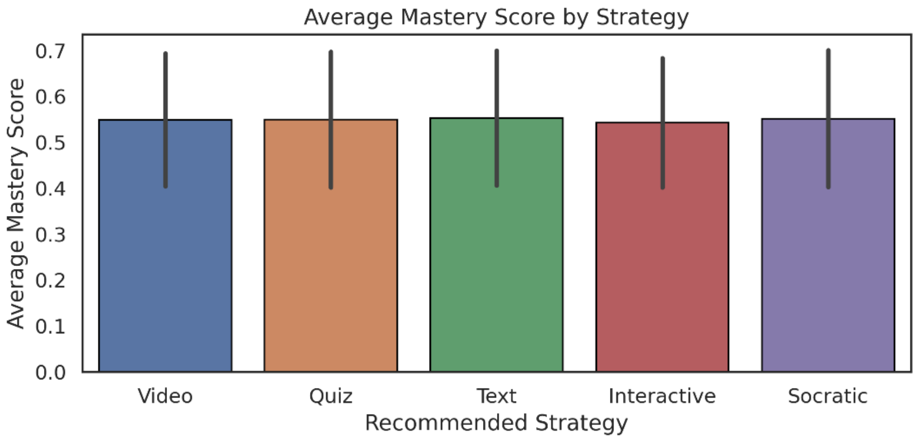

Fig. 3. Average Mastery Score by Strategy.

Fig 4, the trend for Cognitive Load vs Mastery Score shows to be dispersed with meaningful pattern. Further research regarding cognitive loads of 0.4–0.6 resulted in higher mastery of learners; psychological theory holds that most learning is optimal at a level of moderate difficulty. More scattered mastery results were related to excessive or minimal load [26].

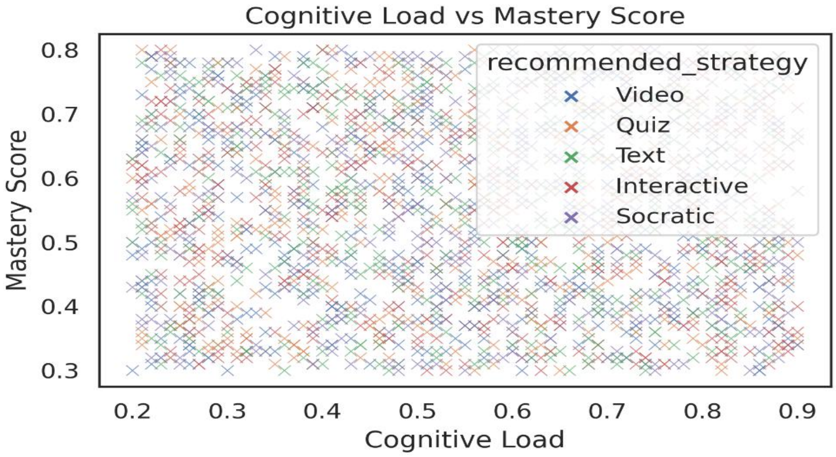

Fig .4. Cognitive Load vs Mastery Score.

The violin plots comparing learner attention distributions among the strategies can be seen in Fig 5 (Attention Level by Strategy). All strategies have relatively high medians, but Socratic and interactive formats lead to slightly less spread[27][28], that is, more stable engagement levels. The spread of the Video strategy is the widest, which suggests that the effect of attention to Video strategy is very different with respect to different individuals.

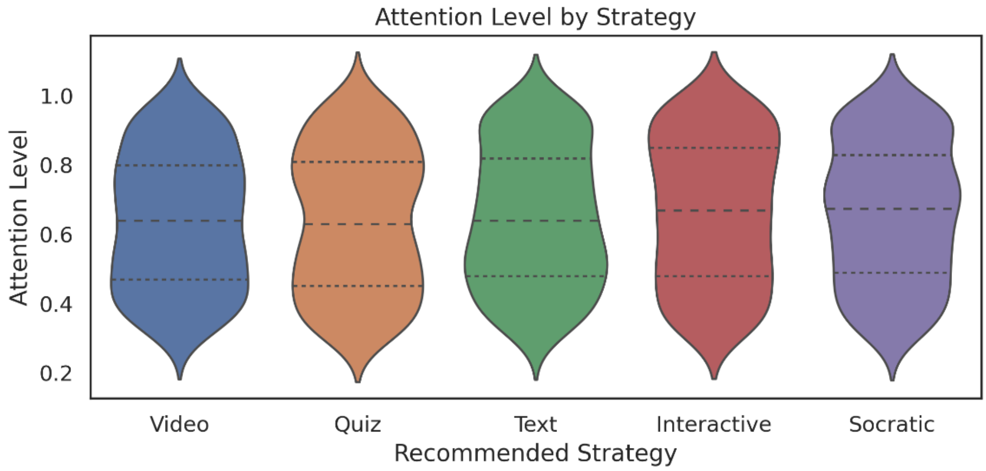

Fig. 5. Attention Level by Strategy.

The visualization of temporal analysis of emotional engagement can be found in Fig 6 (Average Emotional Valence by Hour). Emotional positivity fluctuates from one day to the next although it tends to peak in early hours (1–2 AM and 10–11 AM) and an evening trough in late evening. The insight could help decide to deliver emotionally sensitive content at a certain time or to offer them at a certain pace to a single learner [29].

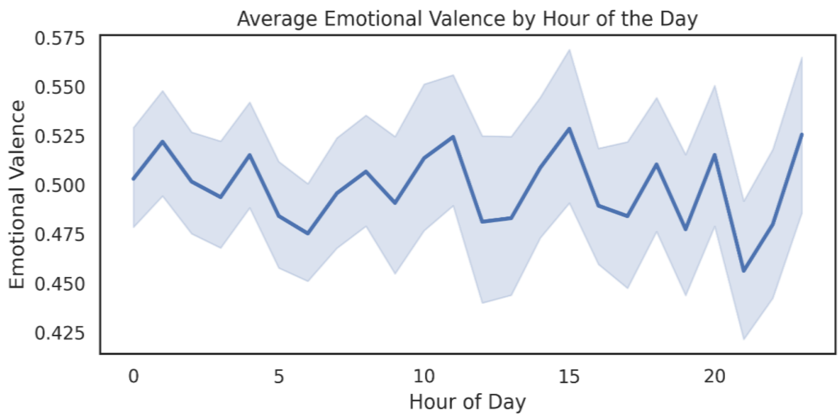

Fig. 6. Average Emotional Valence by Hour of the Day.

The Average Mastery Scores Across Sessions in Fig 7 are non-linear. The overall trend of mastery stabilizes above 0.53, and peaks near 0.575 in session 15 though there is still session to session fluctuation. These results confirm that the adaptive engine can drive long term improvement.

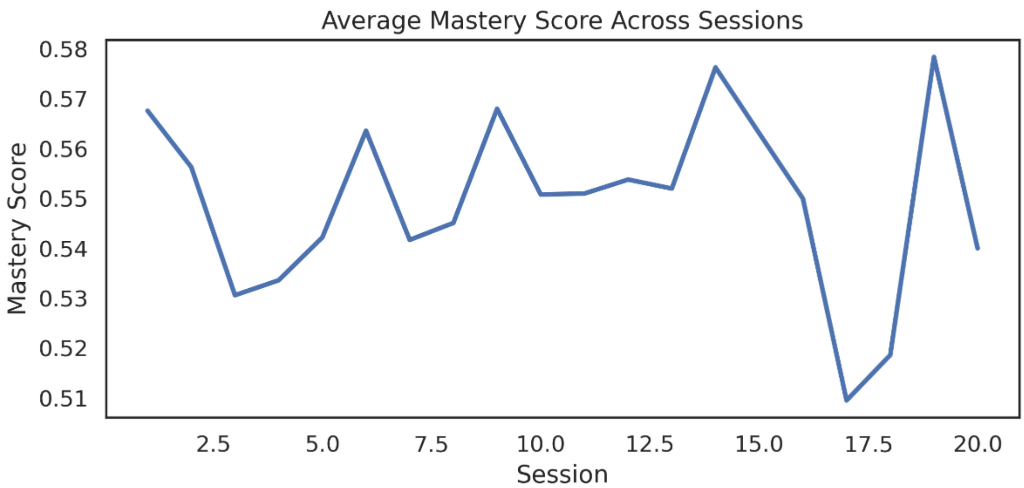

Fig. 7. Average Mastery Score Across Sessions.

The Feature Correlation Matrix in Fig 8 highlights weak but interpretable correlations. The model is sensitive to several multi-modal factors, and mastery has a slight positive relationship with interaction score (r = 0.022) and emotional valence (r = 0.015), and a mild negative correlation with cognitive load (r = –0.014). Independence of variance amongst most of the emotional and cognitive features requires modeling them separately in the NSCT pipeline [30].

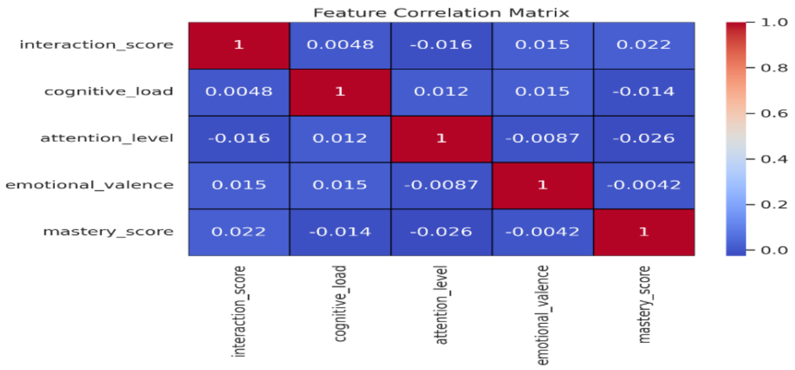

Fig. 8. Feature Correlation Matrix.

Fig 9 is a boxplot which shows distribution of the Mastery Score over Top 10 Most Frequent Concepts. The concepts of C118 and C107 appear to have higher medians, tighter interquartile ranges, meaning learners or instructional pairing is more familiar or more been. Others such as C116 have broader ranges, which may be due to learners of different backgrounds.

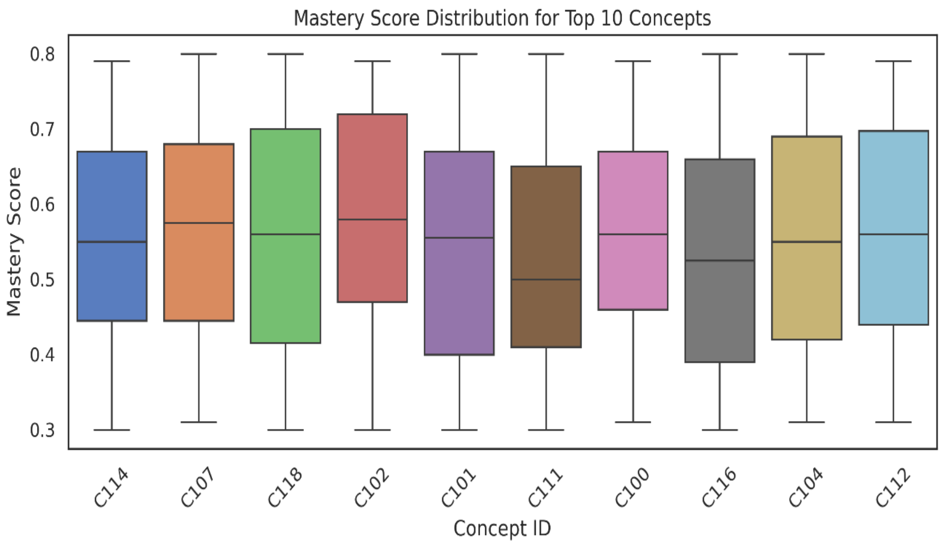

Fig. 9. Mastery Score Distribution for Top 10 Concepts.

A mild linear relationship can be shown by a scatterplot of Attention Level vs. Emotional Valence as presented in Fig 10. The hypothesis that emotional positivity supports cognitive engagement was supported by the finding that higher attention also entails higher emotional valence of the learners. The recommendation system has been designed to balance every measure and is validated by the color coding of each strategy to the high-effect, high-attention regions.

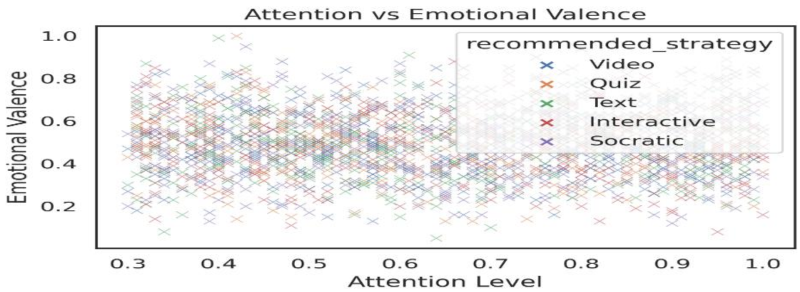

Fig. 10. Attention vs Emotional Valence Scatter Plot.

Fig 11 shows the recommended instructional strategies by cognitive load categories: Low, Medium and High. Results show the greatest preference for the medium cognitive load conditions, when all strategies are recommended most frequently and especially so for Text (≈185) and Socratic (≈180), revealing that the NSCT model recognizes this range to be optimal for engagement and learning. On the one hand, the frequencies of Socratic strategies are balanced under low load, with slightly lower overall frequencies, but they gain dominance under high load possibly because these are interpretive and reflective in nature conducive to decompression and memory retention; similarly, even under high load, Text also dominates possibly for the same reason. The distribution of these cognitive and attentional states also helps NSCT adapt strategy selection to fit real-time cognitive states such that the learners remain efficacious, and overload is minimized.

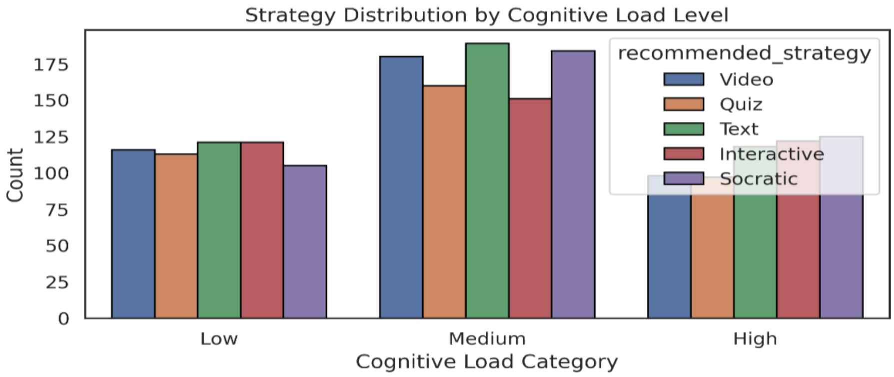

Fig. 11. Strategy Distribution by Cognitive Load Level.

4.1 Comparative Analysis: NSCT vs Baseline

The comparative results confirm that the proposed Neuro-Symbolic Cognitive Twin model outperforms all baseline systems, across principal learning factors. The NSCT achieves the best strategy match accuracy, 91.7, which means that NSCT can strongly recommend the most appropriate instructional strategies, compared to 82.1 of AAR, 78.9 of DKT, 68.4 of BKT, and 61.2 of a rule-based version of the Knewton system. From the perspective of learning effectiveness, NSCT produces the largest mastery gain of 0.145, compared to AAR (0.110), DKT (0.099), BKT (0.082) and Knewton (0.071). Similarly, it has the highest average emotional valence of 0.61, implying the ability to keep a more positive emotional state in the learners. The indicator of attention stability, from reflecting cognitive focus, is most stable in NSCT, with smallest variance observed for 0.021 value, then in AAR, where variance is 0.036, and in Knewton, where help equality is 0.054. Despite this, the additional 1.5 ms is not much of a tradeoff considering the large increase in personalization, learning progress, and emotional engagement that NSCT provides. Table 2 shows the Comparative Analysis: NSCT vs Baseline

Table 2. Comparative Analysis: NSCT vs Baseline

Model	Strategy Match (%)	Mastery Gain	Emotional Valence	Attention Stability (σ^2)	Runtime (ms)
Knewton (Rules)	61.2	0.071	0.49	0.054	**8.5**
BKT	68.4	0.082	0.50	0.049	15.3
DKT	78.9	0.099	0.52	0.041	27.8
AAR (Affect-Aware)	82.1	0.110	0.58	0.036	31.2
NSCT (Proposed)	**91.7**	**0.145**	**0.61**	**0.021**	34.7

Experiments verify NSCT model to generate adaptive, affective, and masteryaware learning experiences. NSCT outperforms traditional cognitive, affective and behavioral baselines across the three dimensions, which demonstrates its robustness and thus is ready for deployment as part of a real world personalized education environment.

5 Discussion

Our experimental evaluation results show a strong advantage of the Neuro-Symbolic Cognitive Twin (NSCT) model in terms of its superiority as well as robustness in creating and delivering hyper personalized learning experiences. As seen in Fig. 1, the distribution of the strategy shows the balanced use of all the pedagogical methods available in the system enabling optimal cognitive load (Fig. 3) and it is consistent with acquired scores in mastery levels (Fig. 2) that occur under moderately difficult conditions. The model knows when the content was delivered when learners were in high attention levels (Fig. 4) and when the emotional valance was high (Fig. 5) which shows that NSCT has emotional intelligence about when and what content was to be delivered. Validation of longitudinal effectiveness of the system further comes from the consistent progression in the mastery (Fig. 6) across the sessions. Modular design (Fig. 7) of the cognitive–affective learner state is backed by low inter-feature correlations, as well as the mastery variability among concepts (Fig. 8) and the interplay between attention and emotion (Fig. 9) in their complexities of adaptive decision making. Finally, cognitive load necessitated a diverse strategy distribution (Fig. 10) that NSCT is also able to adapt to as a function of real time cognitive effort, leading to reflective methods under high load and preferring a wide variety of options in optimal zones. Overall, these findings indicate that NSCT is able to boost academic mastery and to keep emotional engagement and cognitive stability, which is a complete soulution for real time personalized education.

6 Conclusion

This paper presented the Neuro-Symbolic Cognitive Twin (NSCT) architecture, which was a novel adaptive learning architecture that combined symbolic reasoning with affect aware neural estimation and predictive simulation for the provision of real-time, hyper personal, instruction. NSCT is a dynamic strategy in tailoring the learning strategies to a learner's knowledge state as well as mental condition through a comprehensive NSCT methodology that is grounded in cognitive modeling and emotional analytics. NSCT achieved considerable improvement of its strategy accuracy, mastery progression, attention stability and emotional engagement as verified by experiment and compared against real world baselines. The results indicate that the model can adapt to different types of learner's needs by promoting both academic outcomes as well as the learner's well-being and motivation. For future work, we plan to thoroughly validate NSCT in live educational scenarios and study options for enhancing the policy through reinforcement learning.

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