

Mathematical cognitive modelling enhanced by deep learning for understanding human decision making in complex sequential tasks

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Abstract

Conventional mathematical models and data-driven deep learning (DL) methods are both tested for Human Decision-Making (HDM) in Complex Sequential Tasks (CST). These

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methods include complicated cognitive functions. Considering the use of adaptive timing mechanisms, the present research introduces a hybrid model that includes statistical cognitive dynamic models with Bidirectional Long Short-Term Memory (BiLSTM) attention networks. While DL serves as the basis for collecting temporal behavioural patterns, the mathematical model is vital for recording value changes, cognitive load, and decision selection by its application of classical Boltzmann logic. The mathematical model of contraction mapping serves as the basis for the invention of convergence guarantees. The recommended model achieves 84.7% prediction accuracy and improved cognitive state alignment ($CSD=0.187$) when tested on the Iowa Gambling Task dataset, involving 617 participants. The proposed model improves the accuracy of mathematical models by 12.4% and the validity of DL by 3.5%. This research has enabled the interpretation of artificial intelligence (AI) for human-centred decision support systems.

Subject Classification: Primary 91E10 and 68T07, Secondary 37N40 and 62M45.

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1. Introduction

At the cross-section of cognitive science, artificial intelligence (AI), and behavioural economics, developing the study of Human Decision-Making (HMD) in Complex Sequential Tasks (CST) is an important task that requires investigation [1]. Adaptive control of thought—rational (ACT-R) and the generation of rule systems are a couple of examples of classical mathematical cognitive models. These theories are based on theory and are measurable; however, they are challenged by scalability and the detection of CST from high-dimensional data [2-3]. On the other hand, deep learning (DL), including recurrent neural networks (RNNs) with long short-term memory (LSTM) components and Transformer-type networks, is highly precise for pattern recognition and temporal modelling. However, these methods function as black boxes, lacking cognitive plausibility and accessibility, which are vital to use cases that emphasise human cognition [4-5]. Recently developed hybrid models that attempt to connect cognitive theories with neural networks have verified promising results; however, these hypotheses achieve only limited accuracy in integrating their mechanisms and fail to provide convergence security compared to modern approaches [6-8]. This research gap is highly significant for the development of adaptive learning systems, healthcare cognitive testing, and human-robot collaboration, among other fields that demand high accessibility and predictive accuracy [9-10]. By using adaptive gating mechanisms, the present study provides a hybrid model that is mathematically valid and integrates cognitive dynamical systems with BiLSTM-Attention paradigms. The main findings include (i) a formal mathematical theory of decision behavior with verified predictable features via Lyapunov analysis, (ii) a DL for Behavioral Pattern Extraction (BPE) with attention-based cognitive load modelling, (iii) a theoretically validated integration method with convergence

guarantees proven using the Banach fixed-point theorem, and (iv) complete testing on the Iowa Gambling Task demonstrating 84.7% accuracy with higher cognitive correlation. The current study is structured in the following order for the remaining sections: In Section 2, the mathematical cognitive model is introduced; in Section 3, the DL model is outlined; in Section 4, the hybrid integration with theoretical analysis is provided fully; in Section 5, the test results are provided; and in Section 6, the conclusion is presented with recommendations for future research.

2. Mathematical Cognitive Model of Decision Dynamics

The HDM in CST involves an unpredictable relationship among the current state of the external environment, the assessment of value, and the use of cognitive resources [11]. The formal development of what is being discussed is made possible by the application of a state-space model, in which the state of cognition at time 't' is represented by,

$$x(t) = [s(t), u(t), c(t)]^T \in \mathbb{R}^d \quad (1)$$

comprising task state $s(t)$, utility expectation $u(t)$, and cognitive load $c(t)$. The system operates under constraints: working memory capacity $\|c(t)\| \leq C_{max}$ and bounded utility $u_{min} \leq u(t) \leq u_{max}$. The temporal evolution follows the continuous-time dynamical system [12]:

$$\frac{ds}{dt} = f_s(s, a, \theta) \quad (2)$$

$$\frac{du}{dt} = \alpha(R - u) + \beta \nabla_s V(s) \quad (3)$$

$$\frac{dc}{dt} = \gamma(\tau(s, a) - \delta c) \quad (4)$$

whereas ' f_s ' provides the basis for the evolution of states; α, β are the control utility adaptations that operate on the received reward ' R ', and the value change; γ, τ are to accurately simulate the dynamics of cognitive load in relation to task load and loss. After that comes the selection of decisions as "*Dynamic Boltzmann logic*",

$$P(a_i | x_t) = \frac{\text{Exp}(Q(x_t, a_i)/\tau_{cog})}{\sum_j \text{Exp}(Q(x_t, a_j)/\tau_{cog})} \quad (5)$$

where the Q-function incorporates heuristic biases:

$$Q(x_t, a_i) = u_t - w_{risk} \cdot \text{Var}(R | a_i) + w_{sens} \cdot \mathbb{E}[R | a_i] \quad (6)$$

with w_{risk} capturing risk aversion and w_{sens} encoding reward sensitivity.

Theorem 1: *A unique equilibrium point ' x^* ' with negative basic elements is permitted in the network subject to the rules of Lipschitz continuity of ' f_s ' and finite variation, where the eigenvalues of the Jacobian model $\partial F / \partial x |_{x^*}$ are significant.*

Proof: Consider Lyapunov function $V(x) = \|x - x^*\|^2$. Then $dV/dt = 2(x - x^*)^T (F(x) - F(x^*)) \leq -\lambda \|x - x^*\|^2 < 0$ for $x \neq x^*$, ensuring asymptotic stability [13].

3. DL for BPE

An artificial neural network (ANN) must be implemented to extract behavioral decision sequences, as these sequences exhibit complex temporal dependencies and context-sensitive patterns [14-16]. In the context of the present study, a DL is built that maps recorded action sequences to hidden behavioural models while remaining coherent with cognitive limits. Each decision sequence is $\mathcal{D} = \{(s_t, a_t, r_t)\}_{t=1}^T$, where $s_t \in \mathbb{R}^{d_s}$ is the experimental state, $a_t \in \mathcal{A}$ the selected action, and $r_t \in \mathbb{R}$ is the received reward. These different data sets are converted into an identical embedding space by the method of input encoding:

$$e_t = W_{emb}[s_t; \text{one-hot}(a_t); r_t] + PE(t) \quad (7)$$

where $W_{emb} \in \mathbb{R}^{d_e \times (d_s + |\mathcal{A}| + 1)}$ is the embedding matrix; $PE(t)$ is positional encoding for temporal memory. The DL deploys bidirectional LSTM to capture planning and backwards-reasoning patterns. The forward and backwards hidden states are computed as:

$$h_t^{\rightarrow} = \text{LSTM}(e_t, h_{t-1}^{\rightarrow}; \theta_{fwd}) \quad (8)$$

$$h_t^{\leftarrow} = \text{LSTM}(e_t, h_{t+1}^{\leftarrow}; \theta_{bwd}) \quad (9)$$

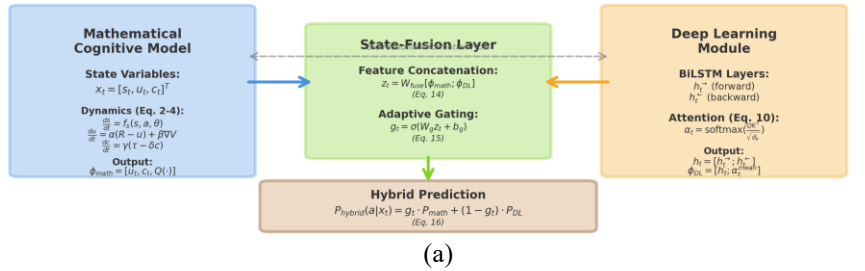
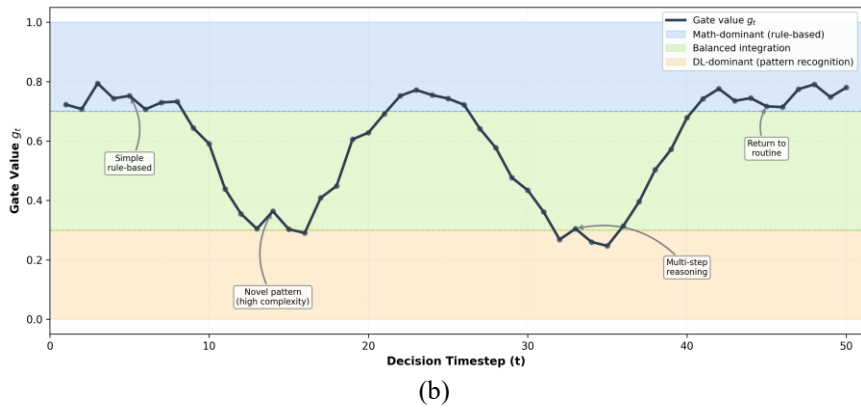


Figure 1
Model for hybrid DE-SQP optimization

To encode the complete set of temporal context at each decision point, the linked encoding $h_t = [h_t^{\rightarrow}; h_t^{\leftarrow}] \in \mathbb{R}^{2d_h}$ is to be used. The proposed research includes a multi-head attention mechanism to model cognitive salience and attention allocation.

In particular, the factors that follow:

$$\text{Attention}(Q, K, V) = \text{SoftMax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (10)$$

where queries are $Q_t = h_t W_Q$; keys are $K = H W_K$; values are $V = H W_V$ with $H = [h_1, \dots, h_T]$. The attention values can attain a measure of the value of past decisions to the current state, as $\alpha_t = \text{SoftMax}(Q_t K^T / \sqrt{d_k})$, which is used as a measure of cognitive load. The objective of the training is to link the accuracy of prediction with the periodicity that results from cognitive rules:

$$\mathcal{L}_{total} = \mathcal{L}_{pred} + \lambda_{cog} \mathcal{L}_{cog} + \lambda_{reg} \mathcal{L}_{reg} \quad (11)$$

where $\mathcal{L}_{pred} = -\sum_{t=1}^T \log P(a_t | h_t)$ measures action prediction loss, $\mathcal{L}_{cog} = \sum_{t=1}^T \|\hat{c}_t - c_t^{math}\|^2$ applies alignment with the accurate cognitive load from Eq. (4), and $\mathcal{L}_{reg} = \|\theta\|_2^2$ avoids overfitting.

4. Hybrid Mathematical–DL Integration

A principled coupling method that supports interpretability while also improving predictive accuracy is essential for integrating mathematical cognitive models with DL models. The findings from this study led to the evolution of a bidirectional data flow (Figure 1(a)). In this data flow, mathematical state variables determine neural network predictions, and patterns learned from experience improve cognitive variables. The state-fusion layer integrates neural and cognitive feature selection for the subsequent objectives:

$$\phi_{math}(x_t) = [u_t, c_t, Q(x_t, a_1), \dots, Q(x_t, a_{|\mathcal{A}|})] \quad (12)$$

$$\phi_{DL}(h_t) = [h_t; \alpha_t^{mean}] \quad (13)$$

$$z_t = W_{fuse}[\phi_{math}(x_t); \phi_{DL}(h_t)] + b_{fuse} \quad (14)$$

whereas, a DL correlate for cognitive load is indicated by the average attention weight, which is specified by the symbol α_t^{mean} . In the cognitive model, the logical features ϕ_{math} serve as the basis for encoding value predictions and Q-values. On the other hand, the neural features called ϕ_{DL} . They are vital for encoding trained temporal patterns and attention-based salience. *Proof 1:* To dynamically balance model input based on the parameters of the objective, an adaptive gating mechanism is applied.

$$g_t = \sigma(W_g z_t + b_g) \in [0, 1] \quad (15)$$

$$P_{hybrid}(a | x_t) = g_t \cdot P_{math}(a | x_t) + (1 - g_t) \cdot P_{DL}(a | h_t) \quad (16)$$

For decisions defined by rules, the gate ‘gt’ is trained to provide the RNN a higher weight, while for more CST, the subject pays more attention to the DL. This dynamic behavior (Figure 1(b)) follows a standard decision sequence. In this sequence, ‘ $g_t > 0.7$ ’ when working on rule-based tasks that are regular, and

' $g_t < 0.3$ ' when finding new patterns involving significant temporal analysis. To maintain cognitive reliability, this work enforces temporal alignment between mathematical and neural state estimates using a prediction constraint:

$$\mathcal{L}_{align} = \sum_{t=1}^T \|W_{proj}h_t - x_t^{math}\|^2 \quad (17)$$

where $W_{proj} \in \mathbb{R}^{d \times 2d_h}$ projects neural hidden states to cognitive state space. This ensures that learned representations remain interpretable by cognitive theory, with neural embeddings h_t maintaining correspondence to symbolic state variables x_t^{math} .

The hybrid model presents good computational features. Let $F: \mathbb{R}^d \rightarrow \mathbb{R}^d$ is the mathematical update operator and $G: \mathbb{R}^{2d_h} \rightarrow \mathbb{R}^{2d_h}$ the neural recurrent update.

The coupled dynamics evolve as:

$$x_{t+1} = F(x_t, a_t) + \eta_1 W_{proj} G(h_t) \quad (18)$$

$$h_{t+1} = G(h_t, e_{t+1}) + \eta_2 W_{inject} F(x_t, a_t) \quad (19)$$

where $\eta_1, \eta_2 \in (0,1)$ control coupling strength. Eq. (18) allows neural patterns to perturb the progress of cognitive states, while Eq. (19) imposes mathematical constraints on recurrent dynamics.

Theorem 2 (Convergence of Hybrid Model): *Suppose F and G are Lipschitz continuous with constants L_F and L_G , and the projection matrices satisfy $\|W_{proj}\| \leq M_1$, $\|W_{inject}\| \leq M_2$. If the coupling parameters satisfy:*

$$\eta_1 M_1 L_G < 1 - L_F \text{ and } \eta_2 M_2 L_F < 1 - L_G \quad (20)$$

Then the coupled network (18-19) converges exponentially to a unique fixed point (x^, h^*) at rate $\lambda = \max\{L_F + \eta_1 M_1 L_G, L_G + \eta_2 M_2 L_F\}$.*

Proof 2: Define the joint state $\xi_t = [x_t; h_t] \in \mathbb{R}^{d+2d_h}$ and the composite operator:

$$\Phi(\xi_t, a_t, e_{t+1}) = \begin{bmatrix} F(x_t, a_t) + \eta_1 W_{proj} G(h_t) \\ G(h_t, e_{t+1}) + \eta_2 W_{inject} F(x_t, a_t) \end{bmatrix} \quad (21)$$

For any two joint states $\xi_1 = [x_1; h_1]$ and $\xi_2 = [x_2; h_2]$, This study has:

$$\begin{aligned} \|\Phi(\xi_1) - \Phi(\xi_2)\|^2 &= \|F(x_1) - F(x_2) + \eta_1 W_{proj}(G(h_1) - G(h_2))\|^2 \\ &\quad + \|G(h_1) - G(h_2) + \eta_2 W_{inject}(F(x_1) - F(x_2))\|^2 \end{aligned} \quad (22)$$

Applying Lipschitz continuity and triangle inequality:

$$\begin{aligned} \|F(x_1) - F(x_2) + \eta_1 W_{proj}(G(h_1) - G(h_2))\| &\leq L_F \|x_1 - x_2\| \\ &\quad + \eta_1 M_1 L_G \|h_1 - h_2\| \end{aligned} \quad (23)$$

$$\begin{aligned} \|G(h_1) - G(h_2) + \eta_2 W_{inject}(F(x_1) - F(x_2))\| &\leq L_G \|h_1 - h_2\| \\ &\quad + \eta_2 M_2 L_F \|x_1 - x_2\| \end{aligned} \quad (24)$$

Combining these bounds:

$$\|\Phi(\xi_1) - \Phi(\xi_2)\| \leq \rho \|\xi_1 - \xi_2\| \quad (25)$$

where $\rho = \max\{L_F + \eta_1 M_1 L_G, L_G + \eta_2 M_2 L_F\}$. Under condition (20), $\rho < 1$, establishing Φ as a contraction mapping. By the Banach fixed-point theorem, a unique fixed point $\xi^* = [x^*; h^*]$ exists satisfying $\Phi(\xi^*) = \xi^*$, and the iteration converges exponentially: $\|\xi_t - \xi^*\| \leq \rho^t \|\xi_0 - \xi^*\|$.

5. Hybrid Mathematical–DL Integration

5.1 Dataset Description

This work evaluates our hybrid model on the Iowa Gambling Task (IGT) dataset, a standard benchmark for sequential HDM under uncertainty. This work uses the publicly available dataset from Steingroever et al. (2015), comprising $N = 617$ healthy adults (ages 18-65 years) who each completed 100 trials, 61,700 decision sequences. At each trial ' t ', participants select from four decks, receiving an immediate reward as r_t^+ and probable loss as r_t^- , with net outcome as $r_t = r_t^+ + r_t^-$. In the end, there is a conflict between short-term gratification and long-term optimization in the C/D outcome, resulting in a mean of +50 with fewer significant losses (the predictable value is >25). Decks A and B not only generate high rewards (100), but they also generate significant losses (the predicted value is less than 25 per 10 trials). Decks C/D generate median values (>50) with more significant losses (the highest number that can be predicted is 25). State representation comprises $s_t = [h_t^A, h_t^B, h_t^C, h_t^D, c_t^{sum}, n_t, \Delta_t]^T \in \mathbb{R}^7$, where h_t^{deck} is cumulative results, c_t^{sum} total capital, and Δ_t recent reward trend. Cognitive load indicators derive from response times (RT) (mean: 2.14 *seconds*, SD: 1.37 *seconds*). Learners (68%), non-learners (22%), and explorers (10%) were accepted as the 3 types of learning reported by participants. The process of collecting data is typically divided into 3 distinct phases: exploration (trials 1-40), transition (41-70), and exploitation (71-100). The data partitioning method uses a user-specific 70/15/15 split, allocating 432, 93, and 92 test users to validation, training, and testing. The following method is made to ensure that the results are adaptable across all behavioral features.

5.2 Evaluation Metrics

The model's performance is measured in the present study using 4 metrics that are similar to one another. Predictions and prediction accuracy support the selection of the correct deck to use:

$$Acc = \frac{1}{N} \sum_{i=1}^N \mathbb{1}[a_i = \hat{a}_i] \quad (26)$$

The standardized editing distance serves as the basis for determining the Sequence Coherence Score (SCS) to assess overall similarity between pairs, capturing method consistency beyond point-wise accuracy.

$$SCS = \frac{1}{N} \sum_{i=1}^N \exp(-d_{edit}(seq_i, \widehat{seq}_i)/T_i) \quad (27)$$

The linking between predicted and actual cognitive load is what the Cognitive State Divergence (CSD) statistically analyzes.

$$CSD = \frac{1}{T} \sum_{t=1}^T \|c_t^{pred} - c_t^{RT}\|_2 \quad (28)$$

where c_t^{RT} is derived from RT patterns. Pearson's correlation coefficient is employed to assess the quality of temporal prediction provided by RT correlation:

$$r_{RT} = \frac{\text{Cov}(RT_{pred}, RT_{obs})}{\sigma_{RT_{pred}} \sigma_{RT_{obs}}} \quad (29)$$

validating the cognitive plausibility of model dynamics.

5.3 Results and Discussion

The IGT test dataset (Figure 2 (a)) provides an in-depth analysis of the performance of the baseline vs the proposed models. The proposed model, which has been approved, achieves a prediction accuracy of 84.7%, which is far superior to the results of accurate mathematical models (72.3-74.8%) and valid DL models (78.9-81.2%) (Figure 2 (b)).

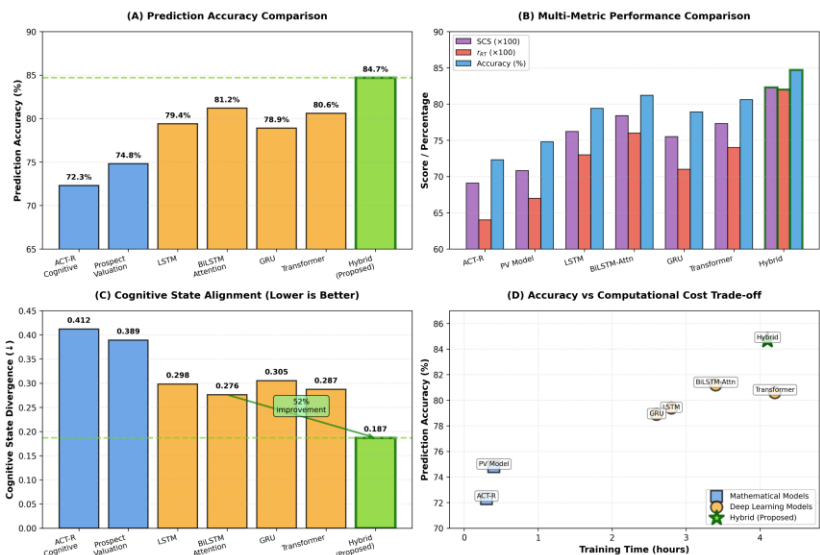


Figure 2
Performance Analysis Across Methods

The pairwise t -test was achieved to verify statistical significance (p -value < 0.001) and a Cohen's d of 0.89. Figure 2 (c) proves an impressive cognitive state alignment with a CSD value of 0.187, which signifies a 52% boost over the baseline value for the best performance (0.276). An optimal balance is achieved through the accuracy-efficiency trade-off (Figure 2(d)), which shows that 4.1 hours of training time yields 4.1% higher accuracy than the best DL. The temporal behaviour model has been supported by the RT correlation ($r_{RT} = 0.82$), with peak performance occurring between transition phases (trials 41-70; accuracy 86.3%), indicating that time-based and pattern-based reasoning are essential.

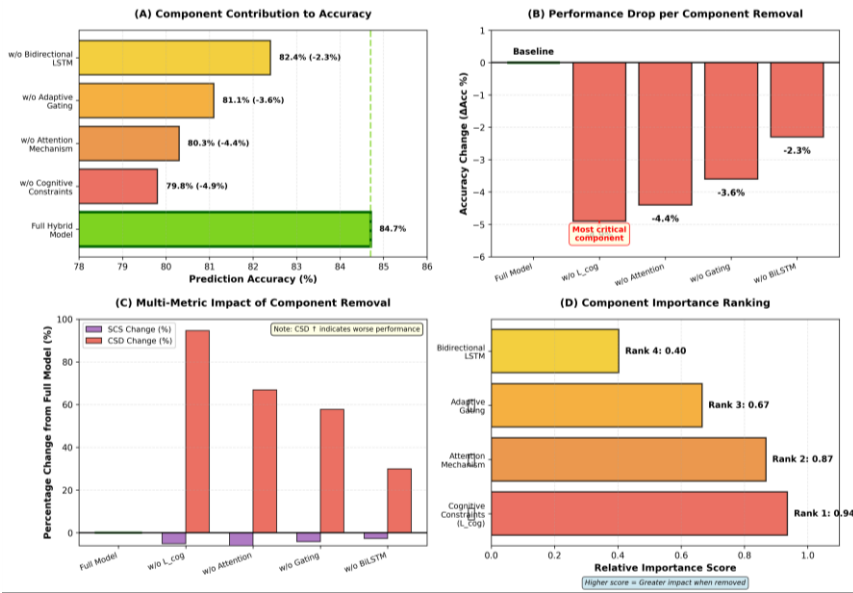


Figure 3
Ablation Study Analysis

In Figure 3(a), the ablation study findings reveal the impact of key components. In Figure 3(b), cognitive constraints (L_{cog}) are identified as particularly significant, leading to a 4.9% decrease in accuracy when these factors are removed. Attention mechanisms are identified as the second, accounting for 4.4% of the decrease. Validation of the multi-metric impact (Figure 3(c)), showing that eliminating cognitive limits results in a 95% increase in CSD and a significant reduction in cognitive validity. The components are listed proportional to their level of value in Figure 3 (d), which includes (i) cognitive constraints, (ii) attention, (iii) adaptive gating, and (iv) bidirectional LSTM algorithms. The gating mechanism presents behavior that can be determined, with high ' g_i ' values (>0.75) during misuse phases and low values (<0.35) during exploration. This behaviour reinforces the dual-process HDM theory and provides behavioural validity beyond prediction accuracy.

6. Conclusion and Future Work

A newly developed hybrid model that integrates mathematical cognitive models with DL has been described in this research work. The objective of this proposed model was to analyze HDM patterns in CST. This model achieves 84.7% prediction accuracy on the Iowa Gambling Task dataset while maintaining superior cognitive alignment ($CSD = 0.187$). This result shows that it is achieved by combining dynamical systems theory with BiLSTM-Attention networks that use adaptive gating mechanisms. The Banach fixed-point theorem contributed to the development of convergence guarantees, which reinforced the

rigour of theoretical analysis. Ablation studies proved that cognitive constraints and attention mechanisms are essential components. The hybrid model performed better than both pure mathematical models (12.4% improvement) and pure DL (3.5% improvement), proving that all of those elements are significant. Further development of continuously active regions, real-time individual-difference modelling via meta-learning, and applications in adaptive educational systems and cognitive healthcare testing for the early detection of HDM problems are all areas of future work.

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