Cognitive Decision-Making Neural Network Model Based on Evidence Accumulation

Authors: Chen Siyu, Pan Wanke, Hu Chuanpeng, Pan Wanke, 胡传鹏

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Abstract

Evidence accumulation models have achieved significant progress in the domain of reaction time modeling, but these models lack important processes such as stimulus encoding. By integrating artificial neural networks, researchers can extract stimulus features and embed them into the evidence accumulation process, thereby enabling full-process modeling from stimulus encoding, cognitive processing to decision-making responses. Cognitive decision neural network models based on evidence accumulation typically comprise three modules: stimulus processing, evidence accumulation, and decision judgment, which have demonstrated preliminary potential in multi-alternative decision-making, temporal stimulus processing, and neural activation simulation. Cognitive decision neural network models provide a novel approach for simulating the complete human decision-making process, and in the future, they may be integrated with digital twin brains to generalize to more complex decision-making scenarios, thereby advancing a deeper understanding of human cognition.

Full Text

Preamble

Cognitive Decision Neural Networks Based on Evidence Accumulation

Siyu Chen[1,2], Wanke Pan[1,2], Chuan-Peng Hu[1,2]

[1]School of Psychology, Nanjing Normal University, Nanjing 210097, China [2]Adolescent Education and Intelligence Support Laboratory, Nanjing Normal University, Jiangsu Provincial University Philosophy and Social Science Laboratory, Nanjing 210097, China

Abstract: Evidence accumulation models have made significant progress in modeling reaction times, but these models lack essential processes such as stimulus encoding. By integrating artificial neural networks, researchers can extract stimulus features and embed them into the evidence accumulation process, enabling full-process modeling from stimulus encoding, cognitive processing to decision responses. Cognitive decision neural networks based on evidence accumulation typically comprise three modules: stimulus processing, evidence accumulation, and decision judgment. These models have demonstrated preliminary potential in multi-alternative decision-making, temporal stimulus processing, and neural activation simulation. Cognitive decision neural networks provide a novel approach for simulating the complete human decision-making process. Future work may integrate these models with digital twin brains, generalize them to more complex decision-making scenarios, and advance our understanding of human cognition.

Keywords: cognitive process, evidence accumulation models, computational modeling, artificial neural networks

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1. Introduction

Reaction time serves as a crucial window for understanding human decision-making processes (Luce, 1986). Since Donders proposed the subtraction method in 1868, reaction time measurement and analysis methods have become central to experimental psychology, enabling researchers to infer the time required for cognitive operations by measuring reaction times across different tasks (Donders, 1969). With the evolution of cognitive science, reaction time analysis has evolved from a mere measurement tool to an important vehicle for theoretical modeling, and modeling reaction times has gradually become a key approach to understanding human decision-making processes (Ratcliff & McKoon, 2008).

Evidence accumulation models (EAMs) represent one of the primary computational frameworks for modeling reaction times (Ratcliff et al., 2016). The fundamental assumption of these models is that decision-makers continuously extract information from stimuli or memory, accumulating evidence relevant to the decision; when the accumulated evidence reaches a specific decision threshold, an observable response and reaction time are generated (Liu & Hu, 2024). This key assumption is supported by some neural data. For example, studies have shown that when macaque monkeys perform visual motion discrimination tasks, the firing rates of neurons in the motor cortex exhibit gradual accumulation, triggering behavioral decisions when the activity reaches a specific threshold (Shadlen & Kiani, 2013). This neural dynamic characteristic aligns highly with predictions from evidence accumulation models, suggesting that decision formation depends on the continuous integration of sensory evidence until it crosses the decision threshold. EAMs have various mathematical formulations and variants (collectively referred to as "EAMs" in this paper). The most classic among them is the Drift Diffusion Model (DDM), which implements evidence accumulation through a stochastic process model based on the Wiener process, specifically manifested as a combination of cumulative increments under a fixed drift rate parameter and Gaussian noise. This model can effectively explain the speed-accuracy trade-off, the asymmetry between correct and error response speeds, and the positively skewed phenomenon of reaction time distributions (Ratcliff & McKoon, 2008; Evans & Wagenmakers, 2020).

However, according to Marr's three-level framework of information processing (Three-Level Framework; Marr, 1982), EAMs remain essentially statistical models that describe decision behavioral outcome data, assuming the algorithm for the decision process only at an abstract level without providing a clear algorithmic description of the full process from stimulus encoding to decision response, nor a clear explanation of how the hardware level (neural circuits, molecular and cellular levels, etc.) implements the decision process (Duggins & Eliasmith, 2024; Lo et al., 2015). The computation explained by EAMs (i.e., the results of empirical research) is typically completed by the hardware of human or primate nervous systems. From this perspective, the evidence accumulation process described by EAMs is relatively independent of the complete process from encoding to decision-making in humans or primates (see Figure 1 [Figure 1: see original paper]) (Duggins & Eliasmith, 2024; Lo et al., 2015). Therefore, EAMs' approach of describing the decision process by adjusting model parameters fails to consider the impact of stimulus features and neural characteristics on behavioral outcomes. Given this, constructing a full-process model encompassing stimulus processing, evidence accumulation, and response output, and aligning human decision processes on non-biological hardware, represents an important issue in understanding human decision-making.

Artificial Neural Networks (ANN) provide the possibility for achieving full-process construction, and their combination with the evidence accumulation theoretical framework may push cognitive modeling to new heights (Saeed Reza Kheradpisheh et al., 2016; Wichmann & Geirhos, 2023; Rajalingham et al., 2022). On one hand, early artificial neural network research focused on pattern recognition as the primary problem. Deep Neural Network (DNN) models inspired by the structure of human sensory and perceptual cortices can complete visual stimulus encoding, compensating for EAMs' deficiency in sensory information processing. For example, the classic deep convolutional neural network AlexNet demonstrates excellent performance in image classification tasks on the challenging ImageNet dataset, and researchers have noted that the model could be optimized in the future to narrow the gap with the human visual system (Krizhevsky et al., 2017). On the other hand, brain-inspired artificial intelligence research is attempting to simulate biological neural circuits of the human brain or animal brain. For example, spiking neural network models constructed based on biological neural frameworks can already generate spike patterns similar to those of visual cortex neurons (Duggins & Eliasmith, 2024). This shows that artificial neural network models may help researchers implement the full process of decision-making behavior on silicon-based hardware (in silico), thereby providing powerful tools for understanding human decision-making processes.

Currently, a small number of studies have combined evidence accumulation models with artificial neural network models with preliminary success. Such models extract experimental stimulus features using artificial neural networks and embed the evidence accumulation process within the neural network, thereby constructing the full process from stimulus encoding, decision process to reaction time and decision outcomes, and attempting to further explore biological hypotheses about cognitive mechanisms. Below, we will first elaborate on the characteristics of cognitive decision neural networks from the perspective of full-process simulation of decision-making, then introduce existing research, analyze their applications, advantages, and limitations, and finally provide an outlook for future cognitive decision neural network models.

2. Cognitive Decision Neural Networks Based on Evidence Accumulation

The main characteristic of cognitive decision neural networks is to expand the theoretical framework of traditional evidence accumulation models, combine them with the functions of artificial neural networks, and construct full-process models from stimulus input to decision output, thereby enabling the simulation of human cognitive processes on silicon-based hardware (see Figure 1). This section will first introduce the core concepts of evidence accumulation models, and then elaborate on the possibilities of combining artificial neural networks with evidence accumulation models.

2.1. Key Assumptions of Evidence Accumulation in Cognitive Models

Evidence accumulation models have been applied to various research paradigms, involving perceptual decision-making, value-based decision-making, and social decision-making (Lee & Usher, 2023; Tump et al., 2020). These models contain two core mechanisms: the evidence accumulation process and the decision mechanism. The evidence accumulation mechanism quantifies the process of continuously accumulating valid information over time through a decision variable (DV); the decision mechanism quantifies the amount of evidence required for decision-making through a decision boundary, thereby explaining when decision-makers make decisions (Liu & Hu, 2024). The speed of evidence accumulation and the range of the decision boundary jointly determine the reaction time of decisions (Boag et al., 2025; Pan et al., 2025).

The evidence accumulation process and decision mechanism of evidence accumulation models are supported by neurobiological research findings (Gold & Shadlen, 2007). For example, Roitman and Shadlen (2002) trained macaque monkeys to judge the direction of random dot motion and found that when the random dots began moving toward the target direction, the firing rates of neurons in the lateral intraparietal area (LIP) gradually increased at a specific rate, and when the firing rate reached its peak, the monkeys would make corresponding responses, similar to the evidence accumulation method. Lo and Wang (2006) discovered that the superior colliculus (SC) brain region might be a key structure implementing the decision threshold mechanism, hypothesizing that during the decision process, the SC brain region is specifically responsible for terminating decisions. When the evidence amount has not reached the decision threshold, the activation level of the SC brain region is low, but when the evidence amount reaches a fixed threshold, the SC brain region becomes activated to control the LIP brain region to stop evidence accumulation. This hypothesis has been confirmed in random dot motion (RDM) tasks. For example, Stine et al. (2023) found that the firing rates of neurons in the LIP brain region continuously increased with stimulus presentation and peaked at the time of response, while the firing rates in the SC brain region suddenly rose to a peak just before the response, with almost no difference in peak values across different response times, providing evidence for the assumption of a fixed decision boundary.

2.2. From Evidence Accumulation to Full-Process Decision Modeling

Traditional cognitive modeling only provides statistical descriptions of the decision process to better fit the pattern of human decision behavioral outcome data, with less involvement of other processes such as sensory information processing. Full-process modeling of decision-making requires starting from sensory information encoding to decision output. To achieve this kind of full-process modeling, cognitive decision neural networks should include at least three main modules (see Figure 2 [Figure 2: see original paper]): stimulus processing and feature extraction module, evidence accumulation and decision judgment module, and reaction time output module. The stimulus processing and feature extraction module mainly handles stimulus encoding, converting sensory information into decision evidence; the evidence accumulation and decision judgment module mainly solves how to achieve evidence accumulation and obtain decision judgment; the reaction time output module is responsible for aligning model decision times with human decision times. Below is a detailed elaboration of the implementation process of cognitive decision neural networks:

The first module of cognitive decision neural networks is data conversion and feature extraction of experimental stimuli. To be compatible with stimulus processing processes in decision tasks, model inputs are often complex data, such as random dot motion, noisy images, or real images. Artificial neural networks achieve temporal mapping and feature extraction of stimulus x through their algorithms (see Appendix 1):

$$e_t = f_\theta(x)_t, \quad t = 1, 2, ..., T$$

where f_θ is a neural network with parameters θ, and e_t is the mapping result of the stimulus at time point t. The processed data not only has "temporality," which can be understood as the amount of stimulus perceived per unit time, but also has "representativeness," reflecting the core features of experimental stimuli. Cognitive decision neural networks use this data as the decision variable at time t, i.e., the evidence value e_t in the decision process. In the theoretical assumptions of evidence accumulation models, evidence refers to the abstract representation obtained after encoding and converting various information related to decision-making. In EAMs, it is specifically manifested as cumulative increments under a fixed drift rate parameter (Liu & Hu, 2024). Similarly, the "evidence" in this paper refers to the latent variable extracted by neural network algorithms that serves decision-making and accumulates over time.

The evidence accumulation and decision judgment module is used to implement the evidence accumulation and decision judgment process. This module is the core of integrating the evidence accumulation model theoretical framework into artificial neural networks. Specifically, cognitive decision neural networks often need to pre-set a decision threshold value (β), similar to the decision boundary parameter in DDM. At the same time, sensory information at different moments is accumulated across the time dimension through integration to achieve the evidence accumulation process, as shown in Equation 2. Once the accumulated evidence amount reaches or exceeds the decision threshold β, the model makes a decision judgment, as shown in Equation 3, and outputs the corresponding decision time, as shown in Equation 4.

$$S_t = \sum_{i=1}^{t} e_i$$

$$\text{Decision} = \arg\min\{t \mid S_t \geq \beta\}$$

$$\text{RT} = \min\{t \mid S_t \geq \beta\}$$

The final module is responsible for adjusting the model's final reaction time output. This requires optimizing the parameters of the data conversion and feature extraction module (such as weights) to evaluate the connection between experimental stimuli and evidence values, ensuring that the model's reaction time can reflect the same cognitive decision characteristics as humans. After initially obtaining its decision time output, two methods are often used for parameter optimization: (1) Parameter fitting using a loss function: $\mathcal{L} = (\text{RT} - \text{RT}_{\text{human}})^2$, adjusting it in backpropagation: $\theta \leftarrow \theta - \eta\nabla_\theta\mathcal{L}$, so that it can ultimately output the same reaction time as humans; (2) Based on variational inference, introducing an approximate posterior distribution $q(\theta;\phi)$ to approximate the true posterior distribution $p(\theta|\text{RT}_{\text{human}})$, where ϕ is the variational parameter. The core lies in minimizing the difference between the two, usually measured using Kullback-Leibler divergence: $\text{KL}(q(\theta;\phi)\|p(\theta|\text{RT}_{\text{human}}))$.

In summary, cognitive decision neural networks integrate artificial neural network algorithms with evidence accumulation model theory. By processing input experimental stimuli, directly extracting features, and using output reaction time as the core indicator, they achieve full-process modeling of decision-making, providing the possibility for comprehensive modeling across the three levels of hardware-algorithm-computation.

3. Current Status and Examples of Cognitive Decision Neural Networks

Researchers have preliminarily applied cognitive decision neural networks to simple perceptual decision-making, achieving full-process modeling from sensory stimulus reception to decision judgment, demonstrating unique advantages over traditional models. This study will illustrate three different types of application examples: simulation of multi-alternative perceptual decisions, simulation of dynamic temporal perceptual decisions, and decision simulation based on neural firing (see Table 1).

Table 1 Examples of Cognitive Decision Neural Network Models

Model	Artificial Neural Network	Evidence Accumulation Process	Reflection of Cognitive Decision Characteristics
RTNet (Rafiei et al., 2024)	Bayesian neural network	Competition model. Evidence accumulation according to weight probability distribution; decision made when evidence accumulation for an option exceeds threshold	Speed-accuracy trade-off, effect of task difficulty on speed and accuracy, confidence level in correct vs. error trials
RTify (Cheng et al., 2024)	Convolutional recurrent neural network (CovLSTM)	Feature value accumulation. Mapping hidden layer feature values to evidence values and accumulating; decision made when threshold exceeded, with corresponding time step determined as decision time point	Speed-accuracy trade-off under task difficulty

Model	Artificial Neural Network	Evidence Accumulation Process	Reflection of Cognitive Decision Characteristics
SN-DM (Duggins & Eliasmith, 2024)	Spiking neural network	Value evaluation. Mapping sensory stimuli to decision variables and cumulative integration. When decision variable exceeds threshold, model's action population neurons become active, decoding decision behavior	Speed-accuracy trade-off

3.1. RTNet: Multi-Alternative Perceptual Decision Simulation

Traditional Convolutional Neural Networks (CNN) can achieve multi-classification tasks, but their output is mainly determined by the model's internal weights after training. Since the model weights no longer change after training, the model's output exhibits mechanical determinism—that is, for the same stimulus input, the model produces consistent output due to the fixed nature of the weights. Additionally, traditional CNNs struggle to reflect the relationship between stimuli and reaction time, as the computation time required for processing different stimuli is almost constant, exhibiting staticity and lacking the ability to model temporal dynamics.

Taking the performance of convolutional neural networks on handwritten digit classification with the MNIST dataset (Deng, 2012) as an example, different variations of the same digit (such as different open-top/closed-top writing styles of "4") introduce uncertainty into human decision-making processes, which affects decision performance. If decision-makers want to respond quickly, they may guess, resulting in fast but more error-prone judgments; conversely, if they want to improve accuracy, they may slow down their decision speed. However, the "decision" of convolutional neural networks is only determined by static weights corresponding to stimulus features, and their reaction speed depends only on hardware running speed, independent of the stimulus itself. To reflect the speed characteristics of human decision-making, Rafiei et al. (2024) proposed the RTNet model to simulate the relationship between uncertainty and reaction time in human perceptual decision-making.

The RTNet model uses Bayesian Neural Networks (BNN) as the stimulus processing and feature extraction module. Based on the AlexNet architecture for image processing, it introduces multiple possible parameter combinations through probabilistic methods to convert visual stimulus input into evidence values, simulating the impact of random evidence fluctuations on human decision-making processes and achieving quantification of uncertainty.

Specifically, after stimulus input, the Bayesian neural network processes it through continuous forward propagation processes across multiple time steps. During each processing step, the weights and biases of the neural network are sampled from posterior distributions approximating the true distribution, causing the evidence values at each time step to change randomly under the same stimulus. When constructing the evidence accumulation and decision judgment module, RTNet draws on the Race-Model approach from evidence accumulation models to implement absolute evidence accumulation—that is, each response option corresponds to a separate evidence accumulator. When one accumulator exceeds a predefined threshold, it outputs a decision and reaction time. By calculating the evidence difference between the selected option and the second-best option, it obtains a confidence level similar to human decision-making confidence, with larger differences indicating higher confidence levels.

Rafiei et al. (2024) used the MNIST dataset as experimental stimuli, containing 60,000 training images and 10,000 test images of handwritten digits from 0 to 9. Researchers randomly selected 480 images for experimental tasks and obtained stimuli images with high and low signal-to-noise ratios by adding Gaussian noise or motion blur kernels. In behavioral experiments, participants received two different instructions: either to respond quickly or to respond accurately, to manipulate their response strategies. After responding, participants also needed to report their confidence level. Each round of stimulus presentation included 4 conditions, with 120 images per condition. Participants underwent two rounds of experiments with the same stimulus images but randomly changed experimental conditions, thereby obtaining human perceptual decision-making data.

Researchers set the model to reasonably adjust decision time according to image complexity (i.e., task difficulty) while outputting confidence values for digit recognition judgments to simulate human confidence levels during decision-making. During the training phase, the posterior distribution of Bayesian neural network weights needed to be adjusted to approximate the true distribution, ensuring RTNet had effective generalization ability for image data recognition. For this, the model used variational inference methods to train the Bayesian neural network on the MNIST dataset, achieving over 97% classification accuracy for handwritten digit images as a core indicator of the model's ability to recognize images. In the testing phase, RTNet's output reaction time and confidence level were used as core indicators to evaluate its simulation of the decision process.

Test results showed that RTNet can achieve decision simulation for multi-alternative tasks, demonstrating differences among options by evaluating the likelihood of each digit being the correct option and comprehensively considering evidence accumulation for each option caused by experimental stimuli. As a cognitive decision neural network, it uses AlexNet for visual stimulus encoding and Bayesian neural networks to simulate noisy evidence accumulation processes in human decision-making, solving the problem that traditional EAMs cannot perform visual encoding. Its results can exhibit the same cognitive decision characteristics as humans (such as speed-accuracy trade-off, decreased accuracy caused by increased task difficulty, and higher confidence levels in correct trials than in error trials), meaning the model simulates human perceptual decision-making to some extent under this task.

3.2. RTify: Dynamic Temporal Decision Simulation

Although RTNet can explain human perceptual decision-making results for ambiguous stimuli, the stimuli themselves are static—that is, from stimulus onset to participant response, the physical features of the stimulus do not change. However, in real life, the physical features of stimuli may also change continuously. In classic random dot motion tasks, the positions of random dots change constantly. Humans can make perceptual judgments about continuously changing stimuli, but RTNet, due to its fixed parameters after each random weight sampling, struggles to explain the impact of continuous stimulus changes on cognitive processes over time (Rafiei et al., 2024). To address this limitation, Cheng et al. (2024) constructed the RTify model, which introduces a time-step-varying evidence accumulation process to account for evidence accumulation in temporal stimuli.

The main difference between RTify and RTNet is its ability to perform feature extraction from temporal stimuli to form latent variables (i.e., evidence values). RTify uses convolutional recurrent neural networks for stimulus processing and feature extraction: the network includes a Long Short-Term Memory (LSTM) layer that can flexibly adjust time steps and a convolutional layer that can reflect the integration process of visual stimuli. Its evidence accumulation module mainly consists of a defined evidence function and evidence accumulator, used to transform temporal stimulus features into evidence values. Specifically, the model first achieves dynamic mapping from stimulus features to evidence values through linear transformation of the fully connected layer and nonlinear transformation of the activation function in the evidence function. It then accumulates the mapped evidence values into the evidence accumulator across time steps. When the accumulated evidence value crosses the predefined decision boundary, a decision judgment is made. Finally, by calculating the difference in evidence accumulation between adjacent time steps as the basis for adjusting model reaction time, it achieves alignment with temporal stimuli, converting model time steps into reaction time output.

The study used random dot motion tasks to present continuous stimulus changes and altered task difficulty by adjusting motion coherence (i.e., the proportion of dots moving in the same direction) to explore the cognitive mechanisms of speed and accuracy. Participants needed to integrate motion dot information and provide direction judgments when sufficiently confident, using their reaction time and accuracy as core indicators. For the model, input stimuli first underwent feature extraction in the convolutional layer and were integrated into feature values of the hidden state in the LSTM layer, serving as latent variables for evidence conversion to ensure that accumulated evidence was consistent with stimulus changes. Then, through the defined evidence function (including fully connected and activation functions), hidden state feature values were mapped to evidence values per unit time step (i.e., decision variables). Based on the recurrent connection structure of the LSTM layer, it incorporated a nonlinear evidence accumulation process. When the sum of evidence accumulation reached the decision boundary, the model made a judgment. Finally, during backpropagation, the difference in evidence accumulation between adjacent time steps was introduced as a factor influencing weight adjustments, simulating dynamic changes in decision variables affected by stimuli. A regularization term was added to cross-entropy loss to maximize accuracy while minimizing model decision time, simulating the decision characteristic that correct trials have faster reaction times than error trials, to achieve final reaction time and decision judgment output.

During the training phase, the model needed to fit human reaction time and accuracy in random dot motion tasks, with experimental data from approximately 40,000 trials completed by 21 participants over four consecutive days. During the testing phase, RTify needed to complete visual classification tasks, using 20 natural images and 112 artificially synthesized images with different backgrounds and object positions from the COCO dataset (Lin et al., 2014) as experimental stimuli, and collected reaction times and decision accuracy from 88 human participants to compare with model output. Finally, researchers extended the experiment by applying RTify to the biophysically realistic cortical network Wong-Wang model (Wong & Wang, 2006), which performs excellently in visual tasks. By testing it on the above random dot motion task and visual classification task, they explored whether a decision model with biological plausibility and supporting multi-category processing could be developed.

Test results showed that RTify can exhibit speed-accuracy trade-off under temporal stimulus changes, adjusting the number of time steps required for decision-making as output reaction time according to task difficulty and accuracy, reflecting the dynamic change process of human cognition and achieving alignment with human reaction time in the temporal dimension. In the final experimental extension, the integrated model, due to its excellent performance under complex stimuli and multi-classification tasks, helps promote comprehensive understanding of brain mechanisms behind dynamic vision. RTify is an improvement over RTNet. Its cortex-like processing network architecture provides more comprehensive simulation of how changes in neural activity for stimulus encoding affect the evidence accumulation process, solving the problems that traditional EAMs cannot encode visual stimuli and lack evidence accumulation algorithms.

3.3. SN-DM: Decision Simulation Based on Neural Firing

Although RTNet and RTify use deep neural networks that can effectively process complex stimulus features, they struggle to directly simulate the neural mechanisms of decision-making. The reason is that deep neural networks are not directly built based on or completely simulating the cellular architecture of the human brain cortex, making it impossible to explore the neural origins of cognitive decision-making from the bottom up (Moustafa et al., 2015). Researchers have pointed out that Spiking Neural Networks (SNN) based on the Neural Engineering Framework (NEF) can generate single-neuron activity patterns highly consistent with visual brain regions such as the lateral intraparietal area (LIP) and superior colliculus (Lo et al., 2015; Shen et al., 2023), providing support for neural coding theories behind decision variables (Steinemann et al., 2022; Stine et al., 2023). Given this, Duggins et al. (2024) constructed a spiking neural decision-making model (referred to as SN-DM in this study), aiming to explore the role of neuron-level spike signals and different functional nuclei in evidence accumulation.

Specifically, SN-DM consists of spiking neural populations and a non-neural component. The non-neural component processes sensory input to simulate possible noise when stimuli are input. The spiking neural populations include sensory populations, memory populations, value populations, gating populations, and action populations. Among them, the encoding and extraction module for input experimental stimuli is composed of sensory populations; memory populations and value populations constitute the evidence accumulation module; and gating populations and action populations constitute the decision judgment module. Taking the random dot motion task as an example, SN-DM first generates perceptual estimates based on the motion coherence of random dots through the non-neural component and introduces noise as experimental stimulus input. The sensory population then performs distributed encoding of input stimuli in the spatial dimension for option comparison, analogous to neuronal direction selectivity. After feature extraction, it is passed to the memory population, which, due to its recurrent connection structure, implements evidence accumulation of perceived (dot) motion intensity information over the temporal dimension. Next, the value population performs value calculations based on the sum of evidence accumulation from the memory population, outputting the current evidence strength for each option, and determines whether the evidence accumulation type is based on absolute evidence (when $L = 0$), relative evidence (when $L = 1$), or a mixture of both ($0 < L < 1$) through its parameter L. Finally, when the evidence strength exceeds the decision threshold T, the model overcomes inhibitory signals from the gating population, making neurons in the action population active and decoding an action to make a decision. The entire time interval from stimulus presentation to decision-making by the action population is the model's reaction time.

During the training phase, the model adjusts parameters by fitting reaction times from macaque behavioral data (from Hanks et al., 2014). During the testing phase, Duggins et al. (2024) first had the model simulate macaque behavior in random dot motion tasks under speed or accuracy emphasis instructions and evaluated whether it could be applied to multi-alternative tasks. By adjusting the decision threshold T, the model needed to judge the main motion direction of random dots, with task difficulty determined by motion coherence. During this process, the model's reaction time and accuracy were recorded to verify whether the model could capture core indicators of speed-accuracy trade-off behavior and determine whether the model's neuronal activity was consistent with actual neural and behavioral data from macaques (both from Churchland et al., 2008). Furthermore, to explore how low-level biological changes affect high-level cognitive performance, researchers attempted to apply SN-DM to simulate the effects of aging on decision-making processes. By artificially reducing synaptic connections between sensory and memory populations, they constructed "elder models" to simulate neurodegenerative characteristics caused by aging. Meanwhile, based on reaction time data from 18-year-old healthy participants collected in Forstmann et al. (2011), they constructed "young models" that could fit reaction times and predict decision accuracy as a baseline. In random dot motion task testing, differences in reaction time and accuracy output between the two models were compared to attempt to explain the impact of biological degradation on cognitive function. Finally, the model was applied to non-perceptual decision simulation in stock market tasks to explore decision characteristics driven by task rewards (speed-accuracy trade-off) and higher-order cognitive strategies exhibited by individuals (reflected in frequent use of different strategies to complete tasks). Due to obvious differences from random dot motion tasks, researchers first selected reaction times of participants showing different strategies (slow but accurate, medium, fast but inaccurate) from human decision datasets in stock market tasks (from Fiedler et al., 2021) as training data, setting model parameter fitting under medium difficulty conditions. In the testing phase of this task, the trained model was applied to easy and difficult conditions to evaluate the model's predicted reaction time and accuracy.

Test results showed that SN-DM can simulate random dot motion tasks with different task difficulties and multi-alternative decisions, non-perceptual stock market tasks, and the effects of aging on decision-making processes. The model not only exhibits similar neuronal activation patterns at the biological level but also shows speed-accuracy trade-off characteristics corresponding to tasks or situations at the cognitive level. The research team explained at the neuronal level, based on synaptic weight magnitudes in SN-DM, how different evidence trade-off methods (absolute or relative), noise levels, and complex cognitive tasks affect speed and accuracy. Notably, by introducing adjustable relative valuation parameter L and decision threshold T, the model can achieve switching or mixing between absolute and relative evidence accumulation processes, while RTNet and RTify only simulate absolute evidence accumulation processes. SN-DM encodes "evidence" related to multiple tasks through spiking neural populations, enabling simulation of more human decision-making processes, representing a direction worthy of in-depth exploration in the future.

4. Summary and Outlook

As one of the key outcome variables when humans and animals make decisions, reaction time provides a unique window for observing the cognitive and neural foundations behind decision-making, offering valuable experience for understanding the neurobiological mechanisms and cognitive processes of decision-making (Gold & Shadlen, 2007; Luce, 1986). Cognitive decision neural networks further expand the evidence accumulation framework, achieving full-process modeling of cognitive decision-making, simulating human encoding of stimuli and key outputs of decision-making: reaction time and choice, providing researchers with new methods for understanding human decision-making processes. Currently, such models have initially achieved human perceptual decision-making characteristics such as multi-alternative decision-making, dynamic temporal processing, and "speed-accuracy trade-off," laying a solid foundation for subsequent research. Although the three different application examples listed in this paper still have limitations, future researchers can achieve comprehensive understanding of cognitive decision-making mechanisms by replacing and updating each module corresponding to the content in the cognitive decision neural network theoretical framework.

As an expansion of traditional cognitive modeling, cognitive decision neural networks combine the characteristics of cognitive models: lightweight architecture design and interpretability. First, cognitive decision neural networks are based on small deep neural networks, and the training process does not require large amounts of data and computing power, using general consumer-grade CPUs and GPUs. Second, because cognitive decision neural networks combine cognitive models, their parameters have relatively close relationships with cognitive processes, offering strong interpretability. For example, all three cognitive decision neural network models listed above have clear evidence accumulation processes.

Notably, current cognitive decision neural networks also carry the limitations of cognitive models, especially in model generalizability. Although the traditional evidence accumulation theoretical framework has broad explanatory power, its application requires more specific settings according to context to form specific computational models that can be combined with empirical data; otherwise, it may lead to mismatches between empirical data and model assumptions (Liu & Hu, 2024; Boag et al., 2025). This characteristic brings the problem that almost every specific experimental task can have its unique computational model. Typical examples are cognitive conflict-related tasks (such as Stroop, Flanker, and Simon tasks), which have multiple special computational models of evidence accumulation models, including the Dual-Stage Two-Phase Model (DSTP), Diffusion Model for Conflict Tasks (DMC), and Shrinking Spotlight Model (SSP) (Evans et al., 2020). Current cognitive decision neural networks may have the same problem. RTNet may not be applicable to random dot motion tasks, while RTify and RTNet may both be unable to simulate cognitive conflict tasks. SN-DM cannot accurately predict human reaction time when making decisions under urgent time pressure: human decision speed and decision boundary will change in this situation (Duggins & Eliasmith, 2024), while SN-DM's decision speed and boundary are determined by pre-set hyperparameters and cannot be flexibly adjusted for this scenario. Considering the large number of decision tasks invented by cognitive psychologists and that humans can complete them without obstacles, the cognitive tasks that current cognitive decision neural networks can simulate are still very limited. Traditional evidence accumulation models have been widely applied in value-based decision-making, social decision-making, and other scenarios, showing good explanatory power for human reaction time and choice results in rapid decision-making under these complex situations. Under these circumstances, how evidence accumulation should be conducted in cognitive decision neural networks—for example, whether additional value calculation modules are needed (Zhang et al., 2025)—represents a new challenge for this field.

To improve the generalizability issues of cognitive decision neural networks and achieve full-process modeling of human decision-making, establishing a "digital twin" of human decision processes still requires substantial work. One possibility is to draw on current Large Language Models (LLMs). As representatives of current artificial intelligence, LLMs have the potential to understand the cognitive processes behind human decision-making. For example, the large model Dreamer algorithm proposed by Hafner et al. (2025) can achieve transfer application across more than 150 different tasks with fixed hyperparameters by learning world models; Centaur built by Binz et al. (2025) based on fine-tuning language models (Llama 3.1 70B) can predict and simulate human behavioral performance in 160 psychology experiments expressible in natural language after training on the large-scale dataset Psych101. Unfortunately, these models cannot predict human decision time. To use computational models to simulate human decision time, more human reaction time data across various tasks is needed. This requires not only more open data but also standardized and quantitative descriptions of cognitive tasks themselves to help future model training understand the relationship between task structure and decision time. In other words, the field of cognitive decision neural networks may need its own "ImageNet." However, it is worth noting that although large language models may enhance the generalization ability of cognitive decision neural networks, this approach is difficult to meet the "lightweight modeling and interpretability" emphasized in cognitive science. Researchers have already attempted to provide solutions. For example, Zhang et al. (2025) systematically proposed principles for constructing human-AI hybrid experimental platforms. Through this platform, continuous multimodal data collection drives parameter optimization and architecture improvement of AI and other computational models, prompting enhanced models to generate more precise dynamic simulations and task context predictions to feed back into the platform's task paradigm design and experimental control strategies, thereby establishing a closed-loop iterative system that promotes deep coupling between data and algorithms. In future cognitive modeling, we call for more researchers to propose more theoretically-driven generalization mechanisms to advance the field of cognitive decision neural networks.

Another possible direction is to continue deepening our understanding of human cognitive processes and train small neural network models to complete human-flexible tasks. Recent tiny RNNs provide valuable references, as their minimal architecture containing only 1-4 computational units can significantly improve behavioral prediction effectiveness through parameter space optimization, surpassing classic cognitive models in six classic reinforcement learning tasks (Ji-An et al., 2025). Currently, neural networks responsible for stimulus processing modules mainly focus on small deep neural networks, and future work could consider replacing them with more advanced neural network algorithms such as these for understanding cognitive processes. Regarding the evidence accumulation module, most examples of cognitive decision neural networks listed in this study are based on absolute evidence accumulation processes (except SN-DM, which proposes dynamic switching between absolute and relative evidence accumulation processes by introducing a value evaluation function for evidence). Future work could attempt to replace them with relative evidence accumulation or mixed evidence accumulation as assumptions about the decision process, or directly implement them using neural network algorithms. For the decision judgment module, current cognitive decision neural networks mainly focus on judgments about experimental stimulus features themselves. SN-DM has successfully simulated stock market tasks in economic decision-making, and future work could introduce more abstract information for decision judgment, such as grasping relationships and intentions. Training and testing are mainly based on behavioral data such as reaction time and accuracy, with neural-level modeling mostly being analogies between algorithms and biological structural functions, lacking precise mapping to specific neural activities or brain regions. In the future, researchers may need to further explore the mapping relationship between cognitive decision neural networks and real neural activities to deepen understanding and optimization of human decision-making process simulation. The decision boundaries of existing cognitive decision neural networks are determined by pre-set hyperparameters and cannot be automatically adjusted according to task contexts. Future researchers implementing adaptive modeling should focus on improving the model's task generalization ability to make it more flexible and universal. Finally, facing the "lightweight modeling and interpretability" emphasized in cognitive science, the trade-off between parameter constraints brought by interpretability and algorithm function realization relying on data-driven approaches still requires consideration from researchers in future cognitive decision neural network modeling.

Furthermore, cognitive decision neural networks may be combined with embodied intelligence in robots in the future, using robotic arms to press buttons for reaction time output. This will further help solve problems difficult to address in traditional cognitive modeling: non-decision time. As a parameter in evidence accumulation models, the meaning of non-decision time remains ambiguous (Zeng et al., 2025). Although some researchers have attempted to clarify its meaning through methods such as recording electromyography, it is still poorly understood (Bompas et al., 2025). If cognitive decision neural networks can be combined with robotic arms, they will be able to fully simulate human rapid decision-making processes, thereby solving the problem of ambiguous parameters in traditional cognitive models.

Current neural network models have broken through the computer field and shown great application prospects in scientific research, also demonstrating potential for application in psychological research. For example, large language models can improve data collection efficiency in cognitive science. After training on large amounts of text data, researchers can quickly obtain behavioral data and artificial neuronal activity data through dialogue with large language models in experimental tasks (Qu et al., 2024). In cognitive process research, besides using neural networks to perform tasks and predict human behavioral responses, neural network models can also be used to solve parameter estimation problems in cognitive modeling. For example, combining neural networks with simulation-based inference can extend traditional cognitive models to more complex scenarios (see Pan & Hu, 2025). Deeper integration of neural networks and other AI technologies with cognitive science research to achieve full-process simulation of multiple aspects of human cognitive processes will help researchers build better models of human cognition. These models may also inspire the development of new AI algorithms, advancing research on the nature of intelligence.

References

Liu, Y., & Hu, C. (2024). Behavioral and cognitive neural evidence for evidence accumulation models. *Chinese Science Bulletin*, 69(8), 1068–1081. https://doi.org/10.1360/TB-2023-1080

Pan, W., & Hu, C. (2025). Neural simulation-based inference: A cognitive modeling approach based on neural networks and simulation inference. *Psychological Science*, 48(4), 826–835. https://doi.org/10.16719/j.cnki.1671-6981.20250406

Appendix

Main Components of Current Cognitive Decision Neural Network Algorithms and Their Corresponding Psychological Processes

Neural Network Layer	Mathematical Principle	Psychological Process Correspondence
Fully Connected Layer	Linear transformation: $\mathbf{y} = \mathbf{W}\mathbf{x} + \mathbf{b}$. Through learned weight matrix and bias vector, maps input data dimensions. Connects every neuron between input and output layers.	Decision variable classification and integration
Convolutional Layer	Local connection and weight sharing: $O(i,j) = \sum_u \sum_v I(i+u, j+v) \cdot K(u,v)$. Extracts local features from input data (e.g., image matrix) through convolution operations, preserving spatial structure information.	Local feature detection and extraction in visual perception
Pooling Layer	Downsampling operation: $O(i,j) = \text{pool}(I[i \cdot s : i \cdot s + w, j \cdot s : j \cdot s + h])$. Samples data by sliding non-overlapping pooling windows across input data, extracting main features and reducing data dimensions.	Information compression and feature summarization

Neural Network Layer	Mathematical Principle	Psychological Process Correspondence
Activation Function	Nonlinear transformation: $\sigma(x) = \frac{1}{1+e^{-x}}$ (Sigmoid example). Maps neuron input nonlinearly to a specific output range. Controls neuron activation state; facilitates gradient calculation in backpropagation for parameter updates.	Neuron activation threshold and nonlinear response to evidence intensity
Loss Function	Quantifies prediction error: $\mathcal{L}(y_{\text{pred}}, y) = \text{Loss}(y_{\text{pred}}, y)$. Quantifies error between model predictions and true values, calculates parameter gradients through backpropagation, and updates weights.	Feedback learning mechanism and decision strategy adjustment

Note: Figure translations are in progress. See original paper for figures.