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# A comparative study of Chinese and foreign research relevant to the drift diffusion model in the last decade

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**Abstract.** This study evaluates the differential research approaches of Chinese and international scholars regarding the drift diffusion model in mental processes through a literature review from the last decade. The application of DDM theory in cognitive research varies between Chinese and foreign study methodologies. The differences in decision-making mechanisms among cultural groups result in this outcome. Inconsistency has been identified in international academic research. They cover reward rate optimization, decision thresholds, decision time, and more. On the contrary, advancements in Chinese studies involve the development of innovative models. They are Bayesian and semi-parametric. These are designed for mixtures combining drift-diffusion processes and the inverse Gaussian distribution. In addition, they encompass elucidating the neural processes and implementing DDM techniques. This use of DDM reveals the rewarding perception and decision-making linked to depression. It also reveals the brain patterns of social anxiety. These comparisons aim to summarize the differences between Chinese and foreign studies. They also analyze them. It will find the causes of these differences. Moreover, it will determine how Chinese clinical care can use them. The DDM studies show its importance in decision-making patterns. Scholars have the opportunity to apply these tools in a variety of scientific fields, including neuroscience, psychology, artificial intelligence, and cognitive research.

**Keywords:** Drift-Diffusion Model, Comparative study, Culture Difference

## 1. Introduction

The perceptual decision model aims to understand how animals detect, differentiate, perceive, and classify information [1]. It occupies an important place in neuroscience and psychology, showcasing the benefits of integrating mathematical and biological approaches to studying the brain and its functioning [1].

The drift-diffusion model is widely recognized and utilized in academia because of its extensive data collection capabilities, particularly in the last decade, where it has garnered interest from researchers worldwide for its integration with psychological research and novel ideas [2].

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As a simple model of the cognitive process of bi-optional decision-making (apply only to fast bi-optional and single-stage decision-making processes), the DDM is an assumption that noise in the decision process is observable and that the line of the picture always goes from a starting point to one of two response criteria or boundaries, with the starting point labeled z and the boundaries labeled a and 0. The rate at which the information accumulates is called the drift rate (v) and is determined by the amount of information extracted from the stimulus quality of the information. In some research, the values of drift rate v are different for each stimulus condition because they differ in difficulty [3]. The analysis allowed measurement of the magnitude of noise in the accumulator's memory [4].

The purpose of this paper is to summarize and analyze the results of DDM research in China over the past decade, to compare the differences between Chinese and foreign research, to analyze the possible reasons for the gap, and to try to assess the possibility of its use for clinical interventions in China.

## 2. Literature review of Chinese and foreign studies related to diffusion drift modeling in the last decade

### *2.1. Foreign studies related to diffusion drift modeling in the last decade*

A study of reward rate optimization in two-choice decision-making explores empirical tests of theoretical predictions [5]. A drift-diffusion model (DDM) implements an optimal decision procedure for a static, two-choice forced-choice task [6]. The height of the decision threshold applied to the accumulation of information on each trial determines the speed-accuracy trade-off (SAT) of the DDM, a finding that explains the ubiquitous character of human performance in rapid-response tasks [7]. Another study by this team investigated a missing link-filling approach linking decision-making to the operant conditioning literature and extending choice proportion prediction to inter-response time prediction [8]. The approach was implemented in an adaptive version of the Drift-Diffusion Model (DDM), which is widely used in decision-making research to explain reaction time distributions [9].

The pacemaker-accumulator (PA) system has been an extremely popular timing model in the 50 years since its introduction by Treisman [10]. Although the dominant PA model during this period - Gibbon and Church's scalar expectation theory (SET) - invokes most of its assumptions, several alternative timing models based on different assumptions have been devised [11]. Like Treisman's model, this time-adaptive, opposing Poisson, drift-diffusion model need not assuming Weber's law in the first place, it is possible to take into account timescale invariance [12]. A preliminary introduction to a hierarchical extension of the Drift-Diffusion Model (DDM) is given [13]. This formal decision-making model is commonly used in cognitive science but has been little used in social and personality research in Western academia [14].

Revealed preference is the primary method for inferring preferences, but is limited in that it can only rely on discrete choice data [15]. When a person chooses one choice over another [16], it is predicted how likely they are to make the same choice again [17. Linking the two main sub-components of internalization - antagonism and inhibition - to specific control processes through a series of inhibitory control tasks and corresponding computational modeling [17]. used a hierarchical drift-diffusion model (DDM) to fit participants' task behavior, partitioning their decisions into a series of specific cognitive processes [17]. Fisher proposed a model that describes how attentional fluctuations to choose set features affect decision-making [18]. One of his studies found that the Attentional Drift-Diffusion model accurately describes choice, reaction time, and how these variables relate to visual attention to attributes and options [18]. Karimi proposed a computational method to quantify decision-making ability in patients with mild cognitive impairment and attention deficit [19]. He also developed a classification model for detecting cognitive impairment based on the estimated parameters of a drift-diffusion model [19].

### *2.2. Chinese studies related to diffusion drift modeling in the last decade*

The main results of cognitive research on drift-diffusion modeling (DDM) in China include:

(1) Developed a novel Bayesian semi-parametric inverse Gaussian drift-diffusion mixture model for multi-choice decision-making processes [20];

(2) Describing the neuron cognitive mechanisms underlying attentional bias to pain using a hierarchical DDM [21];

(3) Applying the DDM to reveal impaired reward-based perceptual decision-making processes associated with depression in girls in late childhood and early adolescence [22].

This study focuses on assessing subject-level heterogeneity in parameter trajectories and demonstrates how a stratified version of the DDM can advance the study of mental processes. In addition, this study states that adults with depression are deficient in accumulating reward-based evidence and quantifies the rate of evidence accumulation and starting point bias in depressed individuals using a stratified DDM [23].

(4) Applying the DDM to reveal the Specificity of different components of emotional processing of social anxiety associated with the fitted parameters of emotional processing [24].

This study recruited 31 university students with an average age of 21.97 to judge whether the lighted walker expressed half of the emotions of anger and happiness and half of sadness and neutrality in an emotional movement recognition task, and recorded accuracy and reaction time, then fitted the behavioral data using a drift-diffusion model (DDM) and evaluated parameters including the non-decision time and the non-decision time, thus achieving the goal of analyzing the relationship between social anxiety and other emotional processes. Decision time) and the non-decision time) to reach the goal of analyzing the relationship between social anxiety and other emotional processing [25].

(5) Incorporating eye gaze to describe individual decision-making behavior models [26].

This study examined the relationship between gaze and decision-making in value-based decision-making using a gaze-based manipulation paradigm and found that manipulating the amount of time, subjects spent looking at options interfered with the choice process, that gaze manipulation primarily affected the late time course of decision-making, and that model parameter estimates were more supportive of proximate cause models. The results of the study show the reliability and validity of the proximate cause hypothesis of the drift-diffusion model [26].

(6) Analyzing the ongoing impact of errors on future decision-making [27].

Results show a relationship between response time on the first trial after an error and the average accuracy on subsequent trials [27]. This study contributes to the understanding of the dynamic decision-making process and addresses the limitations of traditional approaches by developing a multi-category drift-diffusion model with independent latent processes for each decision category [27].

## 3. DDM research areas internal micro-analysis

### *3.1. The speed and accuracy of research of DDM*

In research on the problem of choosing when to choose, the ongoing motivational state of an animal when making a perceptual decision is the central issue [28].

In terms of the speed and accuracy of perceptual decision-making, how this can be achieved at the neural level in both human and non-human subjects has been the subject of recent research. Recent studies have begun to focus on the neural mechanisms by which this is achieved in human and nonhuman subjects. For example, when monkeys are compensated in favor of speed over accuracy, the selection moves more quickly toward the edge. The accuracy of the noisy decision signal is progressively improved during successive sampling, with high bounds leading to slower but more accurate decisions and low bounds reducing consideration time at the expense of performance. Subsequently, the limit level is finally determined by measuring rate and accuracy [28].

Since the accuracy of the uplink selection signal increases bit by bit during successive tests, high bounds lead to slower but more accurate selections, whereas low bounds reduce the time to think, thus affecting the execution. The termination rate in the LIP is linked to an execution similar to that computed by the DDM by encoding the value of the collective selection variable [29]. A common, signal-independent level of neural signaling before eye movements have been shown to support this hypothesis [30]. Although recordings from the FEF, LIP, premotor cortex (PMd), and basic engine cortex (M1) suggested a delineation of results, they reached certain arrangements, such as the unfinished hypothesis of unpredictable content and limited aggregation by the DDM [30].

Meanwhile, in psycho-physical research, the experimenter can decide to control the quality of tactile symbols, either in blocks or previews. In the former case, the winning rate can be improved by applying appropriate constraints, e.g., modules whose level remains stable in each preview within a block [31].

Furthermore, the groundbreaking idea is that the selection could be driven by a strong, unproven quantity called the 'limit'. Selection could be driven by a powerful, unproven quantity known as the ''earnest'' signal, which completes a descending limit from nothing, blowing up the later collector state [31].

### 3.2. Balancing perceptual choices based on likelihood and value in DDM research

This area of related research aims to explore the control of perceptual choices through likelihood and value pairs to discover a wide range of strategies that utilize different modeling frameworks. How do humans and monkeys combine seething tangible evidence with encoded correlational data at the social and brain levels to select the likelihood or value of a situation to make an optimal choice [32]?

In addition, DDM-related research focuses on how humans and monkeys combine encoded contextual information with noisy sensory evidence at the behavioral and neural levels to make optimal decisions [32]. One crucial balance is known as LIP, which emphasizes the adjustment of perceptual choices to boosted values or probabilities [32].

### 3.3. DDM and Decision Confidence

For humans, perceptual orientation is an area of strength determined by certainty or vulnerability, which can be assessed when asked to report on our 'certainty'; and cross-species DDM studies with rodents, monkeys, and humans have begun to show signs of neuron variability in decision confidence [33].

People can explicitly report certainty on scales, and clinicians refer to this type of computation as "brain computation." In "metacognition," how certainty is encoded in brain circuits requires a rational definition. Certainty is understood in terms of how the selected data are read off the decision-referenced representations and preserved in the accuracy-referenced margins (the likelihood of being correct is uniquely associated with the alternating arrangement of brain circuits [33].

## 4. Comparison

In terms of research content and application methods, the similarities and differences between the Chinese and Western uses of DDM are as follows:

(1) The application of the Drift Diffusion Model (DDM) in cognitive research shows the cultural differences in cognitive processes between China and other countries [34]. For example, one study has shown that Chinese and Danish people have very different neural activities and decision-making strategies when applying the drift-diffusion model [34].

(2) One study examined the differences in cognitive mechanisms between cultural groups by comparing DDM parameters, and the results showed that Chinese dependencies were at a higher distance compared to English, thus reflecting the higher syntactic complexity of Chinese texts [35].

(3) The similarity between Chinese and Western DDM studies lies in the fact that the application of DDM in cognitive science aims at exploring and explaining the nuances of cognition in different cultures and contexts, and they both may select subjects for testing in their respective cultural contexts [36]. Moreover, in the applied research of DDM, both Chinese and foreign countries focus more on artificial intelligence cognitive research [36].

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## 5. Conclusion

In DDM research, the differences between Chinese and foreign academic research are reflected in many aspects, which not only reflect the different dimensions and different orientations in DDM modelling research, but also are mainly reflected in the differences in academic tradition and culture. China and the West in the literature of the last decade reflect obvious differences in the focus, research methods and evaluation criteria of DDM issues.

Meanwhile, this difference also demonstrates different academic values and research styles in different academic and cultural contexts. China has had a more exciting performance in the use of mental science in the last decade, while Western academics have focused more on basic research itself.

## 6. Discussion

Through the analysis of comparisons and conclusions, the importance of incorporating the drift-diffusion model into decision-making research is evident, pointing towards the potential integration of this model with advancements in psychological research over the past ten years. The overall success of the DDM research also shows the pivotal position of the decision modeling type of research in neuroscience and psychology, as well as the role of this research in the cognitive research of AI, which will have a direct and profound effect on the productivity development of society. Some of the research integrated with the humanities has also shown the potential of the model to be integrated with psycho-social and therapeutic models, especially in China. In addition, DDM research also transcends the theoretical schools of clinical treatment from the dimension of brain science evidence, and it provides a new line of research that will provide more evidence-based evidence for the various original clinical psychotherapy techniques.

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