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Student Cognitive Profile Classification and Instructional Strategy Design Based on Drift Diffusion Model

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Abstract: In the current field of education, achieving personalized education has become a key pursuit. The core difficulty lies in accurately quantifying students' cognitive differences and translating these differences into practical intervention programs. Traditional psychological indicators often only stay at the level of describing the surface behavior of students and are difficult to deeply explore the internal mechanisms of students' cognitive processes. The Drift Diffusion Model (DDM), as the core mathematical model in the field of cognitive decision-making, brings new ideas for solving this problem with its unique advantages. DDM depicts the dynamic process of evidence accumulation through a Stochastic Differential Equation. Its parameters—drift rate (μ), noise intensity (σ), and decision threshold (A)—quantify individual differences in cognitive abilities. This study extends DDM to educational contexts, establishing an end-to-end theoretical framework: "behavioral data → DDM parameters → cognitive classification → instructional strategies." This framework provides an actionable mathematical foundation for educational personalization. Future research may integrate dynamic parameter estimation methods to enable real-time optimization of instructional strategies.
Keywords: Drift Diffusion Model, stochastic differential equation, cognitive profile classification, instructional strategy design

1. Introduction

The core challenge of educational personalization lies in quantifying students' cognitive differences and translating them into actionable interventions. Traditional psychological metrics only describe superficial behavioral manifestations, whereas the Drift Diffusion Model (DDM) reveals intrinsic individual differences through modeling evidence accumulation mechanisms during decision-making. These differences manifest across dimensions such as information integration efficiency (μ), cognitive stability (σ), and decision strategy (A). Recent successful applications of DDM in neuroeconomics[1] and cognitive Psychology[2] offer a novel paradigm for educational cognition research.

2. Theoretical Foundations of the Drift Diffusion Model

2.1 Drift Diffusion Model

The decision process in DDM is governed by the following stochastic differential equation[3]:

$$\mathrm{d}\boldsymbol{X}(\boldsymbol{t}) = \mu\,\mathrm{d}\boldsymbol{t} + \sigma\,\mathrm{d}\boldsymbol{W}(\boldsymbol{t}),$$

where $\boldsymbol{X}(\boldsymbol{t})$ represents the accumulated evidence at time $\boldsymbol{t}$, μ denotes the drift rate (information integration efficiency), σ quantifies noise intensity (attentional fluctuations), and $\boldsymbol{W}(\boldsymbol{t})$ is standard Brownian motion. $\boldsymbol{A}$ decision is triggered when $\boldsymbol{X}(\boldsymbol{t})$ first crosses either $+\boldsymbol{A}$ or $-\boldsymbol{A}$, the decision thresholds.

2.2 Behavioral Metrics

Reaction Time:

$$\boldsymbol{RT} = \boldsymbol{T}_{er} + \frac{\boldsymbol{A}}{\mu}\tanh\left(\frac{\mu\boldsymbol{A}}{\sigma^2}\right),$$

where $\boldsymbol{T}_{er}$ is non-decision time. The second term represents decision time, showing a nonlinear relationship with μ and $\boldsymbol{A}$.

Error Rate:

$$\boldsymbol{ER} = \frac{1}{1+\boldsymbol{e}^{2\mu A/\sigma^2}}.$$

Error rate depends on μ, σ, and $\boldsymbol{A}$, with higher μ, higher $\boldsymbol{A}$, or lower σ significantly reducing errors. By collecting reaction time and error rate data from students during exams, DDM parameters (μ , σ , $\boldsymbol{A}$) can be estimated[4][5], constructing individualized cognitive decision-making profiles.

3.Cognitive Profile Classification and Instructional Strategies

Students are classified into eight categories based on high (H) or low (L) values of μ, σ, and $\boldsymbol{A}$. Each category corresponds to distinct cognitive patterns and behavioral traits, guiding tailored instructional strategies (Table 1).

Table 1: Cognitive Profiles and Corresponding Instructional Strategies

Category	**Parameter Combination**	**Cognitive Traits**	**Instructional Strategy**
H-H-H	$\mu\uparrow, \sigma\uparrow, \boldsymbol{A}\uparrow$	Efficient information processing but prone to ， distraction, conservative decision-making	Provide structured tasks, minimize environmental distractions
H-H-L	$\mu\uparrow, \sigma\uparrow, \boldsymbol{A}\downarrow$	Fast but volatile processing, impulsive decisions	Implement reflective feedback mechanisms to improve decision calibration

H-L-H	$\mu\uparrow$, $\sigma\downarrow$, $\boldsymbol{A}\uparrow$	Efficient and focused, risk-averse	Assign challenging tasks to stimulate intellectual engagement
H-L-L	$\mu\uparrow$, $\sigma\downarrow$, $\boldsymbol{A}\downarrow$	Rapid and stable processing, hasty decisions	Cultivate deep thinking through multi-perspective analysis
L-H-H	$\mu\downarrow$, $\sigma\uparrow$, $\boldsymbol{A}\uparrow$	Slow but cautious processing, easily distracted	Simplify task complexity with step-by-step guidance
L-H-L	$\mu\downarrow$, $\sigma\uparrow$, $\boldsymbol{A}\downarrow$	Inefficient and unstable processing, error-prone	Strengthen foundational skills to enhance processing efficiency
L-L-H	$\mu\downarrow$, $\sigma\uparrow$, $\boldsymbol{A}\uparrow$	Focused but inefficient, overly cautious	Encourage exploratory learning and adaptive risk-taking
L-L-L	$\mu\downarrow$, $\sigma\downarrow$, $\boldsymbol{A}\downarrow$	Generalized cognitive deficits requiring holistic support	Deliver personalized interventions for incremental cognitive growth

Exams, as time-constrained cognitive decision tasks, require students to balance speed and accuracy for optimal performance. DDM-based cognitive profiling enables targeted parameter optimization through instructional strategies, thereby improving test scores while fostering systemic development of underlying cognitive abilities.

4. Conclusions

This study proposes an end-to-end framework linking behavioral data to instructional strategies via DDM parameters. We establish mappings between DDM parameters and educational cognitive traits, introduce the first computational cognitive model-based student classification system, and provide a differentiated instructional design framework. Future work should explore reinforcement learning-based dynamic parameter estimation systems to enable real-time personalization of teaching strategies.

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