# Dimensional Difference Preference in Intertemporal Decision-Making: Eye-Tracking Evidence

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**Date:** 2022-10-30T00:00:00+00:00

## Abstract

In the field of intertemporal decision-making research, although dimension-based intertemporal models have received some evidential support from outcome tests and process tests, the psychological process of inter-dimensional difference comparison hypothesized by such models still lacks direct process evidence. This study systematically examined the predictive effects of relevant eye-tracking indices on dimensional difference preference through two eye-tracking experiments. The results revealed that individuals' dimensional difference preference in intertemporal decision-making could be effectively fitted using the dimension-based trade-off model, and that indices such as reaction time, saccadic fixation entropy, and static fixation entropy were all negatively correlated with dimensional difference preference, whereas dimension-based attention allocation was positively correlated with dimensional difference judgment. These findings support the relevant hypotheses of the intertemporal eye-tracking model proposed in this study, confirm the link between dimensional difference preference and the cognitive processing of intertemporal decision-making, provide more direct process evidence for dimension-based intertemporal models, and point toward new directions for the future development of eye-tracking models of intertemporal decision-making.

## Full Text

## Preference of Dimension-Based Difference in Intertemporal Choice: Eye-Tracking Evidence

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## Abstract

In the field of intertemporal choice research, although dimension-based models have received some empirical support from outcome-based and process-based tests, the psychological process of dimensional difference comparison posited by these models still lacks direct process evidence. This study systematically examined the predictive effects of relevant eye-tracking indicators on preference of dimension-based difference through two eye-tracking experiments. The results revealed that individual preferences for dimension-based difference in intertemporal choice could be effectively fitted using the tradeoff model, and that response time, gaze transition entropy, and stationary gaze entropy were all negatively correlated with preference of dimension-based difference, while dimension-based attention allocation was positively correlated with dimension-based difference judgment. These findings support the hypotheses of the intertemporal eye-tracking model proposed in this study, confirm the link between preference of dimension-based difference and the cognitive processing of intertemporal decision-making, provide more direct process evidence for dimension-based intertemporal models, and point to new directions for future development of eye-tracking models in intertemporal choice research.

**Keywords:** intertemporal choice, dimension-based models, preference of dimension-based difference, eye-tracking technique

People often face tradeoffs between immediate and delayed outcomes. This decision-making process, which involves weighing outcomes occurring at different time points (especially between the present and future) to make judgments and choices, is called intertemporal choice (Frederick et al., 2002; He et al., 2009; Liang & Liu, 2011). For example, one must decide whether to consume now to satisfy immediate needs or to save for greater future benefits (Dai & Busemeyer, 2014; Zhou et al., 2021). In intertemporal choice research, investigators typically ask individuals to choose between a smaller-sooner (SS) and a larger-later (LL) option to examine their intertemporal preferences (Scholten & Read, 2006; Scholten & Read, 2010; Jiang et al., 2016). For instance, one might choose between "receive 100 yuan immediately" (SS option) or "receive 150 yuan in one month" (LL option).

### 1.1 Alternative-Based versus Dimension-Based Models

Traditional intertemporal choice theories posit that when facing intertemporal decisions, people discount future outcomes to the present at a certain rate and compare the discounted values of each option to make a decision. For example, the discounted-utility model proposed by economist Samuelson (1937), the first rational intertemporal model, suggests that decision-makers discount the utility of future outcomes at a constant rate (i.e., time discount rate) (Jiang et al., 2016; Liang & Liu, 2011). Subsequently, due to the discovery of numerous anomalies that violate the discounted-utility model, researchers revised the discount function and developed modified models such as the hyperbolic discounting model (Ainslie, 1975; Frederick et al., 2002; Loewenstein & Prelec, 1992) and the quasi-hyperbolic discounting model (Laibson, 1997). Although these models employ different discount functions, they all assume an alternative-based processing mechanism in intertemporal choice, whereby decision-makers calculate the discounted value of each option and compare them, ultimately selecting the option with the highest discounted utility. Therefore, these time discounting models can be collectively referred to as alternative-based intertemporal models.

Other researchers, approaching from a decision process perspective, argue that individuals' intertemporal choices are not as rational as envisioned by time discounting models but instead employ some intuitive heuristic strategies. Based on this view, they have proposed a series of models, such as the attribute-comparison model (Read, 2001), similarity model (Leland, 2002), tradeoff model (Read & Scholten, 2012; Scholten & Read, 2010), and equate-to-differentiate model (Li, 2004, 2016). Taking the tradeoff model and equate-to-differentiate model as examples, both assume that individuals compare the relative difference magnitude between outcome and delay dimensions in intertemporal choice. If decision-makers perceive the subjective difference in the outcome dimension as larger, they choose the LL option that dominates on the outcome dimension; conversely, if they perceive the subjective difference in the delay dimension as larger, they choose the SS option that dominates on the delay dimension. These models all assume a dimension-based processing mechanism in intertemporal choice, whereby decision-makers compare differences between dimensions and make decisions accordingly. Therefore, these models can be collectively referred to as dimension-based intertemporal models.

### 1.2 Insufficient Process Evidence for Dimension-Based Intertemporal Models

In recent years, researchers have been committed to testing and comparing these two types of models. On the one hand, some behavioral evidence supports dimension-based intertemporal models. For example, Scholten and Read (2010) found that the dimension-based tradeoff model can explain subadditivity and superadditivity phenomena that time discounting models cannot explain. Some researchers have used behavioral outcomes of intertemporal choice to fit different intertemporal models and found that dimension-based models outperform alternative-based models and better fit people' s intertemporal choice behavior (Cheng & González-Vallejo, 2016; Dai & Busemeyer, 2014; Ericson et al., 2015; Scholten et al., 2014). On the other hand, due to the advantages of eye-tracking technology (Wei & Li, 2015), some researchers have attempted to use it to provide further process evidence for testing intertemporal models. For instance, some studies have found that two-thirds of saccades in intertemporal choice are dimension-based (Arieli et al., 2011), suggesting that individuals may independently process outcome and delay dimension information (Amasino et al., 2019). Other researchers have found that manipulating dimension-based gaze fixation can influence intertemporal choice behavior, verifying the causal effect of dimension-based information processing on intertemporal choice (Fisher, 2021; Liu, Lyu, et al., 2021; Reeck et al., 2017), which suggests that dimension-based information processing plays an important role in intertemporal choice.

Although dimension-based intertemporal models have received some support from eye-tracking process evidence, two issues remain unresolved. First, more direct process evidence is still lacking for the psychological process of dimensional difference comparison posited by dimension-based models. Previous eye-tracking studies have mostly focused on the relationship between dimension-based fixation or saccades and intertemporal choice behavior (e.g., Fisher, 2021; Reeck et al., 2017), with few studies examining the psychological process of dimensional difference comparison itself. Although most researchers agree that a psychological process of dimensional difference comparison exists in intertemporal choice (Arieli et al., 2011), it remains unclear whether this psychological process is reflected in eye-tracking fixation. If the relationship between dimensional difference comparison and eye-tracking fixation can be captured, it would provide further process evidence for dimension-based intertemporal models. Second, the relationship between dimension-based fixation and intertemporal choice still needs further examination. Although much eye-tracking evidence supports dimension-based intertemporal models, some studies have found that the advantage of dimension-based fixation time cannot significantly predict subsequent intertemporal choice behavior (Liu, Lyu, et al., 2021). This may be due to the unclear relationship between dimension-based fixation and dimensional difference comparison. Clarifying this relationship could help understand the information processing mechanism of intertemporal choice and provide evidence for further development of intertemporal models.

### 1.3 Preference of Dimension-Based Difference and Eye-Tracking Models

To address these issues, this study used eye-tracking technology to examine the relationship between dimensional difference comparison and information processing in intertemporal choice, aiming to provide further evidence for dimension-based intertemporal models. According to dimension-based intertemporal models, individuals' intertemporal choice behavior depends on the degree of their dimensional difference judgment—that is, "how large is the difference between the two dimensions." Based on this, this study proposes the concept of preference of dimension-based difference (PDD) to represent individuals' judgment of the relative magnitude of subjective differences between outcome and delay dimensions in binary intertemporal decisions. This study investigates whether

PDD is reflected in eye-tracking indicators related to information processing.

In recent years, scholars have proposed the attentional drift-diffusion model (aDDM) that incorporates eye-tracking fixation and verified its good explanatory power in single-dimension decision-making (Krajbich et al., 2010; Krajbich et al., 2012; Krajbich & Rangel, 2011). This model assumes that decision-makers sample option information through random eye-tracking fixation and accumulate evidence for options; when the accumulated evidence for a certain option reaches a threshold, a decision is made, and the option with greater accumulated evidence is selected (Krajbich et al., 2010). Some researchers have developed a dimension-based intertemporal drift-diffusion model based on this theoretical perspective and fitted it with response time data (Amasino et al., 2019), indicating that using a sequential sampling model framework to explain the information processing mechanism of intertemporal choice is feasible. Combining dimension-based intertemporal models and the aDDM research perspective, this study proposes that intertemporal choice can be hypothesized as a process of sampling dimensional difference information based on eye-tracking fixation and accumulating evidence. When the accumulated evidence for a certain dimension (outcome or delay dimension) reaches a threshold, a decision is made based on that dimension. According to this intertemporal version of aDDM (iaDDM), PDD can also be reflected in the information processing mechanism. De Martino et al. (2013) found, based on drift-diffusion model fitting data, that the difference in accumulated evidence between two options when individuals reach the decision threshold can quantitatively reflect their decision confidence. Given the theoretical correlation between decision confidence and PDD, this study proposes that PDD can be reflected in the difference of accumulated evidence for the two dimensions when decision-makers reach the decision threshold.

### 1.4 Research Hypotheses

Based on the iaDDM model, this study proposes research hypotheses from the following four aspects.

First, this study quantitatively estimates PDD based on dimension-based intertemporal models. The tradeoff model, which performs excellently among dimension-based models, was selected as the fitting model (Read & Scholten, 2012; Scholten & Read, 2010). Previous studies have mostly used the "analogue scale" paradigm to measure PDD in intertemporal choice. This paradigm uses a metaphor to vividly represent the relative difference magnitude between the two dimensions in intertemporal choice, requiring participants to use a 7-point scale to select different tilt levels of a scale to represent their subjective dimensional difference judgment (Jiang et al., 2016). To verify the validity of the PDD estimation method used in this study, the subjective dimensional difference judgment measured by the analogue scale paradigm was used as a criterion. Accordingly, this study hypothesizes that PDD estimated based on the tradeoff model correlates with analogue scale judgment (H1).

Second, this study posits that response time can reflect PDD in intertemporal choice. Response time, as one of the most commonly used indicators in behavioral experiments, can reflect the cognitive processing mechanism of decision-making. Some researchers have used response time as an indicator of preference strength and found that response time is negatively correlated with preference strength (Diederich, 2003; Konovalov & Krajbich, 2019; Tversky & Shafir, 1992)—that is, the stronger an individual's preference for an option, the shorter the response time. The theoretical logic is that stronger preference for an option often means greater value difference between options, thus requiring less time to reach the decision threshold in sequential sampling and make a choice. Similarly, this study argues that according to the iaDDM model, when individuals perceive a larger relative difference in a certain dimension—that is, when PDD is larger—less time is needed to accumulate evidence to reach the threshold, resulting in shorter response time. Accordingly, this study hypothesizes that response time is negatively correlated with PDD (H2).

Third, this study posits that gaze entropy can reflect PDD in intertemporal choice. Gaze entropy is an eye-tracking indicator that quantitatively estimates individuals' information search patterns in tasks based on information theory (Shannon, 1948; Shiferaw et al., 2019). Compared to traditional eye-tracking indicators such as fixation count and average fixation duration, gaze entropy, as an integrated indicator, can provide a holistic estimate of information search patterns in tasks, thereby reducing context dependency of research conclusions and decreasing data noise (Shiferaw et al., 2019). Therefore, this study attempts to examine the sensitivity of gaze entropy to PDD. There are two commonly used gaze entropy indicators (Cuve et al., 2021; Shiferaw et al., 2018). The first is gaze transition entropy, which measures the frequency of random saccades between areas of interest (Krejtz et al., 2014; Shiferaw et al., 2019), reflecting information search efficiency (Shiferaw et al., 2019); higher values indicate lower information search efficiency. The second is stationary gaze entropy, which measures the uniformity of fixation distribution across different areas of interest (Krejtz et al., 2014); higher values indicate more uniform fixation distribution. According to the iaDDM model, when the accumulated evidence for the two dimensions is relatively similar, more fixations are needed to accumulate evidence to reach the threshold, resulting in longer search time and more frequent saccades. Conversely, when the evidence for the two dimensions differs greatly, decision-makers can reach the decision threshold within limited fixation time, and their fixation distribution is relatively less uniform. Therefore, larger PDD means less information search between different dimensions—that is, lower gaze transition entropy—and also means less uniform fixation distribution between dimensions—that is, lower stationary gaze entropy. Accordingly, this study hypothesizes that both gaze transition entropy and stationary gaze entropy are negatively correlated with PDD (H3).

Finally, this study posits that dimension-based attention allocation can reflect dimensional difference judgment. Attention allocation to different decision dimensions can be reflected in differences in fixation time across dimensions (Amasino et al., 2019; Zhou et al., 2021). According to the iaDDM model, the longer individuals fixate on a certain dimension, the more evidence they accumulate for that dimension, and thus the larger they judge the relative difference of that dimension to be. Therefore, this study hypothesizes that dimension-based attention allocation correlates with dimensional difference judgment (H4).

### 1.5 Overview of Studies

In summary, this study used eye-tracking technology to systematically examine the relationship between PDD and information processing in intertemporal choice through two experiments, aiming to provide further process evidence for dimension-based intertemporal models. On the one hand, based on the tradeoff model, this study estimated individuals' PDD from their binary intertemporal choice outcomes and verified the validity of the estimated PDD through criteria such as the analogue scale task (Experiment 1) and choice consistency (Experiment 2). On the other hand, this study examined the relationship between PDD and information processing based on individuals' response time and eye-tracking data during decision-making.

## Experiment 1

Experiment 1 aimed to examine the relationship between PDD and information processing in binary intertemporal choice. To verify the validity of the fitted PDD, this study selected the "analogue scale" paradigm as a criterion, which has been validated by numerous studies as an effective indicator for examining subjective dimensional differences from the perspective of dimension-based intertemporal models (Jiang et al., 2016; Jiang et al., 2022; Liu et al., 2015).

### 2.1.1 Participants

Following Brysbaert and Stevens' (2018) recommendation that multi-trial cognitive experiments involving response time and other indicators should have no fewer than 1600 trials per experimental condition, and given that each participant completed 36 trials per condition in this experiment, the minimum sample size was determined to be N = 45. To increase statistical power, a 1.5-fold correction was applied to the required sample size, yielding N = 68. The experiment recruited 75 university students (mean age = $20.9 \pm 2.4$ years, 61 females). All participants had normal or corrected-to-normal vision and signed informed consent before the experiment. Participants received a basic compensation of 15 yuan and additional performance-related compensation (1-10 yuan) after the experiment. The study was approved by the ethics committee of the institution.

### 2.1.2 Apparatus

The experiment used an EyeLink 1000 Plus eye-tracker to record participants'eye movements at a sampling rate of 1000 Hz. Participants viewed the experimental stimuli binocularly, but only the left eye' s data were recorded. Stimuli were presented on a 17-inch LCD monitor with a resolution of $1024 \times 768$ (refresh rate = 60 Hz). A chinrest was used to stabilize participants' heads and minimize head movement effects on eye-tracking. The viewing distance was 58 cm, resulting in a horizontal viewing angle of 36° and a vertical viewing angle of 29° from the eyes to the screen edges.

### 2.1.3 Materials

The experimental stimuli consisted of binary intertemporal choice problems. The monetary outcomes were set at four fixed amounts: 1, 2, 5, and 10 yuan. The time delays were set at four fixed intervals: immediate, 5 days, 10 days, and 20 days. These monetary amounts and time delays were combined to form 36 pairs of non-dominated options (e.g., "Option A: receive 5 yuan immediately; Option B: receive 10 yuan in 5 days" ). See Table S1 in the supplementary materials (https://osf.io/xtbjk/) for the experimental stimuli.

### 2.1.4 Procedure

The experiment consisted of two tasks: the intertemporal choice task and the analogue scale task.

Participants first completed the intertemporal choice task, during which their eye movements were recorded. In this task, participants were asked to choose their preferred option. To motivate careful decision-making, they were told that one of their choices would be randomly selected after the experiment and they would receive an additional reward at the corresponding time. Before the experiment began, the eye-tracker was calibrated (using 5-point calibration and validation with a maximum validation error of 0.5° visual angle). Participants then completed two practice trials to familiarize themselves with the task before starting the formal experiment. At the beginning of each trial, a circular fixation point appeared at the center of the screen for drift correction. Participants pressed the spacebar while fixating on this point to trigger stimulus presentation. Two intertemporal options were presented on the screen, and participants could view them for an unlimited time but were instructed to respond as quickly as possible once they had made their decision. They pressed the "F"key to select the left option and the "J" key to select the right option. After pressing a key, choice feedback was presented for 1000 ms. The experimental procedure is shown in Figure 1a [Figure 1: see original paper]. The intertemporal choice task consisted of 36 trials divided into two blocks with a 2-minute rest between blocks. The positions of outcome and delay information were balanced across blocks, and the presentation order of the two blocks was counterbalanced between participants.

After completing the intertemporal choice task, participants continued with the analogue scale task. This task, developed by Jiang et al. (2016), uses a scale metaphor to represent the relative difference magnitude between delay and outcome dimensions. If participants perceived the difference in the delay dimension as larger than that in the outcome dimension, they indicated this with a left-tilting scale; if they perceived the outcome dimension difference as larger, they used a right-tilting scale; if the differences were similar, they used a level scale. Participants used numbers 1-7 to indicate their dimensional difference judgment, with higher scores representing larger outcome dimension differences relative to delay dimension differences. The task used the same problems as the intertemporal choice task. Two practice trials preceded the formal experiment to familiarize participants with the task. At the beginning of each trial, a circular fixation point appeared at the center of the screen. Participants fixated on this point and pressed the spacebar to start the trial. Two intertemporal options were then presented at the top of the screen, and an analogue scale was presented at the bottom. Participants pressed numbers 1-7 on the keyboard to indicate their judgment. After pressing a key, feedback was presented for 1000 ms. The experimental procedure is shown in Figure 1b.

#### 2.1.5 Estimation of Preference of Dimension-Based Difference

Based on participants'choices in the intertemporal choice task, their dimensional difference preference for each choice was estimated using the tradeoff model. The tradeoff model was selected for two reasons: First, it can explain almost all intertemporal anomalies and has strong explanatory power for intertemporal choice (Scholten & Read, 2010; Scholten et al., 2014). Second, the dimensional difference comparison process hypothesized by the tradeoff model aligns with the concept of PDD examined in this study. The tradeoff model posits that decision-makers weigh the relative differences between outcome and delay dimensions in intertemporal choice and make decisions based on the dimension with the larger difference (Read & Scholten, 2012; Scholten & Read, 2010). For a binary intertemporal choice where option SS offers x_{SS} at time t_{SS} and option LL offers x_{LL} at time t_{LL} (t_{SS} < t_{LL}, 0 < x_{SS} < x_{LL}), the quantitative formula is:

$$v(x_{LL}) - v(x_{SS}) \sim \kappa(w(t_{LL}) - w(t_{SS})) \tag{1}$$

where the left side of the equation represents the subjective difference in the outcome dimension, the right side represents the subjective difference in the delay dimension, and  is the tradeoff parameter that converts outcome and delay differences into comparable units and magnitudes. When the outcome dimension difference is larger than the delay dimension difference, decision-makers choose the LL option that dominates on the outcome dimension; conversely, when the delay dimension difference is larger than the outcome dimension difference, they choose the SS option that dominates on the delay dimension.

A hierarchical Bayesian approach was used to estimate parameters at the individual level for each participant (see supplementary materials; parameter estimation code is available at: https://osf.io/xtbjk/). Subsequently, based on each participant' s estimated parameter values and the option information for each choice, the difference in dimensional difference judgment for each choice was calculated as dimension-based difference judgment (DDJ):

$$DDJ = \frac{v(x_{LL}) - v(x_{SS})}{w(t_{LL}) - w(t_{SS})} \tag{2}$$

Preference of dimension-based difference (PDD) is the absolute value of DDJ:

$$PDD = |DDJ| \tag{3}$$

Both DDJ and PDD values were standardized.

### 2.1.6 Gaze Entropy Analysis

This study calculated two gaze entropy indicators: stationary gaze entropy and gaze transition entropy. See supplementary materials for details.

### 2.1.7 Data Analysis

This study used mixed-effect models for statistical analysis with the lme4 and lmerTest packages in R (Bates et al., 2015; Kuznetsova et al., 2017). Participant ID and trial order were included as random factors to enhance the generalizability of the results (Baayen et al., 2008; Judd et al., 2012), which is a common statistical approach in decision-making eye-tracking research (Liu, Wei, et al., 2021; Liu et al., 2020; Sui et al., 2020).

### 2.2.1 Descriptive Statistics

In the intertemporal choice task, the mean proportion of LL choices was 64.3% (95% CI = [60.2%, 68.5%]), and the mean response time was 4.03 s (95% CI = [3.71, 4.36]). In the analogue scale task, the mean judgment score was 3.67 (95% CI = [3.50, 3.83]), and the mean response time was 7.76 s (95% CI = [7.18, 8.33]).

### 2.2.2 Preference of Dimension-Based Difference and Analogue Scale Scores

To verify the validity of the dimensional difference judgment estimation, the analogue scale judgment scores were used as a criterion to examine their correlation. Analogue scale scores can reflect individuals' dimensional difference judgment to some extent; higher scores indicate that individuals judge the outcome dimension difference as larger, while lower scores indicate they judge the delay dimension difference as larger. Based on analogue scale scores, scale judgment strength can be calculated as: scale judgment strength = |analogue scale score - 4|, where higher values indicate greater PDD.

First, participants' intertemporal choices (LL choice coded as 1, SS choice as 0) were used as the dependent variable, analogue scale scores as the fixed effect, and participant ID and trial order as random effects (the same below) in a mixed-effects logistic regression. The results showed that analogue scale scores significantly predicted intertemporal choice, $b = 0.71$, 95% CI = [0.64, 0.78], OR = 2.04, $z = 20.23$, $p < 0.001$, as shown in Figure 2a [Figure 2: see original paper]. This result is consistent with previous findings (Jiang et al., 2016), indicating that the analogue scale task can effectively measure individuals' PDD.

Second, the relationship between dimensional difference judgment and analogue scale scores was examined. Analogue scale scores were used as the dependent variable, and DDJ scores as the fixed effect in a mixed-effects linear regression. The results showed that the regression coefficient for DDJ scores was significant, $b = 0.80$, 95% CI = [0.74, 0.86], $t = 28.38$, $p < 0.001$, as shown in Figure 2b.

Finally, the relationship between PDD and scale judgment strength was examined. Scale judgment strength scores were used as the dependent variable, and PDD scores as the fixed effect in a mixed-effects linear regression. The results showed that the regression coefficient for PDD scores was significant, $b = 0.23$, 95% CI = [0.19, 0.27], $t = 12.15$, $p < 0.001$, as shown in Figure 2c.

These results indicate that the DDJ and PDD scores fitted in Experiment 1 can effectively reflect individuals' dimensional difference judgment and strength, supporting H1.

### 2.2.3 Preference of Dimension-Based Difference and Response Time

To test H2, this study examined the relationship between choice response time (time from stimulus presentation to key press in the intertemporal choice task) and scale response time (time from stimulus presentation to key press in the analogue scale task) with PDD. Both response times were log-transformed. PDD scores were used as the dependent variable, and choice response time and scale response time were used as fixed effects in separate mixed-effects linear regressions. The results showed that the regression coefficient for choice response time was significantly negative, $b = -0.12$, 95% CI = [-0.19, -0.06], $t = -3.70$, $p < 0.001$ (see Figure 3a [Figure 3: see original paper]); the regression coefficient for scale response time was also significantly negative, $b = -0.12$, 95% CI = [-0.19, -0.06], $t = -3.81$, $p < 0.001$ (see Figure 3b). These results support H2.

### 2.2.4 Preference of Dimension-Based Difference and Gaze Entropy

To test H3, this study examined the relationship between gaze transition entropy and stationary gaze entropy with PDD. Participants' mean gaze transition entropy and stationary gaze entropy were 0.66 (95% CI = [0.63, 0.69]) and 1.23 (95% CI = [1.20, 1.27]), respectively. PDD scores were used as the dependent variable, and gaze transition entropy and stationary gaze entropy were used as fixed effects in separate mixed-effects linear regressions. The results showed that the regression coefficient for gaze transition entropy was significantly negative, b = -0.19, 95% CI = [-0.33, -0.05], t = -2.71, p = 0.007 (see Figure 3c); the regression coefficient for stationary gaze entropy was also significantly negative, b = -0.27, 95% CI = [-0.43, -0.10], t = -3.17, p = 0.002 (see Figure 3d). These results support H3.

### 2.2.5 Dimension-Based Difference Judgment and Dimension-Based Attention Allocation

To examine the relationship between dimension-based attention allocation and dimensional difference judgment, this study used outcome gaze proportion, a commonly used indicator that reflects dimensional attention allocation (Amasino et al., 2019; Ashby et al., 2018; Franco-Watkins et al., 2016; Zhou et al., 2021). The calculation formula is:

$$\text{Outcome gaze proportion} = \frac{\text{Outcome dimension fixation time} - \text{Delay dimension fixation time}}{\text{Outcome dimension fixation time} + \text{Delay dimension fixation time}}$$

This indicator ranges from [-1, 1], with higher values indicating relatively longer fixation time on the outcome dimension. In this experiment, participants' mean outcome gaze proportion was -0.02 (95% CI = [-0.04, 0.01]). DDJ scores were used as the dependent variable, and outcome gaze proportion as the fixed effect in a mixed-effects linear regression. The results showed that the regression coefficient for outcome gaze proportion was significant, b = 0.31, 95% CI = [0.21, 0.41], t = 5.96, $p < 0.001$, as shown in Figure 3e, supporting H4.

## Experiment 2

Experiment 1 found that response time, gaze entropy, and other indicators could significantly predict PDD. Experiment 2 built upon Experiment 1 with improvements to verify whether these effects are robust. First, to verify the robustness of Experiment 1' s results, Experiment 2 was pre-registered (see https://osf.io/34c6x). Second, the monetary and temporal magnitudes used in Experiment 1 were relatively small; Experiment 2 increased the magnitude of intertemporal options to verify whether the discovered effects still exist in relatively larger-scale intertemporal decisions. Third, to further verify the validity of the PDD estimation method, Experiment 2 required participants to repeat the same intertemporal choice twice to examine the relationship between PDD and choice reversal. Previous studies have found that preference strength correlates with choice reversal (Alós-Ferrer & Garagnani, 2021); stronger preference strength leads to lower likelihood of changing choices (i.e., choice reversal) in subsequent identical choices. Following similar logic, this study hypothesized that larger PDD would lead to lower likelihood of choice reversal in subsequent identical choices.

### 3.1.1 Participants

Based on the results regarding response time, gaze transition entropy, and stationary gaze entropy from Experiment 1, the required sample size for Experiment 2 was calculated using the lmmpower package in R. Using mixed-effects linear regression with statistical power set at 1 - $\beta$ = 0.95 and $\alpha$ = 0.05, the required sample size was N = 51 (3360 trials, based on scale response time results). The experiment recruited 59 university students (mean age = 21.9 $\pm$ 2.1 years, 33 females). All participants had normal or corrected-to-normal vision and signed informed consent before the experiment. Participants received a basic compensation of 20 yuan after the experiment. The study was approved by the ethics committee of the institution.

### 3.1.2 Materials

Unlike Experiment 1, the monetary outcomes and delay times in Experiment 2 were increased in magnitude. The monetary outcomes were set at four fixed amounts: 20, 50, 100, and 200 yuan. The time delays were set at four fixed intervals: immediate, 10 days, 50 days, and 100 days. These were combined to form 36 pairs of non-dominated options (see Table S2 in supplementary materials).

### 3.1.3 Procedure

The tasks and procedure were essentially the same as in Experiment 1, with the difference that the intertemporal choice task in Experiment 2 consisted of two blocks, each containing identical trials—that is, 36 pairs of choices repeated twice—to examine whether participants made inconsistent choices across the two identical intertemporal choices (i.e., exhibited choice reversal). Additionally, due to the relatively larger monetary magnitude, the incentive scheme was modified. Participants were told before the intertemporal choice task began that after the entire experiment, one choice from one participant would be randomly selected for an additional reward, which is a commonly used incentive method in intertemporal choice research (Reeck et al., 2017).

### 3.2.1 Descriptive Statistics

In the intertemporal choice task, the mean proportion of LL choices was 50.0% (95% CI = [42.1%, 57.8%]), and the mean response time was 3.02 s (95% CI = [2.72, 3.31]). In the analogue scale task, the mean judgment score was 3.74 (95% CI = [3.50, 3.98]), and the mean response time was 7.05 s (95% CI = [6.18, 7.93]). The proportion of choice reversal (making inconsistent choices when facing identical options) was 17.4% (95% CI = [14.7, 20.2]).

### 3.2.2 Preference of Dimension-Based Difference and Analogue Scale Scores

First, participants' intertemporal choices were used as the dependent variable, and analogue scale scores as the fixed effect in a mixed-effects logistic regression. The results showed that analogue scale scores significantly predicted intertemporal choice, $b = 0.59$, 95% CI = [0.54, 0.65], OR = 1.81, $z = 21.69$, $p < 0.001$, as shown in Figure 4a [Figure 4: see original paper], similar to Experiment 1.

Second, the relationship between dimensional difference judgment and analogue scale scores was examined. Analogue scale scores were used as the dependent variable, and DDJ scores as the fixed effect in a mixed-effects linear regression. The results showed that the regression coefficient for DDJ scores was significant, $b = 0.68$, 95% CI = [0.64, 0.73], $t = 28.30$, $p < 0.001$, as shown in Figure 4b.

Finally, the relationship between PDD and scale judgment strength was examined. Scale judgment strength scores were used as the dependent variable, and PDD scores as the fixed effect in a mixed-effects linear regression. The results showed that the regression coefficient for PDD scores was significant, $b = 0.26$, 95% CI = [0.23, 0.29], $t = 16.21$, $p < 0.001$, as shown in Figure 4c.

### 3.2.3 Preference of Dimension-Based Difference and Choice Reversal

Choice reversal (coded as 1 for reversal, 0 for no reversal) was used as the dependent variable, and scale judgment strength and PDD scores from the first choice (i.e., trials in the first block) were used as fixed effects in separate mixed-effects logistic regressions. The results showed that scale judgment strength significantly negatively predicted choice reversal, $b = -0.33$, 95% CI = [-0.46, -0.20], OR = 0.72, $z = -4.98$, $p < 0.001$, as shown in Figure 5a [Figure 5: see original paper]. PDD scores also significantly negatively predicted choice reversal, $b = -0.17$, 95% CI = [-0.29, -0.05], OR = 0.85, $z = -2.74$, $p = 0.006$, as shown in Figure 5b. These results indicate that both scale judgment strength and PDD can negatively predict participants' choice reversal behavior, providing another perspective validating the effectiveness of the PDD indicator in this study.

### 3.2.4 Preference of Dimension-Based Difference and Response Time

PDD scores were used as the dependent variable, and choice response time and scale response time were used as fixed effects in separate mixed-effects linear regressions. The results showed that the regression coefficient for choice response time was significantly negative, $b = -0.28$, 95% CI = [-0.34, -0.22], $t = -9.98$, $p < 0.001$; the regression coefficient for scale response time was also significantly negative, $b = -0.17$, 95% CI = [-0.22, -0.12], $t = -6.89$, $p < 0.001$, as shown in Figures 6a [Figure 6: see original paper] and 6b. These results are similar to Experiment 1 and support H2.

### 3.2.5 Preference of Dimension-Based Difference and Gaze Entropy

Participants' mean gaze transition entropy and stationary gaze entropy were 0.63 (95% CI = [0.59, 0.66]) and 1.19 (95% CI = [1.16, 1.23]), respectively. PDD scores were used as the dependent variable, and gaze transition entropy and stationary gaze entropy were used as fixed effects in separate mixed-effects linear regressions. The results showed that the regression coefficient for gaze transition entropy was significantly negative, $b = -0.41$, 95% CI = [-0.53, -0.29], $t = -6.77$, $p < 0.001$; the regression coefficient for stationary gaze entropy was also significantly negative, $b = -0.50$, 95% CI = [-0.64, -0.37], $t = -7.78$, $p < 0.001$, as shown in Figures 6c and 6d. These results are similar to Experiment 1 and support H3.

### 3.2.6 Dimension-Based Difference Judgment and Dimension-Based Attention Allocation

Participants' mean outcome gaze proportion was -0.06 (95% CI = [-0.09, -0.03]). Similar to Experiment 1, DDJ scores were used as the dependent variable, and outcome gaze proportion as the fixed effect in a mixed-effects linear regression. The results showed that the regression coefficient for outcome gaze proportion was significant, $b = 0.27$, 95% CI = [0.18, 0.35], $t = 6.11$, $p < 0.001$, as shown in Figure 6e.

## General Discussion

This study examined the relationship between PDD and information processing in intertemporal choice through two eye-tracking experiments, providing more direct process evidence for dimension-based intertemporal models. The results showed that PDD fitted based on the tradeoff model significantly correlated with dimensional difference judgment in the analogue scale task (Experiment 1) and could negatively predict subsequent choice reversal (Experiment 2), validating the effectiveness of the PDD estimation method. The study further found that decision time, gaze transition entropy, and stationary gaze entropy were all negatively correlated with PDD, while outcome gaze proportion could predict dimensional difference judgment, providing evidence for the psychological mechanism of dimensional difference comparison in intertemporal choice. The study verified the robustness of these results through two experiments, providing more direct process support for dimension-based intertemporal models.

### 4.1 Advantages of Preference of Dimension-Based Difference

This study validated an effective method for estimating PDD. For measuring subjective dimensional differences, previous studies have mostly used the intuitive analogue scale task (Jiang et al., 2016; Jiang et al., 2022). Although this paradigm has the advantage of being intuitive and easy to understand, it requires additional measurement of participants' subjective dimensional difference judgment before or after decision-making. The PDD estimation method proposed in this study is entirely based on individuals' intertemporal choices and can estimate PDD without additional measurement data, making it simple, convenient, and applicable to paper-and-pencil questionnaires. Moreover, this measurement approach is more suitable for quantitative mathematical model construction and has unique advantages.

We believe that compared to intertemporal choice behavioral outcomes, the PDD indicator has three advantages. First, PDD can more finely reveal individuals' patience levels. Even if two people make the same intertemporal choice, if their dimensional difference judgments differ, their patience levels may differ, and they may exhibit different temporal preference patterns in subsequent intertemporal choices. Second, PDD can predict choice reversal. Similar to decision confidence, the strength of preference often predicts choice reversal in subsequent decisions (Alós-Ferrer & Garagnani, 2021; Moran et al., 2015). This study found that PDD can also negatively predict choice reversal; lower PDD means individuals are more likely to make different choices when subsequently facing the same choice. In other words, researchers can use the PDD indicator to predict individuals' future intertemporal choice behavior to some extent. Additionally, some scholars consider choice reversal as an indicator of choice error (Konovalov & Krajbich, 2019), so PDD can also serve as an indicator of decision error to some extent. Third, when intertemporal choice outcomes are unclear, selection can be indirectly inferred through indicators reflecting PDD. Taking response time as an example, suppose we don' t know Zhang' s choices between "receive 1000 yuan in one year" versus "receive 1200 yuan in three years" and between "receive 1000 yuan in one year" versus "receive 1500 yuan in three years." However, we know he spent 5 seconds making the first choice and 4 seconds making the second choice. Since response time can reflect PDD, we can infer that when the outcome dimension difference increased, Zhang' s PDD also increased, indicating that he perceived the outcome dimension difference as larger in the first choice and would therefore select the LL option. Thus, by comparing changes in response time across two choices, we can infer his choice behavior.

## 4.2 Dimension-Based Information Processing and Preference of Dimension-Based Difference

This study provides insights into the relationship between PDD and information processing. In recent years, some researchers have attempted to combine the theoretical framework of sequential sampling models with dimension-based intertemporal models, describing intertemporal choice as an information processing mechanism that accumulates evidence between outcome and delay dimensions, and have verified these models' explanatory power for choices and response times (Amasino et al., 2019; Dai & Busemeyer, 2014; Dai et al., 2018). However, to our knowledge, no study has attempted to develop an intertemporal model incorporating eye-tracking fixation. This study proposes the iaDDM theoretical framework, hypothesizing that decision-makers sample dimensional difference information based on eye-tracking fixation and accumulate evidence, and finds that response time, gaze entropy, and other indicators correlate with PDD. These findings suggest that using the iaDDM framework to explain dimension-based information processing in intertemporal choice is feasible. Compared to fitting DDM with response time and other behavioral data, developing a DDM based on eye-tracking fixation can help us better understand individuals' information processing during decision-making and provide more direct process evidence for validation.

Future research developing quantitative iaDDM models should note four points. First, appropriate theoretical kernels should be selected. This study estimated individuals' PDD based on the tradeoff model (Scholten & Read, 2010), while other dimension-based intertemporal models exist, such as the similarity model (Leland, 2002) and equate-to-differentiate model (Li, 2004, 2016). Although these models share the same basic kernel, they differ in mathematical expressions such as utility functions. Future research should compare and differentiate the explanatory power of different models when developing models. Second, besides considering models' explanatory power for intertemporal choices, future research should carefully consider whether models can replicate the data patterns regarding PDD and eye-tracking indicators discovered in this study when running simulations. Third, compared to single-option, two-dimension decisions (Sullivan & Huettel, 2021), two-option, two-dimension intertemporal decisions should consider the direction of evidence accumulation when constructing eye-tracking models. For example, when individuals fixate on outcome information for the SS option, some researchers believe this increases accumulated evidence for the outcome dimension (Gluth et al., 2020), while others believe it decreases evidence for the outcome dimension because the SS option' s outcome information represents a disadvantage in the outcome dimension (Amasino et al., 2019). This requires further discrimination and testing by future researchers. Fourth, although this study' s results support dimension-based intertemporal models, they do not indicate that alternative-based information processing does not exist in intertemporal choice. In fact, some researchers have used alternative-based hyperbolic discounting models combined with DDM to fit response time data and have also obtained supportive evidence (Konovalov & Krajbich, 2019; Rodriguez et al., 2014).

### 4.3 Application of Relevant Eye-Tracking Indicators in Decision-Making Research

This study discovered the relationship between gaze entropy and PDD, suggesting the application value of gaze entropy in decision-making research. As an integrated eye-tracking indicator, gaze entropy is typically used to measure the complexity of visual search (Krejtz et al., 2015; Schieber & Gilland, 2008). Gaze transition entropy measures the frequency of random saccades between areas of interest, reflecting information search efficiency (Shiferaw et al., 2019). Stationary gaze entropy measures the uniformity of fixation distribution across different areas of interest (Krejtz et al., 2014), reflecting information search distribution patterns. Previous studies have used gaze entropy indicators to examine eye-tracking characteristics in applied scenarios; for example, researchers have found that gaze transition entropy correlates with the difficulty of surgical procedures performed by doctors (Di Stasi et al., 2016), and stationary gaze entropy correlates with lane deviation in simulated driving scenarios (Shiferaw et al., 2018). This study is the first to apply gaze entropy to decision-making research to examine cognitive processing mechanisms, and future research can also apply it to other decision-making studies. For instance, future research could use gaze transition entropy to examine decision process complexity to distinguish between intuitive heuristic strategies and rational analytical strategies (Kahneman & Frederick, 2002). Additionally, while previous studies have used fixation time proportions across different dimensions to measure the uniformity of option information fixation (Su et al., 2013), stationary gaze entropy can provide a more precise holistic assessment of fixation uniformity. Moreover, examining the covariation of the two gaze entropy indicators can help distinguish between two cognitive processing modes in decision-making. Some researchers propose that increased stationary gaze entropy accompanied by increased gaze transition entropy may reflect top-down processing influences on eye-tracking fixation; conversely, increased stationary gaze entropy accompanied by decreased gaze transition entropy often indicates more bottom-up eye movement control (Shiferaw et al., 2019). This research approach can also be applied to decision-making studies to help test the causal relationship between eye-tracking fixation and decision-making behavior (Liu, Lyu, et al., 2021; Liu et al., 2020).

This study verified the relationship between outcome gaze proportion and dimensional difference judgment, providing new reference evidence for further application of this indicator in intertemporal choice. Previous research has established the relationship between relative fixation time on the outcome dimension and decision-makers' patience levels. For example, Amasino et al. (2019) found that relative fixation advantage on the outcome dimension can predict individuals' time discount rates. Similarly, Liu, Lyu et al. (2021) found that when individuals fixate more on the outcome dimension, they are more likely to choose the LL option that dominates on the outcome dimension, and vice versa. However, when using relative fixation advantage on the outcome dimension to predict choice, no significant predictive effect was found. Combined with this study' s findings, we speculate that individuals' intertemporal choices involve many errors and noise that are not easily captured by quantitative eye-tracking indicators such as attention allocation, while the dimensional difference judgment estimated in this study is based on overall decision fitting and can partially separate decision errors, thus more precisely reflecting attention allocation and other eye-tracking indicators. This suggests that future research focusing on the relationship between fixation duration-based eye-tracking indicators and intertemporal choice behavior should be mindful of the confounding effect of decision errors to avoid misinterpreting null results.

One goal of eye-tracking research on decision-making is to "read minds" —

that is, to predict choices based on decision-makers' eye-tracking trajectories (Brandstätter & Körner, 2014; Stewart et al., 2015). Researchers hope to achieve the effect of "I can tell what you want to choose by looking at where your eyes are looking." Within the theoretical framework of dimension-based intertemporal choice, this study's results suggest that through eye-tracking data, we can not only determine which dimension individuals judge as having a larger difference and thus which option they will choose, but also determine how large individuals judge the difference between the two dimensions to be and how strong their preference for the option is. In other words, through eye-tracking data, we can not only know which option you want to choose but also how much you want to choose that option.

## Conclusion

This article examined the relationship between preference of dimension-based difference and information processing in intertemporal choice through two experiments, reaching the following conclusions: (1) Individual PDD in intertemporal choice can be effectively estimated based on the tradeoff model. (2) Response time is negatively correlated with PDD. (3) Gaze transition entropy and stationary gaze entropy are negatively correlated with PDD. (4) Dimension-based attention allocation is positively correlated with dimensional difference judgment.

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