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Measuring time preference: Theory, methods, and applications

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ABSTRACT

Measuring time preference is a fundamental challenge in both the theory and application of intertemporal decision-making. Current approaches can be broadly classified into two paradigms based on their utility representations: Money Earlier or Later (MEL) experiments and Time-Yoked Consumption experiments. This paper comprehensively reviews the theoretical evolution of these approaches. We find this evolution is characterized by the progressive relaxation of restrictive assumptions concerning the utility function, yielding substantial improvements in both measurement accuracy and practical applicability. Upon this methodological foundation, we systematically examine recent applications of time preference measurement across diverse domains, including public choice, labor market decision-making, development economics, health decisions, and political behavior. Finally, we conclude by proposing promising directions.

1. Introduction

Time preference, which reflects individuals' tendency to favor goods available immediately over those available in the future, has long been an important topic in economic thought. It can be traced to Adam Smith's *The Wealth of Nations* (1776), where he underscored its critical role in national wealth accumulation (Smith, 1937). Subsequent economists, including John Rae, Eugen von Böhm-Bawerk, and Irving Fisher, delved deeper into multifaceted nature, identifying a wide array of influencing factors such as self-restraint, uncertainty, the pleasure of immediate consumption, underestimation of future needs, bequest motives, expected income, risk preference, and fashion. However, these diverse psychological motivations remained conceptually distinct until they were elegantly synthesized by Paul Samuelson into a single discount rate parameter (Samuelson, 1937). The advent of his Discounted Utility (DU) model thus inaugurated a new era of mathematical analysis in the study of time preference.

Given that time preference can often be confounded with other factors influencing intertemporal decision-making, such as risk preference and prevailing market interest rates, accurately measuring time preference presents a nuanced challenge. Consequently, precisely measuring the cost of time and eliciting pure time preference are critical issues both in theoretical research and practical application. To achieve this objective, it is essential to isolate and minimize the interference of these extraneous factors.

Capturing the essence of time preference, the fundamental question we need to consider is: all else being equal, do individuals prefer to receive 1 unit of utility immediately or 2 units of utility after a certain period? This fundamental trade-off presents two primary measurement challenges. First, how should utility be measured? If we use money or other consumptions to represent utility, what principles of conversion should we adhere to? Second, how can we ensure the timeliness of utility? Since intertemporal choices are based on expected utility, the validity of measurement hinges on the subject's belief that the delayed reward will be delivered as promised.

In response to these measurement challenges, a diverse array of methods have been developed over the past few decades. Conceptually, measuring time preference is equivalent to determining the “price” an individual places on time, which is revealed by establishing an indifference point in an intertemporal utility exchange. Since utility cannot be directly measured, it is common to use money or consumptions (including real effort) as proxies for utility to capture time preference (Cohen et al., 2020). The former approach is known as the “money earlier or later experiment” (MEL experiment), where participants can choose to receive a smaller amount of money sooner or a larger amount of money later. The second is referred to as the “time-yoked consumption experiment,” where participants' consumption of goods or their exertion of real effort is tied to their choices about when to consume or exert effort. This paper aims to review the development of time preference measurement methods based on this classification.

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The measurability of time preference provides crucial quantitative indicators for both theoretical research and practical applications. Building on this premise, this paper reviews the application of time preference measurement across a wide range of domains, including public choice, labor market decisions, health behaviors, and development economics. By showcasing these applications, this paper aims to stimulate further applied research that leverages these advanced methodologies.

While several excellent and comprehensive reviews have mapped the landscape of time preference research,[1] this manuscript provides a distinct and complementary contribution. Our primary goal is to synthesize the field's methodological progress into an evolutionary narrative. We chronicle a clear trajectory away from early paradigms, which relied on restrictive assumptions about utility, towards more robust and realistic models of choice. Second, we provide a critical comparative analysis of methodological trade-offs. Rather than presenting measurement techniques as equally valid alternatives, we systematically evaluate the strengths, limitations, and underlying assumptions of different approaches, highlighting when and why certain methods may be more appropriate than others. This critical lens helps researchers move beyond simply choosing the most popular or convenient technique. Finally, we place a strong emphasis on connecting these modern measurement techniques to practical applications, aiming to equip researchers with a clear framework for selecting and applying the most suitable methods for their own empirical questions. In essence, this review serves not just as a repository of knowledge, but as a narrative guide that charts the field's progression, bridges methodological theory with empirical practice, and encourages the adoption of more robust methods in applied research.

The paper is organized as follows. Section 2 traces the conceptual and theoretical development of time preference. Section 3 then delves into the development of MEL experiments, analyzing the assumptions that underpin their various designs. Section 4 summarizes existing time-yoked consumption experiments, including real-effort experiments. Section 5 presents the practical applications of these measurement methods across various domains. Finally, based on this comprehensive review, Section 6 concludes by identifying several promising directions for future research.

2. The conceptual and theoretical development of time preference

Discussions on how individuals weigh benefits and losses over time can be traced back to Adam Smith's 1776 work, *The Wealth of Nations*. Smith laid the groundwork by linking national wealth accumulation to intertemporal trade-offs, arguing that the amount of labor allocated to capital production in the present determines the total wealth of the nation in the future. This line of thought was significantly advanced by Scottish economist John Rae. In *The Social Theory of Capital*, Rae (1834) articulated what he termed “the effective desire of accumulation,” arguing that this underlying desire is the critical factor influencing national wealth accumulation. Rae's concept serves as a clear precursor to the modern notion of time preference, demonstrating that a sophisticated understanding of how individuals weigh the future against the present was already emerging nearly two centuries ago.

While the term “time preference” was coined by Irving Fisher in his 1930 work, *The Theory of Interest*, its formal modeling arrived in 1937. This crucial step was taken by Paul Samuelson, then a graduate student at Harvard, in a paper with the unassuming title, “A Note on Measurement of Utility.” The paper introduced the Discounted Utility (DU) model, a framework that marked the beginning of the era of model-based analysis of time preference. The model's power lay in its elegant simplification: it collapsed all complex psychological motivations into a single, constant discount rate and extended the framework to accommodate choices over multiple periods. According to the DU model, the total utility obtained by a decision-maker from intertemporal decision is:

$$U^t(c_t, \ldots, c_T) = \sum_{k=0}^{T-t} D(k)u(c_{t+k}) \tag{1}$$

where $D(k) = \left(\frac{1}{1+\rho}\right)^k$, represents the discount function of the decision-maker, ρ represents the pure time preference, also known as the discount rate, which is the aggregate influence of all psychological motivations on the decision-maker.

The DU model is grounded in the following strong, simplifying assumptions. First, constant discount rate and time consistency, it posits that individuals evaluate time impartially, such that extending or shortening the discount period does not alter their preference. Second, positive time preference rate, it reflects a natural preference for present over future utility. Individuals are inherently impatient. Third, consumption neutrality, it assumes that the discount rate remains consistent across various types of consumption. Fourth, dynamic consistency, when faced with new choices, individuals integrate them into their existing optimal consumption plan without altering the original preference structure. Fifth, utility independence, total utility is merely the sum of each period's discounted utility. Sixth, stationary utility function, the utility function that decision-makers face remains constant over different time periods. Seventh, consumption independence, consumption in one period is independent of consumption in any other period.

These assumptions render the Discounted Utility (DU) model axiomatically elegant and internally consistent. However, this theoretical perfection comes at the cost of descriptive accuracy. By resting entirely on the “rational agent” framework, exponential discounting becomes a normative ideal rather than a reflection of actual human behavior. As methods for measuring time preference advanced, they began to reveal systematic patterns in decision-making. Chief among these findings was the robustly documented phenomenon of declining discount rates over time, which directly contradicts the model's core assumption of a constant rate.

To model the phenomenon where the time preference rate decreases over time, researchers have introduced a variety of alternative functions to replace the exponential discount function. These alternatives range from the simplest forms, denoted as $D(t) = \frac{1}{t}$ (Ainslie, 1975), to more complex variations, denoted as $D(t) = \frac{1}{1+\alpha t}$ (Mazur, 1987), and include the widely utilized hyperbolic discount function (Chung & Herrnstein, 1967; Loewenstein & Prelec, 1992). The expression for the hyperbolic discount function is:

$$D(t) = \frac{1}{(1+\alpha t)^{\frac{\beta}{\alpha}}} \tag{2}$$

This equation implies that the discount rate from the current period to the next period is $\frac{1-\beta\delta}{\beta\delta}$, and the discount rate from the next period to the period after that is $\frac{1-\delta}{\delta}$. When $\beta < 1$, we have $\frac{1-\delta}{\delta} < \frac{1-\beta\delta}{\beta\delta}$, which depicts a trend where the discount rate decreases initially and then remains constant. Compared to the hyperbolic discount function, the quasi-hyperbolic discount function effectively captures individuals' present bias by using $\beta < 1$. Specifically, from the perspective of period 0, the relative value of a good in period 6 compared to period 5 is $\frac{\beta\delta^6}{\beta\delta^5} = \delta$, whereas the relative value of a good in period 1 compared to period 0 is $\frac{\beta\delta}{1} = \beta\delta$. Despite the same time difference, since $\beta < 1$, the value of period 1 relative to period 0 is less than the value of period 6 relative to period 5. Thus, the quasi-hyperbolic discount function more accurately captures the characteristic of a steep decline in the discount rate when

[1] E.g., Frederick et al., 2002; Cairns, 2006; Attema, 2012; Doyle, 2013; Lawless et al., 2013; Cheung, 2016; Cohen et al., 2020 and Lipman & Attema, 2024.

individuals face immediately available goods. In this context, the parameter $\beta(\beta < 1)$ reflects the degree to which individuals value present consumption, the smaller β is relative to 1, the more individuals prioritize the present, indicating a higher degree of myopia.

Among the currently proposed hyperbolic discount functions, the most widely used is the quasi-hyperbolic discount function (Laibson, 1997; Phelps & Pollak, 1968). The quasi-hyperbolic discount function not only reflects the decreasing discount rate over time but also offers computational simplicity, making it a relatively mature tool for calculating discount rates. Its expression is:

$$D(t) = \begin{cases} 1, t = 0 \\ \beta\delta^t, t > 0 \end{cases} \tag{3}$$

where β is the short-term discount factor and δ is the long-term discount factor, satisfying $0 < \delta \leq 1$.

The development of time preference measurement has allowed researchers to intuitively discover that discount rates are not constant but increase rapidly as the time of realization approaches. This insight has led to the optimization of theoretical models of time preference, evolving from the exponential discounting model to the hyperbolic discounting model and the quasi-hyperbolic model. Compared to the exponential discounting model, the (quasi-)hyperbolic discounting model provides a more accurate description and more effective predictive power regarding individuals' intertemporal decision-making. Consequently, these refined models and improved measurement methods have also opened new avenues for practical application.

3. Measuring time preference: MEL experiments

The MEL experiment employs monetary incentives as a proxy for utility, assessing time preference by evaluating the agents' discount rates. The discount rate represents the marginal rate of substitution between current and future consumption, which is depicted by the slope of the agents' indifference curve. Consequently, determining the agents' discount rate necessitates identifying their indifference point. In MEL experiments, three commonly used paradigms are employed to pinpoint the indifference point.

3.1. Foundational paradigms: eliciting the indifference point

(1) Matching paradigm[2] (Thaler, 1981). The question is: "Receiving (or losing) x_1 at time t_1" and "Receiving (or losing) _x_2_ at time t_2" are indifferent to you. Participants in the experiment are required to input a numerical value in the provided space to signify that they are indifferent between the two presented options. This value (x_1, x_2) represents one of the participant's indifference points.

(2) Random Binary Choice (RBC) paradigm (Johnson et al., 1989; Kirby & Maraković, 1996). The RBC paradigm requires participants to weigh a smaller-sooner reward (SS reward) against a larger-later reward (LL reward). The basic question is: "Which do you prefer between receiving (or losing) x_1 at time t_1" and "receiving (or losing) x_2 at time t_2?" Here, the values of x_1, x_2, time t_1, and time t_2 constitute a binary choice pair $(x_1, t_1; x_2, t_2)$. All binary choice pairs in the RBC paradigm are independent and appear randomly, which might prevent participants from influencing their decisions through reference effects. Participants are asked to make choices in n sets of independently and randomly presented binary choice pairs. The point at which participants switch from preferring SS reward to LL reward is considered the indifference point. Generally, these two choices can be regarded as an indifference pair. When processing the data, any indifference pair can be chosen to infer the participants' discount rate.[3]

(3) Multiple Price List (MPL) paradigm (Coller & Williams, 1999; Harrison et al., 2002). In the MPL paradigm, n sets of binary choices are presented sequentially with the LL reward gradually increasing while other parameters remain unchanged—that is, x_1, t_1, t_2 stay constant while $x_{2n} > x_{2(n-1)} > \ldots > x_{22} > x_{21}$. It is easy to see that as the value of LL reward gradually increases, participants will switch their choices from SS reward to LL reward. If a participant chooses SS reward when faced with the binary choice pair $(x_{1p}, t_{1p}; x_{2p}, t_{2p})$ and chooses LL reward when faced with the binary choice pair $(x_{1(p+1)}, t_{1(p+1)}; x_{2(p+1)}, t_{2(p+1)})$, where p is a natural number that is greater than or equal to 1 and less than n, then we consider that for this participant, (x_{1p}, t_{1p}) and (x_{2p}, t_{2p}) are indifferent, and so are $(x_{1(p+1)}, t_{1(p+1)})$ and $(x_{2(p+1)}, t_{2(p+1)})$. In the MPL paradigm, the precision of measuring a participant's discount rate can be adjusted by the increment speed of the LL reward.

Once the indifference point is identified, the discount rate of the experiment participants can be derived. For participants engaging in binary choices, their total discounted utility is:

$$DU = max\{D(x_1)\cdot v(x_1), D(x_2)\cdot v(x_2)\} \tag{4}$$

where $D(\cdot)$ is the discount function that satisfies $D(0) = 1, D' < 0$, $v(\cdot)$is the discount function that satisfies $v(0) = 0, v' > 0, v'' < 0$, at the indifference point, we have:

$$\frac{D(x_1)}{D(x_2)} = \frac{v(x_2)}{v(x_1)} \tag{5}$$

assuming the utility function is linear, we have:

$$\frac{D(x_1)}{D(x_2)} = \frac{x_2}{x_1} \tag{6}$$

At this point, it can be seen that the specific form of the discount function has a significant impact on the estimation of the discount rate. Taking the quasi-hyperbolic discounting function (Eq. (3)) as an example, to estimate β and δ, it is essential to employ two sets of fill-in-the-blank questions, binary choice pairs, or multiple price lists. Additionally, one of the sets should have the SS reward acquisition time set to today. For example: (a) choosing between "today" and "one week later"; (b) choosing between "one month later" and "one month and one week later." Using (b), the parameter δ can be estimated, and combining it with (a), the parameter β can be estimated. It is important to note that assuming a linear utility function implicitly presupposes that the decision-maker is risk-neutral. Therefore, if the decision-maker is risk-averse, the measured discount rate will be biased upwards (Rabin, 2000).

3.2. Critical evaluation of foundational paradigms

A primary trade-off is between the cognitive simplicity for the participant and the precision of the data for the researcher. The Matching paradigm, while simple for subjects, suffers from high variance and practical implementation challenges. Conversely, the Multiple Price List (MPL) provides precise interval data, but at the cost of

[2] Also known as the Fill-in-the-blank task.

[3] Choosing any indifference point as the basis for calculating the discount rate is the most common practice in existing literature. In addition, some studies record both binary choice pairs where participants switch to using interval regression (Stewart, 1983) to examine the relationship between time preference and other variables (e.g., Benjamin et al., 2010). Other studies take the geometric mean of the two discount rates as the participant's discount rate (e.g., Kirby & Maraković, 1996; Xiong et al., 2019).

increased cognitive load, which can lead to participant fatigue and random responses.

Beyond precision, a crucial concern is response consistency. This is the most significant weakness of the Random Binary Choice (RBC) paradigm. It is prone to producing multiple switching points, which complicate analysis and suggest unstable preferences. In contrast, the MPL's ordered structure directly addresses this by encouraging a single switch, yielding cleaner and more readily analyzable data.

Ultimately, the evolution towards MPL reflects a field-wide trend: accepting greater task complexity for more reliable data. This inherent trade-off means no single method is universally superior. The researcher's choice must be a deliberate decision based on the study's specific context, participants, and analytical goals.

3.3. Methods for non-linear utility

The Matching paradigm, RBC paradigm, and MPL paradigm all assume a linear utility function for measurement, which presupposes that all experimental participants are risk-neutral. However, Holt and Laury's (2002) measurement experiment reveals that in the U.S. sample, the proportion of risk-neutral participants is 26 %, 29 %, and 13 % under different incentive mechanisms. Therefore, the assumption of linear utility is not universally applicable. To address the issue, recent research has introduced three advanced paradigms for measuring discount rates that accommodate nonlinear utility functions: the Double Multiple Price Lists (DMPL, Andersen et al., 2008), the Convex Time Budget (CTB, Andreoni & Sprenger, 2012a) and the Two-step paradigm (Abdellaoui et al., 2010).

(1) DMPL paradigm (Andersen et al., 2008). The DMPL paradigm assumes that individuals demonstrate a consistent curvature in their expected utility function when confronted with both risk and temporal factors. This paradigm is divided into two stages: the risk preference measurement stage and the time preference measurement stage. Firstly, in the risk preference measurement stage, Andersen et al. (2008) adopt the Holt and Laury (2002) paradigm,[4] at the indifference point, the curvature parameter of the utility function is estimated. This estimated curvature parameter is subsequently applied to the time preference measurement stage, following the MPL paradigm (Coller & Williams, 1999; Harrison et al., 2002). Again, at the indifference point, the discount rate parameter is estimated. This parameter elucidates both the degree of intertemporal substitution and the extent of risk aversion.

Thus, the validity of the DMPL method hinges on a critical assumption: the equivalence of the utility functions governing risk and intertemporal choice. The accuracy of its time preference estimates is therefore dependent on these functions having identical curvature for an individual. When this assumption is violated, the estimates of the discount rate can be systematically biased.

[4] Which closely mirrors the MPL paradigm but substitutes SS rewards and LL rewards with safe options and risky options. The first row of table presents two options: (A) a 1/10 probability of receiving $2 and a 9/10 probability of receiving $1.6; (B) a 1/10 probability of receiving $3.85 and a 9/10 probability of receiving $0.1. Progressing down the table, the probability of receiving $2 in option (A) incrementally increases to 10/10, while the probability of receiving $1.6 correspondingly decreases to 0/10. Concurrently, the probability of receiving $3.85 in option (B) increases to 10/10, while the probability of receiving $0.1 decreases to 0/10. Analogous to the MPL paradigm, as the probability associated with the risky option increases, participants tend to shift their choices from the safe option (A) to the risky option (B).

(2) CTB paradigm (Andreoni & Sprenger, 2012a). We can readily observe that, whether it is the binary choice paradigm, the MPL paradigm, or the DMPL paradigm, experimental participants are always required to make an either-or choice between the two corner solutions $(X, 0)$ and $(0, Y)$. However, when the utility function is not linear, the optimal choice does not necessarily lie at these corner solutions, leading to potential measurement bias. The CTB paradigm, however, mitigates this issue (Andreoni & Sprenger, 2012a). By introducing additional options (x_1, x_2) between $(X, 0)$ and $(0, Y)$ in each row, as illustrated in Table 1 of the Appendix, the CTB paradigm ensures these options satisfy the budget constraint:

$$Px_1 + x_2 = Y \tag{7}$$

where $P = \frac{Y}{X}$. Hence, we can derive the marginal rate of substitution between the utilities of different periods as:

$$MRS = \frac{x_t^{\alpha-1}}{\beta^{t_0}\delta^k x_{t+k}^{\alpha-1}} = P \tag{8}$$

where $t_0 = \begin{cases} 1, t = 0 \\ 0, t > 0 \end{cases}$. That is,

$$ln\left(\frac{x_t}{x_{t+k}}\right) = \frac{ln\beta}{\alpha-1}t_0 + \frac{ln\delta}{\alpha-1}k + \frac{lnP}{\alpha-1} \tag{9}$$

According to Eq. (9), we can obtain the estimated values of β, δ and α. According to the domain requirements of Eq. (7), the $(X, 0)$ option is excluded from the estimation sample. However, in practice, Andreoni and Sprenger (2012a) found that 17.1 % of experimental participants consistently chose the $(X, 0)$ option. This leads to a significant portion of data being discarded, thereby substantially reducing the measurement's

Table 1
Conceptual framework for measurement methods.

Methodological paradigm	Core assumption	Primary trade-off	Optimal use-case scenario
Matching RBC MPL	Utility linearity	Procedural simplicity vs. Potential bias	Large-scale surveys where cognitive load must be minimized.
DMPL	Risk-time utility equivalence	Disentangling risk and impatience vs. Contested assumption	Large-scale studies that requires disentangling pure time preference from risk preference.
CTB	Non-linear utility	High precision from interior solutions vs. Information loss from corner choices	Studies needing high precision for non-linear utility.
Two-step	Non-parametric utility	Theoretical flexibility vs. High cognitive demand	Foundational research where no functional form should be pre-assumed.
Probability-based	Probability linearity	Bypassing utility vs. Prospect theory critique	Isolating the discount factor when risk neutrality is a plausible assumption.
Direct method	Intertemporal additivity	Mathematical elegance vs. Ignoring consumption smoothing	Quick elicitation where consumption stream effects are not a primary concern.
DEEP	Correct model specification	Statistical efficiency vs. Model dependence	Online experiments with heterogeneous subjects where maximizing individual precision is key.

efficiency. To address this issue, Harrison et al. (2013) employed the Multinomial Logit Regression method for parameter estimation. Although this method resolves the exclusion of corner solutions, it also has the limitation of $\alpha \in (0,1)$, which results in risk-seeking participants being excluded from the estimation sample as well. To further improve the methodology, Andreoni et al. (2015) proposed using Interval Censored Tobit Regression for parameter estimation. Additionally, Andreoni and Sprenger (2012b) introduced probabilities into the CTB paradigm to enhance measurement efficiency. Their experimental results showed that when the payoffs on both dates were subject to a 0.5 probability, the proportion of corner solutions decreased significantly from 80.7 % to 26.1 %. Overall, the CTB method's ability to accurately measure time preference is fundamentally challenged by the prevalence of corner choices, which provide only a boundary for an individual's preference, not a precise estimate.

(3) Two-step paradigm (Abdellaoui et al., 2010). Also proposing a method that does not require pre-specifying the form of the utility function, Abdellaoui et al. (2010) employ a non-parametric, two-step method to cleanly separate utility from time discounting. First, they elicit subjects' utility functions in a timeless risk context using the tradeoff method for both gains and losses. Then, using these individually-calibrated utility functions, they measure the discount function by eliciting indifference points in intertemporal choices, allowing them to directly solve for the discount factor. Abdellaoui et al. (2013) further employ the Two-step paradigm to demonstrate the critical role of sign in intertemporal choice.

3.4. Critical evaluation of non-linear utility methods

The primary division among these methods is that the DMPL paradigm posits that the curvature of the intertemporal utility function matches that of the risk utility function. Operationally, it separately measures utility curvature from risk-preference tasks and the discount function from time-preference tasks, combining them to derive the discount rate. However, numerous studies (e.g., Fehr-Duda & Epper, 2012; Halevy, 2008) indicate that risk aversion and intertemporal substitution represent two distinct preferences, with no empirical evidence suggesting any correlation or consistency between their respective utility functions. Therefore, the discount rate parameter measured using the DMPL paradigm at least does not disentangle the confounding factors brought by risk.

In contrast, the Two-step paradigm avoids this assumption. It first measures the intertemporal utility function directly, then uses this parameter to elicit the discount factor in a second step. While this approach is powerful due to its flexibility in capturing any functional form without prior assumptions, its high cognitive demand on subjects can be a significant drawback.

The CTB paradigm directly measures the curvature of the utility function and the discount rate parameter by modulating the allocation of monetary amounts across different time points. A comparative study by Andreoni et al. (2015) revealed that the CTB paradigm demonstrated superior out-of-sample predictive performance.

3.5. Bypassing utility: direct measures of time preference

All of the aforementioned measurement methods fundamentally require participants to make choices based on varying payoffs at different points in time, thus estimating the discount rate through the estimation of utility itself. Given the two challenges in directly measuring utility discussed earlier in this section, some measurement methods strive to bypass the direct estimation of utility to enhance accuracy.

(1) Probability-base paradigm (Laury et al., 2012). This approach incorporates the probability of receiving future payoffs to simulate the uncertainty associated with future earnings. In this framework, participants simply select the probabilities $\{p_t, p_{t+k}\}$ of receiving a fixed payoff M at different future time points $\{t, t+k\}$, allowing for the estimation of the discount rate based on Eq. (8).

$$D(t)\cdot[p_t\cdot v(M) + (1-p_t)\cdot v(0)] = D(t+k)\cdot[p_{t+k}\cdot v(M) + (1-p_{t+k})\cdot v(0)] \tag{10}$$

Assuming $v(0) = 0$ in Eq. (8), we have:

$$\frac{D(t+k)}{D(t)} = \frac{p_t}{p_{t+k}} \tag{11}$$

X and Y are the key data estimated using the Laury et al. (2012) paradigm.[5] This innovative measurement method skillfully transforms the time cost associated with delayed payments into the probability of receiving future payoffs. By doing so, it circumvents the need for direct utility measurement, thereby addressing the limitations imposed by the inherent difficulties in measuring utility. The experimental results from Laury et al. (2012) indicate that the discount rate they obtained is significantly lower than that estimated using the Multiple Price List (MPL) paradigm. This adjustment effectively corrects the upward bias caused by the assumption of a linear utility function in the MPL paradigm.

(2) Direct Method (Attema et al., 2016) paradigm. The DM paradigm also offers a novel approach that bypasses the need to specify a utility function. Instead of estimating utility, it directly elicits the discount rate by identifying the time point at which a decision-maker is indifferent between two rewards.[6] The fundamental concept of this paradigm is that if participants perceive no difference between receiving a fixed payoff M every week from week 1 to week τ and receiving the same fixed payoff M every week from week $\tau+1$ to week T, then the following equation holds:

$$\sum_{t=1}^{\tau} D(t)\cdot v(M) = \sum_{t=\tau+1}^{T} D(t)\cdot v(M) \tag{12}$$

At this juncture, the utility function cancels out on both sides of the equation, thereby enabling the direct measurement of the discount rate without the need to characterize the utility function. While this approach obviates the necessity for specific assumptions about the utility function, the DM paradigm incorporates a crucial assumption to ensure the stability of $v(M)$: participants consume the payoff immediately upon receipt. Empirical findings from Attema et al. (2016) suggest that the discount rates obtained via the DM paradigm are slightly higher than those measured using the DMPL paradigm. However, the difference is not statistically significant.

(3) Dynamic Experiments for Estimating Preferences (DEEP) methodology (Toubia et al., 2013). This approach addresses the inefficiency and potential biases of traditional static methods. Instead of presenting subjects with a fixed and exhaustive set of choices, the adaptive method operates dynamically. It begins with a diffuse prior belief about an individual's preference parameters and iteratively presents optimal choice pairs designed to maximize the expected value of the determinant of the Hessian of the posterior distribution. In essence, this criterion selects the question that is expected to most effectively "sharpen" the posterior distribution, thereby yielding the most precise parameter estimates. Subsequent to identifying the optimal choice pairs for

[5] Please see Table 2 in the Appendix for details.

[6] For further details, please refer to Table 3 in the Appendix.

each respondent, a hierarchical Bayes framework is used to perform a simultaneous estimation of the discount parameters across all individuals.

(4) Other likelihood-based methods. Besides the DEEP paradigm, some research turns to maximum likelihood techniques. Tanaka et al. (2010), for instance, first elicit choice data using the MPL paradigm, then they apply MLE to derive a point estimate of the discount parameter for each individual. Dean and Ortoleva (2019) conducted a more integrated and comprehensive investigation on individual preference and behavior.

3.6. Critical evaluation of methods that bypass utility measurement

The primary advantage of methods designed to bypass utility is their methodological elegance. By isolating the discount factor, they aim to offer a purer measure of time preference. However, this elegance is achieved by "swapping" one strong assumption for another.

The probability-based method's advantage of avoiding utility measurement comes at the cost of assuming linear probability perception, a premise challenged by Prospect Theory. The DM method's advantage of mathematical simplicity relies on the assumption of inter-temporal utility additivity, which disregards known behavioral patterns like consumption smoothing. The DEEP paradigm must pre-specify a correct, parameterized economic model that accurately describes the respondent's decision-making process.

In summary, the researcher faces a crucial trade-off: the advantage of bypassing the utility function must be weighed against the disadvantage of introducing new assumptions.

3.7. Conceptual framework for measurement methods

The conceptual framework presented in Table 1 synthesizes the preceding discussion to offer a novel and structured perspective on time preference measurement methods. Moving beyond a linear enumeration of pros and cons, our framework provides a multi-dimensional classification. It deconstructs each methodological paradigm along two critical axes: (1) the core theoretical assumption, that is, whether the method's primary identifying assumption lies in the utility function, probability perception, or the intertemporal model itself, and (2) the primary trade-off it forces upon the researcher, such as the classic tension between procedural simplicity and statistical efficiency, or between theoretical flexibility and cognitive burden.

The principal contribution of this framework is to reframe the methodological choice not as a search for a universally 'best' method, but as a deliberate and context-dependent exercise in navigating trade-offs. Ultimately, this framework is intended as a decision-making tool. It equips researchers with a structured lens to select and, importantly, justify a measurement method that is most congruent with their specific research question and practical constraints.

4. Measuring time preference: Time -yoked consumption experiments

In recent decades, MLE experiments have significantly advanced the ability to measure true time preference. Nonetheless, the MEL experiments inherently possess certain limitations. First, the tradability of money means that market interest rates inevitably influence participants' choices, particularly when participants have extensive market experience. As a result, time preference measured using money often cannot entirely exclude the influence of interest rates (Chabris et al., 2008; Cubitt & Read, 2007).[7] Second, the storability of money complicates the experiment's ability to control the actual consumption timing of rewards. Consequently, the time preference information derived from the MEL experiment is prone to being affected by consumption smoothing behaviors (Casari & Dragone, 2015).

In Time-yoked consumption experiments, employing consumption goods or real effort as substitutes for money can effectively mitigate the 'arbitrage' risk prevalent in MEL experiments. Typically, participants are required to rate the attractiveness of the consumer goods involved in intertemporal choices before the experiment, thereby distinguishing between larger and smaller rewards. For instance, in the well-known marshmallow experiment (Mischel et al., 1989; Mischel & Ebbesen, 1970), experimenters initially asked children aged 3–5 to select their preferred item from two food options. The children were then left alone in a room and instructed to wait for the experimenter's return. If they managed to wait until the experimenter came back, they would receive the "more preferred" food. Alternatively, they could ring a bell to summon the experimenter at any time, but doing so would result in receiving the "less preferred" food. This setup required the children to decide between obtaining the "less preferred" food sooner and the "more preferred" food later. During the period the experimenter was absent, the children faced the continual challenge of making this intertemporal choice.

Apart from the marshmallow experiment, existing literature has explored a variety of consumptions as representations of utility. For instance, Loewenstein (1988) utilized video store vouchers as the consumption, engaging students from nearby schools to investigate framing effects in intertemporal decision-making. Loewenstein and Prelec (1993) employed different dining options to test the independence hypothesis in the DU model. Read and Van Leeuwen (1998) explored dynamic inconsistency in time preference by asking participants to choose between healthy and unhealthy foods at two distinct time points: 'now' and 'one week later.' Brown et al. (2009) explained the phenomenon of insufficient savings through the intertemporal allocation of beverages. Additionally, Crockett et al. (2013) and Soutschek et al. (2017) investigated the role of commitment in delayed gratification using pictures of women in lingerie as intertemporal trade-offs. However, despite these innovative approaches, the problem of consumption smoothing remains unresolved due to the inherent storability[8] of consumptions.

Real-effort experiments offer a more robust solution to the problem. These experiments demand participants to exert real effort, whether it be physical strength, willpower, cognitive skills, or other forms of exertion. Participants who exert such effort receive a LL reward, while those who do not receive a SS reward. Because real effort is difficult to store and its "smoothing" is challenging to achieve, real-effort experiments can substantially reduce the issue of consumption smoothing.[9]

Based on this advantage, real effort experiments have rapidly developed in a short period, resulting in a diverse array of tasks. Burks et al. (2012) required participants to sit in a laboratory for 2 h without engaging in any unrelated activities. For every additional 10 min they

[7] It is precisely for this reason that using cash as an experimental medium is only viable in regions where the financial lending market is extremely underdeveloped, in order to eliminate the interference caused by arbitrage. (e.g., Giné et al., 2018).

[8] Although consumptions typically have a limited shelf life or validity period, which reduces their storability compared to money, this challenge has not been adequately addressed.

[9] Real effort tasks are not entirely immune to smoothing. For instance, exerting willpower to resist temptation during an experiment might result in less willpower being available for other activities post-experiment. This is also a form of "smoothing." However, in practice, individuals lack precise control over their willpower or physical stamina, making smoothing in real effort tasks relatively challenging to achieve. Consequently, compared to MEL experiments and consumption experiments, real effort experiments are generally more effective at mitigating the impact of smoothing.

sat, they would earn an extra $5. Participants could opt out at any time by pressing a red button, thereby measuring their time preference levels. Augenblick et al. (2015) examined the dynamic inconsistency of time preferences by assigning letter-copying and Tetris-playing tasks at different time. Casari and Dragone (2015) used a noise-listening task to explore the impact of uncertainty on time preference inconsistency. Houser et al. (2018) employed a counting task to capture the influence of temptation on time preference inconsistency. Soutschek et al. (2018) used a text task requiring participants to cross out letters according to rules and a handgrip task to study brain activity related to the process of delayed gratification. Real effort tasks are also extensively applied in field experiments. Christensen-Szalanski (1984) examined the time preference levels and dynamic inconsistency of pregnant women by observing their decisions regarding anesthesia use before and during childbirth. Della Vigna and Malmendier (2006) analyzed gym membership usage to capture the intertemporal decision-making characteristics of gym members. Charness and Gneezy (2009) similarly investigated the effect of incentives on delayed gratification within the context of physical exercise. Ariely and Wertenbroch (2002) found that self-imposed phased deadlines, compared to a control group, improved students' performance in real effort tasks completed during class, thereby confirming the role of commitment in reducing time preference inconsistency.

Furthermore, existing research has demonstrated that time preference exhibit domain specificity, indicating that the same decision-maker can display different levels of patience across different kinds of intertemporal trade-offs. These domains can be broadly categorized into the monetary and consumption domains[10] (Andersen et al., 2008; Augenblick et al., 2015). McClure et al. (2007) further substantiated the domain specificity of time preference at the neuronal level. Their findings indicated that the brain regions activated during intertemporal decision-making involving juice and water are significantly different from those activated during decisions involving monetary rewards. Consequently, consumption experiments not only address some of the limitations inherent in MEL experiments but also provide valuable supplementary insights.

5. Application of time preference measurement methods

Building upon the review of the theoretical and methodological development of time preference measurement, this section illustrates the remarkable applicability of these methods. These methodological advancements transformed the concept from a theoretical abstraction into an empirically quantifiable variable. Consequently, the application of time preference in empirical work has become synonymous with the application of these very measurement methods. They offer a unifying framework for analyzing intertemporal trade-offs and have become foundational in fields as diverse as Public Choice, Labor Markets, Development Economics, Health Behavior, and Political Behavior. Against this backdrop, our analysis reveals how time preference can deepen our understanding of real-world decision-making, and how time preference shapes the entire landscape of human behavior.

5.1. *Time preference in public choice*

5.1.1. *Charity*

The integration of time preference theory into the study of charitable donations has yielded a powerful insight, revealing that creating a temporal gap between a pledge and its payment leads to higher donation amounts. This effect is primarily driven by present bias, a well-documented human tendency to overweight immediate costs and rewards. When a donation is scheduled for the future, its perceived cost is discounted, making individuals more willing to commit to a larger sum than they would if required to pay on the spot. This transforms a theoretical concept into a practical fundraising strategy.

Breman (2011) explored intertemporal choice in charitable giving through a field experiment, discovering that donors pledged significantly higher amounts when committing to a future donation compared to an immediate one, and that this commitment strategy had long-term efficacy. Building on these findings, Andreoni and Serra-Garcia (2021) confirmed this effect in controlled laboratory experiments using both between-subject and within-subject designs, consistently finding that promised future donations were larger than immediate ones. Taken together, these studies demonstrate strategically incorporating a time delay between a pledge and its payment is a powerful method for optimizing donation mechanisms and increasing total contributions.

5.1.2. *Retirement savings plan*

Viewing the retirement savings decision through the perspective of time preference theory reveals why it is such a challenging choice for many people. The decision requires individuals to make a tangible sacrifice in the present, which means reducing their current consumption—for a large but distant and abstract reward in the future. This structure makes it a classic case for present bias, where the immediate psychological cost of saving is often felt more acutely than the discounted value of future financial security. Consequently, individuals may repeatedly postpone enrollment or contribute less than is optimal, not because they devalue retirement, but because the immediate cost looms larger in their decision-making process.

Research demonstrates a strong link between individual time preferences and retirement savings, with studies like Clark et al. (2019) confirming that more patient individuals are more likely to save and accumulate greater wealth via the RBC paradigm. Building on this principle, subsequent work has developed powerful behavioral interventions to overcome present bias and boost participation. For instance, Madrian and Shea (2001) showed that implementing automatic enrollment as a default can dramatically increase plan participation rates from 20 % to 80 %. Further refining this approach, Thaler and Benartzi (2004) designed plans with gradually escalating savings rates, a strategy that also achieves high participation and long-term adherence. Collectively, these studies show that by engineering choice architecture through defaults and gradual commitment strategies, it is possible to significantly enhance long-term savings outcomes.

5.2. *Time preference in labor market*

5.2.1. *Procrastination*

From an academic perspective, procrastination can be understood as an issue of intertemporal allocation of labor. Procrastination often leads to adverse effects on work progress (Haycock et al., 1998) and results in negative feelings of regret, guilt, and self-blame (Rothblum et al., 1986; Solomon & Rothblum, 1984). Time preferences offer a valuable framework for understanding procrastination and offer useful insights for mitigating the problem. Given its connection to labor supply, real effort tasks have become a widely adopted paradigm for applying time preference to the intertemporal allocation of labor.

Pioneering research by Ariely and Wertenbroch (2002) used an essay-writing task to demonstrate that individuals voluntarily set deadlines for themselves as commitment devices to improve performance, even while struggling to adhere to them due to present bias. Building on this framework, Bisin and Hyndman (2020) designed a more granular experiment distinguishing between single- and multi-task settings. Their findings both confirmed and refined the earlier results: the demand for commitment was robust, and even stronger in complex multi-task scenarios. More notably, they discovered that present bias

[10] Other classification schemes also exist. For instance, a number of studies have explored domain specificity by comparing the health and monetary domains; see, e.g., Attema et al. (2018), Chapman (1996, 2002), Chapman and Elstein (1995), Fredslund et al. (2018), Hardisty and Weber (2009) and Tao et al. (2025).

was significant in single-task contexts but attenuated in multi-task ones, suggesting that task complexity may induce better planning. They also documented a powerful "deadline effect," a clustering of effort just before deadlines. Notably, this effect was absent in the no-commitment groups, which further validates the efficacy of these self-imposed structures.

5.2.2. Cooperation

Cooperation is a cornerstone of labor market efficiency and productivity. The sustainability of such cooperation, particularly over the long term, is intrinsically linked to an agent's time preference. Theoretically, individuals who are more future-oriented (i.e., possess a lower discount rate) are more willing to forgo immediate gains in favor of the larger, deferred rewards that stem from sustained collaboration. This principle is observable across numerous real-world contexts: highly productive researchers often maintain long-standing partnerships, effective teams are characterized by stable memberships, and successful businesses thrive on a loyal base of repeat customers.

The effort to link time preference with cooperation in repeated games began with Davis et al. (2016), who first established the connection but failed to find a stable correlation. Subsequent work by Kim (2016) also failed, even after modifying the experimental design to incorporate real-time intervals. Kim hypothesized that these results stemmed from participants' fears of partner absence, which made non-cooperation the dominant strategy regardless of their discount rates. To resolve these challenges, Kim (2023) implemented a crucial new design: all game rounds were completed on the same day to eliminate partner uncertainty, and participants were exogenously assigned to different discount rate groups via payment frequency (weekly vs. monthly). This approach finally yielded significant results, revealing that the monthly payment group (lower discount rate) cooperated less than the weekly group, and that mitigating present bias through a delayed first payment increased cooperation. These findings demonstrate that the temporal structure of the interaction itself is a critical determinant of cooperative efficiency.

5.3. Time preference in development economics

5.3.1. Savings and poverty

Savings behavior is a classic example of intertemporal decision-making. By limiting current consumption, individuals can save for the future, thus closely linking savings behavior with time preference. Moreover, savings behavior is naturally connected to the issue of poverty, which is a significant concern in society. Understanding this connection holds considerable practical significance.

Some field experiments have established a strong link between patience and savings: Ashraf et al. (2006) employed the RBC paradigm and found that Filipino women with lower discount rates were significantly more likely to open commitment savings accounts and accumulate 81 % higher balances, while Yesuf and Bluffstone (2008), also using the RBC paradigm, demonstrated that impoverished Ethiopian farmers exhibited high discount rates, suggesting poverty reinforces short-term financial decision-making. This predictive power extends to developed countries, as shown by Finke and Huston (2013), who used the matching paradigm and discovered that U.S. college students with lower discount rates were more inclined to save for retirement. Other research investigates the link between time preference and poverty, such as Tanaka et al. (2010), finds that wealthier households are more patient.

5.3.2. Adoption of new agricultural technologies

New agricultural technologies can be adopted at various stages of production. Adopting new technologies entails short-term costs (including the fixed costs of equipment and the opportunity costs of land during the use of the equipment), but ultimately can result in higher productivity. Consequently, farmers' time preferences play a crucial role in their decision-making process regarding the adoption of new technologies.

A growing body of research demonstrates that farmers' time preference is a critical determinant in the adoption of sustainable agricultural technologies, which characteristically involve short-term costs for long-term benefits. This link is consistently observed across diverse contexts: Mao et al. (2021) employed the MPL paradigm and found that Chinese farmers with higher discount rates were less likely to adopt straw incorporation technology, a practice that trades immediate land use for future soil fertility. Similarly, a field experiment in Ethiopia by Yesuf (2004) revealed through the MPL paradigm that farmers in a region with severe soil degradation exhibited significantly higher discount rates, correlating with lower adoption of conservation measures. Collectively, these findings establish the analysis of time preference as a vital framework for policymakers aiming to promote green agricultural practices and foster sustainable development.

5.4. Time preference in health behavior

5.4.1. Addiction

Addictive behaviors, such as smoking, excessive drinking, and drug use, provide significant immediate gratification to individuals while simultaneously causing substantial negative impacts on their future physical health and life circumstances. These adverse effects typically take a considerable amount of time to manifest. Consequently, addictive behaviors involve a trade-off between present enjoyment and future well-being, making them closely linked to time preference.

Experimental studies consistently link higher discount rates with unhealthy lifestyle choices, notably addictive behaviors. Studies like Ida and Goto (2009) used the RBC paradigm and established a strong correlation, finding that smokers, particularly heavy smokers, exhibit significantly higher discount rates than non-smokers. This predictive power was confirmed in longitudinal research by Goto et al. (2009), which showed through the RBC paradigm that smokers with greater impatience were more likely to fail in their cessation attempts over time. Taking the connection a step further, an intervention study by Corazzini et al. (2015) provided causal evidence, revealing that the act of consuming alcohol itself can acutely increase an individual's discount rate. Collectively, these findings illustrate that impatience is not only a marker for unhealthy behaviors but can also be dynamically influenced by them.

5.4.2. Obesity

With the rapid economic growth and the significant improvement in living standards, the study of obesity has gained more practical value. Researchers are exploring the connection between obesity and the preference for immediate food gratification, attempting to understand obesity through the perspective of time preference.

Empirical research consistently links higher rates of time discounting (impatience) to a greater prevalence of obesity, a finding nuanced by various demographic factors. For instance, Cheung et al. (2022) employed the CTB paradigm and established a direct correlation between short-term discount rates and higher BMI in adolescents. This connection extends across generations, as Stoklosa et al. (2018) found through the MPL paradigm that parental impatience predicted a greater likelihood of obesity and higher BMI z-scores in their children. Taken together, these findings illustrate that the tendency to prioritize immediate gratification over long-term health is a key factor in obesity, with its influence being shaped by intergenerational dynamics.

5.5. Time preference in political behavior

5.5.1. Political participation

Political participation can be framed as a quintessential intertemporal decision. It requires citizens to invest present resources, such as time and effort, for societal benefits that are often distant and diffuse rather than immediate. Therefore, an individual's time preference becomes a crucial psychological factor governing their propensity to engage in civic action, as they weigh the certain costs of present engagement against the uncertain prospect of a better collective future.

Shavit et al. (2014) provided key empirical support for this framework by examining the 2011 nonviolent protest movement in Israel. Treating participation in the protest as a direct measure of political engagement, they elicited the time preferences of 192 Israeli students by the matching paradigm. The results revealed a significant negative correlation: individuals who were more patient (i.e., had lower discount rates) demonstrated a greater propensity to participate in the protest, reinforcing the idea that civic action is an intertemporal investment of present effort for future societal gain.

6. Discussion

This manuscript provides a systematic review of theories, methods, and applications in the measurement of time preference. First, we trace the evolution of measurement paradigms, revealing a clear trajectory where advancing methods have progressively relaxed restrictive assumptions about utility functions to yield more robust and realistic models. Second, we review applications across various fields to demonstrate the pervasive influence of time preference on human behavior and to encourage the adoption of newer measurement methods in practice. Lastly, we outline avenues for future research in the following areas:

6.1. Enhancing the application of more accurate and comprehensive measurement methods

6.1.1. Transitioning from point estimates to Bayesian distributions

While methods like MLE provide valuable point estimates of discount parameters, the frontier of preference estimation is moving towards Bayesian approaches (e.g., Toubia et al., 2013). For example, Hierarchical Bayesian models offer two distinct advantages: first, they efficiently estimate individual-level parameters even with sparse data by 'borrowing' information across subjects; second, they yield a full posterior distribution for each individual's parameters, capturing not just the central tendency of their preference but also the uncertainty or stochasticity in their choices. This opens up new avenues for research.

6.1.2. Disentangling risk and time preferences

A central, unresolved challenge lies in cleanly disentangling time preference from risk preference. While paradigms like DMPL make strong assumptions (equal utility curvature) and CTB attempts joint estimation, future work must engage with the reality that *future outcomes are inherently probabilistic*. This requires moving beyond the DU framework to models that integrate non-expected utility theories. For instance, jointly estimating parameters from a model that combines a quasi-hyperbolic discount function with a probability weighting function from Prospect Theory could offer a more accurate depiction of how individuals perceive delayed, uncertain rewards.

6.1.3. Advancing from correlation to causation through structural approaches

Much of the applied literature, as reviewed, establishes robust correlations between measured time preferences and life outcomes. The next frontier is to move towards causal inference and policy simulation. Structural modeling offers a powerful framework for this leap. By estimating preference parameters within a fully specified theoretical model of behavior, this approach crucially enables the simulation of policy counterfactuals, allowing researchers to evaluate the potential impacts of novel interventions ex-ante.

6.1.4. Exploring multilayered measurement approaches

While this paper has centered on experimental methods for measuring time preference, we contend that a truly robust assessment requires moving beyond any single methodology. Future research should therefore aim to triangulate findings from experiments with complementary data from self-reports, behavioral scales, and neuroscientific measures. Integrating these diverse information streams would enable the development of a comprehensive, multidimensional assessment system, yielding a richer and more reliable profile of individual time preference.

6.2. Promoting interdisciplinary cross-research

6.2.1. Investigating the neuroscientific and affective foundations

This paper contends that investigating the neural underpinnings of time preference can significantly advance the field in two primary dimensions. First, neuroscientific methods can investigate the formation and manifestation of time preference. For example, Xiong et al. (2019) examined the role of the dorsolateral prefrontal cortex (DLPFC) in regulating choices in the loss domain. Second, and perhaps more critically, these tools are pivotal for transitioning from correlational evidence to causal inference. For instance, Weygandt et al. (2015) used fMRI to establish a causal link between DLPFC activity during intertemporal tasks and dieting success, while Soutschek et al. (2017) utilized tDCS to demonstrate a causal connection between the frontopolar cortex (FPC) and reduced discount rates through pre-commitment mechanisms. In essence, neuroscience shifts the level of analysis from abstract psychological constructs to their underlying neural mechanisms, offering a more granular and biologically-grounded perspective. Integrating techniques like brain imaging and stimulation with existing research will therefore facilitate a deeper exploration of the nature of time preference and its causal role in shaping behavior.

6.2.2. Applying eye-tracking technology

Eye-tracking technology offers a valuable tool for examining the cognitive processes of intertemporal decision-making. By recording metrics such as eye movements and fixation durations on different choice attributes, researchers can gain insight into how individuals allocate attention, compare options, and ultimately resolve trade-offs over time. This approach allows for a more detailed understanding of preference formation and underlying cognitive mechanisms. For instance, Zhou et al. (2021) find that time preference inconsistency is driven by shifts in visual attention. Jiang et al. (2016) demonstrate that individuals' attentional patterns are consistent with their choices. Reutskaja et al. (2011) show that visual search can reveal how people dynamically explore options and make decisions under time constraints.

6.2.3. Leveraging big data and digital traces for preference measurement

The proliferation of big data technology opens up novel avenues for time preference research, promising to overcome the limitations of traditional data sources. Future studies can capitalize on passively collected digital trace data from platforms like social media, mobile devices, and e-commerce sites to obtain a richer and more ecologically valid measure of behavior. By analyzing these high-granularity data streams, researchers can capture revealed time preferences as they manifest in real-world decision-making. This enhanced measurement will, in turn, enable a more robust identification of the relationship between time preference and other variables, thereby facilitating a deeper investigation into its causal impact on consequential life outcomes.

6.2.4. Conducting longitudinal studies

Given that the formation and development of time preference is a protracted process, future research must move beyond static, cross-sectional analyses. Adopting longitudinal experimental designs is therefore essential. Such an approach would allow researchers to trace the developmental trajectory of time preference across the lifespan, identifying the critical factors and sensitive periods that shape its evolution from a truly temporal perspective.

6.3. Deepening research content

6.3.1. From the perspective of individual agents to policy makers

While extensive research has detailed how time preference governs individual actions, we propose that this knowledge must now be actively applied to policy design. Because intertemporal trade-offs are integral to the functioning of social systems, it is imperative that policymakers leverage an understanding of time preference to steer individual behavior towards beneficial outcomes. This requires exploring how policy interventions can "nudge" people's decisions to enhance long-term societal well-being. For instance, policies that allow individuals to pre-commit to choices can promote patient decisions made in a "cold" cognitive state, thereby avoiding the myopic choices often made as deadlines loom. Similarly, offering commitment devices that prevent last-minute alterations can directly counteract time inconsistency, helping individuals adhere to their long-term goals.

6.3.2. From a micro perspective to a macro perspective

While the impact of time preference is well-documented at the microeconomic and individual levels, we contend that a crucial and underexplored frontier lies in its macroeconomic implications. This shift in focus prompts critical questions: How does a society's collective time preference influence its preferences for income redistribution? To what extent does it drive government investment in long-term projects like scientific research and infrastructure? How does it shape aggregate labor market dynamics, such as savings rates and human capital investment? The burgeoning field of experimental macroeconomics offers a powerful toolkit for these investigations. By applying these methods, researchers can rigorously test how collective patience shapes macroeconomic phenomena, unlocking significant potential for new discoveries.

6.3.3. From domain-specific findings to cross-domain synthesis

While this paper has surveyed applications across various fields, a systematic integration is currently challenged by the fact that most studies focus on a single context. It remains unclear whether the behavioral measures elicited in one domain are stable and predictive in another. Pioneering work by Dean and Ortoleva (2019) demonstrates the feasibility of measuring multiple behaviors within a unified framework, finding that different non-standard behaviors may stem from independent psychological modules. Future research should build on this approach, employing consistent methodologies across diverse decision contexts to determine whether we are measuring fundamental, stable traits or domain-specific patterns of behavior. Answering this question is crucial for both theoretical and practical applications.

CRediT authorship contribution statement

Jinjin Wang: Writing – review & editing, Writing – original draft, Conceptualization. **Yuzhen Li:** Writing – review & editing, Writing – original draft. **Jun Luo:** Conceptualization. **Hang Ye:** Conceptualization.

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Appendix A

Table 1
CTB paradigm (Andreoni & Sprenger, 2012a).

No.	Payment timing	Option A	Option B	Option C	Option D	Option E	Option F
1	Get paid today	$19	$15.2	$11.4	$7.6	$3.8	$0
	Get paid in 5 weeks	$0	$4	$8	$12	$16	$20
		()	()	()	()	()	()
2	Get paid today	$18	$14.4	$10.8	$7.2	$3.6	$0
	Get paid in 5 weeks	$0	$4	$8	$12	$16	$20
		()	()	()	()	()	()
3	Get paid today	$17	$13.6	$10.2	$6.8	$3.4	$0
	Get paid in 5 weeks	$0	$4	$8	$12	$16	$20
		()	()	()	()	()	()
4	Get paid today	$16	$12.8	$9.6	$6.4	$3.2	$0
	Get paid in 5 weeks	$0	$4	$8	$12	$16	$20
		()	()	()	()	()	()
5	Get paid today	$14	$11.2	$8.4	$5.6	$2.8	$0
	Get paid in 5 weeks	$0	$4	$8	$12	$16	$20
		()	()	()	()	()	()
6	Get paid today	$11	$8.8	$6.6	$4.4	$2.2	$0
	Get paid in 5 weeks	$0	$4	$8	$12	$16	$20
		()	()	()	()	()	()

Note: The columns in the first row represent the following options in order: "Receive $19 today and $0 in 5 weeks," "Receive $15.2 today and $4 in 5 weeks," "Receive $11.4 today and $8 in 5 weeks," "Receive $7.6 today and $12 in 5 weeks," "Receive $3.8 today and $16 in 5 weeks," and "Receive $0 today and $20 in 5 weeks." We ask the experimental participants to select their most preferred option from the above six choices and check the box in the corresponding column. Only one box can be checked per row.

Table 2
Probability-base paradigm (Laury et al., 2012).

No.	Option A	Probability	Option B	Probability	Your choice
1	Receive $200 in 3 weeks	50 %	Receive $200 in 12 weeks	50 %	
2	Receive $200 in 3 weeks	50 %	Receive $200 in 12 weeks	50.1 %	
3	Receive $200 in 3 weeks	50 %	Receive $200 in 12 weeks	50.2 %	
4	Receive $200 in 3 weeks	50 %	Receive $200 in 12 weeks	50.4 %	
5	Receive $200 in 3 weeks	50 %	Receive $200 in 12 weeks	50.5 %	
6	Receive $200 in 3 weeks	50 %	Receive $200 in 12 weeks	50.7 %	
…	…	…	…	…	
15	Receive $200 in 3 weeks	50 %	Receive $200 in 12 weeks	52.7 %	
16	Receive $200 in 3 weeks	50 %	Receive $200 in 12 weeks	53.6 %	
17	Receive $200 in 3 weeks	50 %	Receive $200 in 12 weeks	54.5 %	
18	Receive $200 in 3 weeks	50 %	Receive $200 in 12 weeks	56.9 %	
19	Receive $200 in 3 weeks	50 %	Receive $200 in 12 weeks	59.4 %	
20	Receive $200 in 3 weeks	50 %	Receive $200 in 12 weeks	64.7 %	

Table 3
DM paradigm (Attema et al., 2016).

Option A	A	B	Option B
At week 1 [1]			From week 1 to week 13 [13]
At week 1 [1]			From week 2 to week 13 [12]
From week 1 to week 2 [2]			From week 3 to week 13 [11]
From week 1 to week 3 [3]			From week 4 to week 13 [10]
From week 1 to week 4 [4]			From week 5 to week 13 [9]
From week 1 to week 5 [5]			From week 6 to week 13 [8]
From week 1 to week 6 [6]			From week 7 to week 13 [7]
From week 1 to week 7 [7]			From week 8 to week 13 [6]
From week 1 to week 8 [8]			From week 9 to week 13 [5]
From week 1 to week 9 [9]			From week 10 to week 13 [4]
From week 1 to week 10 [10]			From week 11 to week 13 [3]
From week 1 to week 11 [11]			From week 12 to week 13 [2]
From week 1 to week 12 [12]			At week 13 [1]
From week 1 to week 13 [13]			At week 13 [1]

Note: Each option represents receiving $20 per week during that time period or at that specific time point. The final number in each option indicates the total number of weeks.

Data availability

No data was used for the research described in the article.

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