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# Beyond Discounting: Time Preference in Decision-Making



Pelin Gülüm

# **Beyond Discounting: Time Preference in Decision-Making**

Pelin GÜLÜM



# **Beyond Discounting: Time Preference in Decision-Making**

**Dissertation**

for the purpose of obtaining the degree of doctor  
at Delft University of Technology  
by the authority of the Rector Magnificus, Prof.dr.ir. H. Bijl  
chair of the Board for Doctorates  
to be defended publicly on  
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by

**Pelin GÜLÜM**

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*“What if I fall?  
Oh, but my darling, what if you fly?”*

*— Erin Hanson*

Dedicated to the courage it takes to try.



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# Glossary

The following definitions summarize the psychological and behavioral concepts discussed in this dissertation.

**Additive separability:** The assumption that utilities across time can be summed independently.

**Affective forecasting:** Predicting one's future emotional responses to outcomes or events.

**Anchoring bias:** Relying excessively on an initial reference point when making judgments.

**Duration neglect:** Ignoring how long an experience lasts when evaluating it retrospectively.

**False uniqueness bias:** Believing one's preferences or circumstances are more unique than those of others.

**Framing effect:** A change in judgment or choice caused by the way information or options are presented rather than by differences in objective content.

**Gambler's fallacy:** The mistaken belief that random events are self-correcting, leading individuals to expect reversals after streaks despite statistical independence.

**Hot-cold empathy gap:** Failure to anticipate how preferences and behavior change across emotional or physiological states.

**Hindsight bias:** Seeing past outcomes as having been predictable after they occur.

**Hyperbolic discounting:** A descriptive pattern where discount rates decline with delay, causing time-inconsistent preferences.

**Illusion of control:** Overestimating one's ability to control outcomes that are largely determined by chance.

**Impact bias:** Overestimating the intensity and duration of future emotional reactions.

**Intertemporal judgment:** Evaluation of outcomes that occur at different points in time.

**Loss aversion:** The tendency for losses to be perceived as more impactful than gains of equivalent magnitude.

**Memory bias:** Systematic distortions in how past events are remembered.

**Novelty effect:** The tendency for new or unfamiliar options to receive disproportionate attention or weight in judgment and decision-making.

**Optimism bias:** Systematic overestimation of favorable outcomes and underestimation of unfavorable ones.

**Overconfidence bias:** The tendency to overestimate one's own knowledge, abilities, or the accuracy of one's judgments.

**Overcorrection bias:** The tendency to adjust judgments excessively in response to new information, leading to corrections that overshoot the appropriate adjustment.

**Peak-end rule:** Evaluating experiences mainly based on their most intense moment and their ending.

**Perspective taking:** A debiasing strategy involving deliberate consideration of alternative viewpoints or future selves.

**Planning fallacy:** Underestimating the time, effort, or resources required to complete future tasks.

**Present bias:** Overweighting immediate outcomes relative to future ones, leading to impatience and short-term focus.

**Projection bias:** Assuming future preferences, emotions, or constraints will resemble those of the present.

**Recency bias:** Overweighting recent experiences or information relative to earlier ones.

**Recollection bias:** Misremembering the intensity or duration of past experiences.

**Reference class forecasting:** A debiasing technique that uses outcomes from similar past cases to improve forecasts.

**Risk aversion:** A preference for options with more certain outcomes over those with higher uncertainty, even when the uncertain option has a higher expected value.

**Salience effect:** Overweighting information that is vivid, noticeable, or emotionally striking.

**Self-other discrepancy:** The tendency for individuals to judge their own behavior or preferences differently from those of others, often viewing oneself as more rational.

**Self-reporting bias:** Systematic distortion in data arising from individuals' inaccurate, selective, or socially influenced self-reports.

**Temporal trade-off:** A comparison between costs and benefits occurring at different times.

**Time inconsistency:** A violation of stable preferences over time, where choices change as outcomes become imminent.

**Time preference:** The relative valuation of outcomes depending on when they occur.

## List of abbreviations

The following abbreviations are used in this dissertation:

BDR	Behavioral Decision Research
DU	Discounted Utility
IMO	Interactive Multi-Objective Optimization
MADM	Multi-Attribute Decision-Making
MAUT	Multi-Attribute Utility Theory
MAVT	Multi-Attribute Value Theory
OR	Operations Research
RQ	Research Question
WoS	Web of Science



# Summary

Daily life is shaped by countless decisions, most of which involve intertemporal trade-offs. Time preference plays a crucial role in how individuals evaluate alternatives across time and often leads them to make choices that compromise long-term interests. For instance, people generally prefer smaller, sooner rewards over larger, later ones mainly because of their tendency to discount future benefits. Intertemporal judgments are further affected by numerous biases that systematically distort perceptions of time and value, altering trade-offs and often producing deviations from normative models such as exponential discounting. Consequently, decision-making frequently departs from the principles of rational choice, underscoring the importance of investigating time preferences and associated biases to enhance immediate decision outcomes while safeguarding long-term welfare. Given the pervasive role of time in almost every aspect of life, investigating these phenomena can enhance choices and contribute to the overall well-being of individuals and societies. Despite the well-established importance and prevalence of the topic, several key aspects remain underexplored.

This dissertation investigates how time preference and time-related cognitive biases affect judgments and preferences in decision analysis, and discusses strategies to mitigate their negative impacts. Guided by this main objective, the study integrates descriptive and prescriptive perspectives to build a more comprehensive understanding of intertemporal decision-making and its various real-world implications. Methodologically, it adopts a mixed approach that combines systematic literature reviews, conceptual analysis, and experimental studies, thereby drawing on both qualitative and quantitative evidence. This design enables the investigation of mechanisms underlying intertemporal trade-offs, the exploration of their role in multi-objective decision frameworks, and the empirical testing of their effects under controlled conditions.

**Chapter 1** introduces the study by positioning it within the literature on time preferences and intertemporal decision-making. It then presents four research questions. RQ1 investigates the time-related cognitive biases influencing intertemporal judgments and explores potential strategies for their mitigation. RQ2 examines how time preference and these biases shape decision-making when individuals face multiple objectives, and what mitigation strategies may be effective in such contexts. RQ3 focuses on the influence of time preference on attribute-specific value function elicitation and trade-off steps in intertemporal multi-objective decision-making problems. Finally, RQ4 considers how treating intertemporal outcomes as recurring rather than one-off payoffs affects individuals' time preferences and the discount rates they apply. The chapter also outlines the methodological approaches adopted for answering these questions, highlights the contributions of this dissertation, and concludes with a roadmap of the subsequent chapters.

In **Chapter 2**, six biases that influence intertemporal decision-making are systematically identified and then subjected to a structured literature review. By synthesizing empirical evidence from psychology, economics, health, and multiple other disciplines, this chapter describes how these biases shape judgments and preferences, uncovers their underlying cognitive mechanisms, and highlights strategies for mitigating their adverse effects. Importantly, by examining multiple biases together, the study reveals their interrelationships, offering a deeper understanding of complex human behavior. The results indicate the presence of these biases not only in personal choices but also in societal decision contexts and emphasize the need for targeted mitigation strategies. Building on these insights, the chapter proposes a research agenda for future investigation.

**Chapter 3** extends the discussion of time-related biases to a multi-attribute decision-making (MADM) level where multiple conflicting objectives and various alternatives are considered simultaneously. By treating the exponential discounting theory as the normative benchmark, each bias is defined as a systematic deviation from the theory's rationality assumptions. Then, the steps of Multi-Attribute Value Theory (MAVT), a systematic MADM method built on the core principles of value theory, are examined as being subject to negative influences of biases throughout the evaluation. Considering the complex nature of trade-off relations, the sequential dynamic of the MADM framework, and the presence of a decision analyst in the elicitation process, promising strategies are proposed for mitigation purposes. The comprehensive examination reveals that MADM processes can be highly susceptible to time-related biases at various levels, from objective setting to value elicitation. Unaddressed biases can distort evaluations and lead to undesired alternatives, highlighting the importance of adopting preventative strategies from the very early stages. The study also underscores the need to further investigate intertemporal MADM problems and empirically test how time preference and biases affect judgments, while simultaneously searching for strategies to mitigate their impacts.

Chapters 2 and 3 offer a comprehensive examination of time preference and biases, covering simple choice problems and complex MADM cases simultaneously. Next, Chapters 4 and 5 build on these insights to develop theoretical frameworks, formulate hypotheses, and conduct empirical analyses.

**Chapter 4** focuses on empirically investigating time preference in two crucial steps of MADM: attribute-specific value function elicitation and trade-off analysis. I start by introducing what I call the *intertemporal MADM problem*, which requires trade-offs not only over time but also across conflicting attributes. Then, using the MAVT framework, three controlled experiments with a total of 279 participants test hypotheses about how time preference shapes judgments when single or multiple attributes are delayed. The results indicate that both the scaling constants (weights) and perceived values of attributes vary significantly with time delays, and that the effects depend on the specific trade-off relationships involved. While delaying a single outcome generally leads to discounting, postponing multiple outcomes in a multi-objective context does not necessarily produce the same behavior, challenging conventional assumptions. By moving beyond considering only final choices or calculated discount rates, this chapter provides novel empirical insights into the reasoning process underlying intertemporal trade-offs, extending time preference research into MADM contexts. It also offers practical guidance for analysts who deal with preference elicitation in complex, multi-dimensional environments.

**Chapter 5** investigates how considering intertemporal outcomes as recurring, rather than one-off payoffs, influences time preferences and discount rates. While single payoffs are often

studied, recurring outcomes such as salaries, bills, or subscriptions are highly common in real life but largely overlooked in time preference research. Grounded in the choice bundling and bracketing literature, which emphasize how decision framing across multiple outcomes can shift preferences and reduce impatience, this study uses a theory-driven experimental approach. Two controlled experiments with 284 participants test the hypothesis that recurring payoffs promote broader evaluation and lead to lower discount rates than one-off payoffs. The results confirm that recurrence significantly shapes time preferences, offering a potential explanation for the high discount rates often reported in prior research. Recognizing recurrence in payoff structures underscores the context-dependent nature of intertemporal problems. By integrating theoretical perspectives with empirical evidence, the chapter introduces a novel framework for modeling time preference in a common but underexplored decision context. These insights inform behavioral interventions, policy design, and decision-making practices, improving the ecological validity of discount rates and supporting more sustainable choices.

**Chapter 6** concludes the dissertation by integrating the key findings from the preceding chapters to address the main research question: how time preference and time-related cognitive biases influence judgments and preferences in decision analysis, and what strategies can mitigate their negative impacts. It synthesizes the results to provide a comprehensive understanding of the mechanisms underlying intertemporal decision-making, highlighting both theoretical insights and practical implications. The chapter emphasizes the relevance of these findings for improving decision-making practices across domains such as psychology, health, economics, and policy, extending the impact of the research beyond academia. It also reflects on the limitations of the dissertation, including reliance on a limited set of experimental studies and uncertainties regarding the generalizability of results to diverse populations. Remaining gaps include the need to examine time preferences more extensively in multi-attribute decision-making (MADM) contexts, to investigate the interactions between multiple cognitive biases, and to develop targeted interventions that effectively reduce bias in real-world decision environments. Building on these gaps, the chapter outlines a research agenda aimed at advancing more robust models of intertemporal choice and translating theoretical insights into practical strategies for improving decision-making in complex settings.

In conclusion, this dissertation advances our understanding of how time preferences and time-related biases shape judgments in both simple and complex decision contexts, and it evaluates strategies to mitigate their adverse effects. By integrating theoretical frameworks, systematic reviews, and controlled experiments, it offers new insights into the mechanisms of intertemporal decision-making, extends existing models to multi-objective settings, and emphasizes the importance of underexplored problem types, such as decisions involving recurring payoffs. Beyond its theoretical contributions, the findings provide practical guidance for individuals, policymakers, and decision analysts aiming to support informed decisions. The dissertation also highlights avenues for further research, particularly in intertemporal MADM, where understanding and managing time-related biases remains crucial. Overall, the insights presented here are intended to stimulate further empirical and methodological inquiry and to inform both theory and practice in behavioral decision research.



# Samenvatting

Het dagelijks leven wordt gevormd door talloze beslissingen, waarvan de meeste gedreven worden door intertemporele afwegingen. Tijdsvoorkeuren spelen een cruciale rol in hoe individuen alternatieven door de tijd heen evalueren en leiden er vaak toe dat zij keuzes maken die hun langetermijnbelangen ondermijnen. Mensen geven bijvoorbeeld doorgaans de voorkeur aan kleinere, directe beloningen boven grotere, uitgestelde beloningen, voornamelijk vanwege hun neiging om toekomstige voordelen te verdisconteren. Intertemporele oordelen worden verder beïnvloed door talrijke cognitieve vertekeningen die systematisch de perceptie van tijd en waarde vervormen. Dit verandert de afwegingen en veroorzaakt vaak afwijkingen van normatieve modellen zoals exponentiële verdiscontering. Hierdoor komt de besluitvorming vaak niet overeen met de principes van rationele keuze. Dit onderstreept het belang van onderzoek naar tijdspreferenties en gerelateerde vertekeningen om directe beslissingsuitkomsten te verbeteren en tegelijkertijd het langetermijnwelzijn te beschermen. Gezien de alomtegenwoordige rol van tijd in vrijwel elk aspect van het leven kan onderzoek naar deze fenomenen bijdragen aan betere besluitvorming en aan het welzijn van individuen en samenlevingen. Ondanks het goed gevestigde belang van dit onderwerp blijven verschillende kernaspecten onderbelicht.

Dit proefschrift onderzoekt hoe tijdspreferentie en tijdgerelateerde cognitieve vertekeningen oordelen en voorkeuren beïnvloeden binnen de besluitvormingsanalyse, en suggereert strategieën om hun negatieve effecten te beperken. Vanuit dit hoofddoel integreert de studie zowel een beschrijvend als een prescriptief perspectief om een meer omvattend begrip van intertemporele besluitvorming en de uiteenlopende implicaties in de praktijk te ontwikkelen. Methodologisch hanteert het onderzoek een gemengde aanpak die systematische literatuurstudies, conceptuele analyse en experimenteel onderzoek combineert. Deze opzet maakt het mogelijk de mechanismen achter intertemporele afwegingen te onderzoeken, hun rol binnen multi-objectieve besluitvormingskaders te verkennen en hun effecten onder gecontroleerde omstandigheden empirisch te testen.

**Hoofdstuk 1** introduceert de studie door deze te positioneren binnen de literatuur over tijdspreferenties en intertemporele besluitvorming. Vervolgens worden vier onderzoeksvragen gepresenteerd. RQ1 onderzoekt de tijdgerelateerde cognitieve vertekeningen die intertemporele oordelen beïnvloeden en mogelijke strategieën om deze te beperken. RQ2 analyseert hoe tijdspreferentie en deze vertekeningen besluitvorming vormgeven wanneer individuen met meerdere doelstellingen worden geconfronteerd, en welke strategieën in dat kader effectief kunnen zijn. RQ3 richt zich op de invloed van tijdspreferentie op het achterhalen van attribuutspecifieke waardefuncties en de afwegingen in intertemporele multi-objectieve besluitvormingsproblemen. Tot slot analyseert RQ4 hoe de behandeling van intertemporele uitkomsten als terugkerende in plaats van eenmalige opbrengsten de tijdspreferenties en de toegepaste discontovoeten beïnvloedt. Hoofdstuk 1 schetst ook de methodologische aanpak voor het beantwoorden van

deze vragen, benadrukt de bijdragen van dit proefschrift en sluit af met een overzicht van de daaropvolgende hoofdstukken.

In **Hoofdstuk 2** worden zes vertekeningen die intertemporele besluitvorming beïnvloeden systematisch geïdentificeerd en vervolgens onderworpen aan een gestructureerde literatuurstudie. Door empirisch bewijs uit de psychologie, economie, gezondheidswetenschappen en andere disciplines te synthetiseren, beschrijft dit hoofdstuk hoe deze vertekeningen oordelen en voorkeuren vormgeven, onthult het hun onderliggende cognitieve mechanismen en belicht het strategieën om hun negatieve effecten te beperken. Door meerdere vertekeningen samen te onderzoeken, brengt de studie bovendien hun onderlinge relaties aan het licht, wat leidt tot een dieper begrip van complex menselijk gedrag. De resultaten tonen aan dat deze vertekeningen niet alleen persoonlijke keuzes beïnvloeden, maar ook maatschappelijke besluitvorming, en benadrukken de noodzaak van gerichte mitigatiestrategieën. Op basis van deze inzichten formuleert het hoofdstuk een onderzoeksagenda voor toekomstig werk.

**Hoofdstuk 3** breidt de bespreking van tijdgerelateerde vertekeningen uit naar multi-attributieve besluitvorming (MADM), waarbij meerdere conflicterende doelstellingen en alternatieven worden afgewogen. De theorie van exponentiële verdiscontering wordt hierbij als normatief referentiepunt genomen. Elke vertekening wordt gedefinieerd als een systematische afwijking van de rationaliteitsveronderstellingen van deze theorie. Vervolgens worden de stappen van de Multi-Attribute Value Theory (MAVT), een systematische MADM-methode gebaseerd op de kernprincipes van de waardetheorie, onderzocht op hun vatbaarheid voor negatieve invloeden van vertekeningen tijdens de evaluatie. Gezien de complexiteit van afwegingsrelaties, de sequentiële dynamiek van het MADM-kader en de rol van de beslissingsanalist bij het achterhalen van voorkeuren, worden veelbelovende strategieën ter mitigatie voorgesteld. De uitgebreide analyse toont aan dat MADM-processen bijzonder gevoelig kunnen zijn voor tijdgerelateerde vertekeningen op diverse niveaus, van doelbepaling tot het achterhalen van waarden. Indien niet aangepakt, kunnen deze vertekeningen evaluaties verstoren en leiden tot ongewenste alternatieven. Dit onderstreept het belang van preventieve strategieën vanaf de vroegste stadia van de ontwikkeling van het probleem. De studie benadrukt ook de noodzaak om intertemporele MADM-problemen verder te onderzoeken en empirisch te toetsen hoe tijdspreferentie en vertekeningen oordelen beïnvloeden, terwijl gelijktijdig wordt gezocht naar effectieve mitigatiestrategieën. Hoofdstukken 2 en 3 bieden een brede verkenning van tijdspreferentie en vertekeningen, waarbij zowel eenvoudige keuzeproblemen als complexe MADM-situaties aan bod komen. Vervolgens bouwen Hoofdstukken 4 en 5 voort op deze inzichten door theoretische kaders te ontwikkelen, hypothesen te formuleren en empirische analyses uit te voeren.

**Hoofdstuk 4** richt zich op de empirische analyse van tijdspreferentie in twee cruciale stappen van MADM: het achterhalen van attributspecifieke waardefuncties en de analyse van afwegingen. Ik introduceer hierbij wat ik het *intertemporele MADM-probleem* noem, dat afwegingen vereist niet alleen door de tijd heen, maar ook tussen conflicterende attributen. Vervolgens worden binnen het MAVT-kader drie gecontroleerde experimenten uitgevoerd met in totaal 279 deelnemers, waarin hypothesen worden getest over hoe tijdspreferentie oordelen beïnvloedt wanneer één of meerdere attributen worden uitgesteld. De resultaten laten zien dat zowel de schaalkonstanten (gewichten) als de waargenomen waarden van attributen significant variëren met tijdsvertragingen, en dat de effecten afhangen van de specifieke afwegingen. Terwijl het uitstellen van één enkele uitkomst doorgaans leidt tot verdiscontering, hoeft het uitstellen van meerdere uitkomsten in een multi-objectieve context niet hetzelfde gedrag op te roepen, wat

conventionele aannames uitdaagt. Door verder te kijken dan enkel eindkeuzes of berekende discontovoeten biedt dit hoofdstuk nieuwe empirische inzichten in het redeneringsproces achter intertemporele afwegingen. Daarmee breidt het de literatuur over tijdspreferentie uit naar MADM-contexten en levert het praktische richtlijnen op voor analisten die voorkeuren achterhalen in complexe, multidimensionale omgevingen.

**Hoofdstuk 5** onderzoekt hoe het beschouwen van intertemporele uitkomsten als terugkerend, in plaats van eenmalig, de tijdspreferenties en discontovoeten beïnvloedt. Hoewel eenmalige opbrengsten vaak worden bestudeerd, zijn terugkerende uitkomsten zoals salarissen, rekeningen of abonnementen in het dagelijks leven zeer gebruikelijk, maar grotendeels veronachtzaamd in onderzoek naar tijdspreferentie. Gebaseerd op de literatuur over keuze-bundeling en bracketing, die benadrukt hoe de framing van beslissingen over meerdere uitkomsten de voorkeuren kan verschuiven en ongeduld kan verminderen, hanteert deze studie een theoriegedreven experimentele aanpak. Twee gecontroleerde experimenten met 284 deelnemers toetsen de hypothese dat terugkerende opbrengsten leiden tot bredere evaluaties en lagere discontovoeten dan eenmalige opbrengsten. De resultaten bevestigen dat terugkeer een significante invloed heeft op tijdspreferenties en bieden een mogelijke verklaring voor de hoge discontovoeten die vaak in eerder onderzoek zijn gerapporteerd. Het erkennen van terugkerende opbrengststructuren benadrukt het contextafhankelijke karakter van intertemporele problemen. Door theoretische perspectieven te integreren met empirisch bewijs introduceert dit hoofdstuk een nieuw kader voor het modelleren van tijdspreferentie in een veelvoorkomende, maar onderbelichte besluitvormingscontext. Deze inzichten zijn relevant voor gedragsinterventies, beleidsontwerp en besluitvormingspraktijk, en verbeteren de ecologische validiteit van discontovoeten, wat duurzamere keuzes ondersteunt.

**Hoofdstuk 6** sluit het proefschrift af door de belangrijkste bevindingen uit de voorgaande hoofdstukken te integreren met betrekking tot de centrale onderzoeksvraag: hoe beïnvloeden tijdspreferentie en tijdgerelateerde cognitieve vertekeningen oordelen en voorkeuren binnen de besluitvormingsanalyse, en welke strategieën kunnen de negatieve effecten hiervan beperken? Het hoofdstuk synthetiseert de resultaten en biedt een omvattend inzicht in de mechanismen achter intertemporele besluitvorming, waarbij zowel theoretische bijdragen als praktische implicaties worden benadrukt. Tevens wordt de relevantie van de bevindingen onderstreept voor de verbetering van besluitvormingspraktijken in domeinen zoals psychologie, gezondheidszorg, economie en beleid, waarmee de impact van het onderzoek verder reikt dan de academische context. Het hoofdstuk bespreekt ook de beperkingen van dit proefschrift, waaronder de afhankelijkheid van een beperkt aantal experimentele studies en onzekerheden over de generaliseerbaarheid naar diverse populaties. Overblijvende lacunes zijn onder meer de noodzaak om tijdspreferenties uitgebreider te onderzoeken in multi-attributieve besluitvorming (MADM), om de interacties tussen meerdere cognitieve vertekeningen te bestuderen en om gerichte interventies te ontwikkelen die effectief vertekening verminderen in realistische besluitvormingsomgevingen. Op basis hiervan wordt een onderzoeksagenda geschetst gericht op het ontwikkelen van robuustere modellen van intertemporele keuze en het vertalen van theoretische inzichten naar praktische strategieën voor complexe besluitvormingssituaties.

Samenvattend levert dit proefschrift een bijdrage aan ons begrip van hoe tijdspreferenties en tijdgerelateerde vertekeningen oordelen beïnvloeden in zowel eenvoudige als complexe besluitvormingscontexten, en evalueert het strategieën omhun negatieve effecten te beperken. Door theoretische kaders, systematische literatuurstudies en gecontroleerde experimenten te integre-

ren, biedt het nieuwe inzichten in de mechanismen van intertemporele besluitvorming, breidt het bestaande modellen uit naar multi-objectieve settings en benadrukt het de relevantie van onderbelichte probleemttypen, zoals beslissingen met terugkerende opbrengsten. Naast theoretische bijdragen levert dit onderzoek praktische richtlijnen op voor individuen, beleidsmakers en beslissingsanalisten die streven naar beter geïnformeerde keuzes. Het proefschrift benadrukt ook richtingen voor toekomstig onderzoek, met name in intertemporele MADM, waar het begrijpen en beheersen van tijdgerelateerde vertekeningen cruciaal blijft. Al met al beoogt dit onderzoek verdere empirische en methodologische ontwikkeling te stimuleren en zowel de theorie als de praktijk binnen het gedragswetenschappelijk besluitvormingsonderzoek te verrijken.

# Chapter 1

## Introduction

### 1.1 Background

People make numerous decisions every day across all areas of their lives, many of which have consequences unfolding over time. For example, how someone chooses to spend their money today can significantly affect their future financial stability, just as taking preventative health measures can greatly influence long-term well-being. In essence, almost all decisions involve intertemporal trade-offs, where benefits and costs occurring at different time points must be weighed to reach a decision (Frederick et al., 2002).

A central concept in understanding these trade-offs is *time preference*, which refers to the relative value individuals place on receiving outcomes sooner rather than later. Time preference is commonly quantified by the discount rate, a parameter that measures how much future rewards or costs are discounted relative to immediate ones (Samuelson, 1937). For instance, an individual with a high time preference—or equivalently, a high discount rate—tends to favor smaller, sooner rewards over larger, delayed benefits. Conversely, a lower discount rate indicates a greater willingness to wait for future gains. Given its fundamental role in interpreting human behavior, time preference has been extensively studied across a broad range of disciplines, such as economics (Fishburn & Rubinstein, 1982; Loewenstein & Thaler, 1989; Thaler, 1981), finance (Krieger et al., 2021; Berlinger et al., 2022; Hao et al., 2016), psychology (Gilbert et al., 2002; Luo et al., 2014; Soman et al., 2005; Droit-Volet & Meck, 2007), health sciences (Fuchs, 1982; Zhang & Rashad, 2008; Chapman, 1996; Meunier & Ohadi, 2021), marketing (Hahn et al., 2013; Pollai et al., 2010; Atlas et al., 2017), environmental studies (Grandin et al., 2022; Wu et al., 2023; Hardisty & Weber, 2009), public policy (Wie & Kim, 2015; Lipman, 2024), education (Meier & Sprenger, 2013; Wang & Chiou, 2022; Jung et al., 2021) and agriculture (Galor & Özak, 2016; Hou et al., 2023; Mao et al., 2021).

The exponential discounting model has long been the standard framework for modeling time preference and is widely regarded as the normative benchmark in the literature (Samuelson, 1937). This model rests on several key assumptions (Frederick et al., 2002). First, it assumes a constant discount rate, which indicates time-consistent preferences. In other words, it claims that individuals discount the utility of future outcomes at a constant rate over time and that the relative valuation between two outcomes remains the same, independent of when they are compared. Second, preferences between outcomes depend only on the time interval sep-

arating them rather than absolute time points, an assumption named *stationarity* (Koopmans, 1960). According to this assumption, a choice between receiving €100 in 2 years or €120 in 3 years should be the same as choosing between €100 in 5 years or €120 in 6 years. Third, the exponential discounting model upholds the *independence assumption*, meaning adding the same amount of utility to all outcomes resolving at different time points does not affect the preference relationship between them. If an individual prefers A to B, they will still prefer A over B even if both are combined with the same additional outcome, such as C. Fourth, the model assumes *additive separability of utility over time*, meaning the total utility of outcomes occurring at different points in time is the sum of their individual utilities. These assumptions make the exponential discounting theory mathematically convenient and normatively appealing for modeling rational time preference.

Although the exponential discounting has become the dominant theory for modeling time preference, the descriptive validity of the aforementioned assumptions has been subject to much criticism (Thaler, 1981; Laibson, 1997; O'Donoghue & Rabin, 2001). For instance, research dating back to Herrnstein (1961) and later extended by Ainslie (1975) reveals that discount rates decrease over time rather than being constant as assumed in exponential discounting theory. Furthermore, empirical evidence indicates that individuals disproportionately favor immediate rewards, resulting in dynamically inconsistent preferences. As Richard Thaler, Nobel Laureate in Economic Sciences (2017), notably points out, the exponential discounting model treats decision-makers as “homo economicus”, perfectly rational economic agents who consistently maximize the utility of their choices (Thaler, 2000). However, a substantial body of work in behavioral economics and psychology demonstrates the opposite and challenges every single assumption of the exponential discounting model by illustrating how individuals deviate from perfect rationality in real life and how their judgments are affected by numerous biases (Frederick et al., 2002).

The idea of departing from idealized rationality was first discussed in the seminal work of Simon (1955), who introduced the *bounded rationality* and explained how human judgments are shaped by cognitive limitations and contextual factors. His work laid the foundation for a more realistic understanding of decision-making, where individuals are considered as “satisfiers” who rely on heuristics rather than being rational utility maximizers. Building on this work, Tversky & Kahneman (1974) introduced Prospect Theory and revolutionized decision science by showing how people deviate from rationality by overly relying on mental heuristics and exhibiting various biases in their judgments. This fundamental transformation gave rise to experimental investigations to better understand the psychological mechanisms underlying time preference and quantify deviations from normative models. As a result, several alternative theories have been developed, aiming to more accurately capture observed behavior. For instance, the quasi-hyperbolic discounting theory by Laibson (1997) utilizes two parameters to capture short-term impulsiveness (present bias) and long-term patience, allowing the model to account for time-inconsistency observed in the actual human decision-making process. Similarly, O'Donoghue & Rabin (2001) adopts a quasi-hyperbolic discounting in their model while further differentiating between people who are not aware of their present bias (naïves) and the ones who know their future selves might behave differently (sophisticates). By doing so, they could represent the heterogeneity in people's perspectives and better explain variations in observed behaviors. Together with numerous other advances in the time preference literature, these developments highlight the growing recognition of the critical role behavioral drivers play in intertemporal judgments.

Research increasingly shows that understanding how people genuinely think and behave in real-world decision-making is fundamental not only for developing discounting models that capture these behaviors but also for designing effective interventions and policies across various domains. Therefore, examining behavioral and contextual factors through the lens of time preference offers valuable insights and strengthens both the theoretical robustness and practical applicability of decision-making frameworks. Over time, the literature on time preference has made significant strides in uncovering and incorporating behavioral insights, moving beyond purely rational models to better reflect the complexities of human judgment and intertemporal choice (Rambaud et al., 2023). Yet, despite these advancements, several critical gaps in the literature remain unaddressed. The following subsection outlines the key research gaps this dissertation aims to address.

## 1.2 Research gaps and problem statement

In this dissertation, I argue that despite significant advancements in the time preference literature, particularly in exploring human behavior and cognitive factors and integrating them into decision-making models, several important research gaps remain.

First, while intertemporal choice anomalies have been widely studied, there is comparatively little understanding of time-related biases (Rambaud et al., 2023). Psychological research has identified numerous biases that systematically distort how people perceive and evaluate time, leading to deviations from the normative principles of exponential discounting theory (Loewenstein et al., 2003; Fredrickson & Kahneman, 1993; Chen et al., 2019). While the underlying cognitive mechanisms of these biases have been studied by psychologists, there is a need for particular investigation into their dynamics in the time preference and decision-making context. Identifying all the biases that may impact intertemporal judgments and studying them in the decision-making context can also reveal effective strategies for mitigating their negative effects. In addition, existing studies generally consider these biases in isolation, leaving a notable gap regarding how multiple time-related biases may simultaneously interact and collectively influence intertemporal judgments. Addressing these gaps is essential for uncovering the underlying mechanisms of time-related biases, contributing to the development of more robust and realistic models and effective interventions to mitigate their impact on decision-making. Achieving these goals can lead to meaningful practical contributions across diverse fields such as psychology, health, and economics, where time preference plays a critical role in shaping decisions. Moreover, a systematic investigation specifically focused on time-related biases may also highlight important research gaps, providing valuable direction for future studies.

Second, decision analysis generally encompasses three main approaches: normative, descriptive, and prescriptive (Kleindorfer et al., 1993). While the normative approach identifies how individuals should make decisions according to the principles of rationality, the descriptive approach focuses on how they actually make decisions in real-world settings. Prescriptive approach, meanwhile, provides systematic methods to help people make better decisions while bridging the gap between normative ideals and descriptive realities (Bell et al., 1988; Montibeller & von Winterfeldt, 2024). The existing literature on time preference dominantly adopts a descriptive approach and focuses on uncovering how people make decisions under different circumstances and how their judgments deviate from normative models. Although prescriptive

approaches have also been explored and have provided valuable insights into developing intervention strategies (Thaler & Sunstein, 2008; Ariely & Wertenbroch, 2002), the body of research in this area remains relatively limited compared to the extensive work done on the descriptive side. As a result, our understanding of how to effectively guide or improve decision-making is still underdeveloped. Given the importance of supporting individuals to make informed judgments aligned with their long-term plans, investigating time preference and time-related biases from a prescriptive perspective holds strong potential to yield meaningful and actionable insights. Furthermore, addressing this gap can provide valuable benefits to both decision-makers and decision analysts by increasing their awareness of potential negative effects throughout the decision-making process and enabling the development of systematic efforts to mitigate them.

Third, the existing literature on time preference primarily focuses on comparing alternatives that occur at different points in time. The relative evaluation of these alternatives is typically represented by a discount rate, which serves as the basis for interpreting intertemporal judgments (Frederick et al., 2002). While prevalent in existing research, this examination, based on the final choices, provides limited insights into the evaluative processes that precede those decisions. In other words, the experimenter or analyst cannot see the trade-offs made or understand how the decision-maker values alternatives throughout their analysis. Furthermore, unlike the choice problems utilized in many studies, real-life decisions often involve multiple, conflicting objectives and numerous intertemporal alternatives. For these problems, decision-makers must consider trade-offs not only across time but also between competing objectives simultaneously. This introduces an additional layer of complexity to the problem, necessitating a more comprehensive analysis and structured guidance toward a solution. Despite the extent of the literature on time preference, existing studies have been limited to one-dimensional intertemporal trade-offs, leaving multi-dimensional cases largely unexplored. Studying time preference in intertemporal multi-objective problems can provide a more nuanced understanding of the evaluation process than traditional approaches that summarize behavior with a single discount rate. Additionally, such an investigation could contribute to ongoing efforts to bridge real-world problems and empirical research while offering practical solutions.

The fourth research gap pertains to a common type of decision that has been largely overlooked in existing literature: decisions with recurring payoffs. Time preference studies typically rely on isolated, one-off problems such as winning money from a lottery or paying a traffic ticket (Thaler, 1981). As also noted by Frederick et al. (2002), the discount rates observed in these experiments tend to be relatively high, reflecting a general impatience toward delayed rewards. One explanation for these high discount rates lies in the design of the experiments themselves (Loewenstein & Prelec, 1993). Participants are often asked to evaluate intertemporal choices in isolation and within a narrowly defined time frame. This setup restricts the decision-making context and encourages individuals to treat outcomes as isolated one-off events, rather than integrating them into the broader context of their real-life circumstances (Loewenstein, 1988). While some choices in life are indeed isolated, many involve recurring payoffs resolving over an extended period in the future. For example, selecting an insurance policy yields a payoff that recurs monthly over the year. In this case, the time preference toward the insurance payments should be considered by taking into account the recurrence of the payoffs over a period of time rather than simply comparing the outcomes from distinct time points. Despite the prevalence of such decisions in everyday life, there is a noticeable lack of research examining time preference in the context of recurring payoffs. In a world where many significant decisions involve ongoing consequences, it is crucial to understand how people evaluate outcomes in such settings.

Doing so could potentially help address the issue of high discount rates observed in isolated cases by promoting a broader perspective. Addressing this research gap contributes to a deeper understanding of real-life time preference and provides insights into developing interventions.

These identified research gaps revolve around a few critical points. First, the distinction between descriptive and prescriptive approaches plays a central role throughout the dissertation. I aim to build on descriptive findings and extend the investigation further into the prescriptive decision frameworks. Second, aligned with this distinction, the identified research gaps emphasize the differing roles of decision-makers and decision analysts. Since the decision analyst is responsible for structuring the problem and guiding the decision-making process through interaction with decision-makers in a prescriptive setting, it is particularly important to adapt theoretical insights with these dynamics in mind. Finally, the dissertation investigates both single- and multi-objective decisions that require intertemporal trade-offs. These problem types vary in complexity, trade-off dynamics, and evaluation practices, all of which serve to enrich the theoretical and empirical analyses. With these considerations in mind, this dissertation aims to examine how time preference and time-related biases influence judgments and preferences in decision analysis, and to identify strategies that can help decision-makers and analysts mitigate their negative impacts. The following section presents four research questions developed to address the main research question in line with this aim.

## 1.3 Research questions

Taking into account the aforementioned distinctions between descriptive and prescriptive approaches, decision types, and the roles of analysts in prescriptive evaluation frameworks, the central research question (RQ) guiding this dissertation is as follows:

**Main RQ:** How do time preference and time-related cognitive biases affect judgments and preferences in decision analysis, and what strategies can help decision-makers and analysts mitigate their negative impacts?

This main research question breaks down into four sub-research questions:

**RQ 1:** What are the time-related cognitive biases influencing intertemporal judgments, and what strategies can be employed for mitigation?

To answer this research question, I first systematically identify all the biases that influence intertemporal judgments and preferences. Then, by subjecting each bias to a systematic literature review, I gather empirical evidence on the psychological mechanisms driving these biases, their underlying causes and consequences, as well as applied mitigation strategies across various fields, including economics, psychology, health, and finance. Furthermore, by analyzing the co-occurrence relations of biases, I uncover how they may affect evaluations when they emerge together. Answering this research question through systematic literature reviews may also reveal recent trends in the existing literature and highlight areas where further investigation is needed.

**RQ 2:** How do time preference and time-related cognitive biases influence the decision-making process in the presence of multiple objectives, and what strategies can be employed for mitigation?

Building upon the findings from RQ 1, this question extends the evaluation environment to a multi-objective<sup>1</sup> level while utilizing a prescriptive point of view. After identifying and understanding time-related biases and comprehensively examining them for choice problems in the descriptive frameworks, I will turn to multi-objective problems. The impact of time preference and time-related biases will be investigated by focusing on each step of the Multi-Attribute Value Theory (MAVT), one of the fundamental frameworks used to structure complex decisions involving multiple, often conflicting attributes (Keeney & Raiffa, 1975). By integrating insights from behavioral decision research (BDR) and the time preference literature, a critical examination will be conducted on how time-related biases may influence the evaluation, weighting, and trade-offs among attributes over time. Furthermore, by adopting a prescriptive perspective, a set of promising ideas that decision analysts can use to mitigate the negative effects of biases at each step of the evaluation will be outlined. This research question aims to provide new insights into the role of time preference within multi-attribute decision-making (MADM), highlighting both potential mitigation strategies to be tested and future research directions in an area that has received little attention to date.

**RQ 3:** How does time preference influence attribute-specific value function elicitation and trade-off processes in intertemporal multi-objective decision-making problems?

This research question aims to experimentally investigate how time preference manifests within decision frameworks when multiple objectives and alternatives are involved. Specifically, the focus is on MAVT, a structured method that decomposes complex decision problems into sequential steps to evaluate trade-offs among conflicting objectives (Keeney & Raiffa, 1975). By addressing this research question, I will investigate the role of time preference in two critical stages of MAVT: the elicitation of attribute-specific value functions and the trade-offs conducted to derive the scaling constants (weights) of the attributes. Both steps require subjective judgments from decision-makers, who are most likely to be influenced by time preference. Through theoretical framing and experimental investigation, this research seeks to provide some of the first empirical insights into how time preference affects decision processes within the context of MADM. The structured nature of the MAVT method enables a deeper understanding of the decision-making process and the role of time at each step, offering critical insights that are difficult to obtain through traditional experimental approaches relying on discount rates.

**RQ 4:** How does considering intertemporal outcomes as recurring, rather than one-off payoffs, affect individuals' time preference and resulting discount rates?

This research question addresses a type of real-world problem that has received little attention in the time preference literature: decisions involving recurring payoffs. One-off payoffs are isolated outcomes from a single decision, such as receiving a one-time payment, whereas recurring payoffs arise from repeated or ongoing outcomes, like salaries, bills, or subscriptions. Recognizing this distinction is important because most experimental studies focus on one-off payoffs, overlooking the recurring patterns that characterize many real-world decisions. By empirically investigating decisions with recurring payoffs, this study offers an alternative perspective on time preference experiments. Specifically, it examines whether and how individuals adjust their time preference when evaluating recurring payoffs, as opposed to the one-off decisions emphasized in prior research. This approach allows for an analysis of potential changes in

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<sup>1</sup>Objectives denote high-level goals, while attributes are the measurable criteria used to assess how well alternatives fulfill those goals.

discount rates and contributes to a broader understanding of real-life decision-making, informing strategies that help decision-makers achieve better outcomes.

Addressing these four research questions provides a structured path to answering the main research question. RQ 1 identifies the specific time-related cognitive biases and explores strategies for their mitigation, laying the foundation for understanding how these biases influence decision-making. RQ 2 examines how these biases operate in complex, multi-objective decisions, while reporting strategies that could help analysts to mitigate negative effects. RQ 3 empirically investigates the effect of time preference on the elicitation of attribute-specific value functions and trade-offs, revealing how intertemporal considerations shape core steps in decision analysis. Finally, RQ 4 considers intertemporal outcomes as recurring payoffs rather than one-off outcomes, offering insight into the role of context in shaping discount rates. Together, these sub-questions illuminate the mechanisms through which time preferences and cognitive biases affect judgments and preferences, and they inform strategies to mitigate their negative effects in real-life decisions, directly addressing the overarching aim of the study.

## 1.4 Research approach

This dissertation employs a mixed-methods approach, integrating both qualitative and quantitative methodologies across four interconnected studies to address each research question and the overarching research objective. The research design combines deductive reasoning with experimental approaches and encompasses a range of purposes, including exploratory, descriptive, and explanatory elements, reflecting the diverse aims and methods of the individual studies.

The first study involves a two-level, systematic approach starting with the identification of the biases that affect intertemporal trade-offs. The second step is systematic literature reviews, which adopt a qualitative approach to synthesize existing findings on intertemporal biases, mitigation strategies, and identify gaps in the time preference and decision-making literature. As an exploratory study, this research aims to map the landscape of intertemporal biases, highlight patterns across the literature, and generate avenues for future empirical investigation.

The second study goes beyond the synthesis of existing literature by offering a conceptual exploration of a novel topic: time preference and intertemporal biases within the context of MAVT. It integrates and critically synthesizes findings from the time-related biases and debiasing literature, the MADM field, and behavioral decision research (BDR). By weaving these strands together, the applied methodology generates original insights into how intertemporal biases may affect each step of the decision-making process and how such biases might be mitigated throughout the evaluation.

To answer the third research question, I develop a theoretical framework that grounds the study in existing literature and conceptual foundations. From this framework, I deductively derive four hypotheses on how time preference shapes attribute-specific value function elicitation and trade-off procedures. To test these hypotheses, I design three controlled experiments within the MAVT framework, enabling systematic data collection. The quantitative data gathered through these experiments are analyzed using advanced statistical techniques and data-fitting methods, offering explanatory insights into the mechanisms by which time preferences influence decision-making.

To address the fourth research question, a theory-driven deductive experimental approach is adopted. The study constructs a theoretical framework grounded in choice bundling and bracketing literature (Ainslie, 1992; Read et al., 1999). These theories highlight the potential benefits of presenting a decision's outcomes collectively, rather than as isolated payoffs, in fostering future-oriented judgments. Considering the distinction between one-off and recurring payoff problems, I derive the hypothesis that presenting payoffs as recurring, rather than one-off, will promote long-term consideration and reduce individuals' discount rates. Two controlled experiments are designed to test this hypothesis across different outcome types. The quantitative data collected are analyzed using statistical methods, providing explanatory insights into how payoff structures shape intertemporal decision-making.

Together, these diverse research approaches provide a comprehensive understanding of the topic from both theoretical and empirical perspectives. Drawing on this integrated methodological foundation, the following section highlights the key theoretical and practical contributions emerging from the study's findings.

## 1.5 Contributions

This dissertation contributes to the decision science literature and practice in several ways. Its primary contribution lies in advancing the understanding of time preference by examining it within multi-objective decision frameworks from a prescriptive perspective. In doing so, it not only offers valuable insights for decision-makers and analysts seeking to align judgments and preferences with long-term goals but also presents time preference experiments closer to real-life decision contexts by studying more contextually grounded scenarios. The more specific contributions are outlined as follows.

First, this dissertation reviews and synthesizes a comprehensive set of intertemporal biases that influence time preference, along with the empirical evidence on their effects and mitigation strategies. Additionally, exploring the intricate relationships among these biases offers deeper insights into complex human behavior and supports the development of more effective mitigation strategies. These findings are valuable not only for researchers and analysts who seek to better model, predict, and support decision-making over time but also for practitioners and policymakers who make intertemporal judgments in real-world contexts.

Second, given the absence of prior studies examining the role of intertemporal biases in the context of multi-objective decision analysis, this dissertation makes a novel conceptual contribution by drawing attention to this overlooked intersection. Examining the potential vulnerabilities of the MAVT to time-related cognitive biases highlights a critical blind spot in the literature and lays the groundwork for future empirical and methodological investigations. Additionally, it proposes mitigation ideas informed by findings from related fields, offering a starting point for researchers and practitioners to better account for temporal distortions in complex decision-making contexts.

Third, it contributes to the literature by extending time preference research into multi-objective decision-making by incorporating a structured method to explore how intertemporal trade-offs interact with trade-offs between multiple objectives. Moreover, it offers a novel experimental approach that captures the reasoning process behind individual judgments at various

stages of decision-making, rather than relying solely on final choices or discount rates. By doing so, it provides deeper insight into complex human behavior and opens new avenues for both theoretical inquiry and practical application.

Fourth, this dissertation contributes to the literature by introducing a novel perspective for modeling time preference in recurring payoff contexts, offering an alternative to traditional one-off decision frameworks. It also provides an alternative explanation for the high discount rates commonly observed in the literature by highlighting the role of contextual factors. Additionally, the study offers practical insights into how recurring payoff structures can encourage more future-oriented decision strategies, with implications for both behavioral interventions and policy design. These findings are valuable for decision-makers, analysts, and researchers by supporting more informed choices and enhancing the ecological validity of discount rates used in empirical studies.

Together, these findings provide a comprehensive and multi-dimensional understanding of time preference, bridging theoretical insights with empirical evidence and offering practical tools and frameworks that enhance both the study and application of intertemporal decision-making in complex, real-world contexts.

## 1.6 Organization of the dissertation

This dissertation is a collection of four research articles, each addressing one of the research questions outlined above. Figure 1.1 illustrates the organization of the dissertation by mapping each research question to its corresponding chapter.

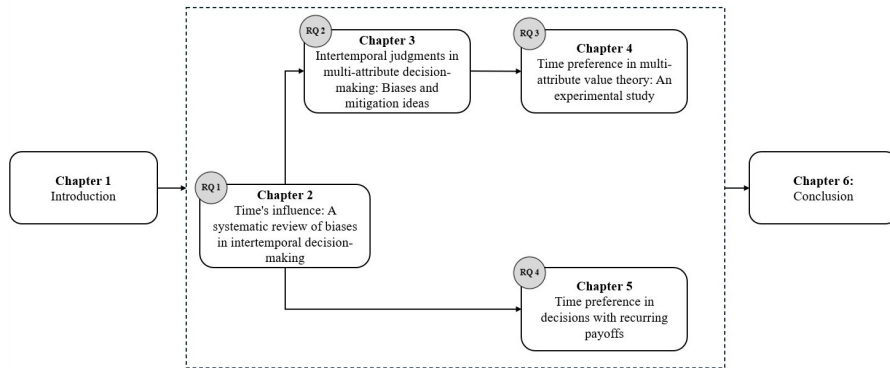


Figure 1.1: Organization of the dissertation

Each chapter is titled after the research article it is based on. Following this introductory chapter, which presents the study's background, research gaps, research questions, approaches, and contributions, Chapter 2 proceeds to address RQ 1. I start by exploring time-related biases and gathering empirical evidence on their effects, together with potential mitigation strategies from different fields. With RQ 1, I illustrate how these biases work in descriptive frameworks.

Recognizing the importance of addressing such biases in prescriptive frameworks, particularly in problems involving multiple objectives, Chapter 3 responds to RQ 2. It explores the role of time preference and intertemporal biases within the context of MAVT and presents potential mitigation ideas based on the literature. Next, I employ the insights gained from Chapters 2 and 3 and theorize the influence of time preference in the MAVT context and develop hypotheses related to attribute-specific value function elicitation and trade-off steps. Consequently, Chapter 4 presents an experimental study focusing on time preference in the MAVT for answering RQ 3. Chapter 5 extends the investigation of time preference to the context of recurring payoffs and addresses RQ 4. It presents two behavioral experiments that explore how recurring payoff structures affect discounting behavior and decision strategies, particularly across gain and loss domains. Finally, Chapter 6 synthesizes the key findings of the dissertation, discusses their implications for theory and practice, and outlines promising directions for future research.

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## Chapter 2

# Time's influence: A systematic review of biases in intertemporal decision-making

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**Abstract:** Cognitive biases significantly influence decision-making by distorting how individuals perceive and evaluate outcomes over time. This systematic review synthesizes research from various domains, including behavioral economics, psychology, and health, to explore six time-related biases affecting intertemporal judgments and trade-offs. We analyze the underlying mechanisms of each bias, map their interrelationships, and uncover their impacts on both individual choices and societal decisions. Drawing upon empirical evidence, we propose tailored strategies to mitigate the adverse effects of these biases. Our findings contribute to the literature not only by enhancing the understanding of time-related cognitive biases but also by providing practical insights for improving decision-making and policy design aimed at promoting long-term well-being. The paper concludes by highlighting critical gaps in the literature and outlining a future research agenda to further investigate and address biases in intertemporal decision-making.

**Keywords:** Time preference; cognitive biases; intertemporal decision-making

This chapter is based on the following journal paper:

Gülüm Taş, P., Maknoon, Y., & Rezaei, J. (2026). Time's Influence: A Systematic Review of Biases in Intertemporal Decision-Making. *Annual Review of Psychology*, 77, 223-254.

## 2.1 Introduction

Time preference is a key concept in understanding how individuals make decisions involving trade-offs between costs and benefits that emerge at different points in time. It reflects the relative value people place on receiving benefits sooner rather than later and can affect every intertemporal decision, ranging from personal savings and investment choices to health behaviors (Thaler, 1981). For instance, people who overvalue future financial security over immediate gratification are more likely to choose to deposit money into a savings account instead of spending it immediately. Conversely, those with a high time preference may opt for a smaller immediate reward rather than waiting for a larger outcome. These preferences are fundamental in shaping a wide range of personal, economic, and societal behaviors and must be understood and balanced for enhanced well-being.

Time preferences and intertemporal choices are often examined through economic theories such as exponential discounting (Samuelson, 1937). This model provides a foundational framework for intertemporal trade-offs, assuming that decision-makers possess time-consistent preferences and act as rational utility maximizers all the time. This means that if an individual prefers a delayed reward over an immediate one today, they will maintain this preference consistently over time, continue to prioritize long-term benefits, and aim to maximize their overall utility. However, empirical evidence reveals that individuals often deviate from rational utility maximization, with preferences changing over time (Fishburn & Rubinstein, 1982). It has been shown that people tend to place a higher value on immediate rewards than delayed ones, even when the latter offers greater overall utility (Thaler, 1981). Various intertemporal choice anomalies illustrate how decision-makers violate time consistency and rationality assumptions of the exponential discounting model by changing their preferences over time depending on the type, magnitude, and sequences of outcomes they evaluate (Loewenstein & Prelec, 1991; Shelley, 1993; Thaler, 1981; Rambaud et al., 2023).

Intertemporal choice anomalies can be better understood through the lens of cognitive biases that systematically distort decision-making processes. Cognitive biases play crucial roles in decision-making, particularly when individuals need to make trade-offs and provide judgmental inputs. Research indicates that people heavily rely on mental shortcuts and heuristics during their evaluations and often make biased judgments (Tversky & Kahneman, 1974). Within the area of intertemporal choices, cognitive biases influence how people perceive time, assess the value of alternatives, and compare the desirability of outcomes (Frederick et al., 2002). Given that most decisions involve predicting and evaluating outcomes across different time points, misperceptions driven by biases can systematically affect intertemporal trade-offs, leading to low utilities, undesirable outcomes, or even financial losses. For instance, individuals tend to underestimate the magnitude of the changes in their preferences over time, a phenomenon named projection bias (Loewenstein et al., 2003). Projection bias leads decision-makers to form their future preferences based on their current circumstances, and it usually causes short-sighted decisions. Similarly, present bias refers to the tendency for individuals to prefer immediate rewards over future outcomes, even when the future rewards are significantly larger. It causes making choices that favor short-term gratification at the expense of long-term benefits, often resulting in decisions that are not aligned with their best interests. Recognizing the underlying reasons and potential impacts of time-related biases is crucial for gaining a nuanced understanding of why people make seemingly "irrational" decisions. The prevalence of these biases

in various aspects of life underscores the need for developing systematic strategies to minimize their negative influences. Moreover, sometimes multiple biases can influence judgments simultaneously and lead to compounding distortions or reinforced errors. Since the interaction of the biases may amplify complexity and escalate the negative influences, it is crucial to be aware of these relationships. Despite extensive research on intertemporal choice anomalies and time preferences, a notable gap remains in the literature regarding a comprehensive exploration of the influences of time-related biases on decision-making. Specifically, there is a limited investigation into how these biases interact with one another in the intertemporal context and a lack of targeted mitigation strategies to reduce their influences on judgments.

This review focuses on time-related biases by examining their effects on judgments and offers mitigation strategies to reduce their negative impacts. Our methodology involves a two-step process, starting with the identification of six biases that influence intertemporal trade-offs or distort time perception in decision-making. We then subject each of these biases to a systematic literature review and gather empirical evidence from a variety of fields, including economics, finance, health, and psychology. By doing so, we reveal insights into understanding how each bias plays a role in different decision contexts and which approaches can help decrease their adverse effects on judgments. Furthermore, we analyze the co-occurrence of biases and show how their combined presence may distort evaluations. By structuring a map that illustrates the relationships between biases, we offer new insights into their interconnections. Finally, based on the analyzed studies and recent trends in the literature, we present a research agenda.

Our research contributes to the existing body of knowledge in several ways by synthesizing the effects of multiple time-related biases on decision-making from a holistic perspective. Exploration of the relationships between these biases provides insights into uncovering complex behaviors and eventually designing more sophisticated approaches to improving judgments and decisions across various domains. The findings of this review can guide practitioners and policymakers aiming to enhance decision-making processes and researchers seeking to develop better mitigation strategies or decision-making methods. Our research extends its impact beyond the current findings by systematically reporting literature gaps and presenting a detailed research agenda for each bias. This proactive approach opens up new avenues for exploration. The conducted comprehensive reviews not only enrich the current understanding of time-related biases but also serve as a catalyst for continued research and exploration in this evolving field.

The structure of this paper is as follows: Section 2.2 provides a background and discusses a few key developments in time preference and intertemporal decision-making literature. Section 2.3 introduces the approach employed in this review, elucidating the research design and article selection procedures. The findings of our analysis, offering insights into the empirical evidence gathered on time-related biases and mitigation strategies, are presented from Section 2.4 to Section 2.9, with each bias discussed in a separate section. The overview of the relationships between the biases is discussed in Section 2.10. Section 2.11 is dedicated to a comprehensive discussion of gaps in the literature and outlines potential avenues for future research, underscoring areas that warrant further exploration and investigation. Finally, in Section 2.12, we summarize our findings and draw conclusions.

## 2.2 Time preference and intertemporal choices

Time preference is significant in many decisions, including personal finance, health, education, policy-making, and environmental planning. Due to the importance and prevalence of this phenomenon, numerous theories have been introduced to model intertemporal choices and understand time preferences. One prominent theory for modeling these choices is *exponential discounting*, which assumes that individuals discount values at a constant rate over time (Samuelson, 1937). This model helps explain how people value immediate rewards over future ones, providing a mathematical framework for predicting and understanding intertemporal decisions. The exponential discounting model has two main assumptions: (i) People have a constant discount rate, which is used for all types of outcomes, and (ii) their preferences are consistent over time. These assumptions imply that decision-makers are rational utility maximizers who always make time-consistent choices. However, the empirical validity of these assumptions was criticized, and various alternative methods have been introduced to account for behavioral aspects that conflict with these assumptions. For instance, the *hyperbolic discounting model* shows discount rates decrease over time rather than being constant, and individuals strongly prefer immediate rewards over long-term benefits (Ainslie, 1975).

On the other hand, *prospect theory* reveals that gains and losses are perceived and evaluated differently in intertemporal decisions (Kahneman & Tversky, 1979). Individuals often prefer smaller immediate rewards over larger future outcomes due to the stronger emotional impact of potential losses and the tendency to heavily discount future benefits. Table 2.1 chronologically presents a few key theories developed to better represent the human decision-making process, particularly in the context of evaluating intertemporal outcomes and incorporating behavioral factors. While some of these theories are related to modeling intertemporal choices (descriptive approaches), a few are about motivating decision-makers to make more informed decisions that are aligned with their long-term well-being (prescriptive approaches). For instance, the nudge theory is about structuring choice environments and influencing people's behavior in a way that encourages them to make decisions that are in their best interest without restricting their freedom of choice (Thaler & Sunstein, 2008). Most of these theories conflict with the rational agent assumption of exponential discounting and incorporate behavioral patterns by aiming to better model real-life preferences.

## 2.3 Research methodology

This systematic review applies a two-level methodology to identify and examine time-related biases. In the first step, we followed an approach to determine which biases can possibly emerge while making intertemporal trade-offs. We started by identifying keywords related to time preference, such as “present,” “past,” “future,” “temporal,” “intertemporal,” “time,” “preference,” and “discounting”. Then, we went through the published bias codex, which illustrates a comprehensive list of the decision biases (Manoogian & Benson, 2017), seminal time preference and decision biases review papers (Cooper & Meterko, 2019; Rambaud et al., 2023; Ehrlinger & Kim, 2016; Kahneman et al., 1991; Loewenstein & Prelec, 1992; Montibeller & von Winterfeldt, 2015; Neal et al., 2022) and bias taxonomies (Arnott, 1998; Peón et al., 2017). By doing so, we reached descriptions and features of many biases and screened them using these

*Table 2.1: A few key developments in the time preference literature*

<b>References</b>	<b>Theories and Developments</b>	<b>Key Contributions</b>
Samuelson (1937)	Exponential Discounting	The first generalized model for intertemporal choices that assumes individuals have a constant discount rate and their preferences are consistent over time
Koopmans (1960)	Notion of time consistency	A set of plausible axioms that show under well-specified circumstances decision-makers have positive time preferences and behave as theorized in the Exponential Utility Model
Ainslie (1975)	Hyperbolic Discounting	Proposed as an alternative to exponential discounting by empirically showing that discount rates do not stay stable but decrease over time and individuals strongly prefer immediate rewards over delayed ones
Kahneman & Tversky (1979)	Prospect Theory	Contributed to time preference literature by introducing psychological insights into how individuals evaluate gains and losses over time and the role of uncertainties in the trade-offs
Laibson (1997)	Quasi-Hyperbolic Discounting	A hybrid model that accounts for present bias and addresses the limitations of both exponential and hyperbolic discounting. It applies a dual parameter approach for addressing short and long-term discounting parameters simultaneously
O'Donoghue & Rabin (2001)	Dynamic Inconsistency and Sophistication	Explores the behavior of individuals who are either naive or sophisticated in their model of procrastination
Trope & Liberman (2003)	Temporal Construal Theory	Suggests that the psychological distance of events affects how people think about them. This difference in mental representation influences decision-making and preferences over time
Thaler & Sunstein (2008)	Nudge Theory	Emphasizes designing choice architectures that help individuals make better long-term decisions by accounting for behavioral biases like present bias

keywords. If the definition of a bias included one or more of the keywords, and if there was an intertemporal dynamic, we considered it for systematic review. This initial step yielded six time-related biases: present bias, projection bias, recency bias, duration neglect, impact bias, and planning fallacy.

In the second step, each of these biases was subjected to a systematic literature review by following the methodology provided by Tranfield et al. (2003). Two main bibliographic databases, Web of Science (WoS) and Scopus, were considered because of their high-impact publications and being important databases with extensive interdisciplinary studies (Rambaud et al., 2023).

The identified keywords were grouped into two categories. The first category ensures that the article is about the bias we are looking for, and the second one limits the search to articles exclusively about intertemporal decision-making or time preference. The keywords were chosen for the broadest possible scope without losing the focus on intertemporal aspects. For example, the search string for impact bias was (“impact bias\*” OR “affective forecast\*”) AND (“time” OR “temporal” OR “intertemporal” OR “discount\*”). The aforementioned databases were searched using strings specific to each bias, which were structured using the same strategy. The search was limited to articles written in English and published in peer-reviewed journals. We did not consider review papers, conference proceedings, and theses. Also, we did not restrict the search to any journal or time range. The initial searches were conducted between November 2023 and February 2024 at different times for each bias. The details of the article selection process and the number of papers are provided in Table 2.2.

The papers’ abstracts, titles, and keywords were screened to identify obviously irrelevant studies before applying the eligibility test. Articles that were found irrelevant were removed in this step and moved to full-text reading. The full texts of the articles were subject to eligibility criteria. Inclusion criteria were (i) Studies that include the bias associated with intertemporal decision-making, (ii) Empirical studies (studies that are based on observed and measured phenomena and derive data from actual experiences), and (iii) Studies conducted with human participants (excluding studies conducted with animals or computer models). Exclusion criteria were (i) Non-peer-reviewed articles (such as editorials, commentaries, or letters) and literature review papers, (ii) Theoretical and conceptual papers that do not present any empirical findings, (iii) Studies that focus primarily on animal models or non-human subjects.

*Table 2.2: The details of the article selection process*

		Biases					
		Present	Projection	Recency	Duration neglect	Impact	Planning fallacy
<b>Initial search</b>	Initial search date	Nov. 2023	Feb. 2024	Feb. 2024	Feb. 2024	Sept. 2023	Sept. 2023
<b>(Identification)</b>	Locations	Title-Abstract-Keywords/Title-Abstract-Keywords					
<b>Initial results</b>	Web of Science	375	49	25	69	91	72
	Scopus	356	45	24	38	81	43
	Total	731	94	49	107	172	115
<b>Screening phase</b>	Removed duplicates	-332	-34	-22	-34	-60	-37
	Screened papers	399	60	27	73	112	78
	Obviously irrelevant	-87	-12	-11	-21	-39	-23
	Full text reading	312	48	16	52	73	55
<b>Eligibility test and inclusion</b>	Not human subject	-0	-0	-0	-3	-0	-0
	Not empirical	-159	-11	-4	-11	-12	-10
	Not related to the bias	-75	-13	-2	-2	-18	-14
	Not time focused	-0	-6	-3	-11	-6	-6
	<b>Included</b>	<b>78</b>	<b>18</b>	<b>7</b>	<b>25</b>	<b>37</b>	<b>25</b>

The number of articles included varies for each bias, with the present bias having the highest number and the recency bias having the lowest number. This variation in numbers can be attributed to a few reasons. A large number of studies have been produced because present bias has been investigated in parallel with the time preference literature for many years in various fields. On the other hand, more recently identified biases like duration neglect or projection bias have yielded relatively fewer outputs. Second, while some biases are straightforward and easy to control in experiments, others are more difficult to measure or to distinguish their effects from other factors. This affects the number of experiments on each bias and, consequently, the number of articles included in this review.

After applying the eligibility test, the selected articles were analyzed to extract all related information. While doing so, we followed a data extraction protocol. This protocol consists of four main elements: (i) influences (of the bias) on judgments and decisions, (ii) additional biases and behavioral factors reported in the paper (if so), (iii) mitigation strategies (if mentioned), and (iv) literature gaps and future research directions. There is always complexity and ambiguity when the human thinking process is concerned. Therefore, in some cases, empirical results were attributed to or explained by more than one bias. Since these relationships between biases may provide insights into understanding the underlying mechanisms, the additional biases and interrelationships were also extracted. By doing so, we aim to extend our analysis beyond the primary findings and show how these biases may emerge and influence judgments together. In order to provide practitioners with systematic ways to decrease the adverse effects of the considered biases, we gathered all the mitigation strategies discussed in the papers.

## 2.4 Present bias

The hyperbolic discounting model shows that people do not discount the future at a constant rate as assumed in exponential discounting theory, and they overvalue the immediate outcomes because of the present bias (Frederick et al., 2002; Thaler, 1981). The origins of present bias are subjects of varied interpretations. Notably, research indicates that individuals' perceptions and treatment of time play a critical role in shaping judgments (Balakrishnan et al., 2020; Jang & Urminsky, 2023; Krčál et al., 2021). Studies have discovered that individuals have subjective perceptions of future time horizons, and they show reduced sensitivity to durations. This reduced sensitivity is posited as one of the reasons for adopting hyperbolic discounting (Zauberman et al., 2009). Further supporting this notion, research shows that individuals tend to create subjective financial periods in their minds and treat time-related outcomes based on these artificial time slots (Jang & Urminsky, 2023). People are more impatient when choosing alternatives from different financial periods than those from the same subjective financial period. The way people think and visualize the future is vital in intertemporal decision-making. For example, in a study demonstrating customers' sensitivity to present bias and time horizons, the concreteness of mental representations was the main driving factor (Malkoc & Zauberman, 2006). It has been found that temporal framing (framing the consumption problem as a deferral or expedite) affects the concreteness of mental representations, influencing the present bias level. Similarly, people with abstract mindsets show less present bias than those with concrete mindsets (Malkoc et al., 2010). The present bias was reported in financial decisions, including debt (Ikeda & Kang, 2015), overspending (Nguyen, 2016), loans (Berlinger et al., 2022), credit card use and borrowing (Meier & Sprenger, 2010). These experiments have shown that present-biased individuals can be more engaged with over-borrowing and debt-holding (Ikeda & Kang, 2015), overspending and impulsive buying (Nguyen, 2016) and credit card use (Meier & Sprenger, 2010).

Recent investigations into the diversity of intertemporal preferences have scrutinized variables such as age (Ikink et al., 2023; Kulati et al., 2023), gender (Horn et al., 2022), cultural differences (Kim et al., 2012), and socioeconomic status (Kulati et al., 2023). A recent study involving three distinct age cohorts revealed that children and adolescents exhibit greater impatience than young adults (Ikink et al., 2023). People are more sensitive to reward magnitudes but

not to delays, which can be interpreted as an indication of increasing patience with advancing age. Parallel findings were observed in an extensive survey conducted across several European nations, suggesting older individuals tend to assign greater value to future rewards, displaying a willingness to postpone immediate gratification (Meissner et al., 2023). Furthermore, gender emerged as an essential determinant of intertemporal choices, with men having a higher present bias than women. This gender-related pattern was similarly noted among Hungarian students, where female participants showed lesser present bias than their male counterparts (Horn et al., 2022). Another research on Poland's elderly population identified a correlation between reduced present bias and enhanced patience with factors such as high numerical abilities, higher income levels, and urban residence (Kulati et al., 2023). Notably, in this study, neither age nor gender was significantly linked to time preference variations, potentially due to the specific emphasis on older demographics. As an essential indicator of many interpersonal differences, the role of culture was revealed in time preferences by comparing the preferences of Western (American) and Eastern (Korean) subjects (Kim et al., 2012). Americans prefer immediate rewards more and show higher discount rates compared to Koreans, drawing attention to the differences between individualistic and collectivistic cultures.

Besides these individual and cultural drivers, time preferences are also affected by big-scale events like natural disasters, pandemics, or political regime changes (Akesaka, 2019; Friehe & Pannenberg, 2020; Meunier & Ohadi, 2021). For instance, a study compared the time preferences of participants from Japan before and after the tsunami caused by the Great East Japan Earthquake (Akesaka, 2019). Although it did not affect the intertemporal discount rates, the tsunami increased the present bias. A longitudinal experiment tested the influence of the COVID-19 pandemic on time and risk preferences (Meunier & Ohadi, 2021). Findings show that the pandemic reduced present bias and led to more patience, especially in older people who faced severe health risks. The effect of political regimes on intertemporal judgments was studied using the separation and reunification of Germany after World War II (Friehe & Pannenberg, 2020). There was a difference between the time preferences of citizens under the socialist and capitalist regimes. While former German Democratic Republic (GDR) residents were less present-biased than the Federal Republic of Germany (FRG) residents, these two groups did not differ in patience levels. It has also been found that people who spent too much time (especially in their early childhood years) under the GDR regime had a more substantial present bias, which shows the formability of preferences at early ages of life.

Present bias has been investigated in relation to various emotional states such as stress and sadness (Haushofer et al., 2013; Lerner et al., 2013; Haushofer et al., 2021). Experiments with monetary and health outcomes revealed that stress does not significantly influence discount rates or present bias (Haushofer et al., 2013). It is important to note that these experiments were conducted only with male participants, and gender differences were not accounted for. Conflicting results were reported when participants' cortisol levels were increased, and their intertemporal preferences over outcomes like money and effort were analyzed (Haushofer et al., 2021). The results show that stress may increase the likelihood of choosing immediate outcomes, regardless of whether they are positive or negative. The role of sadness was tested by comparing the judgments of sad participants with those of neutral or disgusted people (Lerner et al., 2013). The sad people were more willing to accept sooner but smaller rewards than greater but delayed outcomes.

Outcome types such as unpleasant tasks (Augenblick & Rabin, 2019), gains and losses (Hardisty et al., 2013; Shiba & Shimizu, 2020), and reward types (for example, material versus experiential outcomes) (Cheung et al., 2022; Goodman et al., 2019) differ in their relations to present bias. Research on time inconsistency in gains and losses reported that the temporal location of delayed outcomes is the driving factor in direction and degree of inconsistency (Shiba & Shimizu, 2020). Moreover, people's time inconsistencies for gains and losses were strongly related to each other regardless of impatience levels. These findings highlight that people may have similar or even typical time inconsistencies for losses and gains. Contrary to the magnitude effect idea, in a series of experiments, participants discounted small losses less than large ones and large gains more than small gains (Hardisty et al., 2013). Moreover, it has been found that regardless of their magnitude, people tend to resolve both gains and losses immediately. Time inconsistency was investigated across reward categories like food and money, using students from low-income schools in China (Cheung et al., 2022). The students had a present bias for both rewards. Furthermore, individual measures of present bias and impatience were correlated across different reward types, meaning that if someone knows the monetary preferences of a person, it may be possible to guess their food preferences. From a similar point of view, in an experiment where the impatience levels of customers were compared toward material versus experiential purchases, analyses revealed that people are less impatient for material purchases than experiential ones, even when product types, delays, and choices vary (Goodman et al., 2019).

Present bias has been investigated for many health-related decisions, including smoking (Grignon, 2009), exercising (Eberth et al., 2022), eating habits (Courtemanche et al., 2015; Mørkbak et al., 2017; Soofi et al., 2020), and preventive measures like disease screening (Jennings Mayo-Wilson et al., 2023; Lee et al., 2020; Tang et al., 2023). An experiment in France revealed that although they are not likely to start smoking, present-biased people tend to quit smoking later in life after more failed attempts (Grignon, 2009). Similar results apply to exercising behaviors (Eberth et al., 2022; Hunter et al., 2018). Present bias is influential in maintaining physical activity, but its role in the initiation stage is insignificant. However, a survey from Japan shows that present-biased individuals are more likely to develop unhealthy behaviors, and impatience is related to poor health status in general (Kang & Ikeda, 2016). Present bias is an essential driving factor in diseases that are closely related to lifestyle and eating habits, such as obesity and diabetes. In a study conducted with a group of people with diabetes from Denmark who were at different stages of the disease, the present bias was significant both for causing early onset and affecting the after-diagnosis preferences (Mørkbak et al., 2017). Similarly, a significant relationship between body mass index (BMI) and time preferences has been reported in a national longitudinal survey conducted in the U.S. (Courtemanche et al., 2015). The more impatient the participants were, the higher their BMI. The correlation between the probability of being obese and impatience provides further support for the influence of present bias on health (Soofi et al., 2020). The Family Health Habits Survey reveals that the impatience level of parents can significantly affect not only their own but also their children's obesity risk (Stoklosa et al., 2018). These findings show the malleability of preferences depending on other people and environmental factors.

The willingness to undergo preventive health measures can also be related to present bias. For example, a high correlation between screening intention and time discounting was reported in a cross-sectional analysis of cancer screening behaviors in Korea (Lee et al., 2020). Individuals who discounted the future heavily were less likely to undergo lung cancer screening.

Similar results were also reported by a recent study that focused on diabetic retinopathy screening behavior (Tang et al., 2023).

The influence of present bias is also evident in environmental decision-making (Figueroa et al., 2019; Fuerst & Singh, 2018; Schleich et al., 2019; Yue et al., 2023; Wu et al., 2023). Since many environmental decisions require an initial investment and a long wait for the reward to be realized, present-biased people are less likely to switch to environmentally friendly options. For instance, in a study investigating energy-efficient investment preferences in India, present bias was the reason for the under-investment (Fuerst & Singh, 2018). Participants were less likely to buy energy-efficient devices like air-conditioners and refrigerators because they highly focused on upfront costs and underestimated the possible future benefits of the investment. In a recent study about rooftop photovoltaic technology adoption in China, present-biased households were less likely to adopt it because of the long payback period (Wu et al., 2023). Similarly, a study with a large representative sample from eight European countries shows that time discounting, risk aversion, and loss aversion are negatively correlated with energy-efficient technology adoption (Schleich et al., 2019). Research shows that households occupied by present-biased families consume more electricity on average than time-consistent households (Werthschulte & Löschel, 2021). These families devalue future energy consumption since they face outcomes at the end of the month and tend to be less careful at present. The role of present bias is also evident in agricultural decisions, including conservation behaviors (Boonmanunt et al., 2020), warrantage systems participation (Le Cotty et al., 2019), environmental program adoptions (Clot & Stanton, 2014), and contract farming applications (Hou et al., 2023). Consistent with the previous experiments, the present biased farmers are less likely to adopt new technologies (Mao et al., 2021).

### **Present bias mitigation strategies**

Since the present bias is about being tempted by the desirability of immediate outcomes and giving less importance to long-term consequences, using commitment devices is the most reported mitigation strategy (Albrecht et al., 2011; Benschmidt & Carpenter, 2020; Hunter et al., 2018; Imas et al., 2022; Le Cotty et al., 2019; Stoklosa et al., 2018). If people use pre-commitment devices, it is more likely to stick to their long-term plans in various contexts like quitting smoking (Grignon, 2009), enhancing physical activity (Eberth et al., 2022), saving energy (Werthschulte & Löschel, 2021) and saving money (Atlas et al., 2017). Although many experiments support commitment devices' applicability and promising performance in various fields, some mitigation strategies outperform. For instance, providing waiting periods between information-receiving and decision-making stages can be more effective than commitment devices (Imas et al., 2022). It has been argued that individuals should overcome the temptations while committing to an action. However, while provided with a waiting period to think about and mentally stimulate future outcomes, they do not need to deal with temptations. Therefore, waiting periods may provide a better mitigation than commitment devices in some situations. Alternatively, combining commitment devices with a waiting period can be an effective strategy for mitigating present bias.

Framing intertemporal choices as losses reduces the present bias and increases the preference for delayed rewards (Radu et al., 2011). Since people generally prefer gains over losses, when the immediate outcome is framed as a loss, its attractiveness decreases, and the attention

shifts toward the future. This idea was tested in the health domain for preventive measures for HIV (Jennings Mayo-Wilson et al., 2023). Participants' loss aversion was triggered when the consequences were framed as health losses, and they were less tempted by immediate outcomes. A similar idea is framing the future outcomes as large gains or small losses to encourage future-oriented choices (Hardisty et al., 2013). It has been suggested that instead of saying, "saving 10 units a month", framing the problem as "earning 120.000 units in 30 years" may decrease the present bias. Furthermore, framing the problem as a future date, not a delay, also decreases the present bias (Malkoc et al., 2010). If the resolution date of the outcome is provided instead of saying X days later, the decision maker can have more abstract and contextualized thinking and become less subject to present bias. Making future outcomes more salient or attractive and increasing attention toward the future are among the reported mitigation strategies (Carvalho et al., 2016; Guan et al., 2022; Malkoc et al., 2010). If a delayed outcome is described in detail and its advantages presented clearly, decision-makers can be less influenced by the immediate options. From a similar point of view, increasing the cost of tempting options can also achieve this (Courtemanche et al., 2015; Soofi et al., 2020). For instance, making the immediate rewards unreachable (expensive or scarce) for unhealthy eating behaviors may help to decrease present bias and promote healthy eating habits.

Episodic future thinking refers to the human ability to imagine and mentally simulate future events, and it has a significant role in reducing temporal discounting and improving decision-making (Schacter et al., 2017). By making future outcomes more tangible and engaging, this cognitive process can help individuals overcome present bias and make farsighted decisions (Atance & O'Neill, 2001; Bulley & Schacter, 2020; Peters & Büchel, 2010). For instance, mentally simulating future scenarios allows decision-makers to focus on potential long-term benefits over immediate temptations, leading to more informed choices (Benoit et al., 2011).

Offering incentives or nudging to promote future-oriented decision-making is among the most reported mitigation strategies. These methods are discussed for various decisions like disease screening (Lee & Kim, 2017; Tang et al., 2023), physical activity (Hunter et al., 2018), switching to energy-efficient products (Figueroa et al., 2019), and healthier eating behaviors (Guan et al., 2022; Kang & Ikeda, 2016; Soofi et al., 2020). People can be more motivated when they are reminded by an external source (nudge) or when they are promised a reward for doing a "healthy" activity. Furthermore, tailoring the incentives to consider individual differences may increase the effectiveness of these strategies (Tang et al., 2023).

Joint decision-making has been identified as an effective debiasing strategy, as individuals tend to display less present bias when making decisions together with their spouses compared to deciding alone (Kono & Tanaka, 2019; Nguyen, 2016).

## 2.5 Projection bias

Sometimes, individuals cannot sufficiently estimate the future and assume that their current preferences will remain the same, known as projection bias (Loewenstein et al., 2003). Weather and air quality stand as two prominent factors that influence the perceptions of the decision-makers related to the future and lead to time-inconsistent preferences. It has been shown that the consumption decisions related to not only regular daily items such as winter clothes (Conlin et al., 2007) or outdoor movie tickets (Buchheim & Kolaska, 2017) but also durable goods like

solar panels (Lamp, 2023), cars (Busse et al., 2015) or lands (Pan et al., 2022) are significantly affected by projection bias. Since decision-makers could not accurately isolate the effects of the decision moments from future expectations, they ordered more winter clothes when the weather was cold (Conlin et al., 2007), purchased more outdoor movie tickets when it was sunny (Buchheim & Kolaska, 2017) and maybe more seriously decided to adopt solar panels (Lamp, 2023), paid higher prices for lands located in the districts with a heating system (Pan et al., 2022) and bought winter cars (Busse et al., 2015) if the decision was made in a cold day. Similarly, air quality significantly influences individuals while thinking about their future well-being. Participants were willing to pay more for better air quality if the experiment was conducted on a day with low air quality (He & Hu, 2010), and they overvalued air quality relevance for overall well-being if they were exposed to short-term air pollution (Chen et al., 2019). Besides the environment in which the choices are made, the features of the outcomes and the context of the decisions also cause inconsistencies. When asked to choose between intertemporal unpleasant tasks related to their job, individuals exhibited projection bias and mispredicted their future tastes (Augenblick & Rabin, 2019). The distaste of the present tasks affected the value these people attributed to the future.

There are numerous personal drivers that trigger projection bias in intertemporal trade-offs (Kármén, 2023). The changes in tastes, education level, and financial control are some of the factors that may cause a gap between estimated and received utilities. There are also visceral effects, such as hunger, thirst, and sexual desires, that distort individual preferences. People mispredict their future desires when they are in a different visceral state from the anticipated consumption state (Fisher & Rangel, 2014). In a set of experiments, participants reported various willingness to pay values for the same objects depending on their hunger level at the time of the experiment (Briz et al., 2015). Since visceral factors directly affect the perceived value of the evaluated outcomes, they trigger intertemporal biases, including projection bias.

Projection bias may distort not only our future preferences but also our perceptions and assumptions about the preferences of other people. Experiments show that when people are asked how much their future preferences resemble the current ones, they tend to be optimistic about the consistency but assume other people's preferences will change more significantly (Renoult et al., 2016). One of the factors contributing to this difference is social distance. When people think about the preferences of a close friend or a family member, they assume less change than a generic peer's (Bauckham et al., 2019). These findings point to possible mistakes that may emerge when people must decide on behalf of a person or a group. It has been reported that when elderly people were asked to decide about their partners' end-of-life treatment preferences, they were subject to projection and similarity biases (Moorman et al., 2009). They were heavily dominated by their own treatment preferences, and the estimations they reported about their partners were far from reality.

### **Projection bias mitigation strategies**

The most common strategy against projection bias is the "cooling-off period," which means providing people with a period of time to think about their preferences before finalizing the decisions (Camerer et al., 2003). This approach is similar to the "waiting period" idea that has been discussed to mitigate present bias (Imas et al., 2022). The strategy is based on the fact that future preferences can be better evaluated by separating them from current emotions.

The cooling-off period is applied not only to financial decisions but also to emotional ones (Buchheim & Kolaska, 2017; Busse et al., 2015; Loewenstein et al., 2003). For instance, 9% of the couples who applied for divorce suits in Korea changed their minds after being provided with a period of time to think about their decision (Wie & Kim, 2015). Although the cooling-off idea has been widely proposed, it needs to be validated by testing in different decision contexts. There are also other mitigation strategies, such as providing decision-makers with more information related to the problems (Buchheim & Kolaska, 2017; Moorman et al., 2009; Pan et al., 2022) or warning them to be aware of the bias (Hetou et al., 2021; Lemay et al., 2015). It is noteworthy that these ideas do not go beyond general suggestions despite the fact that they are frequently reported for other biases, such as present bias, recency bias, and duration neglect. There are also more unique approaches for projection bias, such as simulating other people's preferences (Renoult et al., 2016), focusing on basic variables instead of thinking of abstract aspects of future preferences (Fisher & Rangel, 2014), or using the social distance phenomena as a debiasing strategy (Bauckham et al., 2019). All these strategies require further investigation and empirical evidence.

## 2.6 Recency bias

According to the APA Dictionary of Psychology (<https://dictionary.apa.org/recency-effect>), the recency effect is “*a memory phenomenon in which the most recently presented facts, impressions, or items are learned or remembered better than the material presented earlier*”. Since they are remembered more clearly than historical events, individuals may disproportionately weigh the most recent events, leading to judgments compromised by recency bias. An illustrative study involving both researchers and students required participants to synthesize findings from studies on a unified topic (Ernst et al., 2018). The results provide robust evidence of recency bias, showing that participants' conclusions are heavily influenced by the information presented last, irrespective of its relevance or the robustness of the evidence. In other words, regardless of the quality or significance of the presented evidence, participants shaped their judgments based on the recent information they were exposed to. This tendency suggests that the temporal sequence of the presented information can significantly skew judgments and decision-making processes.

Major events are essential in changing perceptions of individuals and making them subject to recency bias (Hao et al., 2016; Rabbani et al., 2021; Welch et al., 1998). For instance, after October 3, 2018, investors' financial risk tolerance was significantly decreased (Rabbani et al., 2021). In another study conducted with U.S. Federal Crop Insurance Program members, recent indemnity and weather conditions heavily influenced farmers' crop insurance decisions (Che et al., 2020). Higher past indemnities and harsh weather conditions encouraged farmers to insure their crops.

### Recency bias mitigation strategies

Despite the adverse effects caused by recency bias, our search yielded only one study which explicitly focuses on testing the performance of a mitigation strategy. In an experiment conducted with professional regulators and students, accountability was tested regarding its effects on the

quality of judgments and recency bias (Schillemans, 2022). In this experiment, participants had to evaluate a case and make judgments in the presence and absence of accountability. In other words, some participants had to explain and justify their choices while others did not. Analyses revealed that accountability improves information recall performance and helps to mitigate recency bias. These findings underscore the promising performance of keeping people accountable for their choices to avoid potential distortions of recency bias.

Although accountability is the only empirically tested mitigation strategy among the analyzed articles, there are several suggestions to reduce the recency bias. Educating decision-makers to be aware of the bias is among them (Rabbani et al., 2021; Welch et al., 1998). The common idea is that if people are trained and warned about the possible effects of recency bias, they can reconsider their judgments and make better decisions. In a study about integrating different findings in a research process, a time-reversal heuristic was proposed to decrease the effect of recency bias (Ernst et al., 2018). It has been suggested that if people imagine and evaluate events in reverse temporal order, recency bias can be mitigated. However, similar to other debiasing ideas, this strategy requires further empirical support.

## 2.7 Duration neglect

Duration neglect refers to the cognitive bias where individuals fail to accurately remember the length of an event, instead basing their judgments primarily on the most intense moments and the ending of the experience (Fredrickson & Kahneman, 1993). Building on the foundational work of Fredrickson & Kahneman (1993), subsequent research has explored the nuances of duration neglect and the peak-end rule across various domains. Studies have investigated how the temporal locations and the order of the events influence the overall satisfaction levels of individuals (Godovykh & Hahm, 2020; Weingarten et al., 2021). For instance, in political contexts, voters' evaluations of economic performance and election decisions were disproportionately influenced by more recent economic status, often neglecting the broader temporal scope of an administration's policies (Galiani et al., 2019; Healy & Lenz, 2014). Furthermore, another study conducted with voters in villages has revealed that the peak-end rule may affect not only the judgments about economic situations but also the final decisions about who to vote for (Galiani et al., 2019). The study shows that voters receiving large (peak) or recent (end) money transfers are more likely to vote for the incumbent party. Similar results apply to tourism activities. In an experiment, retrospective evaluations of participants regarding trips were swayed by the most extreme and most recent experiences (Chark et al., 2022; Hansenne & Christophe, 2019; Kemp et al., 2008). Furthermore, these effects were also valid even when participants did not visit the places but watched advertisement videos about them.

The implications of duration neglect and the peak-end rule extend into healthcare, influencing decisions like colonoscopy or pap smear screening (Hetou et al., 2021; Redelmeier et al., 2003; Yen et al., 2023). For instance, a significant difference was reported in remembered pain and future screening behaviors in a clinical experiment with patients who underwent different colonoscopy procedures with various lengths and pain intensity levels (Redelmeier et al., 2003). Patients who experienced a longer colonoscopy procedure that ended with a less painful step recalled the operation as being less unpleasant and painful compared to those who underwent a shorter procedure with a more painful ending. The experiment found a 10% increase in screen-

ing return rates when duration neglect was activated by adding a non-painful end-stage to the procedure. The same approach was adopted in a randomized controlled trial with two groups of patients who had cystoscopy (Hetou et al., 2021). Patients who had the modified screening reported much lower pain and anxiety scores after the procedure. Supporting results were also reported in a study conducted at a cervical cancer screening center with a group of females aged between 30 and 70 (Yen et al., 2023). Of the two groups, the one that had the modified pap smear screening with an added short, non-painful step recalled the procedure as less painful, and these participants were more willing to get re-screened in the future. Since duration neglect and the peak-end rule may influence remembered experiences, they can be used to promote health interventions, as in these examples. Educational decision-making contexts also reveal the impact of duration neglect. For example, in an experiment conducted on learning tasks with primary school children, the peak-end rule was a driving factor for future studying preferences (Hoogerheide & Paas, 2012). If a learning experience ended with a pleasurable activity, students were more willing to study that topic in the future, regardless of its difficulty level or duration (Finn & Miele, 2016).

### **Duration neglect mitigation strategies**

Despite many problems caused by duration neglect, we could only identify a few mitigation strategies in the analyzed papers. Changing the sequences of events is an effective strategy against duration neglect (Rode et al., 2007). Since the order of the events has a crucial role in terms of peaks and ends, changing the order may improve decision-makers' evaluations. From a similar perspective, the timing of evaluations may affect remembered memories, and some studies present mitigation strategies parallel to this idea. Deconstructing the time intervals (Langer et al., 2005; Miron-Shatz, 2009), changing the evaluation time (Woloschuk et al., 2011), and measuring multiple time points (Strijbosch et al., 2019) are among the reported ideas. In one study, increasing the familiarity of the decision makers about evaluated events was tested as a debiasing strategy (Morewedge et al., 2009). It has been found that if people become more familiar with the stimulus, they are less likely to neglect their durations.

Besides these empirically tested approaches, there are also more general ideas, such as keeping a detailed record of past experiences (Kemp et al., 2008), providing transparent information and feedback regarding durations (Galiani et al., 2019; Sels et al., 2019), adopting objective evaluation measures (Strijbosch et al., 2019; Weingarten et al., 2021) and increasing the attention and education levels (Galiani et al., 2019; Hoelzl et al., 2011). These ideas require further testing in various decision contexts to see whether they can effectively mitigate duration neglect.

## **2.8 Impact bias**

When individuals experience an emotion, they can overestimate its intensity and duration, a bias called impact bias (Wilson & Gilbert, 2005). They tend to believe the emotional state will last longer and be more intense in the future than it really is. This overestimation influences intertemporal judgments and distorts estimations in many contexts. Studies have illuminated the correlation between emotional intelligence (EI) and the accuracy of affective forecasting, positing EI as a significant predictor of individual variances in forecasting abilities (Dunn et al.,

2007). Individuals with higher EI exhibit more accurate forecasts and are less prone to impact bias compared to those with lower EI. Like personality traits and individual differences, the impact bias was considered with the age factor and experience (Nielsen et al., 2008; Scheibe et al., 2011; van Dijk et al., 2008). Research indicates that younger adults are more susceptible to forecasting errors and exhibit heightened negative responses to losses than their older counterparts (Nielsen et al., 2008). An experiment found evidence of age-related improvement in affective forecasting accuracy only for positive events (Scheibe et al., 2011). A conflicting finding was reported in a study conducted with track athletes about their estimations related to their feelings after a race (van Dijk et al., 2008). This experiment found that experience does not teach people to make more accurate forecasts or become less subject to impact bias, but it can help them cope better with their emotions.

The phenomena of focalism and immune neglect have been identified as pivotal in fostering impact bias and forecasting inaccuracies (Gilbert et al., 1998; Hoerger, 2012; Lench et al., 2011; Wilson et al., 2000). Focalism, refers to decision-makers' tendency to focus too much on a particular aspect and neglect other relevant factors, generally causes people to consider events from a narrow perspective and end up with inaccurate forecasts. For example, participants were asked to estimate their future happiness in experiments using positive and negative scenarios about football games, space accidents, and national crises (Wilson et al., 2000). Since they were overthinking about the focal event and paying too little attention to other incidents that may require their attention, participants mistakenly estimated their emotions as more intense than they were. Furthermore, estimations about the length of these emotional stages were also biased, attributed to immune neglect, which is the tendency of human beings to underestimate psychological coping strategies that can reduce the impact of adverse events. Research shows that individuals may overestimate the duration and intensity of their positive and negative emotions mainly because they neglect the role of the psychological immune system, which helps to adjust emotions and well-being (Gilbert et al., 1998).

The role of impact bias extends into shaping individuals' risk and time preferences (Chanel et al., 2023; Karl et al., 2021). For example, in a recent survey conducted with Danish soldiers deployed to Afghanistan in 2011, affective forecasting errors influenced soldiers' time, risk, and occupation preferences (Chanel et al., 2023). Moreover, positive affective forecasting errors regarding excitement strengthen the motivation of soldiers to stay in the military services. Similar findings were reported in a study focusing on travelers' perceived coronavirus infection risk and emotions during the COVID-19 pandemic (Karl et al., 2021). Regarding risk perception, two experiments focused on how probabilities and outcome specifications affect people's judgments in affective forecasting (Buechel et al., 2017, 2014). It has been reported that forecasters and experiencers may have different emotional impacts depending on an outcome's magnitude, probability, and duration (Buechel et al., 2017). Forecasters were more sensitive to outcome specifications than experiencers, leading them to rely on these factors in their predictions and become more subject to biases.

The effect of time and temporal factors on impact bias has also attracted attention (Buehler & McFarland, 2001; Eastwick et al., 2008; Finkenauer et al., 2007; Motoki et al., 2023). In a longitudinal study, driving exam participants could forecast linear changes in their affective reactions over time, but they were not good at quadratic changes (Finkenauer et al., 2007). This naivete was attributed to underestimating the speed of change in their emotions and not knowing how time would affect their experiences. In addition, the temporal location of events was

an essential factor in prediction accuracy. People were more accurate in their estimations about positive but distant or negative but closer events. In an experiment about predicting emotions regarding different temporally located videos, participants were more accurate when indicating the sadness of watching a short and distant, or long but near video (Buechel et al., 2017). Similarly, when the estimated adverse events were located close to the present time, people overestimated emotional reactions, but they were more accurate in their long-term predictions (Eastwick et al., 2008). COVID-19 vaccination preferences were studied for near and distant future scenarios by focusing on the time effect in affective forecasting (Motoki et al., 2023). Experiment results revealed that distant future simulations enhance positive affective forecasting and increase vaccination intentions. These findings highlight the importance of temporal distance and forecasting accuracy in attitude changes.

Gilbert et al. (2002) propose a three-step process for understanding intertemporal hedonic experiences. Initially, individuals assess the experience without considering time. Next, they project their current emotions onto future events. Finally, they adjust their preferences based on the timing of the event. However, this adjustment is cognitively demanding, often leading to biased evaluations. It has been hypothesized that people discount the future mainly because their hedonic states regarding the evaluated events become less intense as they move toward the future (Kassam et al., 2008). So, when people mispredict the intensity or length of their emotional states, they tend to discount the future more and make poor decisions. This relationship can be used to explain the phenomenon of immediate gratification to some extent.

Adverse events such as terrorist attacks, wars, fires, or limb losses may cause intense emotions, and some researchers have focused on these scenarios for studying impact bias (Doré et al., 2016; Dunn & Ashton-James, 2008; Peeters et al., 2012). When evaluating the possible emotions toward a future event, if people remembered an extreme past event, their forecasts tended to mirror that extremity. Therefore, the source of the impact bias might be decision-makers' tendency to use atypical past events in their evaluations. Personal health adversities, such as limb amputation or colostomy surgery, were also utilized to study impact bias (Peeters et al., 2012). When asked to predict and recall their well-being expectations, people with new disabilities overestimated their adaptation capabilities. They were more optimistic about adapting to new situations in the estimation phase than in the experience phase. These findings show how our intense emotions and current situation may affect our future preferences and coping strategies with adverse events.

### **Impact bias mitigation strategies**

A widely recognized strategy for mitigating impact bias and estimating future emotions is using surrogate information from people who have undergone similar experiences (Eastwick et al., 2008; Finkenauer et al., 2007; Scheibe et al., 2011). This can improve forecasting accuracy and support people to better regulate their emotions. Another promising strategy is using mental representations, encouraging decision-makers to concretely simulate events and their possible outcomes (Buechel et al., 2014; Finkenauer et al., 2007; Gilbert et al., 1998; Kassam et al., 2008). This will help them to see the events from a broader perspective, focus less on focal events, and eventually provide more accurate estimations. As an alternative strategy, exposing people to simulations or scenarios that mimic real-life cases has also been used (Chanel et al., 2023). The motivation behind this strategy is that instead of relying on mental images, using

real-life simulation can provide better forecast inputs.

One of the primary causes of impact bias is the tendency of decision-makers to overly focus on focal events. To counter this, considering multiple future events occurring simultaneously can help reduce the bias (Buehler & McFarland, 2001; Lench et al., 2011; Morewedge et al., 2005; Wilson et al., 2000). Instead of thinking about how a person will feel regarding one specific event, training them to activate multiple events from a broader range can be motivating to see the bigger picture. This approach may prevent decision-makers from treating an emotional event as a unique experience. Knowledge of the surrounding context and outcome characteristics may also be helpful at this point. Another driver of impact bias is how decision-makers assess events over time and adjust their judgments. This can be mitigated by evaluating temporal forecasts across multiple time periods (Eastwick et al., 2008). It is believed that when asked about their emotions multiple times, people become more aware of them. This chance to reflect on the forecasts may decrease the likelihood of overestimating future emotions. Research shows that emotionally intelligent individuals can provide more accurate estimations and are less affected by impact bias. Therefore, enhancing emotional intelligence skills (Dunn et al., 2007) and improving emotion regulation awareness (van Dijk et al., 2012, 2017) could be used to mitigate impact bias. As in many other cognitive biases presented in this study, there are some general mitigation ideas, such as ensuring transparency and accountability (Lau et al., 2016), increasing public awareness and education (Chanel et al., 2023; Lau et al., 2016; Scheibe et al., 2011), providing feedback to forecasters (Buechel et al., 2014; Chanel et al., 2023; Gilbert et al., 2002) and creating ethical standards, guides and tools (Buechel et al., 2014; Lau et al., 2016). These ideas require further investigation and empirical testing to validate their effectiveness.

## 2.9 Planning fallacy

People often underestimate the time, energy, money, and risks related to future outcomes and make optimistic plans, a behavioral factor known as the planning fallacy (Kahneman & Tversky, 1979). This over-optimism may distort intertemporal evaluations and cause poor judgments. The perceived temporal distance is a crucial factor for the accuracy of future estimations (Nussbaum et al., 2006; Peetz et al., 2010; Wang & Chiou, 2022). For instance, the perceived temporal distance may shorten for an individual who faces a future task that requires high effort (Wang & Chiou, 2022). This delusion makes people less optimistic about task completion predictions and reduces the planning fallacy. The temporal distance may also affect predictions in different ways depending on where individuals focus their attention (Peetz et al., 2010). For instance, emphasizing the potential obstacles rather than the required steps can shift people's focus to more realistic aspects of the planning and mitigate bias. Research reveals that depending on the level of construal information used, temporal distance also affects individuals' confidence while making intertemporal predictions (Nussbaum et al., 2006). High-level construals, which involve more abstract and generalized thinking, are more commonly used when predicting distant future events and cause more confidence in estimations. In contrast, low-level construals, which focus on concrete details, can create difficulty and reduce confidence in predictions.

Similar to temporal distance, how people perceive time also plays a role in the planning fallacy (Boltz & Yum, 2010). There is a difference in estimated durations when people perceive themselves moving through time and when they think of time moving toward them. They may

adopt different thinking styles and ways of evaluation while estimating the future, and these differences may lead to biased judgments. For instance, an experiment revealed essential findings regarding the differences between thinking styles (“why” versus “how”) and task duration estimation accuracy (Siddiqui et al., 2014). While considering simple tasks, if participants focus on “why,” they might overestimate the required time. On the other hand, for complex problems, “how” causes a similar problem. This way of thinking also relates to using different levels of construal while making estimations.

### **Planning fallacy mitigation strategies**

Unpacking a task into smaller components is one of the most reported debiasing strategies against planning fallacy (Aczel et al., 2015; Kanten, 2011; Peetz et al., 2010; Wang & Chiou, 2022). Instead of estimating the duration of a complex project, focusing on each component can help make more accurate estimations. Furthermore, writing a thought list related to each step of a bigger problem is also recommended (Wang & Chiou, 2022). By doing so, decision-makers can realize possible obstacles and make less optimistic judgments. Backward planning is another promising debiasing strategy for the planning fallacy (Wiese et al., 2016). When people start with the end goal and move backward to identify required steps, they provide more realistic time durations and fall less to the planning fallacy bias.

Since decision-makers generally build their future preferences on past experiences, memory is an essential factor in intertemporal trade-offs (Tulving, 2002; Schacter et al., 2012). By adjusting how they recall past experiences, individuals can improve the accuracy of their predictions for similar future tasks (Roy & Christenfeld, 2007). Experiments reveal that participants who take reference information into account can make more accurate estimates of task completion duration (Shmueli et al., 2016). Therefore, motivating people to connect their past experiences to current tasks can serve as a promising debiasing strategy (McDermott et al., 2016; Buehler et al., 1994). As an alternative to the idea of relying on past experiences, providing feedback could also mitigate the planning fallacy (Roy et al., 2008; Thoma & Tytus, 2018). If the memory of an individual is corrected by supplying feedback related to the durations of previous tasks, they can provide more accurate judgments (Roy et al., 2008).

Adopting an external perspective while making predictions can also serve as a mitigation strategy (Buehler et al., 1994; Shmueli et al., 2016; Thoma & Tytus, 2018). It has been revealed that taking the third-person perspective improves judgments and makes decision-makers less subject to planning fallacy. When asked to imagine themselves as someone else, people can be more focused on details, less optimistic about timing, and more realistic in scheduling. Thinking about the preferences of their future selves may also help people mitigate the planning fallacy (Atance & O’Neill, 2001). Episodic future thinking encourages individuals to simulate future events and incorporate detailed context together with potential obstacles (Schacter et al., 2017). This enables decision-makers to be less optimistic about their future plans and consider the practical requirements and potential challenges they may face (Baumeister et al., 2016). It has been found that motivating people to form more concrete and detailed plans may decrease the planning fallacy (Boltz & Yum, 2010; Kanten, 2011; Koole & van’t Spijker, 2000). Since they focus on real details and avoid abstract plans, they come up with more accurate estimations. Receiving feedback from others, asking for advice, and being accountable are among the strategies against the planning fallacy (Kanten, 2011; Katt et al., 2021; Peetz et al., 2010; Roy

et al., 2008; Siddiqui et al., 2014). Experiments show that decision-makers make more accurate predictions if they ask advice from an expert or peer or feel they need to explain their judgments to someone else.

## 2.10 Relationships between biases

Understanding the relationships between biases is essential for uncovering how they interact and influence intertemporal judgments. To offer a comprehensive overview of these relationships, we begin by examining each time-related bias individually, discussing the reported additional biases, and how their coexistence was explained in the analyzed experiments. Then, by using all these findings, we structure a visual bias map. By doing so, we aim to summarize the relationships between biases and provide insights into their working mechanism.

Loss aversion is among the most reported behavioral factors with present bias (Bernedo Del Carpio et al., 2022; Jennings Mayo-Wilson et al., 2023; Meissner et al., 2023; Meunier & Ohadi, 2021; Schleich et al., 2019; Tang et al., 2023). Because loss aversion makes the pleasure of a gain less intense than the pain of a potential loss, a decision-maker is likely to show a stronger preference for immediate gains to avoid the potential loss of not receiving that reward. Such individuals would rather accept a smaller gain now than wait to receive a potentially larger gain in the future. In scenarios where a decision involves a potential loss (e.g., the initial payment), loss aversion may increase the likelihood that the decision-maker will delay or even avoid any action that could lead to the loss (Schleich et al., 2019). This generally results in a preference for immediate gains and present-biased choices. Risk aversion and framing effect can lead to similar behaviors (Grignon, 2009; Hunter et al., 2018; Le Cotty et al., 2019; Malkoc & Zauberman, 2006; Radu et al., 2011). Risk-averse people tend to prefer certain outcomes, even if it means settling for smaller rewards. As such, they often prefer guaranteed immediate outcomes rather than waiting for future payouts, which explains the emerging risk aversion-present bias relationship. When projection bias appears with present bias, it suggests that decision-makers are not only focusing on short-term outcomes but also incorrectly assuming their current preferences will persist into the future (Albrecht et al., 2011; Augenblick & Rabin, 2019). This combination results in decisions that are distorted by both immediate desires and false beliefs about the future.

When people make decisions in groups or on behalf of others, some factors emerge with present bias, like declaration bias (Grignon, 2009), overconfidence bias (Hunter et al., 2018), self-reporting bias (Ikeda & Kang, 2015), and self-other discrepancy (Albrecht et al., 2011). For example, overconfident people may focus too much on short-term gains and overestimate their capacity to handle the long-term consequences of their actions. The self-other discrepancy can amplify present bias in group discussion. These individuals may think they are more future-oriented than other participants, even while prioritizing immediate gratification over future benefits themselves.

The salience effect refers to individuals' tendency to give disproportionate importance to salient outcomes and is the most commonly reported behavioral phenomenon, along with projection bias. It is not always easy to distinguish between the salience effect and projection bias (Bordalo et al., 2013; Busse et al., 2015; Loewenstein et al., 2003). Therefore, when the perceptions of individuals about the future resemble their current preferences, there might be at

least two possible explanations: (i) They might be affected by projection bias and assume that their future tastes will be similar to current ones, or (ii) They may heavily be influenced by the salient features of the present circumstances and attribute disproportionate weight to them. When making decisions, individuals may mistakenly place greater emphasis on outcomes related to their recent experiences and project them into the future, giving rise to the recency bias along with the projection bias (Chen et al., 2019). This combination may create a powerful effect where current circumstances and recent experiences heavily distort future planning and lead to sub-optimal choices. Optimism bias, which is the tendency to overestimate positive outcomes, is also reported with projection bias (Lemay et al., 2015; Meyer et al., 2008). It has been shown that while thinking about the future, optimistic individuals may underestimate adverse outcomes and focus only on positive results. When combined with projection bias, optimism bias may cause a mistaken belief that one's future self will continue to maintain the perceived positive conditions. When they were asked to forecast the future preferences of their peers, individuals showed false uniqueness bias, which is a tendency to think their situation is unique and the preferences of others will be different (Bauckham et al., 2019; Renoult et al., 2016).

Behavioral factors reported alongside recency bias include anchoring bias (Hao et al., 2016). In a study investigating the role of a 52-week high price (the highest trading price of a stock over the past 52 weeks) in predicting future stock returns in Taiwan, recency and anchoring biases were reported together (Hao et al., 2016). While anchoring bias explained why investors used high prices as a reference point and ignored new information about stocks, the recency bias was the answer to why some were influenced by recent information rather than distant analyses, and favored the stocks that recently reached the highest price. These two coexisted biases were used to explain traders' patterns in the stock market (Krieger et al., 2021). Projection bias can also emerge together with recency bias in some situations (Chen et al., 2019). For instance, when asked to report how much they would pay for better air quality, Chinese residents thought their future preferences would resemble the current ones. Their judgments were distorted by recent air quality (recency bias) and the mistaken belief about preferences of their future selves (projection bias).

In alignment with the end effect phenomenon, the recency bias is among the reported biases with duration neglect (Rode et al., 2007; Woloschuk et al., 2011). Since the end rule is dominant in remembering retrospective events, the recency effect could be an influential factor in judgment formation. These two biases can lead individuals to make choices that are heavily influenced by recent or intense experiences rather than the overall circumstances. Although a few other cognitive biases have also been reported with duration neglect, we could not identify any repeated pattern. Nonetheless, there are examples of social desirability bias, the salience effect (Miron-Shatz, 2009), and the illusion of control (Cowley et al., 2015).

Hot-cold empathy gaps and projection bias have been discussed with impact bias (Dunn & Ashton-James, 2008; Gilbert et al., 2002; Nielsen et al., 2008). The hot-cold empathy gap is the challenge of accurately predicting how someone would think, feel, or decide if they were in a different emotional or physical state than they are now (Loewenstein et al., 2003). Therefore, people can mistakenly assume their future emotions will resemble the current ones and end up with impact bias in preferences without considering visceral influences, emotional changes over time, and adaptation factors. The tendency of decision-makers to discount the value of the future is also valid for emotions, and some experiments report discounting factors together with impact bias (Karl et al., 2021; Walsh & Ayton, 2009). Thus, individuals may

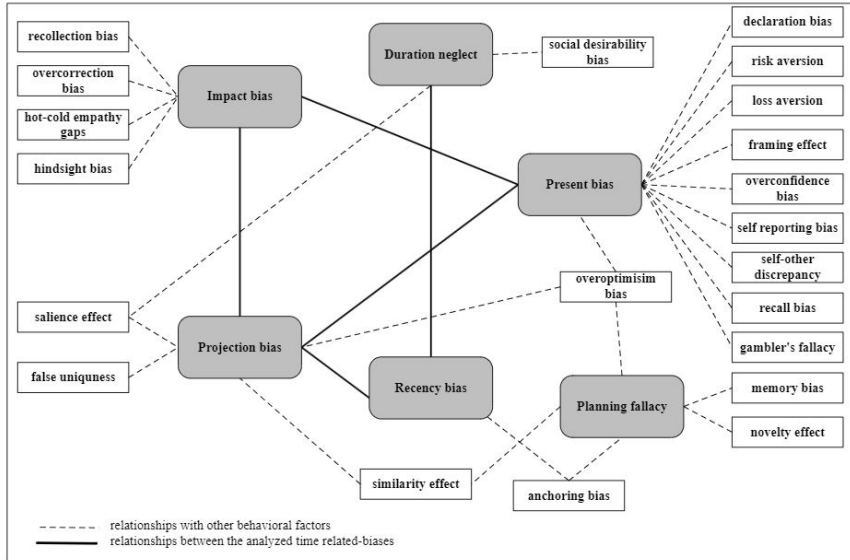


Figure 2.1: The relationships between the biases

underappreciate future emotional values while overestimating how impactful certain events will be, leading to skewed and present-focused judgments. For example, in a study, participants showed discounting and impact bias when asked about their feelings regarding their future travel plans during the COVID-19 pandemic (Karl et al., 2021). When people predict their emotions in response to future events, they sometimes use surrogate information. While doing so, they may also discount other people's information and adopt imagination to adjust forecasts (Walsh & Ayton, 2009). Overcorrection bias, the tendency to adjust the initial thoughts too much based on additional information, is also possible to emerge with impact bias (Lau et al., 2016). The tendency of people to use past events as references to estimate future emotions may trigger some problems. For example, in one study, recollection bias, misremembering past emotional reactions to events, was reported with impact bias (Hoerger, 2012). Because recollection bias causes people to misremember the length and intensity of their past emotions, it also distorts the predictions about the future. Similarly, hindsight bias, also known as the *I-knew-it-all effect*, may appear when people use past experiences to estimate future feelings (Pollai et al., 2010; Sanna & Schwarz, 2004).

Optimism bias, which refers to the tendency of individuals to be overly positive about their estimations, is highly reported together with planning fallacy (Buehler et al., 2012; Peetz et al., 2010; Qian & Zheng, 2012; Rodon & Meyer, 2012; Wang & Chiou, 2022; Weick & Guinote, 2010). If decision-makers are under the influence of optimism bias, they will likely underestimate the time and effort that future tasks require while making estimations, and they end up with a planning fallacy. Another frequently reported bias with planning fallacy is memory bias (Koole & van't Spijker, 2000; Roy et al., 2008; Roy & Christenfeld, 2007; Thomas et al., 2018).

Experiments reveal that sometimes people rely heavily on past experiences or memories while planning the future. If they have distorted memories or difficulty recalling the information correctly, they are likely to underestimate the future task completion times and become subject to planning fallacy. In the planning fallacy context, past experiences in similar tasks can anchor (anchoring bias) people's evaluations and prevent them from adjusting new information or temporal differences in their estimations (König et al., 2015; Thomas et al., 2004; Thomas & König, 2018). Eventually, they end up with skewed judgments and inaccurate forecasts.

Figure 2.1 illustrates the relationships between six time-related biases and the biases that were reported alongside them in the analyzed studies. If any two time-related biases were reported together, they are associated with a thick line. The relationships with other biases are illustrated with dashed lines. For example, duration neglect was discussed along with recency bias (Yang et al., 2018). Therefore, these two biases are associated with a thick line. Duration neglect was also reported with salience effect and social desirability bias, which are not time-related biases considered in the context of this study, so these relationships are represented with dashed lines. It can be seen that the planning fallacy was not reported with any of the time-related biases and stands apart. It must be emphasized that this map is only an overview of the analyzed studies and does not consider the frequencies of the relationships. It only aims to give a general overview of our findings. Identifying patterns between these biases and providing a more systematic diagram requires further investigation and analysis. Also, context dependency should be considered while evaluating the map since there were many different experiments from health, economics, environment, and psychology. Experimental features and chosen cases may cause some of the reported discrepancies.

## 2.11 Future directions and research agenda

There are some research gaps that require further investigation to enhance the understanding of the influences of time-related biases on judgments. This section discusses future lines of research for each bias from both a theoretical and empirical perspective, considering not only the analyzed papers but also recent trends from the literature.

Understanding the mechanisms of the present bias and uncovering underlying psychological and environmental factors remain crucial gaps in the literature (Ikink et al., 2023; Mao et al., 2021; Mograbi, 2022; Werthschulte & Löschel, 2021). Furthermore, looking at neurological aspects and studying the role of emotional states like sadness or stress can yield important insights (Benscheidt & Carpenter, 2020; Hughes et al., 2024). Besides the psychological drivers, reasons that may cause heterogeneity in present bias among individuals, such as country of origin, age, social norms, cultural differences, socio-demographic aspects, political regimes, and financial or educational inequalities, should be explicitly investigated (Eberth et al., 2022; Schleich et al., 2019; Ikink et al., 2023; Irvine et al., 2022; Jennings Mayo-Wilson et al., 2023; Mao et al., 2021). Examining these factors, separately or together, may shed light on why some people make long-term decisions while others consistently fall into present bias.

People respond differently to types of outcomes, which may lead to biased choices (Lipman, 2024). From this point of view, there is a need to conduct experiments with actual incentives instead of hypothetical rewards (Yue et al., 2023), extending the scope of the experiments beyond financial outcomes (Jang & Urminsky, 2023) and testing the role of reward nature (e.g.,

monetary, utilitarian, hedonic) on the present bias (Krčál et al., 2021). This can help to understand present bias and design better systems by knowing the potential reactions of users to outcomes. Although many experiments have been conducted in different fields, the complexity of the preferred tasks and their applicability to real-life decision-making settings is still limited. The present bias should be investigated in more complex real-life choices to uncover the "real" mechanism behind the preferences (Irvine et al., 2019; Augenblick & Rabin, 2019; Ikin et al., 2023). From a methodological point of view, examining the robustness and reliability of preference elicitation methods and developing more complex and realistic approaches that align with real-life choice behaviors may improve the ways present bias is studied (Akesaka, 2019; Mao et al., 2021). As with all biases discussed in this paper, reducing the adverse effects of present bias on judgments is a crucial research gap. In alignment with this, future studies should focus on improving the performance of well-known mitigation strategies like commitment devices and developing more advanced methods against present bias (Eberth et al., 2022; Jennings Mayo-Wilson et al., 2023; Tang et al., 2023).

There are a few significant literature gaps related to projection bias. First, more empirical and methodological research is required to better understand the effects of projection bias. As in the other biases, the underlying mechanisms behind the projection-biased preferences are not yet fully understood (He & Zhang, 2021). Since the pure effects of projection bias have not been revealed in many studies (the projection bias generally appears with other factors such as the salience effect), identifying secondary biases and developing strategies to differentiate between their interdependent relations are among the literature gaps that require consideration (Augenblick & Rabin, 2019; Pan et al., 2022). Second, after understanding the bias and its effects on judgments, developing debiasing strategies is another important research direction. The third literature gap is implementing the identified strategies into laws and helping people to make more informed decisions (Chen et al., 2019). Authorities should consider the possibility of distortions caused by projection bias and provide individuals with better options, which is an area that requires particular attention from a policy-making perspective.

A few future research lines can help better understand and mitigate recency bias in intertemporal decisions. Uncovering psychological variables and cognitive processes behind the bias is crucial (Che et al., 2020). Additionally, studying secondary cognitive biases that appear together with recency bias and developing methods to differentiate between their effects are interesting research areas (Rabbani et al., 2021). Future studies should not only test the performance of existing methods with different cases and participant profiles but also come up with more sophisticated methods to mitigate recency bias (Schillemans, 2022).

Future research directions of duration neglect include exploring psychological and psychophysiological factors, understanding the role of emotions, studying the impact of cognitive load and memory factors, and uncovering cultural differences (Yen et al., 2023; Hetou et al., 2021; Chark et al., 2022; Weingarten et al., 2021; Williams et al., 2019). Similarly, reported empirical findings must be tested in various decision fields to enhance their reliability. Moreover, testing current intervention strategies in different fields and developing new strategies for mitigating the effects of duration neglect stand as crucial literature gaps.

One of the major literature gaps of impact bias is investigating its underlying motivational and psychological mechanisms (Chanel et al., 2023). In addition, personal characteristics, age differences, and cognitive abilities should be studied using diverse participant samples. There is a need to understand problem features that affect impact bias, such as the role of uncertainty

and probabilities in complex decisions and reward magnitudes. Studying the role of temporal distance between forecasting and real events may help with understanding the effect of timing in triggering impact bias. In addition, comparing temporal characteristics like days, weeks, or months, and testing the impact of co-occurring multiple events are among the future research directions. The importance of real-life applications and testing the generalizability of affective forecasting theories requires additional research. In this regard, testing the robustness of the theories in health, different social contexts, and daily life (Karl et al., 2021; Motoki et al., 2023; Villinger et al., 2020), looking at the influence of contextual factors in judgments, and exploring emotional fluctuations over time can be interesting research avenues for the future. Developing mitigation strategies and testing them empirically in various fields is also important for this bias.

There is a need to understand personality traits, underlying psychological mechanisms, and adopted cognitive styles related to planning fallacy and overoptimistic estimations (Wang & Chiou, 2022). Future studies should focus on uncovering planning fallacy in different decision contexts and conducting more field studies. In addition, the applicability and generalizability of the findings should be tested. Investigating the role of episodic future thinking in planning fallacy can reveal interesting findings (Wang & Chiou, 2022). Extending the research into different domains like health and politics may lead to very interesting discoveries and help to design more efficient systems (Katt et al., 2021). From an intertemporal decision-making perspective, the role of temporal distance in estimations and the nature of the intertemporal trade-offs are important areas to look at for a better understanding. Mitigation strategies like perspective-taking, abstract thinking, or different construal-level adaptations require further empirical validation.

## 2.12 Conclusion

People often use mental shortcuts to deal with complex information processing and make quick judgments. Although these shortcuts are generally helpful in simplifying complexity and reducing cognitive load, they can also cause biases. Research reveals that biases systematically distort individual evaluations and lead to poor decisions in various areas of life. Intertemporal judgments are also not immune to these distortions, and trade-offs can become subject to many types of deviations from rationality. Multiple biases, such as present bias, planning fallacy, and projection bias, distort the perceptions that decision-makers have of time and time-dependent outcomes and lead to poor choices. It is crucial to examine the influences of these biases on judgments and develop strategies to reduce their negative effects. In this review, we identified six biases that can influence intertemporal decisions while individuals evaluate time-related outcomes and conducted systematic literature reviews to gather empirical evidence for their influences on judgments. In addition, the interrelationships between time-related biases and their relationships with other behavioral factors were mapped to provide an overview. Finally, mitigation strategies and research directions that require further attention were discussed.

Our analyses reveal that in many personal and societal decision contexts, time-related judgments and intertemporal trade-offs are subject to biases. The frequently reported underlying reasons include psychological and environmental factors, outcome-related features, thinking styles, temporal locations of outcomes, and various behavioral patterns. Our findings emphasize the importance of mitigating time-related biases since they exist in many, if not all, areas of life, such as health, education, finance, environment, research, sports, and law. Although

they have been researched in many fields, there is a lack of mitigation strategies tailored to different circumstances to be used to decrease the adverse effects of the biases. In other words, when the current literature mainly focuses on descriptive research, there remains a significant gap in prescriptive approaches to help decision-makers mitigate the negative influence of time-related biases and make informed choices. Our results emphasize the need to develop more systematic mitigation strategies and test their empirical validity in different fields. Moreover, more sophisticated methods are required to differentiate the influences of multiple biases on judgments. While this review provides insights into identifying, understanding, and mitigating biases in intertemporal trade-offs, there remains a need for further empirical research and particular attention to developing targeted differentiation methods and debiasing strategies.

This research contributes to the literature by explicitly examining time-related biases and their impacts on intertemporal decisions. Our systematic literature reviews gather empirical evidence, shedding light on the prevalence of these biases and their implications for decision-makers. We believe that the findings of this research will lead to new investigations and enhance our understanding of time preferences and behavioral aspects. Despite these contributions, some limitations remain. Acknowledging the scope of our review, future research could extend the analysis by delving deeper into the theoretical underpinnings of intertemporal decision-making. Additionally, utilizing a more systematic approach for uncovering the complex relationships between biases may be an interesting topic for future studies. This comprehensive review will serve as a foundational resource for understanding the impact of biases on intertemporal decision-making and will inspire future research to investigate the application of these biases in diverse real-world contexts and develop more advanced debiasing methods.

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## Chapter 3

# Intertemporal judgments in multi-attribute decision-making: Biases and mitigation ideas

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**Abstract:** Intertemporal judgments are susceptible to biases that can distort evaluations and lead to inconsistent choices. While time-related biases have been studied extensively from a descriptive perspective, little attention has been given to prescriptive approaches and the complex trade-offs involved in multi-attribute decision-making (MADM). This study provides a comprehensive review of the effects of such biases on the MADM evaluation process. Drawing on evidence from behavioral economics, psychology, and decision analysis, we identify six time-related biases and analyze the vulnerabilities they can introduce at the steps of the MADM procedure. We also outline preliminary ideas that may help reduce these biases in the unique context of intertemporal multi-attribute problems. Our findings highlight the importance of addressing biases from the earliest stages, such as problem structuring, and underscore the need for further empirical research to test and refine these proposed strategies.

**Keywords:** Multi-attribute decision-making; time preference; cognitive biases; intertemporal discounting

This chapter is based on the following manuscript:

Gülüm Taş, P., Maknoon, Y., & Rezaei, J., Intertemporal judgments in multi-attribute decision-making: Biases and mitigation ideas (*manuscript under review*)

### 3.1 Introduction

Many decisions require trade-offs between outcomes occurring at different time points. While making these trade-offs, decision-makers' judgments are generally affected by the resolution times of the outcomes (Fishburn & Rubinstein, 1982). A well-known example is that individuals prefer smaller, sooner rewards over larger, later ones. This is mainly because of their tendency to assign greater values to the outcomes as they move toward the present time, a phenomenon known as delay discounting (Samuelson, 1937). Furthermore, numerous biases, defined here as systematic departures from the normative standards of discounted utility theory, distort individuals' perceptions and affect time preferences (Thaler, 1981). For example, present bias refers to the tendency to place disproportionate importance on immediate rewards, often undervaluing larger or more beneficial future outcomes. This leads to short-sighted evaluations and choosing alternatives that are inconsistent with long-term goals (Herrnstein et al., 1997). These biases can sometimes be beneficial. For example, duration neglect (the tendency to overlook the length of an experience) can promote preventive disease screening (Redelmeier et al., 2003). Nevertheless, time-related biases often interfere with intertemporal judgments. They distort assessments and lead to undesirable outcomes, such as poor financial decisions (Morton & Fasolo, 2009) or procrastination (Fredrickson & Kahneman, 1993).

<sup>1</sup> Extensive research on biases is grounded in empirical investigations that adopt a descriptive approach (Loewenstein & O'donoghue, 2003; Hardisty et al., 2013). These studies often use experimental tasks such as multiple price lists, convex time budgets, or binary choice problems, where participants compare outcomes with different resolution times. Researchers then interpret these choices to infer underlying time preferences. For example, in a choice experiment conducted under the assumption of zero inflation, consistently choosing smaller, sooner rewards indicates a high discount rate. This pattern suggests short-sighted decision-making. Descriptive studies have provided valuable insights into understanding intertemporal judgments and related biases across various fields, such as economics (Fishburn & Rubinstein, 1982; Anderhub & Güth, 2001), health (Fuchs, 1980; Zhang & Rashad, 2008), education (Hoogerheide & Paas, 2012; Finn & Miele, 2016), and agriculture (Boonmanunt et al., 2020). However, real-life decisions are far more complex than the problems typically examined in experimental research. Most decisions require comparing multiple alternatives while accounting for several conflicting objectives. In other words, real-life decisions involve trade-offs not only across time points but also across attributes, which expands the decision-making space and increases cognitive demands. Such complexity calls for prescriptive approaches (Bell et al., 1988). Although time-related biases are known to significantly influence judgments and preferences, their operation within complex, prescriptive decision contexts remains underexplored. Building on this gap, we formulate the following research question:

***How do time preference and related biases influence the prescriptive decision-making process in multi-attribute decisions, and what strategies can be employed to reduce their negative effects?***

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<sup>1</sup>In this study, descriptive refers to understanding how people make decisions based on observed behaviors or empirical data, while normative concerns ideal standards, focusing on what rational individuals should do. Prescriptive approaches address methods to guide decision-makers toward better solutions (Bell et al., 1988).

Our approach to addressing this question involves three main steps. First, we identify time-related biases and understand their impact on judgment. Second, we examine the steps of the multi-attribute decision-making (MADM) framework, assessing how each can be affected by these biases. Finally, based on an extensive review of behavioral decision research, we outline some practical suggestions that can potentially help facilitators reduce biases at each step. For the purpose of this study, we focus on Multi-Attribute Value Theory (MAVT), one of the fundamental MADM methods (Keeney & Raiffa, 1975). The method is based on eliciting individual preferences, representing them through a value function, and performing multiple trade-offs. Because the MAVT relies heavily on eliciting judgments from decision-makers, it is particularly vulnerable to distortions caused by time-related biases. Moreover, MAVT shares core principles and procedural steps with many other MADM methods, despite variations in their specific characteristics and evaluation mechanisms. Therefore, the insights obtained from analyzing the influence of such biases on complex decision-making within a prescriptive environment using MAVT can be extended to a broader set of MADM approaches.

This study makes several key contributions to the literature. First, it identifies six time-related biases and describes them as systematic deviations from the discounted utility model. Second, it extends previous research by identifying and discussing time-related biases within the prescriptive framework of MADM. This helps in understanding the biases in complex trade-offs when there are multiple conflicting objectives. Third, it explicitly considers the role of facilitators and their interactions with decision-makers. Fourth, by proposing potential mitigation strategies for each step, this study offers practical ideas to assist facilitators while also outlining a research agenda to empirically test and further develop these strategies in this under-examined yet important area.

The remainder of the paper is structured as follows: Section 3.2 reviews the concept of time preference and introduces six time-related biases. The methodology of MADM is detailed in Section 3.3, while Section 3.4 investigates the procedure through the lens of time preference and biases. Finally, Section 3.5 outlines the conclusions drawn from the study and suggests avenues for future research.

## 3.2 Time preference and biases

To illustrate how individuals evaluate outcomes over time under the rationality assumption, we required a benchmark theory. Accordingly, we adopted the discounted utility (DU) theory, the most widely recognized framework for intertemporal choice. We begin by summarizing the key assumptions of this model and explaining how they define rational time preference, drawing on the work of Samuelson (1937) and Koopmans (1960). We then introduce six time-related biases, defined as systematic deviations from one or more of these assumptions (von Winterfeldt & Edwards, 1986).

In the DU model, the total utility of a consumption stream from period  $t$  to period  $T$  is denoted by  $U_t(c_t, \dots, c_T)$ . It is defined as the sum of the discounted utilities of consumption in each period  $k$ , starting from the present  $t$  and extending to the terminal period  $T$ . Formally, this is expressed as:

$$U_t(c_t, \dots, c_T) = \sum_{k=0}^{T-t} D(k)u(c_{t+k}), \quad (3.1)$$

where  $u(c_{t+k})$  represents the cardinal instantaneous utility derived from consumption  $c_{t+k}$  at period  $t+k$ , and  $D(k)$  is the discount function applied to period  $t+k$ , defined as:

$$D(k) = \left( \frac{1}{1+\rho} \right)^k, \quad (3.2)$$

with  $\rho > 0$  as the discount rate, reflecting the degree of preference for present utility over future utility. In this formulation,  $k$  represents the number of periods from the present, starting at  $k=0$  (corresponding to period  $t$ ) and ending at  $k=T-t$  (corresponding to period  $T$ ). The formulation assumes a finite time horizon from the present to the terminal period (Frederick et al., 2002; Samuelson, 1937).

Several key assumptions underlie the DU model. We summarize these to provide a clear normative framework for identifying and understanding time-related biases. The following definitions draw on the work of Samuelson (1937), Koopmans (1960), Frederick et al. (2002), and Fishburn & Rubinstein (1982).

**Assumption 1** (*Utility Independence or Time Separability*): The utility of each outcome  $c_{t+k}$  contributes independently to the overall utility. Formally, the intertemporal utility  $U_t(\mathbf{c}_t)$  in Equation 3.1 is the sum of discounted instantaneous utilities, with the cardinal utility  $u(c_{t+k})$  independent of consumption at other periods  $c_{t+j}$ , for  $j \neq k$ . This assumption allows each period's consumption to be evaluated separately, ensuring additive separability.

**Assumption 2** (*Constant Discount Rate and Exponential Discounting*): The value of a future reward declines at a constant proportional rate per unit of time. This implies that discounting follows an exponential form as specified in Equation 3.2.

This assumption presupposes that individuals have stable preferences over time and their tendency to devalue future rewards does not change across different time points.

**Assumption 3** (*Dynamic Consistency and Stationarity*): Decision-makers' preferences are consistent over time. If at time  $t$ , a consumption profile  $(c_t, c_{t+1}, \dots)$  is preferred over another, it will continue to be preferred over the delayed versions of those profiles at any future time  $t'$ . Formally:

$$c_{t+k} \succ c_{t+l} \Leftrightarrow c_{t'+k} \succ c_{t'+l}, \quad \forall t' \geq t \quad (3.3)$$

This assumption implies that the relative valuation between outcomes depends only on the time interval between them, not on when they occur. It relies on the idea that individuals maintain a consistent ranking of preferences over time.

**Assumption 4** (*Accurate Predictions and Full Cognitive Competence*): It is assumed that individuals have perfect knowledge of their consumption stream and can accurately evaluate future

*outcomes using the instantaneous utility and discount functions. They are capable of making internally consistent and informed judgments about future consequences. This assumption reflects a rational, fully informed, and computationally capable decision-maker.*

To identify biases specific to intertemporal decision-making we examined the published bias codex, which comprises a comprehensive list of more than two hundred decision biases (Manoogian & Benson, 2017), considered seminal bias and time preference papers (Cooper & Meterko, 2019; Rambaud et al., 2023; Ehrlinger et al., 2016; Loewenstein & Prelec, 1992; Montibeller & von Winterfeldt, 2015; Neal et al., 2022) and went through multiple bias taxonomies (Arnott, 1998; Peón et al., 2017; Arkes, 1991). By reaching definitions and working mechanisms of all reported biases in the literature, we identified the ones that directly influence individuals' intertemporal judgments and distort time perceptions. This systematic search yielded six biases: present bias, projection bias, recency bias, impact bias, duration neglect, and planning fallacy.

For each bias, we indicate the corresponding normative assumption that is breached in biased behavior. To clarify the influences on judgments, we also include illustrative examples. Gulum Tas et al. (2026) provides a detailed examination of the underlying psychological mechanisms of these biases and their presence across various fields. Whereas that study focuses on biases in choice problems limited to alternative comparison in single-objective problems, the present study examines the multi-stage preference elicitation process for multi-attribute decisions. Adopting a prescriptive perspective, it incorporates the facilitator's role and suggests potential strategies for mitigation. These strategies are informed by insights from the behavioral decision research and MADM literature, as well as the observed characteristics of the biases.

**Present bias** refers to the tendency of individuals to overvalue immediate rewards at the expense of future benefits (Ainslie, 1975). It stems from hyperbolic discounting, which shows that the discount rate is not constant over time but declines as the delay to a reward increases. Present bias causes preferences violating the constant discount rate and exponential discounting (Assumption 2) as well as the time consistency and stationarity assumptions (Assumption 3). This bias manifests itself in behaviors such as prioritizing short-term outcomes over long-term planning, leading to sub-optimal decisions. For example, a present-biased individual may prefer purchasing luxury items for immediate gratification rather than saving for future financial security despite the higher long-term benefits of economic stability.

**Projection bias** is the tendency to overestimate the extent to which future preferences and circumstances will align with current tastes and conditions (Loewenstein & O'donoghue, 2003). It leads to violation of the assumption of accurate predictions (Assumption 4), as individuals mistakenly project their current preferences onto future situations. As a result, it may cause distorted utility estimates and irrational intertemporal trade-offs. Projection bias reveals itself through behaviors such as misjudging future satisfaction with current preferences. For example, a projection-biased individual who values a product's price over its comfort may assume this preference will remain unchanged. However, as preferences evolve, such short-sighted judgments may lead to regret or financial loss.

**Recency bias** is a behavioral phenomenon that leads decision-makers to overweight recent events over historical ones while making evaluations (Ernst et al., 2018). This implies that the utility at one time period is influenced by recent outcomes, breaching additive separability and independence across time (Assumption 1). Recency bias frequently leads to behaviors such as

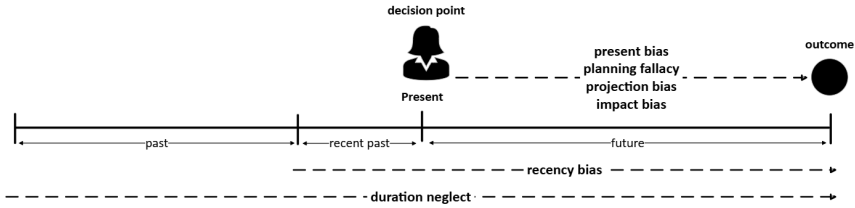


Figure 3.1: Influence areas of the biases on the time axis

overreacting to short-term trends and making judgments that are overly influenced by the most recent experiences. For example, a recency-biased investor may sell a stock that has recently dropped in value, believing that the downtrend will continue, even if the stock’s long-term performance has been strong and promising (Rabbani et al., 2021).

**Impact bias** refers to the tendency of individuals to overestimate both the intensity and the duration of their emotional reactions to future events (Wilson et al., 2000). It represents a failure in the predictive accuracy of future utility, leading to choices violating the assumption of correct evaluation of future consequences (Assumption 4). It often leads to overvaluing anticipated outcomes and prioritizing choices based on exaggerated expectations about the future. For example, impact-biased decision-makers might believe they will experience a powerful sense of happiness if they purchase a particular product. Most of the time, the intensity and length of this emotional state do not persist as estimated, and they face low utilities or even financial losses (Gilbert et al., 2002).

**Duration neglect** is a cognitive bias in which the duration of an experience has little or no influence on how it is later remembered or evaluated (Fredrickson & Kahneman, 1993). As a related concept, the peak-end rule suggests that an experience is considered limited to its most extreme or recent moments. This undermines the idea that each moment of consumption contributes independently to total utility, a core part of additive separability (Assumption 1). Duration neglect may lead to future evaluations that are biased toward misremembered memories. For instance, people tend to rate a longer but gradually improving medical procedure as less unpleasant than a shorter one that ends abruptly with high pain (Yen et al., 2023). This happens because their memory of the experience is shaped more by how it ends than by how long it lasts.

**Planning fallacy**, a concept introduced by Kahneman & Tversky (1979), refers to the tendency of individuals to underestimate the time and resources required to complete future tasks, often resulting in optimistic plans. The DU model assumes that decision-makers hold accurate forecasts about future outcomes and their durations. However, the planning fallacy leads individuals to systematically underestimate the time and effort required to complete future tasks, resulting in over-optimism about their future productivity. This cognitive bias causes distortion in the expected utility of delayed outcomes (Assumption 4). A typical example of the planning fallacy is underestimating the time and budget required to complete a project.

Despite their differences, all these biases affect trade-offs between the past, present, and future. Figure 3.1 illustrates the influence areas of the biases on the time axis. Assuming the decision is made in the present moment, the dashed arrows represent how each bias shapes the

judgments formed at this point. For instance, because recency bias is about the influence of recently experienced incidents on evaluations, the arrow starts from the recent past and goes toward the future. Duration neglect, on the other hand, concerns the perceived length of an experience and is primarily about the past. Therefore, the influence range starts from the past and goes toward the future, implying these distorted memories influence future evaluations.

Biases may also differ in terms of frequency of occurrence, stakes of importance, the magnitude of negative impact, and the ease of detectability and mitigation (Arkes, 1991). These criteria can help distinguish biases that are relatively easier to detect and correct from those that represent more serious and challenging oversights. For example, by distorting health, savings, and prevention decisions, present bias is frequently reported in high-stakes decisions (O'Donoghue & Rabin, 2015). It causes strong devaluation behavior and may require high effort to detect and mitigate. On the other hand, the planning fallacy has a narrower scope, primarily affecting project planning and budgeting. Compared to present bias, it is easier to detect and avoid by referencing outcomes from similar past projects. Our discussion of biases and the proposed mitigation strategies within the MADM process is informed by these differentiating factors.

### 3.3 Multi-attribute decision-making (MADM)

Multi-attribute decision-making (MADM) involves evaluating alternatives characterized by multiple attributes and is used for selection, sorting, or ranking. MADM methods can be broadly categorized as utility-based, outranking, distance-based, and pairwise comparison methods (see Greco et al. (2016) for details). In this study, we focus on the Multi-Attribute Value Theory (MAVT) to explore how time-related biases affect the decision-making process and what strategies can be promising for decreasing negative effects. While MAVT serves as the primary method, the findings are intended to extend to other MADM methods. Early stages—such as setting objectives, identifying attributes, and evaluating performance of alternatives—are largely consistent across different methods, allowing our discussion of time preference and biases to remain widely relevant. In the following, we outline the steps of MAVT based on Keeney & Raiffa (1975) and briefly discuss their roles in the decision-making process.

**Step 1 – Setting the objectives and alternatives:** The first step establishes the foundation for a systematic evaluation by defining clear and measurable objectives and identifying all feasible alternatives, ( $i = 1, 2, \dots, m$ ).

**Step 2 – Identifying attributes related to objectives:** This step is about identifying attributes,  $X_j$ , ( $j = 1, 2, \dots, n$ ) that measure the performance of each alternative. Preferred attributes should be measurable and comprehensive to ensure they fully capture the decision-maker's needs in evaluating the performance of alternatives (Keeney & Raiffa, 1975).

**Step 3 – Evaluating the performance of alternatives on defined attributes:** Each alternative is evaluated based on the identified attributes, providing quantitative and qualitative data for decision-making. The performance of an alternative  $a_k$  can be represented as a vector of outcomes  $a_k = (a_{k1}, a_{k2}, \dots, a_{kn})$ , where  $a_{kj}$  is the level achieved by the alternative  $a_k$  for the  $j$ -th attribute.

**Step 4 – Eliciting value or utility functions over levels of attributes:** A value function  $v_j(a_{kj})$  quantifies the decision-maker's preference for various levels of the attributes  $X_j$ . In case of

uncertainty involvement, a utility function can be used instead. The decision-maker's value functions can be elicited by using various methods, such as the lock-step procedure or mid-value splitting technique.

**Step 5 – Eliciting scaling constants (also known as attribute weights):** The relative importance of attributes is determined by assigning scaling constants  $\lambda_j$ , ( $j = 1, 2, \dots, n$ ) to reflect their significance in the decision-making process (von Winterfeldt & Fischer, 1973). The scaling constants are normalized such that  $\sum_{j=1}^n \lambda_j = 1$ , and they account for trade-offs between attributes, ensuring that their influence is properly reflected in the overall evaluation.

**Step 6 – Aggregation:** The performance of each alternative is aggregated across all attributes to generate an overall score. The overall value  $v(\mathbf{a}_k)$  of an alternative  $\mathbf{a}_k$  is computed as:

$$v(\mathbf{a}_k) = \sum_{j=1}^n \lambda_j v_j(a_{kj}), \quad (3.4)$$

where  $v_j(a_{kj})$  is the normalized value of  $a_{kj}$ ,  $\lambda_j$  is the scaling constant of attribute  $X_j$  and  $\lambda_j > 0$ , and  $\sum_{j=1}^n \lambda_j = 1$ .

When two alternatives are compared, in order for one alternative to be preferred over the other ( $\succ$ ) or to be indifferent ( $\sim$ ), its additive value (Equation 4.3) must be greater than ( $>$ ) or equal to ( $=$ ) the additive value of the other alternative.

The additive value function can be used if the attributes are (i) mutually preferentially independent and (ii) difference independent (Keeney & Raiffa, 1975). If a weaker condition is satisfied (mutual preferential independence and weak difference independence), multiplicative or other non-additive value functions can be used (Currim & Sarin, 1984; Dyer & Sarin, 1979).

In most of these steps, decision-makers must provide judgmental inputs and express personal preferences. While doing so, a variety of biases can distort judgments throughout the process (Montibeller & von Winterfeldt, 2015; Rezaei et al., 2022). Furthermore, this already complex evaluation process is further complicated when intertemporal dynamics are integrated. Therefore, analyzing MADM steps through the lens of time preference can enhance awareness and foster the development of strategies to reduce biased judgments. Motivated by this, we offer a comprehensive analysis and present several promising ideas in the following section.

### 3.4 Time-related biases in multi-attribute decision-making

This section analyzes the impacts of time-related biases at each step of the MADM process and offers suggestions to reduce their negative effects. For each suggestion, we point out which assumption of the DU model (Section 3.2) it relates to, helping clarify how the strategy may address departures from rational decision-making. We also discuss how unaddressed biases at one step can propagate through subsequent stages.

### 3.4.1 Setting the objectives and alternatives

This step lays the foundation for evaluation, requiring systematic objective identification and thorough consideration of alternatives, both of which can be distorted by time-related biases. For example, the *planning fallacy* can lead to overly optimistic estimates of required resources, resulting in the exclusion or inclusion of particular objectives (Katt et al., 2021; König et al., 2015). In addition, research indicates the distinction between setting sub-objectives and concentrating on bigger ones regarding susceptibility to the planning fallacy (Forsyth & Burt, 2008; Rodon & Meyer, 2012; Hadjichristidis et al., 2014). If the decision-maker opts for large objectives instead of setting sub-objectives, this might trigger less realistic estimations in the following steps, such as attribute weighting, where an inappropriate scope of objectives can result in distorted importance weights (Weber et al., 1988; Rezaei et al., 2022). Given additional research emphasizing the significance of the number of objectives and attributes in MADM, it is crucial to be aware of planning fallacy and structure the objective hierarchy systematically (Marttunen et al., 2018; Pöyhönen & Hämäläinen, 1998).

For many decisions, the objective set should extend beyond current circumstances and encompass the problem while considering potential changes in the future. However, the *projection bias* and *recency effect* may cause setting objectives that are valid for the present circumstances but not representative in the long term (Conlin et al., 2007; Loewenstein & O'donoghue, 2003). For example, projection bias may cause individuals to set short-sighted objectives by believing their current situation will be the same in the future. Similarly, the recency bias may lead people to rely too much on recent information and consider recently encountered but unrepresentative objectives for the problem.

*Impact bias* leads to overly concentrating on focal events and disregarding the resilience of the human emotional system in coping with negative feelings (Hoerger, 2012; Lench et al., 2011). This magnifies the difficulty of the current situation, leading individuals to underestimate their ability to cope with problems. As a result, they may set redundant or unnecessary objectives. For instance, during the COVID-19 pandemic, some governments implemented mandatory vaccine policies to increase vaccination rates rapidly. While these measures sought to address immediate concerns about controlling the virus, they have resulted in unintended consequences, such as reduced vaccine confidence and decreased public trust (Bardosh et al., 2022). These negative outcomes indicate how objectives driven by the emotional intensity of the crisis might fail to account for long-term consequences.

Sometimes the objective-setting requires the involvement of multiple decision-makers. Participants discuss the problem from various perspectives in groups and come up with a representative objective set. While doing so, they may become subject to *present bias* and *recency bias*. A few studies reveal that people become more impatient and vulnerable to recent events in group discussions compared to individual choices (Del Carpio et al., 2022; Jackson & Yariv, 2014; Sulistiawan & Rudiawarni, 2019). Consequently, group discussions may yield short-sighted objectives if they are not handled systematically.

Time-related biases may also lead to a poor alternative list. *The peak-end rule* and *recency bias* may lead to incorporating an extreme or popular alternative that is not realistic or applicable in the long term (Fredrickson & Kahneman, 1993; Godovykh & Hahm, 2020; Hands & Avons, 2001). Some alternatives may stand out simply because they are related to intense or dramatic experiences, while more stable, moderate, and potentially more effective alternatives

may be overlooked. *Present-bias* may lead decision-makers to consider alternatives that provide immediate benefits rather than ones that require an initial investment or waiting (Augenblick & Rabin, 2019; Cheung et al., 2022; Hardisty et al., 2013). In this case, good alternatives might be excluded only because of the undesirability of the waiting or the necessity of initial investment. For example, imagine that a group of policymakers is tasked with selecting a strategy for managing Type 2 diabetes in a population (Eghbali-Zarch et al., 2022). Present bias may lead to solutions that offer immediate benefits, such as prescribing drugs for lowering blood sugar and providing quick relief. On the other hand, alternatives that are related to lifestyle modifications can be overlooked because they require effort, and their visible results are slow to appear. From a similar point of view, *projection bias* may cause the inclusion of alternatives that do not apply to long-term changes. The overestimated similarity between the present and the future may lead to considering alternatives that are compatible with current circumstances but not proper for the future (Buchheim & Kolaska, 2017; Conlin et al., 2007).

### 3.4.2 Suggestions to reduce biases in setting objectives and alternatives

As illustrated in Table 3.1, several ideas may be helpful for addressing these negative effects. Because this initial step mainly involves structured thinking and forecasting, the suggested ideas primarily relate to Assumption 4 of the DU model, which concerns accurate predictions and evaluations.

Using a systematic approach rather than a casual interview may reduce the negative effects of biases. Value-focused thinking (VFT) is a method that helps define objectives by grounding decision-makers to focus on their core values before exploring alternatives (Keeney, 1996). Its hierarchical structure clarifies how objectives relate to one another and ensures that all sub-objectives align with these core values. VFT may help control some of the negative consequences associated with the planning fallacy. Because the objective hierarchy is based on thoughtfully identified values, the method may reduce the risk of including unrealistic objectives. This, in turn, can help manage the number of sub-objectives. Systematically thinking about values might also help decision-makers to broaden their perspectives and avoid projecting their current preferences onto the future. By encouraging decision-makers to reflect deeply on long-term values rather than momentary preferences, a facilitator may initiate future-oriented thinking, thereby helping to overcome projection bias. In addition to objective setting, VFT supports comprehensive alternative selection. Decision-makers can generate more innovative alternatives than simply evaluating pre-existing ones when they consider values. For example, the risk of including extreme alternatives because of the peak-end rule can be controlled in this way.

Problem-structuring methods (PSMs) may serve as promising strategies for reducing present bias, the planning fallacy, projection bias, and recency bias. PSMs are used for identifying key elements of a complex issue and organizing its components in a framework toward a solution (Mingers & Rosenhead, 2004). One widely used PSM is cognitive mapping, which helps individuals or groups visually represent causal relationships and objectives in a hierarchical format (Eden, 1988). By following the systematic process of cognitive mapping, a facilitator ensures that the relationships between objectives are considered from a holistic perspective. In doing so, the dominant effect of recently encountered events (recency bias) or the decision-makers' tendency to project their current preferences onto future objectives (projection bias) can be

controlled to some extent. By eliciting all relationships between components and displaying connections between current actions and their potential long-term outcomes, participants can become more resistant to present bias with cognitive mapping. Cognitive mapping also improves structural clarity. It allows for exploring the full set of relationships between objectives and alternatives. This may support more realistic planning and reduce the planning fallacy. When decision-makers have a clearer picture of dependencies and consequences, they are less likely to underestimate timelines or over-commit to unrealistic goals. This, in turn, helps avoid setting redundant objectives or including unnecessary alternatives. Another advantage of cognitive mapping is its facilitation of collaborative thinking. Engaging a diverse group of decision-makers brings together a wide array of perspectives. This diversity can play a balancing role: when a shared map is developed and consensus is reached, opposing viewpoints often cancel out extreme or biased judgments (Bang & Frith, 2017). As a result, group-based cognitive mapping can mitigate the effects of individual cognitive distortions, such as recency and present biases. Other problem-structuring methods, such as scenario planning and strategic options development and analysis (SODA), may be used for reducing biases (Ackermann & Eden, 2020). For example, SODA encourages participants to explore multiple “what-if” scenarios, which fosters future-oriented thinking and may reduce present bias. Scenario analysis similarly enables decision-makers to assess how their objectives might perform across a range of future environments (Schoemaker, 1995). Facilitators can guide decision-makers to consider plausible future states, helping them anticipate external changes and adjust objectives to remain achievable and relevant. This broadens their understanding of the problem and available resources, reducing over-optimism and may mitigate the planning fallacy.

Using a method to facilitate decision-maker engagement for brainstorming may help reduce group-level present bias (Bang & Frith, 2017). The Nominal Group Technique (NGT) stands as a promising method for providing a structured framework and ensuring the contribution of all participants (Delbecq & van de Ven, 1971). It encourages a wide range of ideas and minimizes the influence of dominant participants in brainstorming. Applying NGT may help facilitators control biases that can be exacerbated by group dynamics (Gallagher et al., 1993). Since the method provides a systematic way to manage group interaction and organize ideas, the temptation associated with present bias might be balanced. Similarly, because all participants contribute systematically, recently encountered issues (recency bias) are less likely to distort the objective-setting process, and dominant voices can be counterbalanced by alternative viewpoints. This reduces the risk of groupthink (DiPierro et al., 2022), and prevents the escalation of commitment in group decision-making processes (Mannion & Thompson, 2014).

Initiating mental simulations can help avoid unrealistic and redundant objective settings caused by planning fallacy and impact bias (Wang & Chiou, 2022; Buechel et al., 2017; Finkenauer et al., 2007; Gilbert et al., 1998). Another approach is to encourage stepping outside of the current viewpoint by adopting perspective-taking techniques. Research by Kanten (2011) has shown that decision-makers who adopt an external or future-oriented perspective, whether through consultation with experts or by engaging in perspective-shifting exercises, are less likely to fall into the trap of projection bias. Planning fallacy, recency bias, and impact bias can be reduced by keeping decision-makers accountable (Schillemans, 2022; Lau et al., 2016; Siddiqui et al., 2014). For example, suppose the facilitator senses that the decision-maker has a planning fallacy and includes particular objectives. In that case, they can ask them to provide evidence based on similar past decisions or data. Alternatively, they might encourage participants to think of the worst- and best-case scenarios and justify the inclusion of an objective.

Table 3.1: Suggestions to reduce the impact of time-related biases in setting objectives and alternatives

Time-related biases	Suggestions
<b>Present bias</b>	<ul style="list-style-type: none"> <li>• Using scenario analysis techniques (Motoki et al., 2023)</li> <li>• Using problem structuring methods (Eden, 1988; Mingers &amp; Rosenhead, 2004; Ackermann &amp; Eden, 2020)</li> <li>• Nominal Group Technique (Delbecq &amp; van de Ven, 1971)</li> </ul>
<b>Projection bias</b>	<ul style="list-style-type: none"> <li>• Value Focused Thinking (Keeney, 1996)</li> <li>• Using problem structuring methods (Eden, 1988; Mingers &amp; Rosenhead, 2004; Ackermann &amp; Eden, 2020)</li> <li>• Adopting perspective-taking (Kanten, 2011)</li> </ul>
<b>Recency bias</b>	<ul style="list-style-type: none"> <li>• Using problem structuring methods (Eden, 1988; Mingers &amp; Rosenhead, 2004; Ackermann &amp; Eden, 2020)</li> <li>• Nominal Group Technique (Delbecq &amp; van de Ven, 1971)</li> <li>• Keeping decision-makers accountable (Lau et al., 2016; Schillemans, 2022)</li> </ul>
<b>Impact bias</b>	<ul style="list-style-type: none"> <li>• Using problem structuring methods (Eden, 1988; Mingers &amp; Rosenhead, 2004; Ackermann &amp; Eden, 2020)</li> <li>• Using scenario analysis techniques (Motoki et al., 2023)</li> <li>• Using mental simulations (Buechel et al., 2017; Gilbert et al., 1998)</li> </ul>
<b>Duration neglect</b>	<ul style="list-style-type: none"> <li>• Value Focused Thinking (Keeney, 1996)</li> <li>• Using problem structuring methods (Eden, 1988; Mingers &amp; Rosenhead, 2004; Ackermann &amp; Eden, 2020)</li> </ul>
<b>Planning fallacy</b>	<ul style="list-style-type: none"> <li>• Value Focused Thinking (Keeney, 1996)</li> <li>• Using problem structuring methods (Eden, 1988; Mingers &amp; Rosenhead, 2004; Ackermann &amp; Eden, 2020)</li> <li>• Keeping decision-makers accountable (Lau et al., 2016; Schillemans, 2022)</li> <li>• Using mental simulations (Gilbert et al., 1998; Buechel et al., 2017)</li> </ul>

### 3.4.3 Identifying the attributes

Determining appropriate measurement units plays a crucial role in this step. There is a relationship between *duration neglect* and the preferred information format. While numerical formats often lead to duration neglect, graphical formats can be more resilient to this problem (Liersch & McKenzie, 2009). Therefore, it is important to select measurement units for attributes that do not obscure time-related aspects in the following steps. This point is further reinforced by research on scaling bias—a set of biases that arise when there is a mismatch between how information is measured or presented and how individuals interpret or respond to it (Poulton, 1982; Montibeller & von Winterfeldt, 2015).

When an objective requires evaluation using a time-dependent attribute, the temporal framing of that attribute can shape how it is perceived and may induce time-related biases (Finke-  
nauer et al., 2007; Peetz et al., 2010; Weingarten et al., 2021). For instance, consider a manager

tasked with minimizing the duration of a product development cycle. In this example, the total time taken to complete the desired developments serves as a time-dependent attribute for evaluating the success of the project. If the timeline is framed in terms of “months remaining” instead of “months completed,” this may trigger *present bias* and cause prioritizing short-term gains. *Present-bias* may also cause inclusion of criteria that focus excessively on immediate gains (Hunter et al., 2018; Kang & Ikeda, 2016; Meier & Sprenger, 2010; Millemaci & Waldmann, 2016). Research shows that some individuals may have subjective time periods in mind, which distorts their temporal perceptions in judgment (Balakrishnan et al., 2020; Jang & Urminsky, 2023; Zauberman et al., 2009). Treating time-related outcomes based on subjective rules and limited time horizons may lead to non-comprehensive attributes or adopting unclear, unnatural, or indirect measures. Given the importance of using comprehensive, non-proxy attributes, it is crucial to account for present bias at this stage (Gregory et al., 1987; Keeney & Raiffa, 1975).

*Projection bias* and *recency effect* may lead to using attributes that are perceived as representative in the present but not applicable for the future (Augenblick & Rabin, 2019; Chang et al., 2018). Limiting their perspective to a recent event may cause people to use a measure that is irrelevant to the general problem. Similarly, *the peak-end rule* causes people to remember incidents limited to extreme points, and this tendency may lead to choosing an attribute that is not representative (Weingarten et al., 2021). Individuals with *impact bias* may prefer emotionally salient attributes even if they are less relevant or difficult to measure in practice (Gilbert et al., 1998; Hoerger, 2012; Lench et al., 2011; Wilson et al., 2000). Due to the *planning fallacy*, decision-makers may overlook attributes related to risks or practicalities (Katt et al., 2021; König et al., 2015). Their optimism leads them to focus on positive attributes that may not be representative. For example, a public health agency selecting a vaccination model for an emerging disease like COVID-19 (Saadi et al., 2021) might include cost per vaccination or ease of logistics, while neglecting supply chain risks or public acceptance-related attributes. As a result, the evaluation may be limited and fail to meet population needs.

### 3.4.4 Suggestions to reduce biases in identifying the attributes

Several strategies may reduce biases (Table 3.2), including increasing decision-makers’ familiarity with the objective set (Morewedge et al., 2005). Greater engagement with the problem helps individuals recognize long-term influences and generate more representative attributes. The facilitator should ensure decision-makers are familiar with the objective set, aware of possible long-term influences, and have the understanding and expertise to come up with representative attributes. In alignment with this idea, using multiple decision-makers to incorporate diverse perspectives can reduce individual biases and lead to a better attribute set (Keeney, 1996; Charness & Sutter, 2012). As discussed earlier, managing the brainstorming sessions and group discussions systematically may be useful when there is a group of decision-makers.

Given that varying levels of salience can induce present bias in judgments (Carvalho et al., 2016; Guan et al., 2022; Malkoc et al., 2010), it is essential to maintain consistent levels of detail (van Ittersum et al., 2007). It helps that none of the attributes receives more attention in the next steps. Another crucial factor is the frame of attributes and preferred measurement units (Carvalho et al., 2016; Guan et al., 2022). The identified attributes should not have a gain or loss implication since it may trigger present bias. The facilitator should adopt as neutral as possible attribute frames (Hardisty et al., 2013; Malkoc et al., 2010) and benefit from external, validated

measures when possible (Strijbosch et al., 2019; Weingarten et al., 2021). Using objective, well-defined external measurements can help to decrease present bias. Avoiding language or formats that excessively emphasize either the short- or long-term outcomes is also crucial. Especially time-related attributes should not have delay or speed-up glances that are known to trigger present bias (Loewenstein, 1988). These ideas are closely linked to Assumptions 2 and 3 of the DU model. Careful attribute identification can support dynamic consistency in subsequent steps.

In some cases, using graphical information can provide a more intuitive understanding and reduce duration neglect (Liersch & McKenzie, 2009). The facilitator can structure time-oriented attributes in such a way that numerical formats are supported by visual aids. By enhancing decision-makers' recall of the durations of past experiences, this strategy aligns with Assumption 1 of the DU model and facilitates considering each period's contributions.

Challenging the "current state" thinking may help reduce projection bias and recency effect (Loewenstein & Prelec, 1992; Loewenstein, 1988). When a decision-maker introduces an attribute, the facilitator can ask them to envision future scenarios and consider how preferences might change over time (Chanel et al., 2023). By doing so, they can be motivated to think whether the attribute they suggest is the result of their projection or recency-biased preferences, or if it is really a suitable, long-lasting measurement unit. Similarly, the facilitator can ask decision-makers to justify each proposed attribute and explain how they address not only current needs but also future ones. Alternatively, by adopting reverse thinking, similar explanations might be asked for the excluded attributes to ensure they are not excluded because of their dissimilarity to the current states of the decision-makers. These suggestions relate to the Assumption 4 of the DU model and assist decision-makers in making informed assessments of the anticipated future representativeness of the attributes they identify.

Encouraging perspective-taking can help reduce impact bias (Buechel et al., 2017). By considering others' viewpoints, individuals better regulate emotional reactions and may identify more representative measures (Gilbert et al., 2002; Boltz & Yum, 2010). Facilitators can prompt decision-makers to adopt the perspective of a colleague or affected party, fostering broader evaluation of attributes beyond personal experience. In some cases, the chosen attribute may have the risk of triggering impact bias in the following steps. This can be controlled if the facilitator ensures that emotionally charged attributes are represented in neutral and factual terms. For example, potential attributes and related datasets can be presented in tables or charts to emphasize facts over emotional appeal (Liersch & McKenzie, 2009).

Planning fallacy can be reduced by encouraging decision-makers to examine past similar decisions to identify attributes they may have overlooked. Thinking about the attributes of previous projects or similar problems may help people see the current problem from a more realistic point of view and not overlook the attributes regarding risk or delays (Strijbosch et al., 2019). In addition, listing all the potential attributes and examining them in detail may also help in this matter (Keeney, 1996). The facilitator may initiate a discussion about the suggested attributes and motivate people to talk about their representativeness for different future states. This can help them to consider risk-related aspects and reduce the effect of the planning fallacy. In alignment with Assumption 4, these strategies are meant to help decision-makers toward consistent evaluations and informed attribute choices.

Table 3.2: Suggestions to reduce the impact of time-related biases in identifying the attributes

Time-related biases	Suggestions
<b>Present bias</b>	<ul style="list-style-type: none"> <li>• Adopting neutral frames and using validated measurement units (Strijbosch et al., 2019; Weingarten et al., 2021)</li> <li>• Conducting the brainstorming sessions systematically (Keeney, 1996)</li> <li>• Sticking to the same salience level between the attributes (Carvalho et al., 2016; Guan et al., 2022)</li> <li>• Inviting multiple experts or decision-makers (Keeney, 1996)</li> </ul>
<b>Projection bias</b>	<ul style="list-style-type: none"> <li>• Conducting the brainstorming sessions systematically (Keeney, 1996)</li> <li>• Inviting multiple experts or decision-makers (Keeney, 1996)</li> <li>• Envisioning the future and imagining potential changes regarding the suggested attributes (Chanel et al., 2023)</li> </ul>
<b>Recency bias</b>	<ul style="list-style-type: none"> <li>• Envisioning the future and imagining potential changes regarding the suggested attributes (Chanel et al., 2023)</li> <li>• Conducting the brainstorming sessions systematically (Keeney, 1996)</li> <li>• Inviting multiple experts or decision-makers (Keeney, 1996)</li> </ul>
<b>Impact bias</b>	<ul style="list-style-type: none"> <li>• Representing attributes with neutral and factual terms (Liersch &amp; McKenzie, 2009)</li> <li>• Adopting perspective-taking methods (Buechel et al., 2017; Gilbert et al., 1998)</li> </ul>
<b>Duration neglect</b>	<ul style="list-style-type: none"> <li>• Increasing the familiarity of experts with the problem (Morewedge et al., 2005)</li> <li>• Using graphical information formats (when applicable) (Liersch &amp; McKenzie, 2009)</li> </ul>
<b>Planning fallacy</b>	<ul style="list-style-type: none"> <li>• Inviting multiple experts or decision-makers (Keeney, 1996)</li> <li>• Encouraging decision-makers to examine past decisions and their attributes (Strijbosch et al., 2019)</li> <li>• Systematically listing all possible attributes (Strijbosch et al., 2019)</li> <li>• Envisioning the future and imagining potential changes regarding the suggested attributes (Chanel et al., 2023)</li> </ul>

### 3.4.5 Evaluating the performance of alternatives on defined attributes

Time-related biases can distort the way decision-makers perceive and interpret the performance of alternatives. For instance, the present bias may cause decision-makers to overestimate the performance of alternatives that offer immediate benefits, undervaluing those with long-term advantages (Millemaci & Waldmann, 2016). From a similar point of view, projection bias may lead to judging alternatives based on the current circumstances rather than perceiving them in the objective decision context (Loewenstein & O'donoghue, 2003). For example, a stressed decision-maker may rate an alternative lower on the "ease of implementation" attribute, not due to the alternative's actual complexity, but because their current state influences their perceptions of its performance.

Recency bias may lead to considering recent positive or negative incidents over long-term performance trends, resulting in distorted evaluations (Che et al., 2020). For example, if an alternative was recently associated with a setback, decision-makers may rate it lower, despite a strong overall track record. From a similar point of view, the facilitator might rely on the most recent data points or decision-maker opinions while constructing the performance matrix. Ignoring long-term trends can distort the overall evaluation of alternatives.

Impact bias may cause one to overestimate the emotional significance of certain outcomes, resulting in exaggerated evaluations of an alternative's performance on specific attributes (Wilson & Gilbert, 2005). For example, decision-makers might overrate an alternative because they expect it to bring intense satisfaction even if such emotional responses are likely to be short-lived. The format in which data are presented can influence the perceived performance of alternatives. For example, when performance is assessed using longitudinal data rather than summary scores, the peak-end rule may distort evaluations, leading decision-makers to focus disproportionately on the most intense moments of the trajectory while overlooking the overall performance of outcomes. Similarly, the planning fallacy can cause decision-makers to underestimate the effort, time, or resources required for certain alternatives, leading them to assign overly optimistic scores to attributes like feasibility. For example, an alternative might be rated as easier than it actually is due to an overly optimistic view of challenges caused by the planning fallacy.

### **3.4.6 Suggestions to reduce biases in evaluating the performance of alternatives**

As summarized in Table 3.3, there are several approaches that may potentially reduce the negative effects of biases during performance evaluation. Reference Class Forecasting (RCF) is a method for improving the accuracy of predictions by basing estimates on actual outcomes from comparable past projects, rather than relying solely on subjective evaluations (Flyvbjerg, 2007). RCF follows three main steps: (i) Identify a reference class (a group of similar past projects), (ii) Establish a statistical distribution of outcomes by gathering data on the performance of alternatives, and (iii) Compare the alternatives to this reference distribution to make forecasts. The method forces decision-makers to take the "outside view" and grounds performance judgments in empirical evidence from past cases (Batselier & Vanhoucke, 2016). Although primarily recognized for its role in mitigating the planning fallacy, it may help reduce the influence of present bias, projection bias, recency bias, and duration neglect. Using the full distribution of historical outcomes, RCF limits the effect of current conditions that may distort future expectations (projection bias) and smooths the impact of recent performance changes by highlighting long-term trends (recency bias). This strategy supports more accurate evaluations by grounding judgments in observed outcomes from similar cases, thereby reinforcing Assumption 4 of the DU model.

A common practice in economics is discounting future consequences at a constant rate and using the net present values in evaluations (Fisher, 1930; Mishan & Quah, 2020). A single consolidated score aggregates all future impacts and is used as a basis for performance evaluations. In this method, explicitly stating the discount rate helps mitigate present bias. However, it is crucial to select the discount rate based on empirical evidence rather than intuition. This approach may also reduce recency and projection biases. In discounting, the entire stream of outcomes is taken into account rather than focusing disproportionately on recent periods (reduc-

ing recency bias). It also reduces reliance on subjective impressions by expressing performance in systematically time-adjusted terms (reducing projection bias). Using a constant discount rate (Assumption 2) preserves the independent contribution of each outcome (Assumption 1) and supports consistent evaluations over time (Assumption 3), thereby satisfying most conditions of the DU model.

Presenting the performance profiles of alternatives over time with graphs or visuals may help reduce biases (Eberhard, 2023; Wall et al., 2021). By illustrating the entire trajectory at once, the facilitator helps decision-makers to consider the general picture and not overly depend on recent fluctuations in their performance evaluations (recency bias). Similarly, visual representations put peaks of high or low performance trajectories into context and lower the risk of overemphasizing extreme points in a series (the peak-end rule). The facilitator can present the data in a proper visual format and motivate decision-makers to consider the performance of alternatives over an extended period of time. Reflection is essential at this stage since it allows individuals to pause, critically examine information, and align their evaluations with data (Yelbuz et al., 2022; Criado-Perez et al., 2024). These suggestions primarily relate to Assumption 4 in the DU model, which posits that decision-makers can rationally evaluate performance over time.

### 3.4.7 Eliciting value/utility functions

Research consistently shows that temporal location significantly influences the value of alternatives (Ernst et al., 2018; Godovykh & Hahm, 2020; Jang & Urminsky, 2023; Krieger et al., 2021; Weingarten et al., 2021; Motoki et al., 2023). When there are various resolution times to consider simultaneously, *present bias* may distort the shape of the value functions by systematically shifting the perceived values of certain attribute levels. Furthermore, how alternatives are presented on a time horizon also plays a significant role. For example, there is a difference between framing the questions as deferral or expedited regarding being subject to present bias (Malkoc & Zauberan, 2006). The desirability of any attribute level would differ depending on whether it is framed as delaying the outcome versus speeding it up (Loewenstein, 1988). Since people dislike delays more than they like speeding up rewards, their evaluations will be affected by the time frame.

When there is uncertainty, utility functions are employed instead of value functions. One of the critical parameters in utility elicitation is the risk preferences of individuals, which might also be subject to biases (Chanel et al., 2023; Karl et al., 2021; Nofsinger & Shank, 2019; Schleich et al., 2019). The *duration neglect* may increase sensitivity to small probabilities and transform the risk preferences of decision-makers (Chanel et al., 2023). If a risk-neutral decision-maker is biased by duration neglect, they may become risk-averse, and eventually, their utility function might change. On the other hand, research reveals that individuals who have *planning fallacy* are more likely to be risk-seeking, which may result in a more convex utility function (Puri & Robinson, 2007). Moderated risk preferences and the resulting utility functions can distort the aggregation of attributes, potentially leading to the rejection of superior alternatives.

Besides influencing risk preferences, *planning fallacy* may also lead to over-/undervaluation of the attribute levels (Katt et al., 2021; König et al., 2015). Since they overlook the potential

Table 3.3: Suggestions to reduce the impact of time-related biases in evaluating the performance of alternatives

Time-related biases	Suggestions
<b>Present bias</b>	<ul style="list-style-type: none"> <li>• Discounting future outcomes and using condensed values in performance evaluation (Mishan &amp; Quah, 2020)</li> <li>• Adopting Reference Class Forecasting (Flyvbjerg, 2007; Batselier &amp; Vanhoucke, 2016)</li> <li>• Prompting reflections and considering full performance history (Isler et al., 2020; Yelbuz et al., 2022)</li> <li>• Using visual tools to show long-term performance trends (Eberhard, 2023; Wall et al., 2021)</li> </ul>
<b>Projection bias</b>	<ul style="list-style-type: none"> <li>• Adopting Reference Class Forecasting (Flyvbjerg, 2007; Batselier &amp; Vanhoucke, 2016)</li> <li>• Prompting reflections and considering full performance history (Isler et al., 2020; Yelbuz et al., 2022)</li> </ul>
<b>Recency bias</b>	<ul style="list-style-type: none"> <li>• Discounting future outcomes and using condensed values in performance evaluation (Mishan &amp; Quah, 2020)</li> <li>• Adopting Reference Class Forecasting (Flyvbjerg, 2007; Batselier &amp; Vanhoucke, 2016)</li> <li>• Using visual tools to show long-term performance trends (Eberhard, 2023; Wall et al., 2021)</li> </ul>
<b>Impact bias</b>	<ul style="list-style-type: none"> <li>• Using visual tools to show long-term performance trends (Eberhard, 2023; Wall et al., 2021)</li> <li>• Prompting reflections and considering full performance history (Isler et al., 2020; Yelbuz et al., 2022)</li> </ul>
<b>Duration neglect</b>	<ul style="list-style-type: none"> <li>• Using visual tools to show long-term performance trends (Eberhard, 2023; Wall et al., 2021)</li> <li>• Prompting reflections and considering full performance history (Isler et al., 2020; Yelbuz et al., 2022)</li> </ul>
<b>Planning fallacy</b>	<ul style="list-style-type: none"> <li>• Adopting Reference Class Forecasting (Flyvbjerg, 2007; Batselier &amp; Vanhoucke, 2016)</li> <li>• Using visual tools to show long-term performance trends (Eberhard, 2023; Wall et al., 2021)</li> </ul>

obstacles and assign disproportionate values to attributes that appear easy to achieve, these decision-makers might end up with distorted functions.

Environmental and physiological factors are also crucial. Research on *projection bias* reveals that current circumstances, including weather, visceral factors, air quality, financial well-being, and health, are difficult to isolate from judgments about future preferences (Buchheim & Kolaska, 2017; Chen et al., 2019; Loewenstein & O'donoghue, 2003). If decision-makers are under the influence of one or more of these factors during elicitation, they are less likely to think or behave rationally. They might project influences of their current situation onto the

future and end up with short-sighted assessments. Similarly, experiments from behavioral economics reveal that *recency-bias* causes people to be unable to extend the evaluation period, and form values only considering recently encountered, limited information (Cakici & Zaremba, 2023; Hao et al., 2016; Irani & Kim, 2023; Rabbani et al., 2021). In such cases, the elicited value functions are unlikely to fully reflect the individuals' preferences, limiting the potential to arrive at a satisfactory solution.

### 3.4.8 Suggestions to reduce biases in eliciting value/utility functions

As summarized in Table 3.4, a few strategies can potentially reduce the impact of biases. Mitigating the negative effects first requires awareness (Balakrishnan et al., 2020). A facilitator should acknowledge decision-makers' time preferences and approach elicitation tasks systematically. Providing decision-makers with a waiting period to elaborate more on different attribute levels may reduce present bias (Imas et al., 2022). If this time between information receiving and value elicitation is spent for careful elaboration and reflection, the temptation of immediacy can be reduced (Criado-Perez et al., 2024; Isler et al., 2020). The facilitator may also initiate a discussion and motivate decision-makers to reflect on the decision context. These practices help them to better understand the problem and provide informed judgments.

Before elicitation, it might be useful to discuss with decision-makers the number of time horizons to be considered and the discount rates to be applied to different attributes (Mishan & Quah, 2020). Defining these elements in advance makes the temporal assumptions of the analysis explicit and provides a clear frame for subsequent judgments. This early clarification can also help limit distortions such as present bias, and it is consistent with Assumptions 2 and 3 of the DU model. Encouraging decision-makers to consider multiple future time points simultaneously can help reduce their tendency to focus excessively on the timing of one outcome. For example, while eliciting the value function of environmental impact attribute in a problem, thinking about multiple future time points such as 1 year, 5 years, and 10 years may help decision-makers avoid disproportionately focusing on immediate costs or benefits. The facilitator can ask decision-makers to imagine how the values they provided may differ for these future time points. This mental exercise may foster a broader assessment, allowing for a better understanding of the attribute's long-term implications (Lench et al., 2011; Morewedge et al., 2005), aligning with Assumption 1.

The facilitator should also control for potentially confounding variables like weather, air quality, health, and financial stress (Briz et al., 2015; Buchheim & Kolaska, 2017; Chen et al., 2019; Conlin et al., 2007; Loewenstein & O'donoghue, 2003). For example, they should not prefer a day with extreme weather for elicitation, especially if the problem includes planning-related attributes. Because people often assume that current conditions will persist into the future, their responses are likely to be shaped by extreme weather events and the restrictions these conditions impose (Loewenstein & O'donoghue, 2003). Controlling for external factors relates to Assumptions 1 and 3 of the DU model by helping with balanced contributions from time points and consistency in judgments. Doing a pretest and trying to understand the current status of decision-makers before starting the elicitation can be helpful. For instance, in a problem that requires value elicitation for monetary attributes, the facilitator may apply a short pre-screening survey and identify the participants who have experienced financial pressure recently. These participants can be flagged and observed for signs of discomfort or distraction during the

procedure. By doing so, the elicited functions can then be interpreted with the unique circumstances of these individuals in mind. Prescreening gives the facilitator the opportunity to get to know decision-makers better. Alternatively, for health-related problems, facilitators may ask decision-makers to complete a well-being test to reveal pain or discomfort that could affect evaluations. These strategies relate to Assumption 4 of the DU model, supporting decision-makers in forming well-informed judgments.

Risk preferences must be thoughtfully examined in relation to their underlying drivers, such as stress (Haushofer et al., 2021) and visceral influences (Fisher & Rangel, 2014; Briz et al., 2015). The facilitator should select a time for elicitation when the decision-maker is in a neutral emotional state, free from the influence of visceral factors such as hunger or thirst, and fully prepared to engage with the task. As discussed earlier, these states can be identified by conducting a short survey or directly communicating with decision-makers. If the facilitator thinks decision-makers are stressed or influenced by visceral factors, they should focus on these problems before starting with elicitation. Creating a calm, distraction-free environment, encouraging decision-makers to share their concerns and feelings, and providing regular breaks to prevent fatigue can all be helpful. In relation to Assumption 4, these ideas help decision-makers to engage more and provide informed judgments.

Instead of eliciting the value or utility functions once, doing multiple measurements may help to control for duration neglect and recency biases (Strijbosch et al., 2019). The dominant influence of recently encountered events on judgments can be balanced if the measurements are repeated at different times. This suggestion relates to the utility independence principle of the DU model (Assumption 1) and increases the likelihood of evaluating each period independently, without them influencing or distorting one another. However, as elicitation is an interactive and cognitively demanding process, conducting multiple measurements can lead to decision fatigue. Facilitators should be mindful of this and design the process to minimize unnecessary cognitive load while maintaining the quality of the elicited preferences.

Episodic future thinking (EFT) refers to a cognitive ability to imagine and simulate specific events that can happen in the future, and it can serve as a promising strategy for reducing planning fallacy (Atance & O'Neill, 2001). The facilitator can prompt decision-makers to adopt EFT, enabling them to better anticipate potential obstacles and provide more realistic judgments about the outcomes (Schacter et al., 2017). Another strategy for reducing the planning fallacy might be providing empirical benchmarks from historical datasets (Shmueli et al., 2016). Drawing on a similar past example can encourage decision-makers to approach the problem holistically and consider potential obstacles.

Individuals generally elicit values by comparing the desirability of different levels to a reference point in mind. If they have distorted memories, they will likely end up with biased value functions (Roy & Christenfeld, 2007). For example, duration neglect may result in the elicitation of functions based on an altered reference point. The facilitator could ask more detailed questions or use external information sources. Prompting decision-makers to provide more detailed narratives of their experiences (Schwarz, 1999), asking follow-up questions that challenge oversimplifications, and leveraging external data (Wilson & Schooler, 1991) are among the strategies that can be used to reduce these memory problems. These ideas help decision-makers better anticipate their future preferences and are therefore related to Assumption 4 of the DU model.

Table 3.4: Suggestions to reduce time-related biases in eliciting value or utility functions

Time-related biases	Suggestions
<b>Present bias</b>	<ul style="list-style-type: none"> <li>• Providing a waiting period between information receiving and elicitation steps (Imas et al., 2022)</li> <li>• Group decision making (Delbecq &amp; van de Ven, 1971)</li> </ul>
<b>Projection bias</b>	<ul style="list-style-type: none"> <li>• Eliciting functions in a controlled environment (Buchheim &amp; Kolaska, 2017; Loewenstein &amp; O'donoghue, 2003)</li> <li>• Controlling for psychological drivers and visceral effects (Haushofer et al., 2021; Fisher &amp; Rangel, 2014)</li> </ul>
<b>Recency bias</b>	<ul style="list-style-type: none"> <li>• Performing multiple measurements (Strijbosch et al., 2019)</li> <li>• Group decision making and accountability (Delbecq &amp; van de Ven, 1971; Lau et al., 2016; Schillemans, 2022)</li> </ul>
<b>Impact bias</b>	<ul style="list-style-type: none"> <li>• Motivating people to think about multiple time points (Lench et al., 2011; Morewedge et al., 2005)</li> <li>• Group decision making and accountability (Delbecq &amp; van de Ven, 1971; Lau et al., 2016; Schillemans, 2022)</li> </ul>
<b>Duration neglect</b>	<ul style="list-style-type: none"> <li>• Performing multiple measurements (Strijbosch et al., 2019)</li> <li>• Using external information sources (Roy &amp; Christenfeld, 2007)</li> </ul>
<b>Planning fallacy</b>	<ul style="list-style-type: none"> <li>• Exercising episodic future thinking (Schacter et al., 2017; Atance &amp; O'Neill, 2001)</li> <li>• Considering empirical benchmarks from historical datasets (Shmueli et al., 2016)</li> </ul>

Inviting multiple decision-makers with diverse viewpoints can help balance short- and long-term considerations (Charness & Sutter, 2012). Although collective decision-making could help attenuate extreme preferences and present bias, it is crucial to ensure structured deliberation and facilitated discussions. Embracing a systematic procedure can bring implicit individual biases to the surface and encourage group members to reflect on their preferences (Dalkey & Helmer, 1963). Receiving feedback from each other or trying to reach a consensus in a group setting can help decision-makers realize if and how their judgments might be biased (relates to the Assumption 4). In addition, group decision-making can benefit from the accountability aspect, which has been found to serve as an effective strategy against recency and impact biases (Lau et al., 2016; Schillemans, 2022).

### 3.4.9 Eliciting attribute weights

Time-related biases can distort decision-makers' preferences and judgments, leading to higher or lower attribute weights. *Present bias* will likely lead individuals to assign higher weights to attributes that reveal sooner benefits (immediate gratification) (Cheung et al., 2022; Hardisty et al., 2013; Shiba & Shimizu, 2020). When an attribute involves a waiting period or outcomes emerging in the distant future, decision-makers may perceive it as less desirable. They might

be more likely to trade off this attribute for immediate gains, leading to lower scaling constants.

The temporal framing of attributes can shape decision-makers' willingness to pay (Frederick et al., 2002). As a result, they may end up with higher or lower weights (Hardisty et al., 2013; Malkoc et al., 2010; Thoma & Tytus, 2018). For example, if an attribute is framed with an acceleration glance, it can get higher weights because of *present bias*. On the other hand, framing an attribute with a delay hint may lead the same decision-maker to assign a lower weight to this attribute.

Because of the *peak-end rule* and *recency bias*, decision-makers tend to remember extreme examples or recently encountered events more vividly. Given that memory is an indispensable factor while identifying the relative importance of an attribute, these outliers could influence the trade-off procedure as being salient (Chen et al., 2020; Forster & Kuhbandner, 2022; Hoogerheide & Paas, 2012; Krieger et al., 2021; Rabbani et al., 2021). For example, suppose that a group of authorities is tasked with formulating a national healthcare policy after experiencing a pandemic outbreak and its severe consequences. These decision-makers may place significantly higher weights on pandemic-related attributes, such as supply chain robustness or crisis response capacity, while potentially undervaluing future-oriented and less salient attributes, such as preventative healthcare and environmental sustainability (Guerriero et al., 2020). From a similar point of view, *projection bias* may cause to assign higher weights to attributes similar to current preferences. Believing current preferences will remain unchanged can lead individuals to prioritize attributes relevant to present circumstances, often overlooking a thorough evaluation of their long-term implications (Augenblick & Rabin, 2019; Briz et al., 2015; Chang et al., 2018; Fisher & Rangel, 2014; Lemay et al., 2015).

When a sequence of undesirable events ends with a positive experience, people remember the duration as shorter and the experience more positive. Suppose there is an attribute related to the duration of an experience in a MADM problem. In this case, the decision-maker may be unable to call memories correctly, which causes assigning distorted importance weights to these attributes (Redelmeier et al., 2003; Hetou et al., 2021). For example, if a patient's memory is distorted by *duration neglect* about the length of a painful medical procedure they went through, they will likely assign a lower weight to this attribute next time (Yen et al., 2023).

Decision-makers with *impact bias* may assign higher weights to some attributes by assuming their future impacts will be powerful and prolonged (Buechel et al., 2014; Karl et al., 2021; van Dijk et al., 2008). Continuing with the national healthcare policy example, if the decision-makers believe failing supply chain robustness will cause them a feeling of powerful regret in the future, they may overestimate the impact of this feeling and assign higher importance to this attribute. Similarly, *planning fallacy* may cause decision-makers to assign lower or higher weights to some attributes by making overoptimistic judgments (Katt et al., 2021; König et al., 2015).

### 3.4.10 Suggestions to reduce biases in eliciting attribute weights

Table 3.5 illustrates a few useful strategies. Given the extensive research highlighting the differences in attribute weighting methods and their susceptibility to various biases (Montibeller & von Winterfeldt, 2015; Pöyhönen & Hämäläinen, 2001), preferring a well-structured elicitation method not only helps maintain consistency but also can mitigate present and projection biases.

Table 3.5: Suggestions to reduce time-related biases in eliciting attribute weights

<b>Time-related biases</b>	<b>Suggestions</b>
<b>Present bias</b>	<ul style="list-style-type: none"> <li>• Using a systematic method instead of direct rating (Keeney &amp; Raiffa, 1975)</li> <li>• Using mental simulations (Gilbert et al., 1998; Buechel et al., 2017)</li> </ul>
<b>Projection bias</b>	<ul style="list-style-type: none"> <li>• Using social distance phenomenon (Bauckham et al., 2019; Buechel et al., 2014; Gilbert et al., 1998)</li> <li>• Using mental simulations (Gilbert et al., 1998; Buechel et al., 2017)</li> <li>• Using a systematic method instead of direct rating (Keeney &amp; Raiffa, 1975)</li> </ul>
<b>Recency bias</b>	<ul style="list-style-type: none"> <li>• Using time-reversal heuristic (Ernst et al., 2018)</li> <li>• Using social distance phenomenon (Bauckham et al., 2019; Buechel et al., 2014; Gilbert et al., 1998)</li> <li>• Using mental simulations (Gilbert et al., 1998; Buechel et al., 2014)</li> <li>• Adopting different perspectives (Boltz &amp; Yum, 2010; Thoma &amp; Tytus, 2018)</li> </ul>
<b>Impact bias</b>	<ul style="list-style-type: none"> <li>• Motivating people to think about multiple time points (Eastwick et al., 2008; Lench et al., 2011)</li> <li>• Using mental simulations (Gilbert et al., 1998; Buechel et al., 2017)</li> <li>• Using social distance phenomenon (Bauckham et al., 2019; Buechel et al., 2014; Gilbert et al., 1998)</li> </ul>
<b>Duration neglect</b>	<ul style="list-style-type: none"> <li>• Using external information sources (Kanten, 2011; Katt et al., 2021; Peetz et al., 2010; Weick &amp; Guinote, 2010)</li> <li>• Encouraging retrospective reflection and increasing familiarity of decision-makers (Morewedge et al., 2009)</li> </ul>
<b>Planning fallacy</b>	<ul style="list-style-type: none"> <li>• Exercising episodic future thinking for the attributes (Schacter et al., 2017; Atance &amp; O'Neill, 2001)</li> <li>• Considering empirical benchmarks from historical datasets (Shmueli et al., 2016)</li> </ul>

For example, opting for a method that requires decision-makers to perform multiple explicit trade-offs can help initiate a thought process to consider the long-term effects of each attribute. By doing so, decision-makers can reflect their judgments more deliberately rather than impulsively favoring short-term attributes (Assumption 4). Additionally, tools such as consistency ratios built into systematic weighting methods can help facilitators uncover inconsistencies in decision-makers' preferences and take action to ensure that assigned weights are consistent not only with the overall decision context but also with individuals' long-term objectives (Assumption 3).

While determining the importance of the attributes, the facilitator may support decision-makers with external information sources rather than solely relying on memories and intuitions (Assumption 4). This can reduce duration neglect and recency bias (Kanten, 2011; Katt et al., 2021; Peetz et al., 2010; Weick & Guinote, 2010). For example, when evaluating a time-related attribute, providing decision-makers with information about the duration of a similar past in-

cident can help reduce bias (Flyvbjerg, 2007; Batselier & Vanhoucke, 2016). When external sources are unavailable, a facilitator can encourage retrospective reflection and motivate decision-makers to rethink their past experiences (Morewedge et al., 2009; Yelbuz et al., 2022; Isler et al., 2020).

A facilitator can help decision-makers elicit attribute weights aligned with their values rather than biased judgments by shifting their time perception. For instance, if they are aided to adopt the time reversal heuristic and reverse past events' chronological order while deciding on the importance level of related attributes, they can become less subject to recency bias (Ernst et al., 2018). This strategy helps ensure that different time points are considered equally when forming judgments about weights (Assumptions 1 and 4).

Another strategy for managing the influences of the current circumstances or recently experienced events can be motivating decision-makers to embrace the social distance phenomenon (Bauckham et al., 2019; Peetz et al., 2010). If they are encouraged to distance themselves from the problem and look at the attributes from a different point of view, decision-makers can extend the evaluation beyond recent experiences (Assumption 4). For instance, the facilitator may ask, "What would your colleague (or your future self) think about the importance relationship between these attributes?". This perspective reduces the over-involvement of present circumstances and helps decision-makers to judge attribute importance from a broader perspective.

The facilitator may reduce the influence of impact bias by motivating decision-makers to think about multiple future aspects of an attribute (Eastwick et al., 2008; Lench et al., 2011). In relation to the Assumption 4 of the DU model, broader thinking with multiple parameters can lead to more balanced trade-offs and reduce the influence of impact bias (Yelbuz et al., 2022). Similarly, encouraging future simulations with data-driven methods, such as what-if scenarios or visualizations of long-term trends, can help the facilitator control impact bias in attribute weighting (Eberhard, 2023).

Decision-makers with planning fallacy may underweight risk-related attributes and overweight positive ones. Episodic future thinking could help counteract these tendencies by encouraging decision-makers to envision future scenarios more realistically (Atance & O'Neill, 2001; Schacter et al., 2017). The facilitator could motivate episodic future thinking for mentally simulating scenarios where risks could materialize. Imagining potential future obstacles may lead to revising the timeline to include contingency for risks and to re-evaluate the attribute weights.

### **3.4.11 Propagation of time-related biases in the MADM process**

As briefly mentioned in previous sections, biases in the initial steps can trigger a cumulative chain reaction, propagating distortions throughout subsequent steps of the MADM process. Since each step's outcome becomes the input for the next, and the problem's foundations are laid in the initial stages, biases arising early in the process can have disproportionately large effects. For example, if the planning fallacy leads to setting biased objectives in the first step, this can affect attribute identification, influencing which attributes are considered and how they are prioritized. Moreover, the number and nature of identified attributes will affect how scaling constants are distributed and values are elicited, potentially reinforcing biased perspectives. As a result, the aggregated values of the alternatives will be affected, and this sequence of

distortions will ultimately lead to the selection of a less desirable alternative. Therefore, initial steps require particular attention to ensure the problem is structured systematically and the influences of time-related biases are reduced as much as possible.

It is also possible that a bias emerging within a step is intensified by another bias either in the same step or across steps. For instance, a projection bias and recency effect can have this type of relationship in the attribute weighting step. While the recency effect leads decision-makers to believe that recently encountered attributes hold much more importance than others, projection bias may intensify this belief for attributes with future implications. Eventually, these two biases may cause the over-weighting of some attributes. The successive dynamic of the MADM framework necessitates a holistic approach and robust mitigation at each phase of the evaluation to avoid such negative effects.

It can also happen that the adverse effects of biases cancel each other out, as discussed by Lahtinen & Hämäläinen (2016). Depending on the sequence of steps followed in the decision-making process, some biases may lead to different results, either by accumulating in favor of one alternative or canceling each other's effects throughout the evaluation. While some biases distort intertemporal judgments, their interplay can sometimes result in a balancing effect. For example, impact bias magnifies the intensity of emotional outcomes, while duration neglect underestimates the length of experiences. In choosing between two alternative projects, impact bias may cause an overestimation of the satisfaction from completing an important short-term project. On the other hand, duration neglect might result in undervaluing the steady benefits of a longer-term project. Together, these two biases may lead to a more balanced assessment. Recognizing potential cancellations or propagation within or across the steps requires a careful understanding of how each bias operates within the MADM process. The insights provided by this research are intended to support and enhance these practices.

### **3.5 Conclusion and future research directions**

This study explored time-related biases in the prescriptive context of the MADM. Our critical review of the MAVT framework reveals numerous vulnerabilities at various stages, contributing to the literature by discussing potential distortions in evaluations and proposing some ideas for mitigation. A thorough analysis of each step demonstrates that the MADM process might be highly susceptible to time-related biases, necessitating careful consideration from the initial stages of objective setting toward attribute weighting and value elicitation. We illustrated how unaddressed biases can lead to follow-up problems and cause undesired outcomes. Our review highlights the imperative of incorporating related behavioral insights and adopting systematic methods for mitigation at each step. From a practical point of view, this study helps practitioners and facilitators to understand the role of biases in intertemporal trade-offs and make more informed decisions with MADM methods.

The findings of this study should be interpreted in light of certain limitations. First, we reviewed the literature, which mainly relies on choice experiments, and projected the empirical findings onto the MADM process to discuss the potential impacts of the biases. Although these studies were cautiously taken from the literature and discussed in relation to the MADM dynamics, real-life problems may introduce different challenges. Experimental validation of the reported deviations will be crucial to generalizing our findings. Subsequent investiga-

tions could also examine the reported ideas through real-life case studies, investigating how time-related biases emerge in specific contexts and how they can be mitigated in practice. Such case studies may yield valuable insights for better understanding the role of these biases in real-world decision-making. Second, given the limited literature in the prescriptive domain, we approached all time-related biases with equal consideration, regardless of whether they might be perceived as more serious or more trivial. Future research could build on this by developing a taxonomy of these biases, enabling facilitators to more effectively prioritize mitigation efforts. Third, this study has presented several promising ideas that could inform debiasing strategies in MADM processes. However, these ideas are primarily conceptual and have not yet been empirically tested. Future research should focus on validating these approaches through controlled experiments and real-world case studies to evaluate their effectiveness and refine their practical application. A promising avenue for further investigation involves assessing the suitability of the proposed mitigation ideas for certain decision situations. Fourth, this study employed MAVT, a value/utility-based method, to discuss the identified biases and mitigation strategies. Although the examined steps are largely common to many MADM methods, future research could explicitly test other approaches, such as pairwise comparison. Additionally, comparing the susceptibility of different methods to biases presents an interesting avenue for further investigation.

We believe this study will spark further research into time preferences and biases in MADM, leading to more resistant decision-making frameworks. In parallel, more debiasing strategies will be developed and validated, considering the unique dynamics of the trade-off process. By understanding and mitigating intertemporal biases, we can achieve more reliable decisions, benefiting from more practical applications.

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## Chapter 4

# Time preference in multi-attribute value theory: An experimental study

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**Abstract:** Research on time preference has predominantly employed a descriptive approach, focusing on unidimensional intertemporal choices (usually for monetary outcomes). However, real-world problems are often multi-dimensional, requiring trade-offs not only over time but also between conflicting objectives. This complexity calls for prescriptive approaches that move beyond description and support decision-making in the face of intertwined trade-offs. Addressing these gaps, the present study investigates time preference within a multi-attribute decision-making (MADM) context using the Multi-Attribute Value Theory (MAVT). First, we theorize the potential impact of time discounting on attribute-specific value functions and scaling constants (weights), formulating four research hypotheses. Then, three experiments are conducted around a health-related intertemporal MADM problem involving two conflicting attributes. A total of 279 participants participated in the experiments, each completing two scenarios that varied the timing of the attributes. The results indicate that both the scaling constants and the perceived values of the attributes vary significantly with time delays, with the underlying drivers of these changes depending on the specific trade-off relationships involved. While delaying a single outcome typically leads to discounting, our findings indicate that postponing multiple outcomes in a multi-objective context does not necessarily result in the same behavior. The presence of multiple objectives challenges conventional assumptions about time discounting. These insights are particularly relevant for researchers and practitioners in decision analysis, economics, psychology, health, and public policy who deal with complex, multi-dimensional intertemporal decisions.

**Keyword:** Time preference; multi-attribute decision making; intertemporal trade-offs; multi-attribute value theory

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## 4.1 Introduction

Few forces shape human behavior as powerfully as the pull of the present. Whether it is choosing dessert over a healthier meal, putting off studying or exercising, or buying something luxurious now instead of saving money for later, people often favor what feels rewarding in the moment over what is beneficial in the long run. These everyday choices mirror broader patterns in domains such as health, finance, and sustainability, where individuals often overlook substantial long-term gains in favor of immediate comfort or convenience.

This pervasive tendency is rooted in time discounting, through which individuals systematically value future outcomes less than immediate ones (Samuelson, 1937; Ainslie, 1975; Laibson, 1997). Such discounting alters intertemporal trade-offs, often leading individuals to favor immediate rewards, even when delayed options may offer greater long-term benefits (Thaler, 1981). Unsurprisingly, time discounting has been linked to a range of suboptimal behaviors, including insufficient retirement savings (James et al., 2020), poor adherence to medical regimens (Zhang & Rashad, 2008; Kang & Ikeda, 2016), underinvestment in preventive health care (Lee et al., 2020; Chapman, 1996), and environmentally unsustainable decisions (Gao & Tavoni, 2024). Understanding intertemporal decision-making is therefore essential to supporting more informed decisions across diverse domains such as economics (Zhang et al., 2022; Kölle & Lauer, 2024), operations management (Guan et al., 2024; Li et al., 2025), health (Madsen & Kjær, 2024; Chapman, 1996), project management (Shi et al., 2023), education (Meier & Sprenger, 2013; Hoogerheide & Paas, 2012), and agriculture (Duflo et al., 2011; Boonmanunt et al., 2020).

Research on time preference often employs experimental methods to describe how people make intertemporal judgments. This is commonly quantified by representing an individual's time preference with a single parameter—the discount rate (Hardisty & Pfeffer, 2017). Various methods exist for eliciting individual discount rates, including choice tasks, matching tasks, multiple price lists, and convex time budgets (Frederick et al., 2002). In a typical choice task experiment, participants choose between smaller-sooner and inflation-adjusted larger-delayed rewards (Harrison et al., 2002). Responses to multiple binary choices, where reward magnitudes and delay periods systematically vary, are then used to calculate discount rates. Another common approach is the matching task, where participants adjust the monetary amount of a delayed reward until it is perceived as equivalent to a fixed immediate reward (Thaler, 1981; Shelley, 1993; Guyse & Simon, 2011). Despite methodological differences, these approaches share some common features. In all of them, the primary emphasis is on participants' final choices and the resulting discount rates to determine and interpret how they value intertemporal outcomes. While effective for capturing outcome preferences, the underlying reasoning and trade-offs that individuals consider throughout the decision process will still remain unclear. In other words, the intermediate steps of the decision-making process are largely overlooked by experimenters. There is a need to better understand how individuals evaluate outcomes step by step, how the various stages of the decision-making process interact, and how these interactions ultimately shape final decisions. Moreover, most experimental studies rely on simple decisions that involve comparisons of monetary outcomes at different points in time. Yet, real-world decisions often require evaluating multiple alternatives across numerous, and often conflicting, objectives. While prior research has extensively documented the implications of time preference and associated behavioral patterns, our understanding of their role in decision-making problems

with multiple objectives remains limited (Greco et al., 2009). Adopting a prescriptive lens to examine these complex interactions can offer valuable insights and help decision-makers form more informed judgments and preferences.

Building on these gaps, the present research investigates time preference in a multi-attribute decision-making (MADM) context by adopting a prescriptive perspective. First, we introduce the properties of what we call *intertemporal MADM problem*, in which alternatives from different time points must be evaluated across multiple attributes. We then theorize how time preference might influence various stages of this evaluation process and propose four research hypotheses. To test these hypotheses, we conduct three experiments grounded in Multi-Attribute Value Theory (MAVT), a fundamental method in MADM that consists of systematic steps for evaluating complex decision problems and performing trade-offs between conflicting objectives (Keeney & Raiffa, 1975). Unlike traditional studies that focus on final choices, our participants proceed through a systematic evaluation process, providing judgments and preferences at several stages. This design enables us to derive individual value functions and scaling constants, offering a more detailed picture of how time influences decisions step by step.

This study contributes to the field of time preference and decision-making in several ways. We theorize time preference for a decision-making problem with multiple objectives, pushing beyond the conventional focus on discount rate. We design an experiment that reflects the complexity of real-world decisions, using MAVT to systematically elicit individual preferences and explore how people conduct trade-offs over time and across multiple objectives. Through both theoretical development and empirical investigation, we provide a deeper understanding of how time preference shapes intertemporal decision-making with multiple objectives. In practice, our findings offer insights for designing more effective decision aids, policy interventions, and behavioral strategies across areas such as health, finance, and education. Ultimately, this research supports better long-term decision-making by revealing how time preferences shape judgments in complex scenarios.

The remainder of the paper is organized as follows. Section 4.2 reviews time preference and MAVT. Section 4.3 develops a theoretical framework for intertemporal MADM and formulates four research hypotheses. Section 4.4 presents the experimental studies, and Section 4.5 reports the results. Finally, Section 4.6 concludes the paper and outlines directions for future research.

## 4.2 Preliminaries

This section begins with an overview of the normative model of time preference, followed by a discussion of the MAVT framework.

### 4.2.1 Time preference and intertemporal decision-making

Time preference refers to the tendency of individuals to place a higher value on receiving a good or service sooner rather than later (Loewenstein & Prelec, 1991). This concept is central to intertemporal decision-making, where individuals face trade-offs between immediate and delayed outcomes (Loewenstein & Thaler, 1989). The exponential discounting theory provides a foundational framework for understanding intertemporal choices (Samuelson, 1937). This

model assumes a constant discount rate, meaning that the present value of a future reward decreases exponentially as the delay to receive it increases.

In the exponential discounting model, the utility  $U_t(c_t, \dots, c_T)$  of a consumption stream  $(c_t, c_{t+1}, \dots, c_T)$  is given by the sum of discounted utilities of consumption at each period  $k$ , from the present period  $t$  up to  $T$ . The discount function  $D(k)$  is a decreasing function of  $k$ , representing the individual's time preference. It is typically modeled as:

$$U_t(c_t, \dots, c_T) = \sum_{k=0}^{T-t} D(k)u(c_{t+k}), \quad (4.1)$$

where

$$D(k) = \left( \frac{1}{1 + \rho} \right)^k. \quad (4.2)$$

While  $\rho$  represents the discount rate,  $k$  denotes the time delay from the present.

Despite the theoretical appeal and widespread use of the exponential discounting model, empirical studies have repeatedly shown that individuals do not discount future rewards at a constant rate, and their preferences are not time consistent (Thaler, 1981). As detailed in the review by Frederick et al. (2002), these empirical findings have given rise to numerous concepts and theories to investigate and model time preference. For example, the hyperbolic discounting model was introduced as an alternative by showing how discount rates decrease over time and why individuals strongly prefer immediate rewards over delayed ones (Ainslie, 1975). Later, by combining the features of the hyperbolic and exponential discounting models, the quasi-hyperbolic discounting model was introduced by Laibson (1997). This model uses two parameters to effectively account for present bias and long-term outcomes, better explaining why individuals often overvalue immediate rewards and fail to stick to long-term plans.

While traditional models provide a foundational framework for understanding intertemporal decision-making, they often overlook the complexities involved in trade-offs. The emergence of models that integrate psychological and behavioral factors underscores the need for further research into the broader range of human evaluation and decision-making processes (Sun & Abbas, 2025). In particular, the study of time preference should be expanded to encompass more complex problems that involve multiple objectives and alternatives. From this perspective, this study extends the context of time preference by examining it within a multi-attribute decision-making framework. Given the recognized importance of behavioral considerations in MADM (Sun et al., 2025; Wallenius et al., 2008; Montibeller & von Winterfeldt, 2015; Korhonen et al., 1992; Montibeller & von Winterfeldt, 2024), investigating time discounting is essential not only for understanding how individuals make complex decisions but also for developing strategies to support these evaluations.

#### 4.2.2 Multi-attribute decision-making (MADM)

Multi-attribute decision-making (MADM) refers to evaluating several alternatives, each characterized by multiple, often conflicting attributes representing the objectives. MADM methods

assist decision-makers and facilitators in structuring and solving complex problems for various purposes, such as ranking, selecting, or sorting, depending on the primary goal of the problem (Phillips, 2025). Among these methods, Multi-Attribute Value Theory (MAVT) stands out due to its strong theoretical foundation in value theory (Keeney & Raiffa, 1975). MAVT relies on a value function to combine evaluations across attributes into a single overall score. While both additive and non-additive forms can be used, the additive value function is applied more frequently (Smith & Dyer, 2021). The MAVT procedure is outlined below, as presented by Keeney & Raiffa (1975):

Let  $\mathbf{x} = (x_1, \dots, x_n)$  denote a multi-attribute alternative with  $n$  attributes  $X_1, \dots, X_n$ . A normalized additive value function has the form

$$v(x_1, \dots, x_n) = \sum_{i=1}^n \lambda_i v_i(x_i), \quad \sum_{i=1}^n \lambda_i = 1. \quad (4.3)$$

where  $v_i(x_i)$  is an attribute-specific value function for  $X_i$ . If we let  $\bar{x}_i$  and  $\underline{x}_i$  denote the best and worst levels for attribute  $X_i$ , then  $\underline{x}_i = 0$ , and  $\bar{x}_i = 1$  and the scaling constants (weights)  $\lambda_i$  are scaled to be between 0 and 1.

The additive value function is applicable when the attributes are (i) mutually preferentially independent and (ii) difference independent (Keeney & Raiffa, 1975; Currim & Sarin, 1984; Smith & Dyer, 2021).

Although various methods exist for eliciting value functions and identifying scaling constants, we focus on the mid-value splitting technique and trade-off procedure as outlined by Keeney & Raiffa (1975) while maintaining generalizability for other approaches. The mid-value splitting technique constructs value functions by iteratively identifying midpoints representing equal trade-offs, ensuring the function accurately reflects the decision maker's preferences. The trade-off procedure quantifies the willingness to sacrifice one attribute to improve another, determining scaling constants for a weighted value function. We outline the assessment procedures for these techniques using a problem characterized by two monotonically increasing attributes,  $X$  and  $Y$ , consistent with our experimental setup. However, the following definitions are readily generalizable to scenarios with  $n \geq 3$  attributes. For further detail, see Keeney & Raiffa (1975).

**Definition 1.** For any interval  $[x_a, x_b]$  of  $X$ , the *mid-value point*  $x_c$  is defined as the point where the willingness to go from  $x_a$  to  $x_c$  is the same as the willingness to go from  $x_c$  to  $x_b$ , making the pairs  $(x_a, x_c)$  and  $(x_c, x_b)$  differentially value-equivalent.

Assume the range of  $X$  is  $x_0 \leq x \leq x_1$ , and the range of  $Y$  is  $y_0 \leq y \leq y_1$ , and that the corresponding trade-off condition holds. We aim to find a value function  $v$  expressed as:

$$v(x, y) = \lambda_1 v_x^*(x) + \lambda_2 v_y^*(y), \quad (4.4)$$

where:

$$v_x^*(x_0) = 0 \text{ and } v_x^*(x_1) = 1 \quad (4.5)$$

$$v_y^*(y_0) = 0 \text{ and } v_y^*(y_1) = 1 \quad (4.6)$$

$$\lambda_1 > 0, \quad \lambda_2 > 0, \quad \text{and} \quad \lambda_1 + \lambda_2 = 1 \quad (4.7)$$

The mid-value-splitting procedure is carried out as follows:

1. Determine  $v_x^*$  as follows: (i) Identify the mid-value point of  $[x_0, x_1]$ ; call it  $x_{0.5}$  and set  $v_x^*(x_{0.5}) = 0.5$ . (ii) Identify the mid-value point  $x_{0.75}$  of  $[x_{0.5}, x_1]$  and set  $v_x^*(x_{0.75}) = 0.75$ . (iii) Identify the mid-value point  $x_{0.25}$  of  $[x_0, x_{0.5}]$  and set  $v_x^*(x_{0.25}) = 0.25$ . (iv) As a consistency check, ensure that  $x_{0.5}$  is the mid-value point of  $[x_{0.25}, x_{0.75}]$ ; if not, adjust the entries for consistency. (v) Construct the  $v_x^*$  curve through points  $(x_k, k)$  for  $k = 0, 0.25, 0.5, 0.75, 1$  and possibly additional points obtained by a mid-value splitting technique.
2. Repeat the same process for  $v_y^*$ .
3. Determine the scale factors  $\lambda_1$  and  $\lambda_2$ : Identify any two  $(x, y)$  pairs that are indifferent, say  $(x', y')$  and  $(x'', y'')$ . Then we have:

$$v(x', y') = v(x'', y''), \quad (4.8)$$

or

$$\lambda_1 v_x^*(x') + \lambda_2 v_y^*(y') = \lambda_1 v_x^*(x'') + \lambda_2 v_y^*(y''), \quad (4.9)$$

Given that  $v_x^*(x')$ ,  $v_y^*(y')$ ,  $v_x^*(x'')$ , and  $v_y^*(y'')$  are known values and  $\lambda_1 + \lambda_2 = 1$ , we can solve for  $\lambda_1$  and  $\lambda_2$ . This procedure ensures a consistent and comparable construction of the value functions across attributes while revealing scaling constants systematically.

### 4.3 Intertemporal MADM and hypotheses development

In this section, we begin by defining the intertemporal MADM problem and discussing the key trade-offs it entails. We then introduce four hypotheses designed to examine time preferences in this context.

#### 4.3.1 Intertemporal MADM problem

Time preference literature predominantly focuses on trade-offs between alternatives occurring at different points in time (Frederick et al., 2002). In most studies, decision-makers are asked to identify the options they believe will yield the greatest subjective value in the given situations. In this section, we revisit the widely used approach to studying time preference, examining it from a new perspective that emphasizes the number of objectives involved and the nature of the trade-offs made. We then extend the discussion to the intertemporal multiple-objective context.

Although it is not deliberately mentioned, trade-offs in most time preference studies are confined to a single objective, like minimizing cost or maximizing income. They are generally performed between the present and another time point in the future. For instance, in the well-known example of receiving €100 immediately or €120 next year, there is a single objective (maximizing the income), two distinct time points (now and the next year), and two alternatives

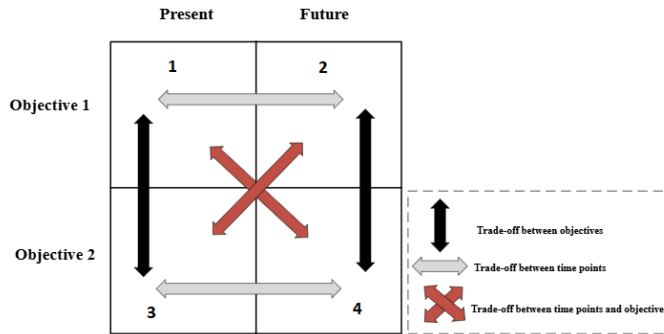


Figure 4.1: Intertemporal trade-offs for single and multi-attribute problems

(€100 and €120). A decision-maker is expected to compare the value of these monetary outcomes depending on their resolution time and choose one that they believe will maximize their wealth. In this case, the trade-off is unidimensional, as illustrated by gray horizontal arrows in Figure 4.1.

On the other hand, MADM problems require trade-offs between multiple conflicting objectives. Suppose that there is a problem with two objectives named Objective 1 and Objective 2. In this case, the decision-maker performs trade-offs between these conflicting objectives, as illustrated by the black vertical arrows in Figure 4.1. Most MADM studies in the literature address these trade-offs without incorporating specific time considerations. In other words, objective trade-offs are consistently made for a single point in time, either focused on the present or the future, and in most studies, no particular time factor is incorporated.

In real life, MADM problems are often intertemporal, where some objectives have immediate consequences while others unfold in the future. Consider a cancer patient deciding on a new treatment. This decision involves balancing the immediate treatment burden with the long-term quality of life. In our representative figure, minimizing the immediate treatment burden (Box 1) and maximizing long-term quality of life (Box 4) require trade-offs across different time points. This trade-off is illustrated by the red crossed arrow in Figure 4.1. As shown, it is neither purely single-objective, as in the time preference literature, nor solely confined to a single time point, as in standard MADM problems. Instead, this scenario requires simultaneous consideration of both objective and time trade-offs. In other words, the intertemporal MADM problem should model time preference and attribute trade-offs together. From this perspective, any MADM problem represented with  $n$  objectives ( $n \geq 2$ ) can be classified into one of the following cases: (i) All  $n$  objectives have outcomes realized in the present time (Case 1), (ii) Among the  $n$  objectives,  $n_1$  objectives have outcomes realized in the present time and  $n_2$  objectives have outcomes realized in the future, while  $n = n_1 + n_2$  (Case 2) and (iii) All  $n$  objectives have outcomes realized in the future (Case 3).

This intertemporal context introduces several layers of complexity. First, the trade-offs become multi-dimensional, challenging the static nature of traditional MADM evaluations. The already complex interactions between conflicting objectives are further complicated by time-related considerations and uncertainty about the future. Among the cases mentioned above, Case 2 stands out as the most complex one since it requires intertemporal trade-offs between

multiple time points in addition to objective trade-offs. Second, the dynamic nature of decision-makers' preferences over time makes establishing representative relationships between time points difficult. Third, decision-makers' sensitivity to particular attributes or time frames can trigger intricate relationships that require careful evaluation.

These factors highlight the uniqueness of the intertemporal MADM environment and emphasize the need for empirical research to uncover hidden relationships, capture multi-dimensional trade-offs, and improve decision-making frameworks by accounting for behavioral aspects. In the next section, we propose hypotheses to study the time preference phenomenon in this intertemporal MADM context and address some of the complex relationships.

### 4.3.2 Hypotheses development

Time discounting can be modeled using exponential (Samuelson, 1937), hyperbolic (Ainslie, 1975), quasi-hyperbolic (Laibson, 1997), or less common functions such as power-law (Huang & Wu, 2007) and growth rate maximization (Adamou et al., 2021). Despite the diversity of functional forms, there is a broad consensus that delayed outcomes are systematically devalued over time. Let us now extend this concept into the intertemporal MADM context.

Let  $\mathbf{x} = (x_1, x_2)$  represent an alternative, where  $X_1$  and  $X_2$  are two attributes of the decision. An additive value function can be defined to evaluate the alternative  $\mathbf{x}$  based on these attributes:

$$v(x_1, x_2) = \lambda_1 v_1(x_1) + \lambda_2 v_2(x_2) \quad (4.10)$$

where  $v_1(x_1)$  and  $v_2(x_2)$  are the value functions for attributes  $X_1$  and  $X_2$ , and  $\lambda_1$  and  $\lambda_2$  are positive scaling constants reflecting their relative importance, with  $\lambda_1 + \lambda_2 = 1$ .

Thus, the value of an alternative  $\mathbf{x}$  relies on two components: <sup>1</sup> Attribute-specific values  $v_i(x_i)$  and scaling constants  $\lambda_i$ . Given the vast literature on time discounting, delaying the outcomes of an attribute in an MADM problem can also lead to a similar devaluation behavior. When a single attribute is delayed, its contribution to the overall evaluation of an alternative, often referred to as the aggregated alternative value, is likely to be discounted. Delay asymmetry is a significant concept playing a role in this relative valuation (Laibson, 1997; Loewenstein & Thaler, 1989; O'Donoghue & Rabin, 1999). It occurs when one option is available immediately and the other becomes available only after a delay, or when two outcomes differ in timing. This uneven timing often leads to distortions in the perceived values of outcomes since it puts individuals in a "comparison mode" where they generally favor immediacy. In alignment with this, we argue that time preference can modify how outcomes emerging at different times are valued, leading decision-makers to overvalue attributes based on immediate needs over long-term goals. Building on the discounting concept from the time preference literature, a similar discounting is assumed to exist between immediate and delayed attribute values in an intertemporal MADM context. Based on these arguments, we propose testing the following hypothesis:

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<sup>1</sup>Attribute-specific value refers to a value derived from an attribute-specific value function, which transforms the performances into a normalized value considering the decision-maker's preferences. The term "attribute value" represents the contribution of each one to the additive value function either in the form  $v_i(x_i)$  or in its normalized form  $\lambda_i v_i(x_i)$ .

**Hypothesis 1.** *The delay of a single attribute in a multi-attribute decision-making context results in a decrease in the value of that attribute.*

Many problems involve attributes that are resolved simultaneously at a future point (Case 3). Figure 4.1 shows these relationships with the black arrow on the left representing the trade-off between attributes at the present. When all outcomes are delayed, the same trade-off is shifted to a future time point, preserving its structure while reflecting the postponed time frame. In such cases, the delay asymmetry phenomenon is not relevant, and decision-makers are not in a “comparison mode” since the timings of attributes are identical. In other words, the same trade-offs are made either for the present or for a future time point. Since none of the attributes has the dominant power of immediacy or advantage of early reveal, none should be perceived differently when they are deferred. The relative evaluation should have the same structure as it would in the present. This is likely to result in a balanced evaluation where temporal discounting does not alter the perceived values. We test this with the following hypothesis:

**Hypothesis 2.** *The equal delay of all attributes in a multi-attribute decision-making context results in no change in the values of those attributes.*

A deeper analysis of the components comprising attribute values can provide further insight into the hypothesized discounting behavior. Scaling constants arise from objective trade-offs, where decision-makers provide indifference pairs that are evaluated using attribute-specific value functions. So, scaling constants depend on (i) changes in indifference pairs, (ii) changes in attribute-specific value functions, or (iii) changes in both. Thus, any variation in these two is likely to cause a change in scaling constants. The following proposition illustrates how these changes affect a MADM problem with two monotonically decreasing attributes,  $X_1$  and  $X_2$ , under the additivity assumption.

**Proposition 1** *Let  $X_1$  and  $X_2$  be two attributes with respective value functions  $v_1(x_1)$  and  $v_2(x_2)$ , and scaling constants  $\lambda_1, \lambda_2$  where  $\lambda_1 > \lambda_2$ . Assume that the pair  $(\bar{x}_1, \bar{x}_2)$  is initially considered indifferent to  $(x_{1*}, \bar{x}_2)$ , where  $x_{1*}$  represents the given trade-off score. Then any change in value function  $v_1(x_1)$  or the trade-off score  $x_{1*}$  will lead to changes in the scaling constants  $\lambda_1$  and  $\lambda_2$ .*

**Proof:** The condition of indifference between the pairs  $(\bar{x}_1, \bar{x}_2)$  and  $(x_{1*}, \bar{x}_2)$  implies that the overall value derived from both pairs must be equivalent as explained in Equation 4.9. Thus, the indifference relationship can be formulated as:

$$\lambda_1 v_1(\bar{x}_1) + \lambda_2 v_2(\bar{x}_2) = \lambda_1 v_1(x_{1*}) + \lambda_2 v_2(\bar{x}_2) \quad (4.11)$$

Given the normalization conditions  $v_1(\bar{x}_1) = 1$ ,  $v_2(x_{1*}) = 0$ , and  $v_2(\bar{x}_2) = 1$ , the equation simplifies to:

$$\lambda_1 = \lambda_1 v_1(x_{1*}) + \lambda_2 \quad (4.12)$$

Isolating  $\lambda_2$  and applying the constraint  $\lambda_1 + \lambda_2 = 1$  results in:

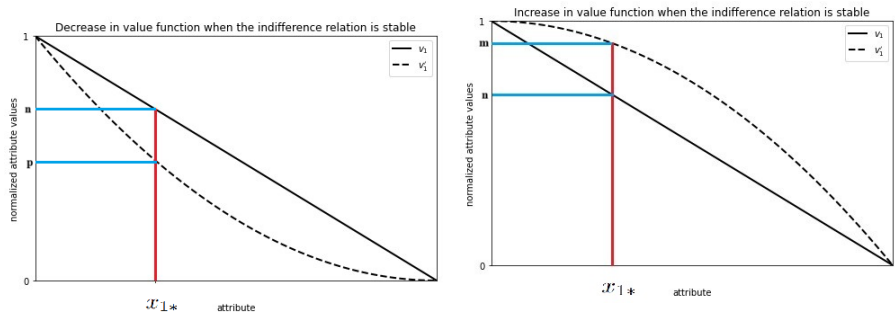
$$\lambda_1 = \frac{1}{2 - v_1(x_{1*})} \quad (4.13)$$

Equation 4.13 confirms that any change in the value of the attribute  $X_1$  will impact the scaling constants  $\lambda_1$  and  $\lambda_2$ . If  $v_1(x_{1*})$  increases, the denominator  $2 - v_1(x_{1*})$  becomes smaller, resulting in a larger value of the fraction that defines  $\lambda_1$ . Conversely, if  $v_1(x_{1*})$  decreases, the denominator becomes larger, leading to a smaller  $\lambda_1$ .  $\square$

To illustrate how such changes affect the scaling constants, we consider two cases: (i) modifications in attribute-specific value functions and (ii) changes in indifference pairs, with the corresponding propositions and proofs provided in the following.

**Case 1: When the value function changes but the trade-off relation remains stable:**

Assume that the attribute-specific value function changes because of time preference, while all other factors, including the assigned trade-off scores, remain stable. If the shape of the value function changes downward (for example, from linear to convex), as exaggeratedly illustrated in Figure 4.2a, the value for the same attribute level ( $v_1(x_{1*})$ ) decreases ( $p < n$  in Figure 4.2a). According to Equation 4.13, this results in a reduced scaling constant assigned to the same attribute. Conversely, we anticipate an increase in the attribute's scaling constant if the shape of the value function changes upward (for example, from linear to concave), as illustrated in Figure 4.2b. This new shape maps the same attribute level to a higher value ( $n < m$  in Figure 4.2b), resulting in an increased scaling constant. More critically, the value function's shape does not need to undergo significant changes to result in an alteration in the mapped values. Even if the overall shape remains consistent, adjustments to its parameters, such as steeper concavity or greater convexity, can produce different outcomes for the same scores, leading to variations in the scaling constants.



(a) Change in value function from linear to convex

(b) Change in value function from linear to concave

Figure 4.2: Changes in value function when the indifference relation is stable

**Proposition 2** Let  $X_1$  and  $X_2$  be two attributes with respective value functions  $v_1(x_1)$  and  $v_2(x_2)$ , and scaling constants  $\lambda_1, \lambda_2$  where  $\lambda_1 > \lambda_2$ . Then, modifying the value function  $v_1(x_1)$  to  $v'_1(x_1)$  such that  $v'_1(x_1) \not\equiv v_1(x_1)$  will lead to changes in the scaling constants  $\lambda_1$  and  $\lambda_2$ .

**Proof:** Suppose that  $v'_1(x_1) < v_1(x_1)$  for  $x_1$  values between  $\underline{x}_1$  and  $\bar{x}_1$ . Since  $v'_1(x_{1*})$  is less than  $v_1(x_{1*})$ ,  $2 - v'_1(x_{1*})$  becomes larger than  $2 - v_1(x_{1*})$  in Equation 4.13. This results in a decrease in the  $\lambda_1$  and an increase in the  $\lambda_2$ . Conversely, if  $v'_1(x_1) > v_1(x_1)$  for  $x_1$  values

between  $\underline{x}_1$  and  $\bar{x}_1$ ,  $2 - v'_1(x_{1*})$  gets smaller, resulting in an increase in  $\lambda_1$  and a decrease in  $\lambda_2$ .  $\square$

A reduction in  $v_1(x_1)$  decreases the sensitivity to changes in  $x_1$ , which in turn increases the relative importance of  $x_2$  within the decision model. Consequently, the overall value of alternatives favoring  $x_1$  declines, while those favoring  $x_2$  are likely to increase. Conversely, an increase in  $v_1(x_1)$  heightens sensitivity to  $x_1$ , diminishing the relative influence of  $x_2$ . This shift generally raises the aggregated value of alternatives favoring  $x_1$  and lowers that of alternatives favoring  $x_2$ . These effects illustrate how variations in  $v_1(x_1)$  directly impact the scaling constants, ultimately influencing the aggregated values of alternatives and final decisions.

**Case 2: When the value function remains stable but the trade-off relation changes:**

Trade-off relations between attributes may vary even if their value functions remain stable. For instance, an impatient decision-maker may be more willing to trade an attribute if its benefits are delayed. When the provided trade-off score increases, leading to a lower evaluation due to the value function, the scaling constant of the affected attribute is expected to decrease accordingly. Conversely, a decrease in the trade-off score, leading to a higher evaluation for the attribute, will likely increase its scaling constant. This adjustment reflects a greater importance assigned to the attribute, thereby strengthening its influence on the aggregated decision outcome.

**Proposition 3** *Let  $X_1$  and  $X_2$  be two attributes with respective value functions  $v_1(x_1)$  and  $v_2(x_2)$ , and associated scaling constants  $\lambda_1$  and  $\lambda_2$ , where  $\lambda_1 > \lambda_2$ . Suppose the value function  $v_1(x_1)$  remains stable. Then, a change in the trade-off score  $x_{1*}$  leads to a change in both  $\lambda_1$  and  $\lambda_2$ , despite the stability of  $v_1(x_1)$ .*

**Proof:** Since  $v_1(x_1)$  is assumed to be monotonically decreasing, a lower trade-off score  $x_{1*}$  results in a higher value  $v_1(x_{1*})$ . This reduces the denominator  $2 - v_1(x_{1*})$ , thereby increasing  $\lambda_1$  in Equation 4.13. Given the normalization condition  $\lambda_1 + \lambda_2 = 1$ , an increase in  $\lambda_1$  necessitates a decrease in  $\lambda_2$ . Conversely, a higher trade-off score  $x_{1*}$  decreases  $v_1(x_{1*})$  and increases the denominator  $2 - v_1(x_{1*})$ . This results in a lower  $\lambda_1$ , with a corresponding increase in  $\lambda_2$ .  $\square$

Simultaneous changes in both the value functions and the trade-off relations are also possible. In this scenario, the scaling constants may follow one of the patterns outlined in Propositions 1 and 2, depending on the magnitudes of the changes. Alternatively, if the changes occur in opposite directions, the scaling constants may also remain stable.

These propositions demonstrate that scaling constants in intertemporal MADM are sensitive to contextual changes. Whether driven by shifts in value functions, changes in trade-off scores, or both, such alterations can affect the constants. Accordingly, changing an outcome's timing from immediate to delayed is likely to reduce its perceived value. Drawing on findings from single-objective problems and the demonstrated link between value changes and scaling constants, we anticipate a decrease in the scaling constant of a delayed attribute in an MADM problem. By extending the experimental setting to an intertemporal MADM problem, we want to test the following hypothesis:

**Hypothesis 3.** *In a multi-attribute decision-making context, delaying the outcome of an attribute leads to a reduction in its scaling constant.*

When all attribute outcomes are equally delayed (Case 3), the trade-off between them shifts to a common future point. Unlike cases where only some attributes are delayed, a uniform delay eliminates asymmetry (Laibson, 1997; Loewenstein & Thaler, 1989; O'Donoghue & Rabin, 1999). Because all attributes occur simultaneously, their relative valuation is unaffected by timing, and the scaling constants should remain unchanged. We formally state this hypothesis as follows:

**Hypothesis 4.** *In a multi-attribute decision-making context, delaying the outcomes of all relevant attributes equally does not lead to a significant change in their scaling constants compared to when all outcomes are immediate.*

We now test these hypotheses through three experiments involving an MADM problem with two monotonically decreasing attributes. Although we focus on this case, the framework generalizes to problems with more than two attributes, monotonically increasing attributes, and mixed increasing–decreasing functions.

## 4.4 Experimental studies

We conducted three experiments, with Studies 1 and 2 testing Hypotheses 1 and 3, and Study 3 focusing on Hypotheses 2 and 4. Each experiment included a “base case”, where all attributes were immediately available (Case 1, as explained in Section 4.3.1), and a “time-related case” where one or two attribute outcomes were delayed, depending on the tested hypothesis (Cases 2 and 3). To strengthen the experimental manipulation and control for carryover and learning effects (Charness et al., 2012), we inserted an unrelated discounting task between cases. This aimed to prevent participants from directly comparing treatments or guessing the study’s purpose, while also enhancing psychological separation between conditions (Tourangeau et al., 1989). The two scenarios were presented in counterbalanced order, with the discounting task always placed between them. The tasks followed by each participant are summarized in Figure 4.3.

The experiments were designed using Qualtrics, a customizable online survey platform for creating, distributing, and analyzing surveys (Boas et al., 2020; Barnhoorn et al., 2014). Each participant first completed the preferential independence checks. Then they responded to mid-value-splitting questions to determine the 0.25, 0.5, and 0.75 points of their value functions, and to trade-off questions to elicit indifference pairs and derive scaling constants. To ensure the reliability and validity of the experimental tasks, we adopted the Three-Step Test Interview (TSTI) framework. This qualitative cognitive interviewing technique helped us to pretest our questionnaire and identify potential misunderstandings, errors, or difficulties participants may encounter (Hak et al., 2004). The experiment was launched once saturation was reached after interviewing six subjects, and no further clarifications were needed.

Participants completed all tasks consecutively, without breaks or a time limit. The option to revisit previous questions was disabled in all stages. By having each individual complete both scenarios in a within-subject design, we could test whether a delay affected elicited scaling constants and value functions. Finally, participants provided demographic information and completed a well-being test. Since the experimental scenario addressed a health-related problem, we adopted the EQ-5D-3L, a self-reported questionnaire developed by the EuroQol Group

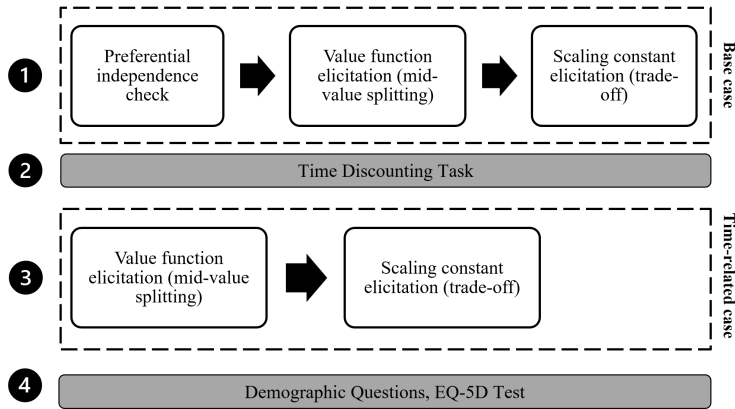


Figure 4.3: Experimental tasks followed by each participant

and widely used as a generic measure of well-being (The EuroQol Group, 1990; Janssen et al., 2013). Incorporating this instrument allowed us to control for the potential effects of participants' current health status on their stated preferences.

#### 4.4.1 Decision scenario

Our experimental problem asked participants to assess different magnetic resonance imaging (MRI) alternatives with respect to two key attributes: cost and screening duration. The questions were structured based on the principles of MAVT. In the base case scenario, the problem is described to participants as follows:

“Imagine you’ve been feeling tired and dizzy, with disrupted sleep and brain fog for a few weeks. After consulting a doctor and undergoing several tests, a conclusive full-body Magnetic Resonance Imaging (MRI) is recommended to finalize your diagnosis and decide on a treatment plan. An MRI is a safe, non-invasive imaging test using magnetic fields and radio waves to capture detailed images of the body’s internal structures. Although painless, the MRI can be uncomfortable as it requires wearing a hospital gown, staying awake, and remaining perfectly still inside a tunnel-like, tight, noisy device throughout the procedure. Screening duration varies from 15 minutes to 90 minutes, depending on machine type, and the cost for an MRI screening ranges from 197 to 706 Euros, which is not covered by insurance and must be paid out-of-pocket. The hospital provides three MRI options (A, B, and C), each varying in screening duration and cost. All other aspects of these options are identical. The details are outlined in Table 4.1. Once you have chosen, you can pay and start the screening process immediately.”

While the base case was consistent across all three studies, the time-related case introduced a 4-week delay to one or both attributes. In Study 1, the time-related case ended with: “The

Table 4.1: Attributes and MRI alternatives for the base case

Alternatives	Cost (€)	Payment time	Screening duration (min.)	Screening starting time
A	627	immediately	20	immediately
B	434	immediately	50	immediately
C	283	immediately	80	immediately

screening process can start immediately, but the payment should be sent 4 weeks after the procedure because of the hospital’s payment policy”, accompanied by a table similar to Table 4.1, except the payment time column indicated “4 weeks later” instead of “immediately”. In Study 2, the screening start was delayed, with the statement: “In order to have a screening appointment, you must pay immediately after choosing. However, due to the long waiting list for MRI procedures at the hospital, your screening will be done after four weeks.” Study 3 combined both delays: “There is a long waiting list for MRI procedures at the hospital. Therefore, your screening will be done after four weeks. Similarly, the payment should be done after 4 weeks.” Correspondingly, participants saw a table where both the payment time and screening start time columns read “4 weeks later”.

#### 4.4.2 Participants

The total sample for this research comprises 279 participants, with each study including a different number of subjects. The demographic characteristics of the participant pool across the studies are presented in Table 4.2 with further details provided in the following subsections. To ensure adequate statistical power, a power analysis was conducted using G\*Power 3.1 (Faul et al., 2007). Of the total sample, 57 participants (20.43%) are students and employees from Delft University of Technology who voluntarily participated without incentives, while the remaining 79.57% were recruited via Prolific, an online data collection platform, and received an average payment of £2 for their participation.

Table 4.2: Demographic characteristics of study participants (n=279)

Characteristics	Levels	N (%)
Education	High school	50 (17.9%)
	Bachelor’s	138 (49.5%)
	Master’s	80 (28.7%)
	PhD	11 (3.9%)
Age	18-22	39 (14%)
	23-28	130 (46.6%)
	29-34	56 (20.1%)
	35-40	38 (13.6%)
	41+	16 (5.7%)
Gender	Female	124 (44.5%)
	Male	148 (53%)
	Non-binary	7 (2.5%)

Eligibility criteria required participants to be at least 18 years old, reside in one of the following European countries: Germany, the Netherlands, Denmark, France, Belgium, or Luxembourg, and provide informed consent at the beginning of the study. These residency restrictions were implemented to control for potential confounding factors related to currency differences, as all decision scenarios involved trade-offs with monetary outcomes in euros (€) (Wang et al., 2016; Falk et al., 2018). Participants were excluded if they: (i) Provided random values outside the given attribute range in the mid-value splitting task, (ii) Typed the given attribute range instead of inputting their own mid-values, (iii) Assigned nearly identical mid-values for different levels, or (iv) Completed the study in under 5 minutes, significantly below the 20-minute average. The same eligibility criteria applied to all three studies.

## 4.5 Results and discussion

This chapter presents the results of three experiments and discusses their main findings and implications.

### 4.5.1 Results of Study 1: Single attribute delay (cost)

A total of 154 participants took part in the experiment. Following the data exclusion criteria detailed in the previous section, 6 people were excluded for entering random mid-value scores, 15 for inputting attribute ranges, 17 for providing narrow score ranges, and 2 for completing the experiment in under 5 minutes. After these exclusions, the final analysis included data from 108 participants. Of these, 20 participants (18.5% of the total sample) were students and employees from Delft University of Technology, while the remaining 81.5% were recruited via Prolific. All participants completed the base case, the discounting task, and the “delayed payment” scenario, where the resolution time of the cost attribute was manipulated. Participants’ responses to mid-value splitting questions were used to elicit attribute-specific value functions. The resulting trade-off scores, combined with these functions, were then used to calculate scaling constants. The same steps were followed for both the base case and the delayed payment case.

#### Test of Hypothesis 1

To test Hypothesis 1, we first compared the values of the cost attribute in the base case and the delayed payment case for all three alternatives. A paired-sample  $t$ -test shows that the mean value for the cost attribute in the base case ( $M = 0.266$ ,  $SD = 0.198$ ) is significantly higher than in the delayed payment case ( $M = 0.230$ ,  $SD = 0.176$ ),  $t(323) = 4.68$ ,  $p < 0.001$ . In contrast, for the screening duration attribute the mean value in the base case ( $M = 0.181$ ,  $SD = 0.162$ ) is significantly lower than in the delayed payment case ( $M = 0.204$ ,  $SD = 0.181$ ),  $t(323) = -3.831$ ,  $p < 0.001$ . These results suggest that participants assigned higher values to the same cost levels when payment was immediate and discounted these values when it was delayed. Conversely, the value of the screening duration was perceived as lower in the base case compared to the delayed payment case.

Given the observed discounting behavior for the delayed attribute, we then applied data fitting using three widely studied time discounting functions: exponential discounting (Samuelson, 1937), hyperbolic discounting (Ainslie, 1975), and power-law discounting (Stevens, 1957; Huang & Wu, 2007; Doyle, 2013). This was done to further examine the relationship between the immediate and delayed attribute values. In the exponential discounting model, the relationship between present values ( $y$ ) and delayed values ( $x$ ) is modeled using the discount rate ( $k$ ), time delay ( $t$ ), and Euler's number ( $e$ ) to ensure the continuous nature of discounting over time (Hardisty et al., 2013). The estimated parameter  $k$  determines how quickly future values are devalued. In the hyperbolic discounting model, the relationship between immediate and delayed values is captured using a rational function to reflect decreasing sensitivity to time over longer delays. This model also estimates the discount rate ( $k$ ). The third model, the power-law discounting, is similar to Stevens' power-law function (Stevens, 1957). It does not include time delay as an explicit parameter and models the relationship between present and delayed values independently of particular time units. The constant ( $a$ ) adjusts the magnitude of the function, reflecting a baseline valuation. The discounting parameter ( $b$ ), analogous to the discount rate ( $k$ ) in the other models, plays a central role. For this parameter, three cases are relevant: when  $0 < b < 1$ , the future is strongly discounted; when  $b = 1$ , there is no discounting and the value relationship is linear; and when  $b > 1$ , future outcomes are overvalued.

The goodness of fit for each model was evaluated using several performance metrics: Adjusted  $R^2$  (variance explained, adjusted for model complexity), RMSE and MSE (average prediction error), MAE (average absolute error), and AIC and BIC (fit measures penalizing complexity) (Cheung & Rensvold, 2002; Schermelleh-Engel et al., 2003). The results are summarized in Table 4.3. As exponential and hyperbolic discounting produced nearly identical outcomes, only one is reported.

Table 4.3: Goodness of fit for each candidate function in Study 1 for  $t = \frac{1}{12}$

Function	Adjusted $R^2$	RMSE	MSE	MAE	AIC	BIC	Estimated parameters
Exponential discounting $y = x \cdot e^{-k \cdot t}$	0.463	0.145	0.021	0.099	-1250.154	-1246.373	$k = 0.357$
Power-law discounting $y = a \cdot x^b$	0.526	0.136	0.019	0.102	-1288.296	-1280.735	$a = 0.765, b = 0.673$

The exponential and hyperbolic discounting models performed almost identically across all metrics, likely because the delay between immediate and deferred rewards in this experiment was short. With only two time points, discounting progresses gradually, so both models yield nearly the same predictions of participants' perceptions of delay (Hardisty et al., 2013). In our analysis, each model achieved an adjusted  $R^2$  of 0.463, RMSE of 0.145, MSE of 0.021, and MAE of 0.099. The estimated  $k$  values were 0.357 (exponential) and 0.352 (hyperbolic), corresponding to devaluation rates of 35.7% and 35.2%, respectively. These results suggest a clear, though not extreme, preference for immediate outcomes.

While exponential and hyperbolic discounting models fit the data similarly, the power-law function outperforms both. It provides the best overall fit, with an adjusted  $R^2$  of 0.526, RMSE of 0.136, and MSE of 0.019. The MAE is slightly higher at 0.102. Although the model captures about 50% of decision-making behavior, some discrepancy remains between predicted and observed values. The estimated scaling constant ( $a$ ) is 0.765, and the discounting parameter ( $b$ ) is 0.673, reflecting strong diminishing sensitivity toward delayed outcomes. Overall, these results

support the hypothesis that delaying a single attribute reduces its value, with the power-law model providing the most accurate representation of this discounting.

### Test of Hypothesis 3

After characterizing the discounting behavior of the delayed attribute, we conducted a more detailed analysis of the scaling constants to test Hypothesis 3. As shown in Figure 4.4, delaying the payment reduces the weight assigned to the cost attribute, while correspondingly increasing the weight of the screening duration. A paired-sample  $t$ -test comparing the cost weights revealed a significant difference: the mean weight in the base case was 0.609 ( $SD = 0.174$ ,  $SEM = 0.017$ ), compared to 0.569 ( $SD = 0.182$ ,  $SEM = 0.018$ ) in the delayed payment condition, with a mean difference of 0.039,  $t(107) = 2.502$ ,  $p = 0.014$  (two-tailed).

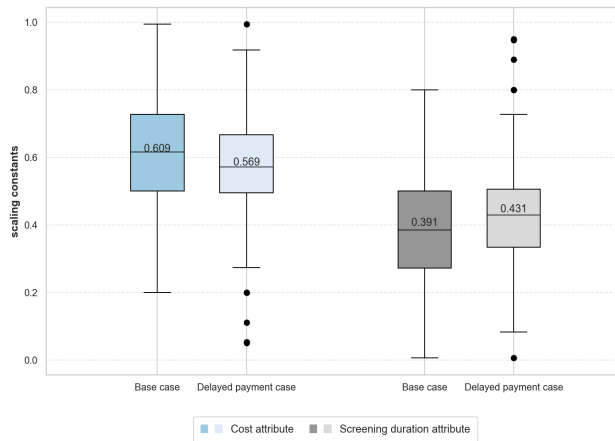


Figure 4.4: Changes in scaling constants when the payment is delayed

Scenario order did not affect participants' scaling constants ( $p = 0.929$ ), nor was there a significant difference between volunteers and paid participants in the base case ( $p = 0.395$ ). Among participants, 18 reported a chronic illness and 12 reported claustrophobia; neither group differed significantly from the rest regarding scaling constants ( $p = 0.372$  and  $p = 0.961$ , respectively). Pearson correlations between well-being scores and base-case scaling constants were very weak and non-significant ( $r = 0.037$ ,  $p = 0.705$ ), indicating no evidence of a linear relationship.

On a within-subject level, 71.3% of the participants report the cost attribute as being more important than the screening duration in both cases. While 19.4% think the screening duration is more important, 9.3% do not consistently report one of the attributes as being more important and change their preferences from one case to another. Furthermore, 51% of participants lower the weight of the cost attribute when it is delayed, and 15% do not change their weights.

We could think of three potential explanations for the observed changes in scaling constants. First, a reduction in the weight of the cost attribute may result from a shift in its value function. Since the trade-off process is influenced by the value function of the more important attribute,

and participants in this study are predominantly cost-sensitive, a decrease in the perceived value of cost levels could account for the observed change. Second, delaying payment may influence the trade-off scores, making decision-makers more willing to trade money for a shorter screening duration. Third, this shift may reflect an increased emphasis on the importance of screening duration rather than a decrease in the weight assigned to the cost attribute. Given that the sum of the weights is equal to one, a decline in the weight of one attribute can be attributed to an increase in the weight of the other attribute. The three potential explanations will be examined one by one in the following.

**Changes in Value Functions:** The average value functions for the cost and screening duration attributes are shown in the left-hand plots of Figure 4.5 and Figure 4.6, respectively. Delaying the payment changes the average value function for both attributes. The areas between the functions are 13.64 and 0.75 for cost and screening duration, respectively. Because these figures represent the overall patterns derived from the full participant sample, we additionally analyzed the changes in value functions at the individual level. First, the slopes of the fitted piecewise value functions were identified and categorized as linear, concave, or convex. The change in shape from one scenario to the other was assessed to identify the influence of time preference. The analyses reveal that out of 108 participants, 63 exhibit changes in the shape of the cost function. Specifically, 37% of the participants change their value functions from concave to linear, concave to convex, or linear to convex when the payment is delayed. For the screening duration attribute, 40 participants changed the shape of their value function, with only 12 aligning with the direction of change illustrated in Figure 4.5 (left side).

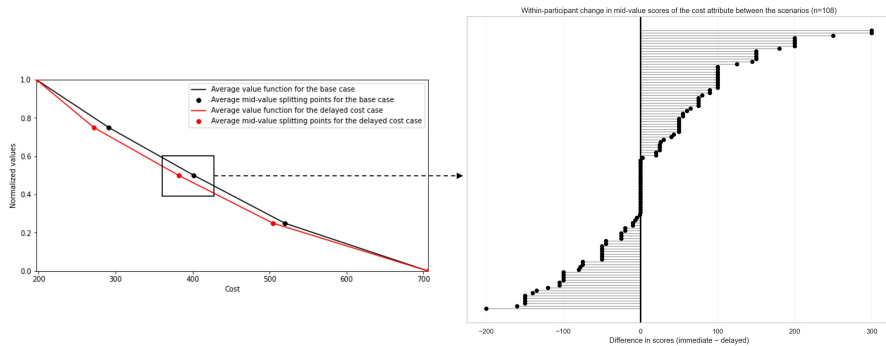


Figure 4.5: Average value functions for the cost attribute (left) and the within-participant differences in mid-value scores at the 0.5 value level (right) in Study 1

Changes in the shape of the value functions can explain how delays affect perceived values to some extent. However, such changes in valuation do not always manifest as a change in the overall functional form. For instance, the value function may remain convex across conditions, yet the degree of curvature or steepness may vary due to differences in time preference. Therefore, we performed another analysis and compared the mid-value splitting scores provided for the 0.5 level during value function elicitation. Since these mid-value scores are used to structure the value functions, and the scores at the 0.25 and 0.75 levels are positioned relative to this value, they could serve as a representative reference point for this analysis. Figure 4.5 (right side) displays the within-participant change in mid-value scores (immediate - delayed) for the

cost attribute. Each dot shows how much a participant's 0.5-value point shifted when costs were delayed rather than immediate. Most participants exhibit positive difference scores, meaning that the score they assigned to the 0.5-value point is higher in the immediate scenario than in the delayed scenario. This indicates that participants generally reduced their mid-value point when the cost was delayed. A smaller number of participants have negative difference scores, meaning they assigned a higher mid-value point in the delayed scenario, and only a subset shows little or no change.

To compare the mid-value scores between the scenarios, we performed both the paired sample  $t$ -test and the Wilcoxon signed-rank test. The results of paired sample  $t$ -test reveals a statistically significant decrease in the mid-value for the cost attribute from the base case condition ( $M = 401.62, SD = 88.94$ ) to the delayed payment condition ( $M = 381.80, SD = 71.99$ ),  $t(107) = 2.12, p = 0.036$ . A one-tailed Wilcoxon signed-rank test provides further support for this decrease in the cost attribute's values from the base case to the delayed payment case ( $Z = -1.881, p = 0.03$ ).

Figure 4.6 (right side) shows within-participant differences in mid-value scores for screening duration attribute (immediate - delayed). Because screening duration itself was not delayed, this distribution reflects whether delaying the cost attribute indirectly influenced how participants evaluated duration.

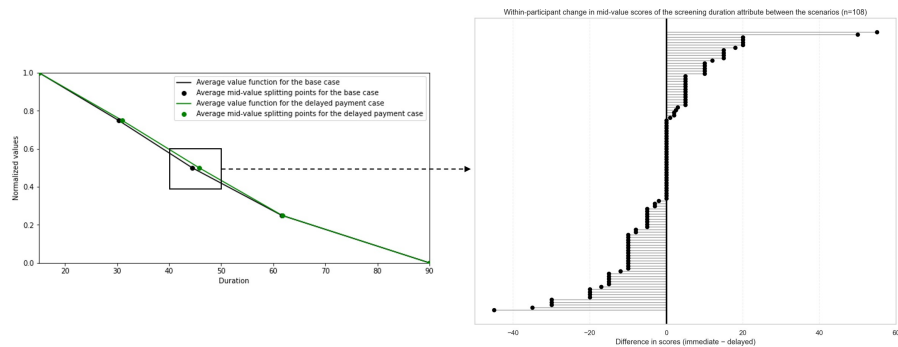


Figure 4.6: Average value functions for the screening duration attribute (left) and the within-participant differences in mid-value scores at the 0.5 value level (right) in Study 1

The pattern is relatively balanced: positive, negative, and near-zero difference scores all appear in substantial numbers. This indicates that delaying the cost attribute produces no consistent directional shift in participants' duration value functions. Many participants show minimal change (scores close to zero), suggesting that their evaluation of duration remains largely stable when the complementary attribute is delayed. Others show small increases or decreases, reflecting individual-level variability.

In alignment with this, there is not statistically significant difference between the mid-values from the base case ( $M = 43.66, SD = 12.00$ ) and the delayed payment case ( $M = 45.16, SD = 12.16$ ),  $t(107) = -1.14, p = 0.256$ . Furthermore, a Wilcoxon signed-rank test results also align with this finding, indicating no difference between cases ( $Z = -1.550, p = 0.121$ ). These results suggest that delaying the payment reduces the mid-values of cost attributes and leads to different value functions. However, the mid-value scores of the screen-

ing duration attribute do not change. These findings support the notion that at least part of the change in weights can be attributed to a shift in the value function of the cost attribute.

**Changes in trade-off scores:** The trade-off procedure requires decision-makers to provide alternative pairs that are equally preferable. Generally, the most important attribute is used at this stage for structuring the questions. In this study, 77 participants reported the cost as the most important attribute in both cases, where 21 chose the screening duration, and the others changed the most important attribute from one case to another. Therefore, the trade-off questions asked of these subjects differed. While cost-sensitive participants were directed to provide a cost score for indifference pairs, the other group received a question that asked for a screening duration value. To see if delaying the payment changes the answers to the trade-off questions, a paired sample *t*-test and a Wilcoxon signed-rank test were performed. The paired sample *t*-test results indicate no significant difference between the cost scores in the base condition ( $M = 389.68, SD = 115.43$ ) and the delayed payment condition ( $M = 400.58, SD = 118.72$ ),  $t(76) = -1.16, p = 0.249$ . This finding is also supported by the Wilcoxon signed-rank test results ( $Z = -1.010, p = 0.313$ ).

For the screening duration attribute, paired sample *t*-test results reveal no significant difference between the base case and the delayed payment case,  $t(20) = -0.39, p = 0.698$ . This finding is further supported by the Wilcoxon signed-rank test ( $Z = -0.411, p = 0.681$ ). These results suggest that the change in scaling constants is less likely to originate from the alteration in trade-off scores. Participants do not change their scores when the delay in payment is introduced, and provide very similar trade-off values in both conditions.

**Influence of the complementary attribute:** Given that the sum of the scaling constants is one, the decrease in the weight of one attribute could be the result of an increase in the complementary set. Although the average value function slightly increases, the value changes in the screening duration attribute are not significant enough to support this explanation. Moreover, the trade-off scores of the 21 participants who think duration is more important than cost do not differ between the two conditions. We must therefore conclude that the decrease in the scaling constant of the cost attribute is not due to an increase in the complementary attribute. Rather, it can be attributed to a shift in how the value of the cost attribute is perceived.

## 4.5.2 Discussion of findings from Study 1

This study provides evidence that postponing the outcomes of a single attribute affects how individuals perceive and prioritize it in MADM. The observed decrease in the value of the cost attribute in the delayed payment condition aligns with standard discounting theories, which propose that individuals perceive future costs as less burdensome than immediate costs (O'Donoghue & Rabin, 1999). Our results show that this discounting effect is best represented by a power-law discounting function, which outperforms exponential and hyperbolic models regarding goodness of fit. This finding supports studies suggesting that power-law discounting better accounts for the way people perceive delayed consequences, particularly in contexts where delay intervals are relatively short (Huang & Wu, 2007; Takahashi, 2006).

Consistent with changes in discounted attribute values, the scaling constants for the cost attribute are significantly lower when payment is delayed than when it is required immediately. Further analysis suggests that this shift in scaling constants primarily stems from changes in the

value function of the cost attribute rather than shifts in trade-off preferences or attention toward the complementary attribute. When payment is delayed, participants exhibit lower sensitivity to cost changes, leading to a lower scaling constant for cost in the decision-making process. These findings align with temporal construal theory (Trope & Liberman, 2003), which posits that temporal distance influences mental representations of future events. When payment is delayed, participants likely adopt high-level construals, perceiving cost more abstractly, which reduces its immediate psychological impact and relative importance. On the other hand, trade-off scores remain stable, suggesting that fundamental cost-duration trade-offs are unaffected by the delay. Similarly, the scaling constant of the screening duration attribute does not significantly increase, indicating that the observed shift is not driven by heightened attention to the complementary attribute.

Unlike traditional time preference studies that primarily compare outcomes based on their timing, this study highlights the interdependence of attribute valuations in MADM. A delay in one attribute's resolution time can alter its perceived value and affect complementary attributes, necessitating a holistic evaluation of trade-offs. Study 1 shows that when cost, the initially more important attribute, is delayed, its weight decreases. However, the effect of delaying a less important attribute remains unclear. To address this, Study 2 tests the reverse condition by delaying the screening duration and re-testing Hypotheses 1 and 3.

### 4.5.3 Results of Study 2: Single attribute delay (screening duration)

A total of 133 participants took part in the experiment. Following the same exclusion criteria as in the previous study, 6 participants were excluded for providing random mid-value scores, 21 for entering values outside the attribute ranges, and 11 for using an overly narrow score range. The final dataset involves a sample of 95 participants, of whom 74 were recruited from Prolific and 21 were volunteers from Delft University of Technology. As in Study 1, participants answered a series of questions in a within-subjects design. Stimuli and the questions in the base case scenario and the discounting task were the same as in Study 1. In the time-related scenario, which will be referred to as “delayed screening” from now on, the screening duration attribute was four weeks delayed. The same steps were followed as in Study 1.

#### Test of Hypothesis 1

To test Hypothesis 1, we compared the elicited values of the screening duration attribute in the base and delayed screening cases. A paired-sample *t*-test shows that the mean value of the screening duration attribute in the base case ( $M = 0.173$ ,  $SD = 0.153$ ) is significantly higher than in the delayed screening case ( $M = 0.158$ ,  $SD = 0.148$ ),  $t(284) = 2.975$ ,  $p = 0.003$ . In contrast, for the cost attribute, the mean value in the base case ( $M = 0.256$ ,  $SD = 0.198$ ) is significantly lower than in the delayed case ( $M = 0.280$ ,  $SD = 0.215$ ),  $t(284) = -2.709$ ,  $p = 0.007$ . These results indicate that participants assigned higher values to screening duration when it was immediate and discounted it when delayed, while the cost attribute was valued more highly in the delayed condition. As in the previous study, three functions were tested to model this discounting behavior.

As in Study 1, both the exponential discounting and the hyperbolic discounting models demonstrate the same performance across all metrics, with an adjusted  $R^2$  of 0.654, RMSE of 0.090, MSE of 0.008, and MAE of 0.054. The estimated  $k$  values of 0.209 show that future values are discounted by 20.9%. As illustrated in Table 4.4, the power-law model yields the best overall fit, with an adjusted  $R^2$  of 0.699, a lower RMSE of 0.084, and a lower MSE of 0.056 compared to both the exponential and hyperbolic discounting models. The MAE for this model was 0.007, further confirming its superior fit. The power-law discounting model explains almost 70% of the variance in how participants perceive delayed screening duration values, indicating a strong fit to the data. Moreover, the model's predictions deviate from participants' responses by about 0.007 units on average, which is a relatively small discrepancy. The estimated discounting parameter  $b = 0.739$  indicates a very strong devaluation with delay. All these findings suggest that the power-law model captures a significant portion of the discounting behavior with high accuracy, and it is the most effective choice for modeling this relationship.

Table 4.4: Goodness of fit for each candidate function in Study 2 for  $t = \frac{1}{12}$

Function	Adjusted $R^2$	RMSE	MSE	MAE	AIC	BIC	Estimated parameters
Exponential discounting $y = x \cdot e^{-k \cdot t}$	0.654	0.090	0.008	0.054	-1371.647	-1367.994	$k = 0.209$
Power-law discounting $y = a \cdot x^b$	0.699	0.084	0.056	0.007	-1409.180	-1401.875	$a = 0.742, b = 0.739$

### Test of Hypothesis 3

Delaying the screening procedure influences the scaling constants, as shown in Figure 4.7. Participants assign a lower scaling constant to the screening duration attribute when it is delayed, resulting in an increase in the scaling constant of the cost attribute. In the base case, the mean weight of the screening duration attribute is 0.379 ( $SD = 0.162, SEM = 0.017$ ), while in the delayed screening case, it decreases to 0.351 ( $SD = 0.162, SEM = 0.017$ ). The mean difference between the two conditions, 0.028, is statistically significant,  $t(94) = 2.592, p = 0.011$  (two-tailed).

Scenario order did not affect participants' scaling constants ( $p = 0.215$ ), nor was there a significant difference between volunteers and paid participants ( $p = 0.155$ ). Among participants, 15 reported a chronic illness and 12 reported claustrophobia; neither group differed significantly from the rest regarding scaling constants ( $p = 0.429$  and  $p = 0.139$ , respectively). Pearson correlations between well-being scores and assigned weights were very weak and non-significant ( $r(93) = 0.032, p = 0.762$ ), indicating no evidence of a linear relationship.

On a within-subject level, 83.16% of the participants report the cost attribute as being more important, while 13.68% consistently choose the screening duration in both conditions. Moreover, 53.68% of the participants lower the weight of the screening duration attribute when it is delayed, 31.58% show an increase, and 14.74% do not change the assigned weights. Similar to Study 1, additional analyses were performed to uncover the underlying reasons for these shifts in scaling constants.

**Changes in value functions:** The average value functions for the screening duration and cost attributes are illustrated in the left-hand plots of Figure 4.8 and Figure 4.9, respectively.

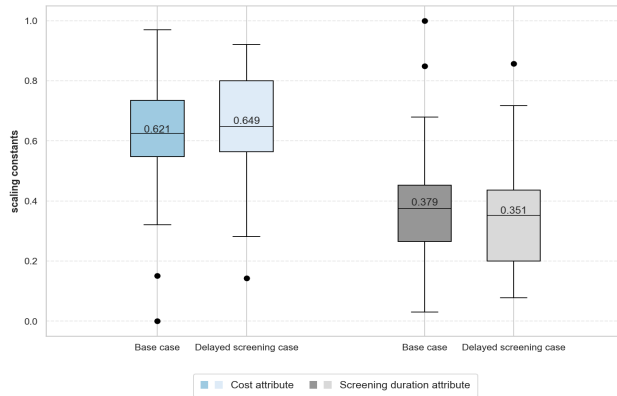


Figure 4.7: Changes in scaling constants when the screening procedure is delayed

Delaying the screening procedure changes the average value function for both attributes. The areas between the functions are calculated as 1.14 and 7.87 for the screening duration and cost, respectively. More detailed individual-level analyses regarding the value function's shapes reveal that, out of 95 participants, 28 change the shape of their cost function in a way that aligns with the Figure 4.9 (left side), and 52 people do not change it at all. When the screening duration attribute is concerned, only 14 people show a behavior parallel to the average pattern illustrated in Figure 4.8 (left side), while 69 people do not change their functions.

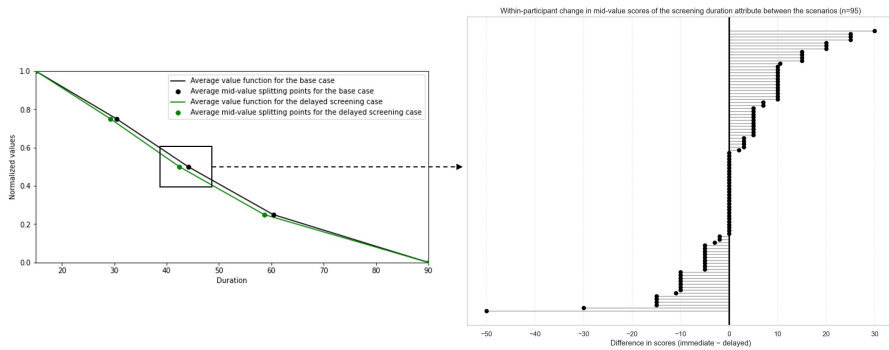


Figure 4.8: Average value functions for the screening duration attribute (left) and the within-participant differences in mid-value scores at the 0.5 value level (right) in Study 2

As illustrated in Figure 4.8 (right side), the distribution of difference scores indicates a slight asymmetry: more participants show positive values than negative ones. This means that, for a larger share of individuals, the 0.5-value point for the screening duration attribute was higher in the immediate scenario than in the other scenario. Nonetheless, a noteworthy portion of participants still exhibit negative or zero scores. We compared the mid-value scores given to the 0.5 level using a paired sample  $t$ -test and a Wilcoxon signed-rank test. For the screening duration attribute, the mean score is 44.14 ( $SD = 11.58$ ,  $SEM = 1.19$ ) in the base condition and 42.45

( $SD = 12.67$ ,  $SEM = 1.30$ ) in the delayed screening condition. The mean difference between the conditions is not statistically significant,  $t(94) = 1.478$ ,  $p = 0.143$  (two-tailed). Similarly, the Wilcoxon signed-rank test reveals no significant difference ( $Z = -1.884$ ,  $p = 0.065$ ) (two-tailed), suggesting that delaying the screening procedure does not influence the value function of the screening duration attribute.

For the cost attribute, the distribution of difference scores is predominantly negative (Figure 4.9), indicating that most participants assigned a higher 0.5-value point to the cost attribute in the delayed scenario than in the immediate scenario. This pattern suggests that, for the majority of individuals, the mid-value point shifted upward when cost was delayed. A smaller portion of participants exhibit positive scores, reflecting the opposite adjustment, and only a few show little or no change. The mean score for the base condition is 377.46 ( $SD = 91.38$ ,  $SEM = 9.38$ ), and the mean score for the delayed screening condition is 396.58 ( $SD = 103.37$ ,  $SEM = 10.61$ ). The mean difference between the mid-values for cost is marginally statistically significant,  $t(94) = -1.948$ ,  $p = 0.054$  (two-tailed). This finding is further supported by the Wilcoxon signed-rank test, which reveals a significant difference between the cases ( $Z = -1.984$ ,  $p = 0.047$ ) (two-tailed). These results indicate a tendency toward increasing the mid-value points of the cost attribute under the delayed scenario.

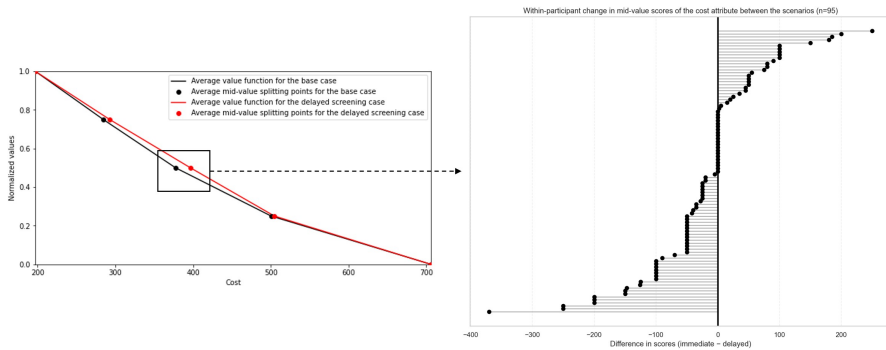


Figure 4.9: Average value functions for the cost attribute (left) and the within-participant differences in mid-value scores at the 0.5 value level (right) in Study 2

**Changes in trade-off scores:** In this study, 83.16% of the subjects are cost-sensitive, and 13.68% are time-sensitive. Paired sample  $t$ -test and Wilcoxon signed-rank test were used to examine the possible influence of the delay on the assigned trade-off scores. The results indicate no significant difference between the cost scores in the base case ( $M = 394.18$ ,  $SD = 117.06$ ) and in the delayed screening case ( $M = 385.03$ ,  $SD = 118.65$ ),  $t(78) = 1.312$ ,  $p = 0.193$ . The Wilcoxon signed-rank test results further support this finding ( $Z = -1.575$ ,  $p = 0.115$ ). Similarly, the results reveal no significant difference for screening duration attribute between the base case ( $M = 45.00$ ,  $SD = 23.80$ ) and the delayed screening case ( $M = 49.77$ ,  $SD = 21.21$ ), with a mean difference of  $-4.77$  which is not statistically significant,  $t(12) = -1.867$ ,  $p = 0.087$ . The Wilcoxon signed-rank test also yields a non-significant difference between the trade-off scores ( $Z = -1.676$ ,  $p = 0.094$ ). These results suggest that changes in scaling constants cannot be explained by changes in trade-off scores.

Given that the trade-off scores and value functions for the screening duration attribute remain consistent across the two conditions, the observed change in scaling constants must stem from an increase in the weight assigned to the complementary attribute rather than a reduction in the weight of the delayed attribute. In other words, delaying the screening procedure enhances the relative importance of cost, thereby leading to a proportional decrease in the weight of the screening duration attribute.

#### **4.5.4 Discussion of findings from Study 2**

As in Study 1, the value of the delayed attribute is discounted, and this relationship is best described by a power-law function. The observed change in the value of the attributes results in a shift in scaling constants. When the screening procedure is delayed, the weight of the screening duration attribute decreases. Unlike in Study 1, the shift in scaling constants is not driven by changes in preferences toward the delayed attribute but rather by the influence of the complementary attribute. Altering the resolution time of the screening duration does not affect its own value function or trade-off scores. However, it affects the cost attribute's value function, increasing its weight.

The change in values could be attributed to the time gap between purchase (immediate payment) and consumption (delayed service). Research by Shafir & Thaler (2006) on mental accounting reveals that people treat outcomes differently depending on these time gaps. The perceived value of many products varies based on whether they are consumed immediately or at a later time and whether they are consumed as intended or in a different context. Although our study differs by involving two objectives and focusing on health services rather than consumption goods, the observed changes in values may still be partly explained by mental accounting and the time gap between payment and service receipt. Decision-makers may become more interested in cost when they are told they need to pay immediately, but wait four weeks to receive the service.

The change in scaling constants can be explained by the heightened salience of the more important attribute due to its immediacy. As noted earlier, over 80% of participants report the cost attribute as more important than the screening duration attribute. While the payment time is immediate in both conditions, the timing of the screening procedure changes from immediate to 4 weeks later. This delay in the screening procedure likely increases the salience of the cost attribute because the immediacy of the payment becomes more noticeable. In the context of MAVT, where decisions are made by evaluating trade-offs between attributes, the delay in the screening procedure may have made the immediacy of the cost more prominent, thus causing an increase in its salience. This is further supported by the time preference literature, which consistently reports the dominant influence of immediacy (Thaler, 1981; Ainslie, 2002; O'Donoghue & Rabin, 2015; Chakraborty, 2021). As a result, participants may have become more sensitive to the timing of cost, leading to a shift in how its value is perceived and a corresponding increase in its weight. This also aligns with the findings of van Ittersum et al. (2007), who suggests that changes in the salience of attributes can significantly alter the weighting of those attributes.

So far, we have focused on the influence of delaying a single attribute and tested Hypotheses 1 and 3. In the following experiment, both attributes are delayed simultaneously to test Hypotheses 2 and 4.

### 4.5.5 Results of Study 3: Dual attribute delay

A total of 98 participants took part in the experiment. Following the same exclusion criteria as in the previous studies, 6 people were excluded for providing random mid-value scores, 7 for entering values outside of the attribute ranges, and 9 for having a narrow score range. The final dataset involves a sample of 76 participants, of whom 60 were recruited from Prolific and 16 were volunteers from the Delft University of Technology. As in the previous studies, participants completed three tasks in a within-subjects design. The base case and discounting task were the same as in Studies 1 and 2, while the time-related scenario (will be referred to as “both delayed” from now on) was the revised version of the base case, where the timing of both attributes was delayed by four weeks. Participants followed the same steps as in the previous studies to provide data for value functions and scaling constants.

#### Test of Hypothesis 2

To test Hypothesis 2, a paired sample  $t$ -test was performed. For the cost attribute, the mean value in the base case ( $M = 0.230, SD = 0.188$ ) is slightly lower than the both delayed case ( $M = 0.244, SD = 0.197$ ). However, this difference is not statistically significant,  $t(227) = -1.292, p = 0.198$ , suggesting that the delay does not lead to a significant shift in the perceived value of the cost attribute. For the screening duration attribute, the mean value in the base case ( $M = 0.199, SD = 0.176$ ) is slightly higher than in the delayed case ( $M = 0.188, SD = 0.170$ ). This difference is also not statistically significant,  $t(227) = 1.43, p = 0.155$ . These results indicate that simultaneously delaying both attributes does not cause a significant shift in their perceived values. Since discounting behavior is not evident in this case, the functional relationship developed in previous experiments cannot be established here. As a result, there is insufficient evidence to reject Hypothesis 2.

#### Test of Hypothesis 4

As illustrated in Figure 4.10, delaying both attributes simultaneously does not influence the scaling constants. The paired sample  $t$ -test results indicate no significant difference between the base case ( $M = 0.591, SD = 0.177$ ) and the both delayed case ( $M = 0.595, SD = 0.182$ ),  $t(75) = -0.211, p = 0.833$ .

Scenario order did not affect participants' scaling constants ( $p = 0.774$ ), nor was there a significant difference between volunteers and Prolific participants ( $p = 0.998$ ). Among participants, 13 reported a chronic illness, and 7 reported claustrophobia; neither group differed significantly from the rest regarding scaling constants ( $p = 0.641$  and  $p = 0.382$ , respectively). Pearson correlations between well-being scores and attribute weights were weak and non-significant ( $r(76) = -0.161, p = 0.164$ ), indicating no evidence of a linear relationship.

On a within-subject level, 73.68% of the participants report the cost attribute as more important in both cases, and 6.85% do not consistently report one of the attributes as being more important and change their preferences. Furthermore, 46.05% of participants lower the weight of the cost attribute when it is delayed, 44.74% increase it, and 9.21% do not change their assigned weights. Although the weights and values do not significantly differ between the conditions, we still performed the same additional analyses as in the previous studies.

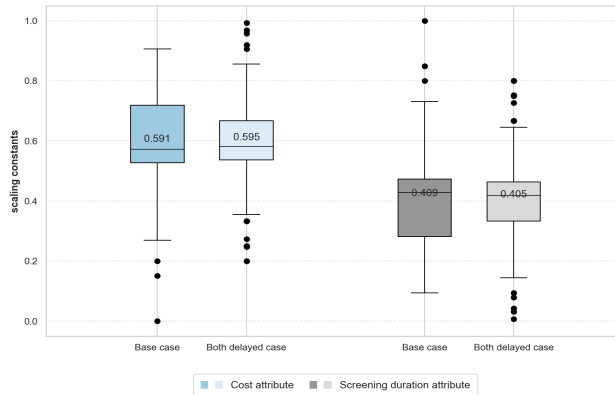


Figure 4.10: Changes in scaling constants when both attributes are delayed

**Changes in Value Functions:** The average value functions for the cost and screening duration attributes are shown in the left-hand plots of Figure 4.11 and Figure 4.12, respectively. The areas between the functions are 12.83 and 1.29 for cost and screening duration, respectively. An individual-level analysis of function shapes indicates that out of 76 participants, 45 do not change the shape of their cost function, while 21 exhibit a change consistent with Figure 4.11 (left side). For the screening duration attribute, only 25 participants changed the shape of their function, 13 of whom aligned with the average function illustrated in Figure 4.12 (left side).

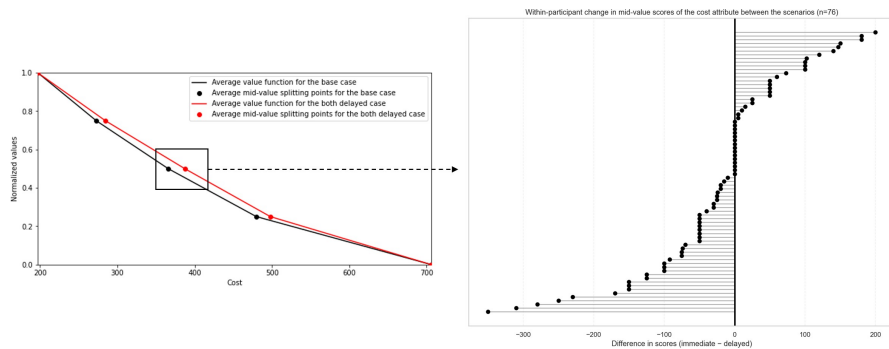


Figure 4.11: Average value functions for the cost attribute (left) and the within-participant differences in mid-value scores at the 0.5 value level (right) in Study 3

As illustrated in Figure 4.11 (right side), the majority of participants exhibit negative difference scores, indicating that the 0.5-value point they assigned to the cost attribute is higher in the both-delayed scenario than in the immediate scenario. This pattern shows that most individuals increased their mid-value point when both attributes were delayed. A smaller group displays positive scores, indicating the opposite shift, and a few participants show minimal or no change. As in the previous studies, the mid-value splitting scores assigned to the 0.5 level were compared to see if the changes observed in average value functions are significant. The

paired sample  $t$ -test reveals a non-significant difference in the mid-values of the cost attribute between the conditions  $t(75) = -1.767$ ,  $p = 0.081$  (two-tailed). This finding is further supported by the Wilcoxon signed-rank test, which also reveals no significant difference between the cases ( $Z = -1.564$ ,  $p = 0.118$ ) (two-tailed).

For the screening duration attribute (Figure 4.12 (right side)), the difference scores are mostly positive, indicating that a larger share of participants assigned a higher 0.5-value point to the screening duration attribute in the immediate scenario than in the both-delayed scenario. Although there is a meaningful number of participants with negative scores, the distribution is not symmetric; positive values are more frequent and extend over a wider range. Only a small subset shows little or no change. Similar to the cost attribute, the mid-value scores of the screening duration attribute do not significantly differ between the cases,  $t(75) = 1.168$ ,  $p = 0.247$ . In alignment with this finding, the Wilcoxon signed-rank test also reveals insignificant results ( $Z = -0.917$ ,  $p = 0.359$ ) (two-tailed).

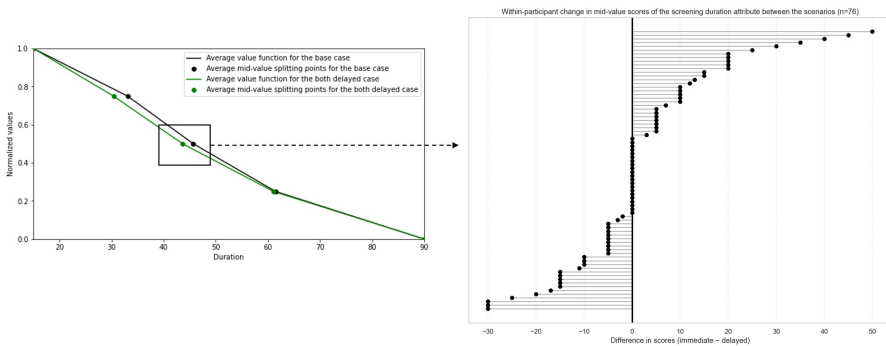


Figure 4.12: Average value functions for the screening duration attribute (left) and the within-participant differences in mid-value scores at the 0.5 value level (right) in Study 3

These findings indicate that delaying both attributes simultaneously does not lead to a significant change in value functions. Despite the lack of statistical significance, the increase in the cost attribute's function warrants further examination, as the area between the two average value functions is not negligible and statistical tests approach significance. The observed increase is likely offset by compensatory adjustments in another component of the evaluation framework.

**Changes in trade-off scores:** The sample included 56 cost- and 11 time-sensitive participants. A paired sample  $t$ -test reveals a statistically significant difference in cost trade-off scores between the conditions,  $t(55) = 2.231$ ,  $p = 0.030$  (two-tailed), with a mean difference of 24.411. Though it approaches significance, the Wilcoxon signed-rank test does not fully corroborate this finding ( $Z = -1.849$ ,  $p = 0.064$ ) (two-tailed). These results provide moderate evidence that higher trade-off scores are assigned when attributes are delayed, but warrant cautious interpretation due to the discrepancy between parametric and nonparametric test results. The difference in screening duration trade-off scores is not statistically significant,  $t(10) = 1.841$ ,  $p = 0.095$ , with a mean difference of 4.818. The Wilcoxon signed-rank test reveals further support to this finding ( $Z = -1.556$ ,  $p = 0.120$ ). Although it is not reflected in the scaling constants, according to the paired sample  $t$ -test results, the cost-sensitive participants are willing to trade more money for the duration time when both attributes are delayed.

### 4.5.6 Discussion of findings from Study 3

Unlike Studies 1 and 2, which focus on delaying a single attribute, this experiment examines the scenario where all attributes are delayed simultaneously. The results reveal that, when all attributes are postponed together, the relative value structure is preserved, with no clear evidence of discounting behavior over time. At first glance, this might suggest that time preference does not influence the decision-making process. However, a deeper analysis of the components of the attribute values uncovers more nuanced insights. Specifically, the trade-off analysis reveals that participants are willing to pay more for the same improvement in screening duration when both attributes are delayed. This indicates a sensitivity to cost, which is more pronounced when the payment is immediate, but diminishes as the delay increases.

As discussed in Section 4.3, an increase in trade-off scores should typically result in a decrease in the scaling constant of the cost attribute, assuming the value function remains stable. However, despite the significant increase in trade-off scores, no statistically significant change in the scaling constants was observed. One possible explanation for this is that the increase in trade-off scores may be offset by an opposite change in the value function. In other words, two opposing changes could counterbalance each other, leading to no apparent change. Alternatively, while the statistical test indicates a significant increase in trade-off scores, the difference may not have been large enough to influence the normalized values derived from the value function, thus explaining the observed stability in the scaling constants.

The presence of two attributes in this experiment challenges the traditional discounting principle, which claims that outcomes lose value over time. Contrary to this, we report no significant change in the values of the attributes. This could be attributed to the nature of the trade-off procedure and the relative valuation between the attributes. When considered together, the attributes do not adhere to conventional discounting patterns; instead, they interact dynamically, influencing preferences in more complex ways. These findings highlight the importance of adopting a systematic approach to studying time preferences. While the aggregated results for scaling constants and values suggest no time effect, further analyses reveal the underlying mechanisms that drive the observed outcomes. The interplay between attributes and trade-off dynamics reveals more nuanced relationships underlying the seemingly stable scaling constants.

### 4.5.7 General discussion

In three experiments, we show how time preference influences decision-making while MAVT is utilized. As hypothesized, delaying one of the attributes has an impact on the assigned values and attribute weights. The change in attribute values is best modeled with the power-law function, explaining at least 50% of the variance in the datasets. On the other hand, delaying both attributes together does not significantly affect the values or attribute weights.

Figure 4.13 presents the changes in attribute weights from the base case to the time-related cases, offering an overview of the findings. In Study 1, delaying payment leads to decreased cost and increased screening duration weights. Conversely, in Study 2, delaying the screening procedure results in a higher weight for the cost attribute. In Study 3, no significant change is observed between conditions, as the nearly parallel lines indicate.

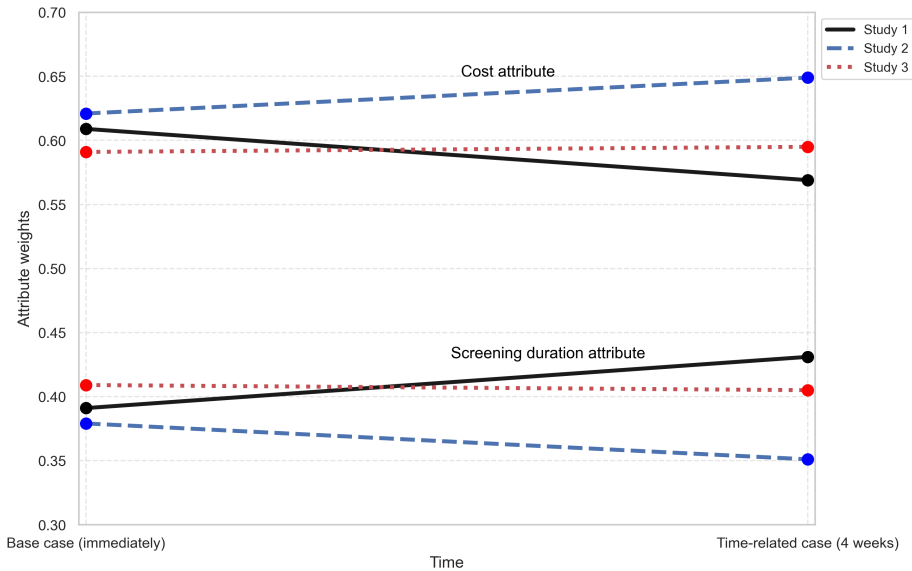


Figure 4.13: Comparison of cost and screening duration attribute weights across time and studies

These changes in attribute weights are driven by different factors in each study. In Study 1, the decrease in the cost attribute's weight is due to the change in the value function. Our findings in Study 2 diverge from existing literature, which suggests that the perceived value of a delayed outcome changes with time (Thaler, 1981). However, we observe a shift in the value function of the complementary attribute rather than the delayed attribute. Initially, it appears that decision-makers assign lower weights to the delayed attribute, but further analyses suggest this is more a result of changes in the complementary attribute. We believe this is due to the trade-off relationship between the attributes within the MADM context. In Study 3, attribute weights remain unchanged. However, further analysis reveals an increase in trade-off scores and a slight rise in the average value function of the cost attribute. These effects may have offset each other, resulting in no visible change in weights. Similar to Study 2, these findings diverge from the time preference literature. Follow-up analyses underscore the importance of investigating the underlying factors influencing final choices. While participants may appear to prefer one alternative over the other or show no sensitivity to delays, hidden processes likely drive the observed patterns. Understanding these dynamics provides deeper insights into intertemporal decision-making and offers potential explanations for many decisions in real life.

## 4.6 Conclusion

This study represents the first experimental investigation into time preferences within a multi-attribute decision-making framework. We conducted three experiments on a healthcare decision problem, examining how delaying one or all attributes impacts attribute weights and values.

Our findings reveal that the timing of resolution influences these factors differently, challenging traditional time preference literature that suggests the value of an outcome decreases with delay. Our findings highlight the complexity of intertemporal decisions involving multiple attributes and contribute to a deeper understanding by providing a systematic approach that accounts for temporal factors. It also sheds light on the differences between directly engaging with an outcome and following a more systematic way while eliciting preferences. These findings offer insights for researchers and practitioners in economics, psychology, health, and public policy who engage with intertemporal trade-offs.

Despite its contributions, this study has some limitations. We utilized the mid-value splitting technique while structuring the experimental tasks. This is an unusual and cognitively demanding task compared to other time preference experiments from psychology and behavioral economics. Although we simplified the tasks and systematically pretested them using the Three-Steps Test Interview (TSTI), the complexity of the method remains a limitation. Furthermore, while the theoretical framework is broadly applicable, our study was confined to a single health-related intertemporal MADM problem involving two attributes. Future research should extend this framework to encompass more than two attributes and investigate diverse case studies, objectives, and alternatives to gain a better understanding of time preferences in MADM contexts. It may also be worthwhile to explore time preference in problems where outcomes of an attribute are distributed across different future points. While our study focused on the same delays across attributes, there may be cases where outcomes are subject to varying delays. Investigating time preference for these problems could offer new insights and serve as a promising direction for future research. Moreover, given that our experiments utilized a value-based method, alternative approaches such as pairwise comparison methods may offer valuable complementary insights. Future research could also refine different MADM methods to incorporate time preferences, offering improved tools for practitioners and researchers. We believe this study will serve as a catalyst for further research, encouraging a deeper exploration of the role of time preferences within prescriptive frameworks, particularly in MADM, and driving the development of more effective methods that account for intertemporal factors and behavioral influences.

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# Chapter 5

## Time preference in decisions with recurring payoffs

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**Abstract:** Time preference plays a central role in intertemporal decision-making, shaping how individuals value outcomes based on when they occur. Research in this area often relies on behavioral experiments involving one-off intertemporal payoffs, from which individual discount rates are calculated and interpreted. In practice, many real-world decisions generate recurring payoffs that unfold over time, requiring decision-makers to evaluate outcomes within a broader temporal context than that implied by isolated payoffs. Building on the choice bundling and bracketing literature, we investigate the difference between two decision types: one with a one-off payoff, consistent with standard time-preference experiments, and another with recurring payoffs. A total of 284 participants were randomly assigned to either a gain or loss version of the same experiment and completed four conditions varying by payoff type (one-off vs. recurring) and outcome magnitude (small vs. large). Results indicate that prompting individuals to consider the recurrence of payoffs leads to meaningful changes in time preferences. Participants exhibited significantly lower discount rates in recurring payoff conditions than in one-off counterparts, suggesting that discounting behavior is at least partially shaped by the contextual factors of the intertemporal problem. These findings underscore the potential of using recurring payoff structures to promote future-oriented decisions, offering actionable insights for policy-makers and practitioners designing behavioral interventions.

**Keyword:** Time preference; discount rate; recurring payoffs; intertemporal decision-making

This chapter is based on the following manuscript:

Gülüm, P., Maknoon, Y., & Rezaei, J., Time preference in decisions with recurring payoffs (*manuscript under review*)

## 5.1 Introduction

Time preference refers to the relative value individuals place on receiving rewards sooner rather than later, a concept that shapes a wide range of decisions in many areas, including financial planning and health (Jain & Chen, 2023; Fuchs, 1982; Thaler, 1981; Hardisty et al., 2013a; Kang & Ikeda, 2016; Loewenstein & Elster, 1992). A standard approach to modeling time preference involves eliciting decision-makers' intertemporal preferences, representing them with a discount rate, and using this rate to interpret their behavior (Mazur, 1987; Samuelson, 1937; Hardisty & Pfeffer, 2017; Baron, 2000).<sup>1</sup> For example, a higher discount rate typically indicates a stronger preference for immediate benefits, often manifesting in more impatient and short-sighted behaviors such as favoring smaller-sooner financial rewards and accumulating debt (Nguyen, 2016; Chakraborty, 2021), or avoiding preventive healthcare measures in favor of current comfort (Lee & Kim, 2017; Tang et al., 2023). Given its prevalence and importance in decision-making, the discount rate therefore should be calculated and interpreted with careful attention to contextual factors to better capture real-world complexities and improve the relevance of empirical findings (Frederick et al., 2002; Loewenstein & Prelec, 1993).

A common approach to eliciting discount rates is to expose individuals to intertemporal choice scenarios that simulate real-life problems (Doyle, 2013; Hardisty et al., 2013b). Typically, these experiments begin by introducing a case, such as winning money in a lottery or needing to pay an unexpected bill (Frederick et al., 2002; Rambaud et al., 2023; Thaler, 1981). Participants are then presented with a series of choices between smaller-sooner and larger-later payoffs, enabling estimation of discount rates. This widely adopted approach has generated a substantial body of research, yielding valuable insights into the cognitive and behavioral processes underlying time discounting, contributing to theoretical models and empirical findings across multiple disciplines (Laibson, 1997; Ainslie, 2002; O'Donoghue & Rabin, 2015; Hardisty et al., 2013a; Chapman, 1996). Despite these significant contributions, as also acknowledged by Frederick et al. (2002) and Ainslie et al. (2018), much of the existing literature on time preference focuses on discrete, isolated payoffs. When considered in isolation, such payoffs are likely difficult to relate meaningfully to future prospects or even to present needs (Ainslie, 1992; Loewenstein & Thaler, 1989; Ainslie, 2001). As a result, this may exaggerate the appeal of immediate rewards, contributing to the high discount rates, a problem frequently reported in the literature (Read, 2001).

Although some real-life choices are indeed isolated incidents, most decisions we encounter result in recurring payoffs that unfold over extended periods (Kosíková et al., 2024; Herrnstein et al., 1997). For example, consider an individual who earns a regular salary and manages multiple financial commitments on varying schedules, such as monthly mortgage and utility payments, weekly grocery expenses, and daily commuting costs. In addition to these, they may receive supplemental income from side hustles or investment returns. They are also likely to maintain various subscriptions, such as internet, cable television, or health insurance, all of which involve recurring billing. These recurring patterns observed across numerous real-life decisions suggest a potential misalignment between how intertemporal choices are commonly

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<sup>1</sup>Implicit discount rates, inferred from observed intertemporal choices, capture how individuals actually value outcomes over time, whereas normative discount rates reflect how they should discount under ideal conditions (Frederick et al., 2002). For simplicity, we refer to the rates derived from participants' choices as "discount rates," though they are technically implicit.

represented in experimental settings and how they unfold over time in everyday contexts. Extending the experimental investigations to consider the recurring patterns of these problems is crucial to enhance both ecological validity (the extent to which the findings of a study can be generalized to real-life settings (Bronfenbrenner, 1977)) and interpretive relevance of the resulting discount rates. Decision scenarios involving recurring payoffs can shed light on how decision-makers assess such problems, potentially guiding the development of more effective intervention strategies.

Despite the prevalence of real-life decisions with recurring payoffs, most experiments are limited to isolated, one-off scenarios (Loewenstein & Prelec, 1993; Guyse et al., 2024). This discrepancy between real-life problems and experimental scenarios with one-off outcomes raises the question: What if, rather than being placed in an isolated, one-off case, individuals were motivated to consider the recurrence of the payoffs resulting from their decision? Would their preferences remain the same in such cases? If they were explicitly informed that the decision they are about to make has recurring outcomes, would they still prefer smaller-sooner outcomes over larger-later ones and end up with a high discount rate? This paper attempts to answer these questions by using real-life problems with recurring payoffs.

Investigating recurring payoff decisions provides important insights into how individuals adjust their time preferences when faced with such problems, and whether these contexts produce systematic changes in calculated discount rates. Understanding recurring payoffs can also strengthen behavioral economics, public health, and financial planning interventions. These domains often involve time preference problems with recurring outcomes and rely heavily on interpretations of individual discount rates.

To examine time preferences in decisions with recurring payoffs, our study primarily draws on the literature on choice bundling and choice bracketing (Ainslie, 1992; Read et al., 1999). While these concepts differ in focus (bundling emphasizes aggregating identical intertemporal choices resolving over time, whereas bracketing concerns the scope of decisions considered together), both suggest that evaluating choices within a broader context, rather than in isolation, promotes more consistent and forward-looking judgments (Ainslie et al., 2018; Kirby & Guastello, 2001). Experiments across different fields have revealed the power of these approaches to increase self-control by reducing excessive discounting (Ashe & Wilson, 2020). Building on this insight, we test whether a similar extension of the temporal horizon occurs when individuals face a single decision that produces recurring outcomes over time. Unlike bundling and bracketing, our approach embeds recurrence directly in the payoff structure, naturally encouraging long-term consideration through the decision itself, without requiring explicit grouping or aggregation of choices as in bundling. We hypothesized that time preferences would shift from one-off to recurring payoffs, driven by the need to account for outcomes that unfold repeatedly over time.

We tested this hypothesis with two controlled experiments, one focused on gains and the other on losses, reflecting the well-documented gain-loss asymmetry (Kahneman & Tversky, 1979; Hardisty et al., 2013a). Each experiment employed a fully within-subjects design, manipulating payoff type (one-off vs. recurring) and payoff magnitude (small vs. large) to account for the magnitude effect (Thaler, 1981; Chapman, 1996). To ensure conceptual clarity and experimental control, we intentionally implemented two structurally distinct conditions: one in which the payoff is delivered at a particular time point (one-off), and another in which an identical amount recurs at fixed intervals (recurring). Many decisions in life, such as salary

payments, subscriptions, or installment plans, follow regular, recurring patterns consistent with our experimental condition. At the same time, we acknowledge that some real-life decisions may involve more timing and outcome amount variability. Using two controlled conditions, our study isolates the conceptual and psychological shift from evaluating one-off payoffs to evaluating recurring ones, allowing for a precise examination of how payoff structure influences intertemporal discounting.

This study makes three main contributions to the literature on intertemporal decision-making. First, it advances the theoretical understanding of decisions with recurring payoffs. In doing so, it draws on the concepts of choice bundling and choice bracketing, refining models of time preference to better capture a decision type that has thus far been largely overlooked. Moreover, the study extends insights on bundling and bracketing by demonstrating how these frameworks may operate when people face multiple recurring outcomes to be bundled, thereby broadening their applicability to more complex decision environments. Second, the findings emphasize the importance of contextual factors in experimental design by empirically testing a strategy to overcome the isolation effect and promote a long-term perspective. In doing so, we contribute to the ecological validity of derived discount rates. Moreover, we provide deeper insights into the processes underlying intertemporal choices by illustrating how individuals shift their perspective from one-off to recurring payoff conditions in real-life problems. These insights may contribute to a better understanding of the cognitive frameworks individuals use when making intertemporal decisions and inform the design of future experimental studies. Third, our findings contribute to the literature on the magnitude effect by examining it in real-life decision contexts involving recurring outcomes. By adopting an established methodological framework, we demonstrate that the magnitude effect generalizes beyond isolated, single-payoff settings to environments in which outcomes unfold repeatedly over time. In doing so, our findings bridge the magnitude-effect literature with insights from bundling and framing by showing how outcome size interacts with temporal aggregation in recurring payoff structures. Fourth, by testing the recurring gains and losses in different experiments, this study lays the groundwork for practical applications. These include developing behavioral interventions and decision-making tools that leverage the recurring-payoff approach to encourage more consistent, future-oriented choices. Our results suggest that explicitly highlighting the recurring nature of outcomes can facilitate a shift in perspective, one that systematically lowers discount rates and encourages choices that maximize long-term utility. In this way, we extend our contributions into the prescriptive domain by offering a practical framework that decision analysts can adopt to help individuals prioritize long-term utility over immediate gratification. Overall, this study enriches how discount rates are elicited in experimental settings and offers actionable insights to support better individual and societal decision-making.

The remainder of the paper is structured as follows: Section 5.2 outlines the development of the hypothesis, drawing on choice bundling and bracketing theories and prior research on time preference. Section 5.3 describes the experimental studies conducted to test the hypothesis, beginning with an overview and followed by detailed accounts of the loss and gain experiments, including their respective results and discussions. Section 5.4 offers a general discussion of the findings, examining their theoretical and practical implications. Finally, Section 5.5 concludes the study by acknowledging its limitations and proposing directions for future research.

## 5.2 Hypothesis development

In developing our hypothesis on the differences between one-off and recurring payoff decisions, we build on the choice isolation argument (Frederick et al., 2002), and draw from related ideas in choice bundling (Ainslie, 1992) and choice bracketing (Read et al., 1999).

A common approach in time preference research presents individuals with hypothetical problems requiring intertemporal trade-offs to maximize utility. In these experiments, evaluation is typically confined to a single incident within a limited time interval, such as comparing an immediate outcome with a delayed one. Despite offering valuable insights into the mechanisms of intertemporal decision-making and time preference, this approach remains constrained by inherent limitations. As demonstrated extensively by Frederick et al. (2002), most of these experiments report high discount rates, implying that decision-makers significantly devalue delayed outcomes. At least in part, these elevated discount rates reflect the framing of decision scenarios used to investigate time preference in experiments. In their seminal paper on intertemporal decision-making Frederick et al. (2002) criticize the way experimental designs force people to think about rewards as isolated, instantaneous events, whereas in real life, consumption and utility are more continuous and interrelated.

One influential theoretical response to this isolation argument is Ainslie's concept of *choice bundling*, which refers to evaluating a single intertemporal decision not in isolation but as part of a series of similar future decisions (Ainslie, 1992, 2001). Effective bundling requires establishing an overarching goal that organizes individual choices, encouraging individuals to treat each decision as a precedent for future actions. The benefit of this approach is that it promotes consistent, long-term decision-making by amplifying the perceived value of sustained action, thereby helping individuals resist short-term temptations and align their choices with broader goals.

Similarly, the concept of *choice bracketing* highlights the benefits of evaluating decisions as part of a broader set rather than in isolation (Read et al., 1999; Webb & Shu, 2017; Redelmeier & Tversky, 1992). Choice bracketing is the process by which individuals determine the scope over which to evaluate a group of decisions, whether to consider each one in isolation (narrow bracketing) or to evaluate multiple decisions together as a set (broad bracketing). When each decision is considered without reference to other decisions, people tend to become overly risk-averse, focusing on potential losses of the immediate choice. By contrast, considering choices as part of a larger pattern encourages risk diversification and long-term planning, resulting in more balanced and informed decision-making.

Although choice bundling and bracketing share the principle that broader evaluation encourages consideration of long-term consequences, they differ in important ways. Bundling relies on establishing a higher-order goal that links identical decisions across time, giving it a distinctly temporal focus. Bracketing, by contrast, depends on the scope of evaluation: decisions may be considered narrowly, one at a time, or broadly, as part of a larger set, and this framing applies to any related decision, not just intertemporal ones.

In our study, one-off decisions correspond to the isolated intertemporal choices that dominate the time preference literature. Our primary interest lies in how time preferences and discount rates change when a decision yields recurring payoffs rather than a single, isolated outcome. While our approach is conceptually related to the bundling and bracketing literature,

several important distinctions set it apart. Classical bundling and bracketing paradigms typically rely on repeated decisions or explicit grouping of choices, encouraging long-term thinking by highlighting that each decision belongs to a broader sequence. In contrast, our experimental task involves a single decision whose consequences recur over time. Rather than prompting individuals to connect multiple decisions, we embed recurrence directly into the payoff structure itself. As a result, participants are naturally encouraged to consider the long-term implications of the outcome, even though they face only one choice. In this sense, our design builds on the core insight of bundling and bracketing—that aggregation over time matters—while demonstrating that similar future-oriented evaluation can arise through scenario-based recurrence without requiring explicit commitment, repeated choice, or conscious grouping.

Just as framing multiple choices as a bundle encourages a longer-term perspective, a single decision with recurring payoffs may also prompt participants to account for the broader consequences of their choice. Since real-world outcomes are rarely isolated and often repeat over time, emphasizing the recurring nature of payoffs in experiments will likely encourage participants to adopt a more future-oriented perspective, potentially leading to lower discount rates. Given this line of reasoning, we conjecture that when the recurring nature of payoffs is made salient, the appeal of immediate gratification diminishes, encouraging choices that favor long-term utility. The evaluation framework extends beyond isolated instances in such contexts, accounting for delayed benefits. Based on these converging theoretical and empirical insights, we formally state our hypothesis as follows:

**Hypothesis:** While evaluating recurring payoffs, decision-makers exhibit significantly lower discount rates compared to one-off payoffs.

Although the hypothesis is formulated independently of outcome valence, we examine gains and losses separately to account for potential differences in how individuals process recurring positive and negative outcomes over time. This intentional separation reflects the well-established gain-loss asymmetry (Fan et al., 2025; Kahneman & Tversky, 1979; Hardisty et al., 2013a; Hardisty & Pfeffer, 2017). Empirical studies reveal that losses are typically discounted less steeply than gains, and people often show more sensitivity toward potential losses, a phenomenon consistent with loss aversion (Loewenstein & Prelec, 1992; Hardisty et al., 2013a). By testing the hypothesis for recurring gains and losses, we aim to control for these distinct evaluative patterns.

Although our primary focus is the comparison between one-off and recurring outcomes, we also examine the magnitude effect as a secondary, exploratory dimension. A substantial body of research has shown that smaller rewards are discounted more steeply than larger rewards (Thaler, 1981; Green et al., 1997; Kirby & Maraković, 1995). Extending this well-documented effect to recurring payoff structures yields new insights into the mechanisms of intertemporal choice. With these considerations in mind, we next present the experimental design used to test how recurrence influences discounting behavior across different outcome types and sizes.

## 5.3 Experimental studies

To empirically test the hypothesis outlined in the previous section, that recurring payoffs lead to systematically lower discount rates than one-off payoffs, we conducted two behavioral experiments: one focused on gains and the other on losses. Each experiment employed a  $2 \times 2$  within-subjects design, manipulating payoff structure (one-off vs. recurring) and outcome magnitude (small vs. large). This resulted in four conditions: one-off small magnitude, recurring small magnitude, one-off large magnitude, and recurring large magnitude.

We adopted a within-subjects design to maximize experimental sensitivity and control for individual differences. Our primary goal is to examine how moving from one-off to recurring payoff conditions influences temporal perceptions and resulting discount rates. To achieve this, it is crucial that comparisons between conditions are made within the same individuals. A within-subjects design allows each participant to serve as their own control, thereby reducing variability arising from individual traits or cognitive styles (Keren, 2014). This approach enables direct comparisons of how the same individual evaluates one-off versus recurring outcomes, allowing us to better isolate the specific effects of recurrence on discounting behavior, something that would be more difficult to achieve with a between-subjects design (Greenwald, 1976; Charness et al., 2012). Following the same rationale on changing time perception from one-off to recurring payoff conditions, the treatment order was fixed rather than randomized, to preserve the logical and temporal structure of the hypothesized effect. In both experiments, the one-off scenario was presented first, followed by its recurrent equivalent. As such, the design aligns with the quasi-experimental repeated-measures framework (Shadish et al., 2002) and is appropriate to measure the hypothesized change in our study (Greenwald, 1976).

In the one-off scenarios, participants completed standard delay-discounting tasks by identifying indifference values between smaller-sooner and larger-later outcomes. These scenarios were framed as single, hypothetical events, such as surprisingly receiving a lottery reward or winning a contest in the gains experiment, and facing an unexpected bill payment in the losses experiment. The task and scenario framing for one-off decisions align with widely preferred approaches to studying time preference (Frederick et al., 2002; O'Donoghue & Rabin, 1999; Hardisty et al., 2013a). On the other hand, to capture how temporal preferences may shift across the frequency of payoffs, the recurring payoff scenarios were designed as direct counterparts to their one-off equivalents, using identical monetary values and delay intervals to highlight the effect of recurrence. For instance, in the one-off loss scenario involving small magnitudes, participants identify an indifference value at which paying an unexpected bill of €100 on the 1<sup>st</sup> of the month is equally preferable to paying a larger amount on the 30<sup>th</sup>, assuming the decision is made on the 1<sup>st</sup>. The corresponding recurring payoffs scenario involves the same task but framed as a recurring health insurance payment—requiring participants to identify an indifference value between paying €100 on the 1<sup>st</sup> of each month versus a larger amount on the 30<sup>th</sup> of each month. By presenting the one-off scenarios first, followed by their recurring-payoff counterparts, we aim to examine how an extended time perspective and a focus on recurrence influence discounting behavior. Holding both outcome magnitudes and delay intervals constant across scenarios allows us to prioritize examining recurrence while controlling for other decision variables.

In both experiments, the dependent variable was the discounting parameter  $k$ , computed separately for each condition. In particular, we adopted the hyperbolic discounting formulation

proposed by Ainslie (1975) in which the subjective present value of a delayed outcome is given by

$$V(D) = \frac{A}{1 + kD},$$

where  $A$  denotes the objective monetary amount,  $D$  is the delay, and  $k$  is an individual-specific discounting parameter. Larger values of  $k$  indicate steeper discounting and a stronger preference for immediacy.

For one-off scenarios, discounting parameters were derived directly from participants' indifference points. For recurring payoff scenarios, we followed the logic of intertemporal bundling proposed by Ainslie (1992), according to which sequences of outcomes are evaluated jointly rather than in isolation. Participants were presented with recurring-payoff scenarios and were asked to indicate the recurring delayed payment amount  $L$  that would make them indifferent to receiving a fixed, smaller-sooner payment  $SS$  each month starting immediately. The delayed stream began one month later and continued for the same number of periods.

Assuming hyperbolic discounting, the present value of a sequence of payments equals the sum of the discounted values of its individual components. Thus, for a sequence of payments  $\{A_t\}$  received at times  $\{t\}$ , the total present value is given by

$$PV = \sum_t \frac{A_t}{1 + kt}.$$

Given a participant's reported indifference point  $L$ , we recovered the implied discounting parameter  $k$  by numerically solving for the value of  $k \geq 0$  that equates the present values of the two recurring streams over a horizon of  $T$  periods:

$$\sum_{t=0}^{T-1} \frac{SS}{1 + kt} = \sum_{t=1}^T \frac{L}{1 + kt}.$$

Because this equation does not admit a closed-form solution for  $k$ , we obtained individual-level estimates numerically using a bisection search procedure.

To test the magnitude effect for one-off payoffs, we adopt the approach proposed by Kirby (1997). Specifically, we estimated individual discounting parameters separately for small- and large-magnitude outcomes while holding the delay structure constant. A systematic difference between these estimates constitutes evidence of a magnitude effect. We extended this logic to recurring payoff sequences as well. For each magnitude condition, participants completed an intertemporal tradeoff between a smaller-sooner bundle and a larger-later bundle with an identical temporal structure. Assuming a hyperbolic representation, we estimated an individual discounting parameter for each magnitude condition by equating the discounted present values of the  $SS$  and  $LL$  bundles. This yielded two discounting parameters per participant for the bundled outcomes: one for the small-magnitude sequence and one for the large-magnitude sequence. Analogous to the one-off case as presented by Kirby (1997), a systematic decrease in the estimated discount rate with increasing bundle magnitude provides evidence for a magnitude effect in recurring payoffs.

All participants reported demographic information, including income, age, gender, perceived financial security, and education. These variables were later assessed as potential con-

finds to reduce unexplained variability and increase the precision of estimated effects (Cohen, 1988). Accounting for them also strengthens the generalizability of our findings across diverse participant profiles (Falk et al., 2018). The following sections detail the experimental procedures, analyses, and results for the loss and gain experiments.

### 5.3.1 Study 1: One-off vs. recurring losses

Participants were residents of the Netherlands and were recruited via Prolific, an online data collection platform. They received £0.50 for their participation, consistent with prior research showing that fair compensation improves engagement and data quality in online studies (Buhrmester et al., 2011; Peer et al., 2021; Douglas et al., 2023). Eligibility criteria required participants to be at least 18 years old, provide informed consent prior to participation, and complete the study for the first time using their unique Prolific ID.

To ensure participants clearly understood the task of providing indifference points for outcomes occurring at different times, the experiment began with a detailed explanation and a step-by-step example. Participants were required to carefully read the instructions, review illustrative examples, and type the word “confirm” to indicate that they had read and understood the task. They were then presented with an example indifference-point question, for which the correct answer was explicitly stated in the instructional text. This question served as a comprehension and attention check, as only participants who understood the concept of indifference would be able to provide the correct response.

Only data from participants who successfully passed these comprehension and attention checks were retained for further analysis. The final sample consisted of 151 participants (mean age = 31.67, SD = 9.47). Additional demographic characteristics of the sample are reported in Table 5.1. An a priori analysis was conducted for both experiments using G\*Power as suggested by Faul et al. (2007) to determine the minimum sample size required to achieve adequate statistical power. In each case, the final sample size exceeded the estimated requirement, ensuring sufficient power to detect the effects of interest.

The experiment utilized a 2 (payoff type: one-off vs. recurring)  $\times$  2 (outcome magnitude: small vs. large) within-subjects design. All participants responded to four decision scenarios involving one-off and recurring losses with discounting tasks on small and large outcome magnitudes. In the one-off scenario with small magnitudes, participants read:

*“Imagine that you are making the following decision on the 1<sup>st</sup> of the month. You are given a choice between paying an unexpected €100 bill immediately or another larger amount on the 30<sup>th</sup> of the month. You should specify the magnitude of the delayed payment that would make these two options equally preferable to you.”*

After providing an answer for this one-off scenario, participants move to its recurring equivalent, where they read:

*“Imagine you have been using the same health insurance package for five years, costing you €100 per month. You have been paying your insurance bill on the 1<sup>st</sup> of each month. Recently, your insurance provider has offered new payment schedules.*

Table 5.1: Demographic characteristics of participants in Study 1 (N=151)

Characteristics	Categories	n (%)
Education	High school	36 (23.84%)
	Bachelor's	60 (39.74%)
	Master's	45 (29.80%)
	PhD	10 (6.62%)
Age	18-22	21 (13.91%)
	23-28	43 (28.48%)
	29-34	43 (28.48%)
	35-40	18 (11.92%)
	41+	26 (17.22%)
Gender	Female	66 (43.71%)
	Male	84 (55.63%)
	Non-binary	1 (0.66%)
Employment status	Unemployed	17 (11.26%)
	Homemaker	2 (1.32%)
	Self-employed	11 (7.28%)
	Employed part-time	46 (30.46%)
	Employed full-time	75 (49.67%)
Annual income (after tax)	Below 30.000 €	41 (27.15%)
	30.000 €–49.999 €	44 (29.14%)
	50.000 €–69.999 €	27 (17.88%)
	70.000 €–89.999 €	22 (14.57%)
	90.000 €–119.999 €	11 (7.28%)
	€120.000 and more	6 (3.97%)
Feeling financial security	No	44 (29.14%)
	Unsure	27 (17.88%)
	Yes	80 (52.98%)

*You now have the option to pay your monthly insurance later, on the 30<sup>th</sup> of every month, with a slight increase in its price. The price you identify for the new payment date will be valid for the next two years. You should specify the magnitude of the delayed payment that would make these two options equally preferable to you.*

After completing these two tasks concerning small outcome magnitudes, participants move to the large magnitude cases and again start with the one-off case, where they read:

*“Imagine that you are making the following decision on the 1<sup>st</sup> of the month. You are given a choice between paying an unexpected €1000 bill immediately or another larger amount on the 30<sup>th</sup> of the month. You should specify the magnitude of the delayed payment that would make these two options equally preferable to you.”*

This was followed by the recurring loss large magnitude scenario, which reads:

*“Imagine you have been living in the same apartment for five years, and your current rent is €1000, which you have always paid on the 1<sup>st</sup> of each month. Your*

*landlord is now considering changes to your payment schedule. You have the option to pay your rent later on the 30<sup>th</sup> of each month with a slight price increase. The price you identify for the new payment date will be valid for the next two years. You should specify the magnitude of the delayed payment that would make these two options equally preferable to you.”*

After completing these four scenarios, each participant answers the demographic questions and completes the survey.

### Study 1 Results

The average time to complete the study was 5 minutes, and four discount rates ( $k$ ) were calculated per participant. As shown in Figure 5.1, average discount rates varied across payoff types (one-off vs. recurring) and outcome magnitudes (small vs. large). The highest mean discount rate was observed in the one-off, small-magnitude condition ( $M = 0.084$ ,  $SD = 0.227$ ), followed by the recurring small-magnitude condition ( $M = 0.061$ ,  $SD = 0.289$ ). In contrast, larger magnitudes were associated with lower discount rates: the one-off large-loss condition yielded a mean of  $M = 0.037$  ( $SD = 0.069$ ), while the recurring large-loss condition showed the lowest average discount rate ( $M = 0.021$ ,  $SD = 0.055$ ).

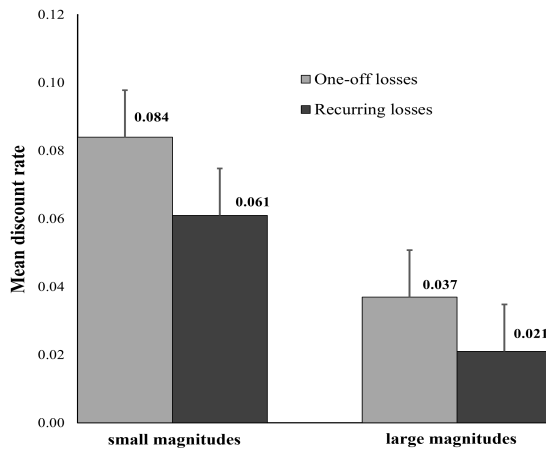


Figure 5.1: Average discount rates for one-off vs. recurring losses with small and large outcome magnitudes

At the within-subject level, 36.42% of participants exhibited a lower discount rate for recurring payoffs than for one-off payoffs, while 29.14% showed no change in their discount rate between the two payoff structures.

Normality checks indicated that the paired differences between one-off and recurring payoffs were not normally distributed in either the small- or large-magnitude conditions. Therefore, Wilcoxon signed-rank tests were used to compare one-off and recurring payoffs within subjects. A significant difference in discount rates was observed between one-off and recurring losses at

both magnitude levels. For small magnitudes, discount rates were higher in the one-off condition than in the recurring condition ( $Z = -2.44$ ,  $p = 0.015$ ,  $r = 0.24$ ). A similar but stronger pattern was observed for large magnitudes ( $Z = -2.98$ ,  $p = 0.003$ ,  $r = 0.30$ ), indicating lower discounting when losses were experienced as recurring rather than one-off.

Using Kirby's approach, we also examined the magnitude effect for one-off and recurring payoffs by comparing individual discount rates across two within-subject scenarios that differed only in outcome magnitude. In the one-off payoff case, of the 151 participants, 40 (26.49%) produced identical discount rates in the small- and large-magnitude conditions for one-off scenarios. Among the remaining 111 participants, 72 (64.86%) exhibited the magnitude effect ( $k_{\text{small}} > k_{\text{large}}$ ), whereas 39 (35.14%) showed the opposite pattern. An exact binomial test on the non-tied cases indicated that the proportion exhibiting the magnitude effect was greater than chance (two-sided  $p = 0.002$ ). For recurring payoffs, we conducted the same analysis to assess the magnitude effect. Of the 151 participants, 73 (48.34%) reported identical discount rates in the small- and large-magnitude conditions. Among the remaining 78 participants, 76 (97.44%) exhibited the magnitude effect ( $k_{\text{small}} > k_{\text{large}}$ ), whereas only 2 (2.56%) showed the opposite pattern. An exact binomial test on the non-tied cases indicated that the proportion exhibiting the magnitude effect for recurring payoffs was significantly greater than chance (two-sided  $p < 0.001$ ). These findings extend the magnitude effect phenomenon from one-off payoffs to recurring scenarios.

Additional analyses were conducted to assess whether within-subject changes in discount rates varied by participants' income, education level, and employment status at the time of the study. We initially classified income into six ranges—from "below 30,000 €" to "120,000 € and more." To ensure each subgroup had a sufficient sample size, we consolidated these into two broader categories. Specifically, the "below 30,000 €", "30,000 €–49,999 €", and "50,000 €–69,999 €" ranges were grouped as low income, while the "70,000 €–89,999 €", "90,000 €–119,999 €", and "120,000 € and above" ranges were combined into the high-income category. A Mann-Whitney U test indicated that income level did not significantly influence the within-subject difference in discount rates between one-off and recurring payoffs for either small ( $U = 2116.50$ ,  $Z = -0.21$ ,  $p = 0.835$ ) or large magnitudes ( $U = 1810.50$ ,  $Z = -1.48$ ,  $p = 0.140$ ). Similarly, for both small and large magnitudes, Kruskal-Wallis tests revealed no significant effects of education level or employment status on within-subject differences in discount rates between one-off and recurring payoffs (all  $p > 0.10$ ).

## Study 1 Discussion

The results from Study 1 support the hypothesis that recurring losses lead to significantly lower discount rates than one-off losses. Participants in our study discounted losses more heavily when these were presented as one-off events. In contrast, when the recurring nature of the same losses was explicitly stated, participants exhibited less steep discounting, resulting in lower discount rates.

One possible explanation is that one-off losses are perceived as more isolated and immediate events, leading to greater sensitivity to the timing of costs. In contrast, recurring losses may be interpreted as part of a broader, ongoing financial obligation, which diminishes their perceived urgency and reduces the emotional and cognitive impact of deferring them. These

are consistent with the isolation argument proposed by Frederick et al. (2002). One-off losses in our experiment likely elicited stronger immediate reactions due to their perceived novelty, whereas recurring losses were more easily integrated and normalized over an extended time horizon. This pattern aligns with the literature on choice bundling and bracketing, suggesting that viewing a decision as part of an ongoing process encourages individuals to account for long-term consequences and adopt more future-oriented preferences (Read et al., 1999; Webb & Shu, 2017; Ainslie, 2001).

A higher discount rate in the one-off condition suggests that future losses are perceived as substantially less painful than immediate ones. As a result, individuals may be more inclined to delay payment, since the emotional impact of future losses is diminished (Hardisty et al., 2013a). Conversely, in the recurring loss condition, future losses retain much of their psychological salience, motivating individuals to resolve them sooner to “get the loss over with” and avoid the persistent anxiety or distress associated with impending losses (Loewenstein, 1987; Ariely & Wertenbroch, 2002). Emphasizing recurrence, therefore, can help discourage payment delays and reduce negative consequences, such as accumulated interest or late fees, commonly associated with steep delay discounting.

Our results also provide consistent evidence for the magnitude effect in intertemporal choice, while highlighting important differences between one-off and recurring payoff structures. Using Kirby’s approach, we observed that for one-off payoffs, a majority of participants exhibited higher discount rates for smaller than for larger outcomes. This heterogeneity is consistent with previous findings that one-off intertemporal outcomes are sensitive to the magnitudes of outcomes (Kirby & Maraković, 1995; Kirby, 1997; Thaler, 1981). When outcomes were framed as recurring payoffs, the magnitude effect became markedly stronger and more uniform: nearly all participants who exhibited any difference showed higher discount rates for small than for large recurring outcomes. This pattern suggests that when payoffs recur, people may make more similar discounting decisions and are more consistently influenced by outcome size. One possible explanation is that recurring payoffs encourage participants to mentally aggregate outcomes over time, thereby reducing the salience of immediate trade-offs and increasing attention to total magnitude. By shifting evaluation from isolated payments to outcome streams, recurring payoffs may effectively dampen present bias and amplify sensitivity to differences in magnitude. This interpretation is consistent with theoretical accounts of bundling in intertemporal choice, which predict reduced discounting and more stable preferences when outcomes are evaluated collectively rather than in isolation.

The observed patterns were robust across income levels and consistent with prior findings by Green et al. (1996), who argue that income does not exert a simple or direct effect on discount rates but instead interacts with other individual characteristics, such as the decision-maker’s age. Moreover, the absence of systematic differences across other socioeconomic indicators, including education level and employment status, suggests that the observed discounting patterns are not confined to specific subgroups. Together, these results indicate that the findings are likely generalizable at least to the individuals within the studied sample of Dutch residents. To assess whether similar discounting patterns hold for gains, the subsequent study re-examines the hypothesis that recurring outcomes are associated with lower discount rates, employing the same experimental design.

### 5.3.2 Study 2: One-off vs. recurring gains

Participants were residents of the Netherlands and were recruited via Prolific. They received £0.50 for their participation. Eligibility criteria were identical to those in Study 1, and the same procedure was used to ensure that participants clearly understood the task of providing indifference scores. This procedure included detailed instructions, illustrative examples, and a comprehension check requiring participants to correctly answer an example question and type the word “confirm”. Only participants who successfully passed this comprehension check were retained for analysis.

In addition, the data were screened for quality to identify implausible or non-informative responses. Participants who provided extreme or random numerical responses outside the acceptable range (e.g., values inconsistent with the monetary amounts under evaluation) were excluded from the analysis. After applying these criteria, the final sample consisted of 133 participants (mean age = 32.36, SD = 9.97). Additional demographic characteristics of the sample are reported in Table 5.2. As in Study 1, we utilized a 2 (payoff type: one-off vs. recurring)  $\times$  2 (outcome magnitude: small vs. large) within-subjects design. In the one-off scenario with small gains, participants read the instructions:

*“Imagine that you are making the following decision on the 1<sup>st</sup> of the month. You are given a choice between receiving €100 unexpected reward from a lottery on the 30<sup>th</sup> of the same month or another smaller amount immediately. You should specify the magnitude of the immediate reward that would make these two options equally preferable to you.”*

This was followed by the recurring payoff equivalent of the scenario where participants read the instructions:

*“Imagine that for the past five years, you have been supplementing your income by writing short articles for an online content platform. Each month, you consistently earn €100 from your published stories. Payments are transferred to your bank account on the 30<sup>th</sup> of each month. The platform is now considering adjusting its payment schedule, offering you the option to receive your earnings earlier, on the 1<sup>st</sup> of every month, in exchange for a slight decrease in the amount. The amount you identify for the earlier payment date will be valid for the next two years. You should specify the magnitude of the sooner income that would make these two options equally preferable to you.”*

After completing these two tasks, participants move to the large magnitudes case, where they read:

*“Imagine that on the 1<sup>st</sup> of the month, you win an unexpected contest that will pay you €1000 reward on the 30<sup>th</sup> of the same month. Alternatively, you can choose to receive a smaller amount immediately. You should specify the magnitude of the immediate reward that would make these two options equally preferable to you.”*

This was followed by the recurring payoff version, which reads:

Table 5.2: Demographic characteristics of participants in Study 2 (N=133)

Characteristics	Categories	n(%)
Education	High school	28 (21.05%)
	Bachelor's	59 (44.36%)
	Master's	42 (31.58%)
	PhD	4 (3%)
Age	18-22	19 (14.28%)
	23-28	37 (27.82%)
	29-34	33 (24.82%)
	35-40	19 (14.28%)
	41+	25 (18.8%)
Gender	Female	64 (48.12%)
	Male	68 (51.13%)
	Non-binary	1 (0.75%)
Employment status	Unemployed	24 (18.04%)
	Homemaker	3 (2.26%)
	Self-employed	11 (8.27%)
	Employed part-time	34 (25.56%)
	Employed full-time	61 (45.87%)
Annual income (after tax)	Below 30.000 €	43 (32.33%)
	30.000 €–49.999 €	31 (23.31%)
	50.000 €–69.999 €	19 (14.29%)
	70.000 €–89.999 €	21 (15.79%)
	90.000 €–119.999 €	9 (6.76%)
	120.000 € and more	10 (7.52%)
Feeling financial security	No	35 (26.32%)
	Unsure	26 (19.54%)
	Yes	72 (54.14%)

*“Imagine that for the past five years, you have been receiving €1000 monthly interest income from a fixed deposit account with a bank. The interest payments are deposited into your bank account on the 30<sup>th</sup> of each month. The bank now offers you the option to receive your interest payments earlier on the 1<sup>st</sup> of each month, with a slight reduction in the payment amount. The new payment amount you identified for the earlier date will be valid for the next two years. You should specify the magnitude of the sooner income that would make these two options equally preferable to you.”*

Consistent with the previous study, the dependent variable, discount rate, was derived from participants' responses to each scenario.

## Study 2 Results

On average, participants completed the task in approximately five minutes. Figure 5.2 illustrates the mean discount rates obtained across the different decision scenarios. The highest average

discount rate was observed in the one-off, small-magnitude condition ( $M = 0.136$ ,  $SD = 0.227$ ), followed by the recurring small-magnitude condition ( $M = 0.087$ ,  $SD = 0.331$ ). In contrast, larger magnitudes were associated with lower discount rates: the one-off large-loss condition yielded a mean discount rate of  $M = 0.058$  ( $SD = 0.132$ ), while the recurring large-loss condition exhibited the lowest average discount rate ( $M = 0.047$ ,  $SD = 0.124$ ).

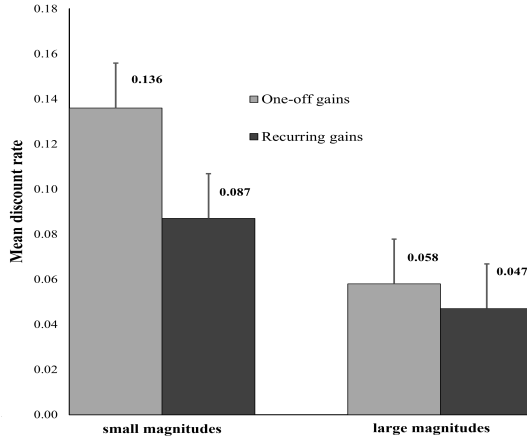


Figure 5.2: Discount rates for one-off vs. recurring gains with small and large magnitudes

At the within-subject level, 56.39% of participants exhibited a lower discount rate in the recurring condition than in the one-off condition for small outcome magnitudes, while 18.05% maintained the same discount rate. For large magnitudes, 45.11% of participants exhibited lower discount rates in the recurring setting, whereas 33.08% showed no change and 21.80% exhibited higher discount rates.

Tests of normality indicated that the paired differences between one-off and recurring gains were not normally distributed for either magnitude condition. Consequently, Wilcoxon signed-rank tests were employed to compare one-off and recurring payoffs within participants.

Wilcoxon signed-rank tests revealed that discount rates for gains were significantly lower in the recurring condition than in the one-off condition for both magnitude levels. For small magnitudes, discount rates were lower under recurring gains than under one-off gains ( $Z = -4.47$ ,  $p < 0.001$ ), with the majority of participants exhibiting a reduction in discounting. A similar but weaker pattern was observed for large magnitudes ( $Z = -2.81$ ,  $p = 0.005$ ).

As in Study 1, the magnitude effect was examined using Kirby's approach by comparing individual discount rates across two within-subject scenarios that differed only in the magnitudes of the gains. In the one-off scenarios, 31 of the 133 participants (23.31%) produced identical discount rates in the small- and large-magnitude conditions. Among the remaining 102 non-tied cases, 80 participants (78.43%) exhibited the magnitude effect ( $k_{\text{small}} > k_{\text{large}}$ ), whereas 22 participants (21.57%) displayed the opposite pattern. An exact binomial test conducted on the non-tied cases showed that the proportion of participants exhibiting the magnitude effect was significantly greater than would be expected by chance (two-sided  $p < 0.001$ ). For the recurring gains, 61 participants (45.86%) produced identical discount rates in the small- and

large-magnitude conditions. Among the remaining 72 non-tied cases, 50 participants (69.44%) exhibited the magnitude effect ( $k_{\text{small}} > k_{\text{large}}$ ), whereas 22 participants (30.56%) showed the opposite pattern. An exact binomial test on the non-tied cases indicated that the proportion exhibiting the magnitude effect was significantly greater than chance (two-sided  $p = 0.0013$ ).

In the small-magnitude condition, income level influenced within-subject differences in discount rates between one-off and recurring payoffs. A Mann-Whitney U test indicated that high-income participants exhibited larger reductions in discount rates than low-income participants when moving from one-off to recurring gains ( $U = 1416.50$ ,  $Z = -2.32$ ,  $p = 0.020$ ). In contrast, income level did not significantly influence within-subject changes in discount rates for large gains ( $U = 1819.50$ ,  $Z = -0.45$ ,  $p = 0.652$ ).

The education level did not significantly influence within-subject differences in discount rates between one-off and recurring gains for either small or large magnitudes (both  $p > 0.10$ ). Employment status likewise showed no significant effect for large gains. However, for small gains, employment status was associated with significant differences. Specifically, a Kruskal–Wallis test indicated that the reduction in discount rates from one-off to recurring small gains differed by employment category ( $H(3) = 8.63$ ,  $p = 0.035$ ). No corresponding effect was observed for large gains ( $p = 0.104$ ). Taken together, these results suggest that while education does not systematically shape how individuals respond to payoff recurrence, employment status may moderate the impact of recurrence for small gains, consistent with the idea that individual circumstances matter most when outcomes are relatively modest.

## Study 2 Discussion

Study 2 extended the investigation into the domain of gains, yielding results that both mirror and complement those observed in Study 1. Consistent with our hypothesis, participants exhibited significantly lower discount rates for recurring gains compared to one-off gains.

A higher discount rate in the one-off condition implies that decision-makers perceive the value of a gain as much lower when the time to receive it increases. These findings regarding one-off payoffs are consistent with the time preference literature, which extensively reports the diminishing value of gains by time (Frederick et al., 2002; Samuelson, 1937; Laibson, 1997; Ainslie, 2002; Hardisty et al., 2013a; Benzion et al., 1989; O'Donoghue & Rabin, 2015). As discussed in Study 1, one plausible explanation is that the isolated nature of one-off gains alters the perceived values of immediate and delayed rewards, increasing discount rates (Frederick et al., 2002).

What is interesting and new in our study is that participants' discount rates dropped significantly when they were deliberately confronted with a scenario in which the same amount of gain was recurring over time. This finding is closely related to, yet distinct from, the choice-bundling literature. Classic bundling accounts emphasize reduced discounting when individuals evaluate outcomes as part of an explicit bundle or commit to intertemporal choice policies. In contrast, our results show that discount rates can be substantially reduced even without presenting outcomes as formal bundles or requiring commitment, simply by embedding the same payoff within a recurring scenario. By shifting attention from an isolated gain to a repeated outcome structure, the scenario itself appears sufficient to encourage more future-oriented valuation. In this sense, our study builds on the bundling insight that aggregation over time matters, while

demonstrating that explicit bundling is not necessary for discount rates to decline. Together, these findings extend the choice bundling and bracketing literature by showing that long-term considerations and lower discount rates can emerge from a single decision involving recurring payoffs, even in the absence of explicit commitment or repeated choice, simply through the presentation of gains as recurring outcomes in the decision scenarios (Ainslie, 1992; Read et al., 1999).

Similar to losses, smaller gains were discounted more steeply than larger ones, consistent with prior research indicating that delayed rewards are devalued more sharply when the amounts are smaller (Thaler, 1981; Wang et al., 2015). These results extend and strengthen existing evidence on the magnitude effect in intertemporal choice (Benhabib et al., 2010; Hardisty et al., 2013a; Baker et al., 2003; Green et al., 1997). Beyond replicating the magnitude effect for gains, our results show that framing outcomes as recurring substantially alters their strength and consistency. While discounting of one-off gains varied considerably across individuals, recurring gains produced a markedly more uniform pattern: among participants who exhibited any difference in discounting behavior, the vast majority discounted smaller recurring gains more steeply than larger ones. This finding suggests that recurrence may stabilize sensitivity to outcome magnitude, reducing heterogeneity in individual discounting behavior. One plausible explanation is that recurring gains encourage participants to evaluate outcomes as integrated streams rather than as isolated payments, thereby shifting attention to cumulative magnitude rather than immediate trade-offs. In this way, recurrence may dampen present-focused valuation while amplifying the role of outcome size, a pattern consistent with theoretical accounts of bundling and bracketing in intertemporal choice.

Supplementary analyses probing the potential moderating roles of income level, education level, and employment status showed that individual characteristics shape the impact of payoff recurrence in a selective and magnitude-dependent manner. Income and employment status moderated the effect of recurrence for small gains, with higher-income participants and certain employment groups exhibiting larger reductions in discount rates when outcomes were framed as recurring rather than one-off. This finding is consistent with the results reported by Haushofer et al. (2013), suggesting that individuals across income groups may respond differently to outcome magnitudes.

By contrast, no such differences emerged for large gains, and education level did not systematically influence responses to payoff recurrence at either magnitude. This pattern suggests that recurring payoff structures are most sensitive to individual circumstances when gains are relatively modest, whereas sufficiently large gains elicit more uniform discounting behavior across socioeconomic groups. Consistent with our broader findings, these results reinforce the view that recurrence can reshape the perceived salience and relevance of outcomes rather than uniformly altering time preferences across individuals.

## 5.4 General discussion

Building on the common approach to studying time discounting with isolated, single-payoff scenarios and the choice bundling literature, we hypothesized that an alternative framework using recurring payoff scenarios would encourage more comprehensive evaluation and yield lower discount rates. By embedding recurrence directly into the payoff structure, our design prevents

participants from treating the outcome as a one-off event and naturally encourages them to consider its long-term implications. We could therefore examine the shift in time preference from one-off to recurring payoffs and uncover insights into the evaluation processes.

In two experiments focusing on gains and losses, we found that highlighting the recurring nature of payoffs leads to significantly lower discount rates than when payoffs are framed as isolated, one-off events. Across both domains, participants consistently reduced their discount rates when transitioning from single to recurring payoff conditions. We interpret this shift as a reduction in the isolation effect, whereby recurring outcomes are more readily integrated into a broader decision context. In their seminal review, Frederick et al. (2002) argue that treating intertemporal outcomes as isolated and discrete events encourages myopic evaluation and inflates discount rates. By contrast, our scenario-based manipulation does not require explicit bundling or commitment, yet it similarly promotes an aggregated evaluation of outcomes over time. In this sense, our findings complement the choice bundling and bracketing literature (Ainslie, 1992; Read et al., 1999) by showing that the cognitive benefits of aggregation can arise even from a single decision involving recurring payoffs, extending bundling insights beyond repeated choices or policy commitments.

The findings of this study also align with a distinct line of research in the time preference literature, offering an alternative perspective on intertemporal choice. A key distinction is often drawn between two methodological approaches used to investigate choice over time: pairwise matching and the relative valuation of outcome sequences (Guyse et al., 2024). The pairwise matching task closely resembles the isolated, one-off scenarios used in our experiments, asking participants to judge equivalences between different quantity–timing pairs (Guyse & Simon, 2011). In contrast, the sequence-based evaluation investigates time preference by examining patterns in sequences of outcomes over time (Loewenstein & Prelec, 1993). This latter approach places decision-makers in a context in which the same outcomes emerge in an increasing or decreasing sequence over time (Duffy & Smith, 2013). As a result, it often reveals intertemporal preferences that contradict those observed in pairwise matching tasks (Guyse et al., 2002; Loewenstein & Prelec, 1993; Guyse et al., 2020). A seminal study by Loewenstein & Sicherman (1991) found that individuals tend to prefer income sequences that begin with lower amounts and increase over time, rather than those that start with higher amounts and decline. These preferences challenge the positive discount rate assumption observed in pairwise matching tasks. Empirical investigations have repeatedly reported that people prefer smaller, sooner outcomes over larger, later ones, implying a positive discount rate. However, in the sequential context, preferring a sequence that starts with a low income level implies a negative discount rate. In other words, when the sequential structure of outcomes is made salient, individuals appear not to discount future rewards as they do in traditional choice tasks (Loewenstein & Prelec, 1993). This divergence underscores the importance of context in shaping time preference. It suggests that the anomalies observed in intertemporal choice may be sensitive to the structure and frame of the decision task (Guyse & Simon, 2011). Loewenstein & Prelec (1993) highlights this effect with the observation that: “... when the decision frame draws attention to the sequential nature of choice, negative time discounting typically prevails; however, when the frame draws attention to individual components of the choice, positive time preference predominates.” Although our experiments differ from the outcome sequences explored in this line of research, the highlighted importance of contextual factors and the role of considering extended time period in the elicitation process provides further support for our findings (Guyse et al., 2002; Frederick & Loewenstein, 2008; Loewenstein & Prelec, 1993). Similar to the sequential context, plac-

ing decision-makers in a recurring context seems to encourage them to view decisions within a broader time horizon. As a result, they consider the long-term consequences and exhibit lower discount rates. From this perspective, our findings show a degree of alignment with previous studies.

Our results also provide additional support for the magnitude effect. As documented in numerous studies, small gains tend to be discounted more steeply than large gains (Thaler, 1981; Benhabib et al., 2010; Hardisty et al., 2013a; Baker et al., 2003; Green et al., 1997). Consistent with this finding, our experiment on gains revealed significantly higher discount rates for smaller gains compared to larger gains. While the pattern for gains is relatively straightforward and well-established, the literature on losses is more conflicted and less extensive. Some studies, such as those by Baker et al. (2003) and Estle et al. (2006), report that the magnitude effect does not apply to losses. Others argue for a negative magnitude effect, suggesting that large losses are discounted more steeply than small losses (Hardisty et al., 2013a; Breuer et al., 2024). A third line of research indicates that the magnitude effect applies to losses like gains, with small losses discounted more heavily than large ones (Thaler, 1981; Chapman, 1996; Loewenstein, 1987; Ben Zion et al., 1989). Our findings align with this third group, showing that small losses are discounted more steeply than large losses, thus reinforcing the generalizability of the magnitude effect across both gains and losses.

A further contribution of this study is the extension of the magnitude effect beyond isolated payoffs to decisions involving recurring outcomes. In addition to the classic magnitude effect, which compares isolated smaller-sooner and larger-later payoffs, our analysis evaluates discounting across outcome streams that repeat over time and differ only in their timing. By holding the payoff structure constant and embedding magnitude differences within recurring sequences, we show that sensitivity to outcome size persists (in some cases even becomes more pronounced) when decisions involve recurring gains or losses. This finding suggests that the magnitude effect is not limited to isolated intertemporal choices but also operates at the level of outcome streams, with implications for how individuals evaluate subscriptions, salaries, annuities, and other recurring payments. More broadly, it reinforces the view that temporal aggregation and payoff structure jointly shape time preferences, extending magnitude-based accounts of intertemporal choice to settings that more closely resemble real-world financial decisions.

These insights advance our understanding of how individuals evaluate intertemporal choices when the isolating nature of outcomes is reduced through decision scenarios that reflect recurring patterns commonly observed in real-world settings. By moving beyond the standard experimental focus on isolated one-off payoffs, our study offers a more nuanced account of time discounting. Moreover, the findings point to potentially important implications for improving decision-making processes. The following subsections elaborate on the study's theoretical contributions and discuss its practical relevance for behavioral interventions.

### 5.4.1 Theoretical Implications

The findings of this study offer theoretical implications that contribute to a better understanding of intertemporal decision-making and provide insights into improving existing models of time discounting. Our results demonstrate that the structure of outcomes (being one-off or recurring) significantly influences discounting behavior. These findings indicate that people do not merely

discount outcomes by considering their time delays but also respond to how these outcomes are defined in the problem and unfold over time. Therefore, incorporating contextual elements into theoretical models may improve ecological validity in representing intertemporal trade-offs. By doing so, these frameworks can move beyond static parameterizations toward a richer understanding of how individuals perform intertemporal trade-offs.

The distinction between one-off and recurring payoffs parallels concepts such as choice bundling and bracketing, suggesting that evaluating outcomes in a broader context fosters more consistent and future-oriented decision-making. While previous research on choice bundling and bracketing has typically focused on multiple separate decisions, our experiment found similar results for a single decision generating recurring payoffs over time. From this perspective, our findings extend these concepts by showing that recurrence built into payoff structures can implicitly broaden evaluative perspectives without requiring explicit rules or conscious grouping. This opens up new avenues for theorizing about “recurring bundles” or “bracketing decisions with recurring outcomes,” where multiple problems (each yielding recurring payoffs) are considered together. By drawing attention to these more complex decision structures, our results can contribute to refining theories of choice bundling and bracketing.

Finally, while this study focuses on monetary outcomes, the mechanisms we identify may generalize to other domains where intertemporal trade-offs are prominent. In contexts such as health behaviors or environmental decision-making, individuals frequently face recurring consequences rather than isolated outcomes (Chapman, 1996; Guye et al., 2002). As such, the recurrence-based perspective may provide a broadly applicable theoretical lens for understanding time-sensitive behaviors across different settings.

## 5.4.2 Practical Implications

Beyond informing theory and empirical frameworks, this study offers actionable insights for shaping real-world decision-making. By emphasizing the recurring nature of payoffs, decision scenarios can encourage individuals to adopt more future-oriented perspectives. For instance, a savings app could present enrollment in an automatic savings plan not as a one-off choice but as a decision that yields recurring benefits, such as weekly savings growth. Framing decisions in terms of repeated outcomes may enhance the perceived value of long-term choices and increase engagement with commitment tools.

Our findings also carry implications for managing losses and obligations. Individuals were less willing to delay debts when the negative consequences recurred over time. From this perspective, highlighting the recurring nature of financial obligations could motivate earlier repayment and reduce procrastination. Policy-makers and financial advisors could leverage this insight through targeted reminders or communication strategies designed to emphasize the ongoing costs of delayed action.

The recurring-payoff perspective may further improve the design of policies and programs that involve routine decisions, such as tax payments, subscription renewals, or public health interventions. By making the recurring nature of benefits or costs salient, authorities could reduce procrastination and encourage timely compliance. Likewise, marketing and behavioral strategies, such as loyalty programs or subscription services, could benefit from highlighting recurring rewards so that consumers perceive them as delivering consistent value, potentially

increasing retention and engagement. Collectively, these findings demonstrate that incorporating the temporal structure of payoffs into decision design can create scalable interventions that foster more consistent and future-oriented decision-making.

## 5.5 Conclusion

This study investigated whether discount rates vary when decision payoffs occur repeatedly over time, rather than as one-off outcomes typical of most experiments. Our results on gains and losses consistently revealed that transitioning from one-off to recurring payoff conditions significantly decreases discount rates. We also provided further support for the magnitude effect in one-off and recurring payoff problems.

By examining recurring payoff scenarios that reflect real-world patterns, we were able not only to capture descriptive insights into decision-making but also to highlight prescriptive implications, showing how analysts can leverage our findings to support better decisions and mitigate the isolation effect.

While the present study offers valuable insights into intertemporal decision-making, several limitations should be acknowledged, each of which suggests promising directions for future research. The primary limitation concerns the design of the recurring payoff scenarios. In our experiments, the recurrence cycles and outcome magnitudes were fixed (e.g., paying €1000 every month). Although this framework aligns with numerous real-life situations, such as receiving a salary or making recurring subscription payments, it falls short of representing all decision types, where both the timing and size of payoffs may vary. In everyday life, recurring events, such as monthly utility bills, might also involve irregular amounts and varying time intervals. For instance, while individuals typically pay the same type of utility bills each month, the exact amount and timing of these payments can slightly fluctuate. Our controlled design simplified these factors to reduce cognitive load and isolate the effects of recurrence. However, we acknowledge that real-life decisions often lie between the extremes (fixed amount and fixed recurrence cycle) we used in this study. Future research should extend our findings by exploring different decision structures, incorporating variability in both the timing and magnitude of recurring outcomes within the same scenario.

Testing different time windows for recurrent payoffs could provide additional validation of the observed effects. In our experiment, there was a one-time 60-day window when decision-makers switched to a new payment schedule. While our results suggest that this did not alter participants' preferences—and in fact reinforced the findings—it may still be valuable to examine different windows to further confirm these effects. Designing interactive, game-based experimental environments could be especially fruitful. Such environments would allow participants to engage with dynamic payoff structures and learn from experience by making choices across varying recurring cycles. This approach could not only enhance validity but also open new avenues for studying decision-making and potentially inform training tools to improve long-term decision strategies.

In addition to the structural limitations of the recurring payoff design, sample characteristics may constrain the generalizability of our findings. Although our sample was relatively diverse regarding age, gender, educational background, employment status, and income level,

participation was limited to individuals residing in the Netherlands. Given the well-documented cross-cultural differences in time discounting and intertemporal preferences (Wang et al., 2016), this geographical limitation may affect the external validity of our results. As such, future research should seek to replicate and extend these findings across different cultural and national contexts to assess their broader applicability. It would also be valuable to examine the emotional states of participants, as emotions have been identified as an important factor influencing utilitarian judgments (Choe & Min, 2011).

In developing our hypothesis, we drew on the theoretical frameworks of choice bundling and bracketing. While prior studies on these concepts have focused on considering multiple separate decisions, our experiment shows that even single decisions generating recurring payoffs can also influence time preferences and promote a broader evaluative perspective. Building on this insight, future work could examine scenarios such as “recurring bundles” or “bracketing recurring outcomes,” where multiple problems with recurring payoffs are considered together. Investigating these structures may further advance theories of choice bundling and bracketing and provide insights into complex decision-making processes.

Another limitation of the current study is its exclusive focus on monetary decision-making. While financial outcomes provide a clear and quantifiable context for studying intertemporal preferences, they represent only one domain. In real life, individuals face many other intertemporal trade-offs and recurring payoffs in health, environmental management, and education. Future research should investigate whether similar patterns emerge in these domains. Such work would help determine the domain generality of our findings and offer valuable insights for designing interventions across a broader range of decision-making contexts. In conclusion, we hope this paper helps further research on this relevant topic in intertemporal decision-making, given its relevance to business and personal decisions and the limited evidence about the role of recurring payoffs.

### **Declaration of generative AI and AI-assisted technologies in the writing process:**

During the preparation of this work, the author(s) used ChatGPT (chatgpt.com) and Grammarly (grammarly.com) in order to improve the writing style and proofreading. After using this tool/service, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the published article.

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# Chapter 6

## Conclusion

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This dissertation examines how time preference and time-related biases shape judgments and preferences, and explores strategies to mitigate their adverse effects in decision analysis. It considers both decision-makers' and analysts' roles, offering descriptive and prescriptive perspectives simultaneously. Chapter 1 introduced four guiding research questions and outlined the dissertation's relevance, aims, and contributions. Chapter 2 systematically identified six time-related biases, analyzed their effect on judgments and preferences, and reviewed mitigation strategies from various fields. Chapter 3 extended this analysis to multi-attribute decision-making (MADM), showing how each step can be affected by these biases and highlighting promising strategies to reduce them. Chapter 4 theorized and empirically tested the impact of time preference on value function and scaling constant elicitation steps of the multi-attribute value theory (MAVT), thus extending the study of time preference to a multi-attribute level. Finally, Chapter 5 focused on a particular problem type that has been overlooked in the time preference literature: decisions with recurring payoffs. In the following, I summarize the key findings resulting from each research question, highlight their contributions to understanding time preference in decision analysis, and conclude with practical implications and directions for future research.

## 6.1 Key findings

The main research question was investigated through four sub-questions. So I begin by outlining the key findings of each study and then integrating them to address the overarching question.

**RQ 1:** What are the time-related cognitive biases influencing intertemporal judgments, and what strategies can be employed for mitigation? (Chapter 2).

In Chapter 2, I employed a two-level systematic approach. First, I identified multiple keywords related to time preference and examined the definitions of over two hundred biases listed in the cognitive bias codex, seminal time preference studies, and established bias taxonomies. From this analysis, six key biases emerged: present bias, projection bias, recency bias, duration neglect, impact bias, and the planning fallacy, addressing the first part of the research question. Second, each of these biases was investigated through a systematic literature review. By synthesizing findings across disciplines such as finance, economics, health, agriculture, politics, education, and environmental sustainability, I extracted the following information: (i) the influence of each time-related bias on judgment and decision-making, (ii) secondary biases or behavioral factors associated with each bias, (iii) mitigation strategies, and (iv) gaps in the literature along with directions for future research. Finally, the relationships between the biases and other reported behavioral factors were depicted in a visual map, providing insights into their connections and underlying mechanisms.

The findings suggest that time-related biases are pervasive, affecting a wide range of decisions in public and personal health, economics, finance, agriculture, politics, environmental sustainability, education, sports, military, and project management. They lead to serious distortions by impacting the way time is perceived, outcomes are compared, and judgments are shaped. The analyses revealed that the negative effects of time-related biases stem from a complex interplay of behavioral variables, cognitive processes, environmental influences, and individual characteristics.

Multiple biases have been reported across diverse disciplines, yet present bias remains the most extensively studied one. More recently identified biases, such as recency bias and projection bias, have received comparatively little attention. Another crucial finding is the lack of systematic mitigation strategies against biases. The findings reveal an over-reliance in the literature on descriptive approaches to investigate the impact of biases on judgments. Although some biases have been the subject of relatively more empirical testing, mitigation strategies for most biases remain limited and largely consist of general recommendations. The findings indicate the need for developing and testing prescriptive approaches to support in mitigating the adverse effects. Our results also show that most of the time, a particular judgment or choice is shaped by more than one bias, in alignment with the complexity of human thinking. From this perspective, the existing literature provides limited insights into systematically distinguishing the effects of multiple biases.

This study makes several key contributions to the literature on intertemporal decision-making. It provides the first systematic review that holistically examines six major time-related cognitive biases, drawing together insights from economics, psychology, health, and policy. By mapping the interrelationships among these biases, it advances understanding of how they interact and compound in shaping judgments. The study also synthesizes existing mitigation strategies, critically evaluates their effectiveness, and identifies gaps that require further empirical testing.

Finally, it sets out a structured research agenda, thereby extending the theoretical foundations of the field while offering practical guidance for designing interventions and policies that foster more farsighted decisions.

A crucial insight from this systematic review is that research on time preference and time-related biases has predominantly relied on simple choice problems involving direct comparisons of intertemporal outcomes, usually with a single objective. Such approaches overlook the fact that real-life decisions often involve multiple, and sometimes conflicting, objectives that require the evaluation of complex trade-offs. Building on this gap, Chapter 3 extended the analysis of time-related biases to a multi-attribute setting. In doing so, it addresses the following research question:

**RQ 2:** How do time preference and time-related cognitive biases influence the decision-making process in the presence of multiple objectives, and what strategies can be employed for mitigation? (Chapter 3).

Having examined time-related biases in single-objective choice problems in Chapter 2, it became evident that human judgments and preferences are susceptible to many biases. The negative impacts will likely become even more pronounced when multiple conflicting objectives and alternatives are involved. Building on these insights, Chapter 3 explored the influence of time-related biases in the multi-attribute decision-making process and discussed mitigation ideas from a prescriptive point of view.

First, the exponential discounting model was treated as the normative benchmark, with each bias conceptualized as a deviation from its rationality assumptions (Samuelson, 1937). Then the steps of the MAVT were examined for their potential susceptibility to biases (Keeney & Raiffa, 1975). By synthesizing insights from behavioral decision research, time preference, and MADM literature, this chapter focuses on the potential impacts of biases for each phase of the evaluation. Furthermore, strategies for reducing these negative effects were discussed with reference to the underlying assumptions of the normative model, considering the role of an analyst in the process. The key findings from this study can be summarized as follows:

- i. Existing research has predominantly focused on single-objective choice problems, leaving a limited understanding of how time-related biases operate in MADM contexts.
- ii. Time-related biases have largely been studied from a descriptive perspective. When approached from a prescriptive standpoint, various strategies could benefit mitigation efforts and help increase decision quality in the MADM.
- iii. Time-related biases can affect nearly every step of the MAVT process, highlighting the need for awareness from the very beginning, like problem structuring and objective-setting stages.
- iv. Trade-off relations in MADM add another layer of complexity to the problem and warrant particular attention to gain a good understanding of the impact of time-related biases.
- v. Utilizing systematic approaches such as Nominal Group Technique (Delbecq & Van de Ven, 1971), Value Focused Thinking (Keeney, 1996), or Reference Class Forecasting (Flyvbjerg, 2008; Batselier & Vanhoucke, 2016) may help gather insights from decision-makers while potentially controlling the negative impact of time-related biases.

- vi. The sequential nature of the MAVT process can lead to a propagation effect, whereby an unaddressed bias at one stage may compound and create further issues in subsequent stages of the evaluation (Lahtinen et al., 2020).
- vii. Numerous mitigation strategies have been discussed for each step. However, these remain as promising suggestions and require further empirical investigation across diverse contexts.
- viii. The analyst can play a significant role in reducing the adverse effects of biases throughout the evaluation process.
- ix. There is a need to develop a taxonomy of time-related biases, as not all biases exert the same influence. Such differentiation would allow analysts to more effectively direct and prioritize mitigation efforts.

This study contributes to the literature by extending the analysis of time-related biases from simple intertemporal choice problems to the more complex domain of MADM. By adopting a prescriptive perspective, the study not only highlights the role of analysts in shaping preference elicitation and trade-offs but also proposes preliminary strategies to mitigate these biases. In doing so, it advances theoretical understanding of intertemporal decision-making in complex contexts and provides practical guidance for improving the quality of decisions involving multiple objectives. Moreover, this study motivates a new line of inquiry by encouraging researchers to investigate time-related biases in new settings.

The findings of this study highlighted the lack of empirical evidence regarding the role of time preference in the MADM context. To address this gap, I focused on the following research question:

**RQ 3:** How does time preference influence attribute-specific value function elicitation and trade-off processes in intertemporal multi-objective decision-making problems? (Chapter 4).

This chapter presented one of the first experimental investigations of time preference in the multi-attribute context. I began by introducing the *intertemporal MADM problem*, which extends the evaluation environment to incorporate trade-offs not only between attributes but also across time points. I then theorized how time preference might affect two crucial steps of MAVT: value function elicitation and trade-off. Across three experiments, I examined how delaying one or more attributes influences value elicitation, trade-off judgments, and resulting scaling constants.

**Study 1** focused on the effect of delaying the more important attribute (cost). The delay reduced both the perceived value of cost and its corresponding scaling constant in the evaluation process. This effect reflected classical discounting behavior in a multi-attribute context. **Study 2** reversed the manipulation by delaying the less important attribute (screening duration). Here, the delayed attribute again lost weight, but the shift was driven less by changes in its own perceived value and more by an increase in the salience of the complementary attribute, cost. This highlights that the consequences of delay cannot be understood in isolation: changes in one attribute's timing can alter how the other is perceived and weighted. **Study 3** examined the simultaneous delay of both attributes. In this case, no significant changes occurred in values or scaling constants, suggesting that when all outcomes are postponed equally, the relative structure of preferences remains stable. Interestingly, however, trade-off scores shifted, indicating

subtle changes in willingness to exchange between attributes even when their absolute values were unaffected. These findings challenge the assumption that time always reduces value in a straightforward manner. Taken together, these studies demonstrate that time preference in MADM does not simply follow the patterns observed in unidimensional discounting tasks.

Methodologically, this chapter underscores the value of using a systematic method like MAVT to trace how time influences each stage of the decision process, providing insights that conventional approaches relying on discount rates cannot provide. Substantively, the results highlight that intertemporal trade-offs in real-world, multi-objective settings require a more nuanced understanding and further investigation than traditional models allow. The findings not only enhance our understanding of time preference with complex problems but also provide practical suggestions for analysts who elicit preferences in the intertemporal MADM problem.

Chapter 4 advances the understanding of intertemporal MADM problems by bridging theoretical research with practical decision contexts. In parallel to this motivation, I next addressed the following research question, which concerns a type of decision that is frequently encountered in real-life yet often overlooked:

**RQ 4:** How does considering intertemporal outcomes as recurring, rather than one-off payoffs, affect individuals' time preference and resulting discount rates? (Chapter 5).

In Chapter 5, I presented another experimental study focusing on the relationships between time preference and payoff structures. More specifically, I examined how time preferences change when individuals evaluate decisions that generate recurring payoffs rather than isolated, one-off outcomes. Drawing on the concepts of choice bundling (Ainslie, 1992; Ainslie et al., 2018) and choice bracketing (Read et al., 1999), I hypothesized that embedding recurrence directly into payoff structures would encourage broader evaluation, thereby lowering discount rates (Kirby & Guastello, 2001). To test this, I conducted two within-subjects experiments on losses and gains, each manipulating payoff type (one-off vs. recurring) and outcome magnitude (small vs. large).

**Study 1** investigated recurring losses. Results showed that discount rates were significantly lower in recurring conditions compared to one-off conditions, with the effect moderated by outcome magnitude. Participants discounted small losses more heavily than large ones, consistent with the magnitude effect, but recurrence reduced discounting across both conditions. These findings suggest that recurring losses are likely integrated into a broader financial perspective, reducing their perceived urgency relative to isolated, one-off losses. **Study 2** extended the investigation into recurring gains. Similar to losses, discount rates were substantially lower, again moderated by outcome magnitude. Small gains were discounted steeply in the one-off condition, but far less so when presented as recurring outcomes over an extended period. The decrease in discount rates indicates that repetition may help embed outcomes in a broader evaluative horizon, making them seem less tempting.

The findings indicate that time preferences are context-dependent: when outcomes are framed as recurring, people adopt broader evaluative perspectives that foster patience and lower discount rates. Theoretically, this work extends models of time preference by highlighting the role of recurrence as a structural determinant of intertemporal choice, complementing insights from choice bundling and bracketing. Practically, it suggests that interventions which emphasize recurring consequences, such as framing savings, debt repayment, or health behaviors in recurring terms, may promote more consistent and future-oriented decision-making. Overall,

these findings not only deepen our understanding of a common decision-making problem but also offer a practical strategy for reducing high discount rates.

The insights from these sub-research questions were used to address the following main research question:

**Main RQ:** How do time preference and time-related cognitive biases affect judgments and preferences in decision analysis, and what strategies can help decision-makers and analysts mitigate their negative impacts?

Based on the combined answers to the four research questions, I conclude that time preference and time-related cognitive biases systematically distort judgments and preferences by shaping how outcomes are perceived, compared, and weighted across time. The biases arise from a complex interplay of behavioral, cognitive, and contextual factors and rarely act alone, which makes their influence both pervasive and difficult to differentiate from other behavioral parameters. When decisions involve multiple attributes, the influence of time preference and related biases may become even more pronounced. Multiple biases can emerge at any stage of the evaluation process, accumulate across consecutive steps, and alter crucial evaluations such as value elicitation and trade-offs in ways that challenge the assumptions of rational decision models. Importantly, the distortions caused by time preference are not uniform as in the simple choice problems but depend on the relational structure and the relative importance of the attributes in MADM problems. Moreover, the interplay between the decision-maker and the analyst, along with the complex trade-offs involved, creates a distinctive environment for these problems. This underscores that intertemporal MADM problems cannot be fully understood through simplified models of discounting and require particular attention.

While investigating the influence of time preference in decision analysis, a further dimension resulting from this dissertation is context-dependence, which lies in the way outcomes are structured over time. I demonstrated how discounting behavior responds to variations in outcome and timing structures by employing the recurrence phenomenon. By fostering a broader evaluative perspective and promoting future-oriented choices, outcome recurrence has been proposed as a promising strategy to mitigate high discount rates and reduce impulsive behavior.

Multiple strategies have been reported to reduce the influence of time-related biases in simple choice problems. The existing literature shows that strategies for some biases, such as present bias, have undergone empirical validation across different contexts. In contrast, for other biases, such as recency bias and projection bias, the proposed strategies remain largely speculative and are not yet backed by robust empirical evidence. Despite its prevalence and potential importance, the intertemporal MADM problem has received little to no attention in the literature. This dissertation represents an initial step toward understanding time preference and time-related biases in MADM, thereby expanding the scope of inquiry in this field. To advance this line of research, related problems should first be more precisely defined across different contexts and empirically tested with respect to time preferences and related biases. Building on such evidence, systematic mitigation strategies can then be developed. These strategies should account not only for the decision-maker but also for the analyst, thereby addressing the complex dynamics inherent in intertemporal MADM.

Together, these insights indicate that although time preference and time-related biases can undermine decision quality, their adverse effects can be controlled with targeted strategies to some extent. They can be mitigated through systematic and prescriptive approaches that ac-

count for trade-offs, involve active guidance from analysts, and strategically re-frame outcomes. In doing so, decision analysis can move beyond merely documenting the presence of biases toward developing actionable methods that foster more consistent, balanced, and future-oriented decisions.

## 6.2 Theoretical and practical implications

The findings of this dissertation have important implications for both theory and practice. By systematically examining time preference and time-related biases in decision analysis, this research advances understanding of temporal dynamics and provides insights for improving decision models, developing and applying mitigating strategies, and guiding real-world decision-making processes.

From a theoretical perspective, this dissertation demonstrates that time preference, traditionally studied in economics and psychology, is also highly relevant in MADM. In a world where problems are increasingly complex and intertemporal, incorporating time-related behavioral factors into trade-off evaluations has become essential. By introducing the intertemporal MADM problem and examining how time preference influences various stages of decision making, this work broadens the theoretical foundations of time preference and extends its application beyond classical settings, which typically rely on outcome comparisons. Moreover, the experimental approach developed in this dissertation, which captures reasoning processes rather than focusing solely on final outcomes, enriches the methodological toolkit available for studying intertemporal decision making.

The findings indicate that when problems involve multiple objectives, the classical concept of delay discounting may no longer fully apply. Traditional discounting models assume a single stream of outcomes and thus cannot account for the complexities introduced by simultaneous trade-offs across attributes. This suggests that time preference in multi-objective contexts operates through mechanisms beyond simple temporal discounting, highlighting the need for theoretical extensions of existing models. By revealing this limitation, the dissertation advances time preference theory and provides a foundation for developing intertemporal frameworks that account for both temporal and multi-objective trade-offs.

Our experiment on recurring payoffs expands the scope of time discounting by challenging the dominance of one-off decision frameworks and providing a richer theoretical account of intertemporal evaluation. The findings suggest that time preference is not fixed but interacts with the structure of the decision problem. While traditional models assume isolated intertemporal choices, this dissertation shows how decision makers evaluate repeated outcomes over time, revealing systematic patterns overlooked by classical formulations. This perspective deepens our understanding of why individuals discount the future and opens avenues for incorporating contextual considerations into intertemporal choice models. Collectively, these insights offer a more comprehensive, behaviorally grounded understanding of time preference.

Beyond its theoretical contributions, this dissertation also carries significant practical implications for decision-making in complex, real-world contexts. Our systematic review on time-related biases raises awareness among decision-makers, practitioners, policymakers, and analysts of the systematic distortions that shape intertemporal judgments. This awareness is critical

in fields such as finance, health, business, education, agriculture, and public policy, where decisions often involve long-term trade-offs. Furthermore, the collection of mitigation strategies provides actionable tools that can be directly applied to reduce the adverse effects of biases and improve the alignment of decisions with long-term objectives. Taken together, these insights support more informed evaluations and foster the development of advanced strategies for bias differentiation and mitigation.

The integration of time-related biases into multi-objective decision-making highlights a blind spot in existing practice: the vulnerability of widely used decision-aiding methods, such as MAVT, to temporal distortions. For practitioners, recognizing these vulnerabilities creates opportunities to refine evaluation processes and to apply structured approaches that better account for interacting objectives and intertemporal trade-offs. In addition, the mitigation strategies proposed in this dissertation provide a foundation for developing training programs and decision-support tools that enhance resilience against such biases while contributing to the advancement of this emerging and highly promising field.

Finally, the novel perspective on recurring payoff contexts has direct implications for both individual and policy-level decision-making. By demonstrating how recurring structures can encourage more future-oriented strategies, it offers practical avenues for designing behavioral interventions and policy mechanisms that promote sustainability, financial responsibility, and health-oriented behaviors. For analysts and researchers, it also highlights the importance of contextual factors in shaping observed discount rates, thereby improving the ecological validity of models used in applied settings.

When considered together, these insights provide practitioners and policymakers with both conceptual frameworks and concrete tools to recognize, differentiate, and mitigate intertemporal biases. In doing so, they contribute not only to informed judgments but also to advancing an emerging and highly promising area of decision science with broad practical relevance.

### **6.3 Limitations and future research directions**

This dissertation focuses on understanding time preference and related biases in decision analysis and providing systematic ideas for mitigating the adverse effects. To support this objective, four research questions were developed, and key findings were summarized in Chapter 6.1. The following section will be devoted to highlighting potential avenues for future research, where the insights and outcomes of this dissertation can be further explored and expanded.

In Chapter 2, time-related biases were identified and examined alongside strategies for their mitigation. Furthermore, the relationships between biases and secondary behavioral factors associated with them were reported. While this effort was limited to a visual map showing the biases reported together, a more systematic investigation could yield deeper insights. Future research should systematically focus on the interplay between time-related biases and study the secondary behavioral factors. Such an analysis would deepen our understanding of their complex interactions, help distinguish the individual effects of each bias on judgments, and inform the design of more effective mitigation strategies. Moreover, the current literature on time-related biases is largely descriptive, with relatively few efforts directed toward prescriptive research. To advance the field, future studies should move beyond merely describing biases

and instead develop prescriptive frameworks and interventions that guide decision-makers in overcoming the adverse effects of biases in different domains.

While Chapters 3 and 4 represent some of the earliest systematic attempts to examine time preferences and related biases in the MADM context, Chapter 3 was confined to conceptual discussions built on behavioral decision research, whereas Chapter 4 was restricted to a single experiment addressing a specific MAVT problem. A promising extension of this dissertation, therefore, would be a more comprehensive investigation of the time preference and time-related biases using different MAVT problems. Future studies should begin by developing a deeper theoretical understanding of time preference in intertemporal MADM problems. While a two-attribute case was investigated in this dissertation, MAVT problems with more than two attributes may have different dynamics and yield new insights. It is also important to note that the experiments reported in this dissertation primarily involved participants from European countries. Future research should replicate and extend these studies in different cultural and geographic contexts to examine the generalizability of the findings across diverse populations. Once the effects of biases on judgments and preferences are better understood and generalized, targeted mitigation strategies must be developed, tested, and validated.

While this dissertation primarily focused on MAVT, other MADM methods, such as those based on pairwise comparisons or outranking relations, share similar initial steps but differ in how preferences are elicited. Examining these methods could extend the scope of this research and deepen the understanding of how time preference and time-related biases emerge under different decision dynamics. Future work could also explore time preferences across various attribute types and alternative sets. Given the influence of attribute characteristics and alternative profiles on temporal perception (Cubitt et al., 2018), studying these factors may provide valuable insights. These efforts will benefit the advancement of MADM research by providing a more nuanced understanding of how time shapes decision processes.

Beyond empirical investigations, a crucial direction for future research is the refinement of existing MADM methods to better account for time-related factors. Our experimental analyses demonstrated the vulnerability of different steps in MAVT to time preferences, underscoring the need for methodological advancements. Refining these methods to incorporate time-related behavioral factors would enhance the robustness and validity of the outcomes in complex intertemporal contexts. Such efforts could also inspire novel methodological extensions. Addressing these gaps has the potential to establish a new line of research in an area that has thus far received only limited attention.

Another promising direction for future research is to extend intertemporal MADM to account for decision-makers' risk preferences. While this dissertation primarily focused on MAVT, which addresses decisions under certainty, future studies could integrate risk attitudes toward uncertain outcomes using approaches such as Multi-Attribute Utility Theory (MAUT) (von Winterfeldt & Fischer, 1975). Experimental research with single-objective decisions has already demonstrated intricate interactions between time and risk preferences, suggesting that an even more nuanced relationship may emerge in multi-attribute, intertemporal settings. Incorporating risk preferences into this already complex environment would therefore provide a particularly compelling avenue for investigation.

The findings of this dissertation also suggest promising directions for research in interactive multi-objective optimization (IMO). IMO methods identify Pareto-optimal solutions through

iterative dialogues with decision makers, making them highly dependent on human judgment, which is susceptible to time-related biases (Bandaru & Deb, 2016). Future research could build on this work by examining how time preferences influence iterative decision-making and incorporating these insights into dynamic preference models. Such approaches could enhance the reliability of IMO solutions and make them more robust against behavioral distortions. Designing bias-aware elicitation protocols might be especially fruitful to distinguish between genuine preference changes and bias-driven inconsistencies in evaluation.

This dissertation also highlights important differences in the roles of decision-makers and analysts within a prescriptive framework. Future research could extend this work by examining how time preferences and related biases influence the elicitation, structuring, and weighting processes when these roles interact. In particular, studies could investigate how analysts can support decision-makers in recognizing and mitigating such biases during MADM applications, and how methodological refinements might formalize this support within prescriptive models. This line of research could also be extended to group decision-making, where the interaction of multiple stakeholders introduces additional layers of complexity and potential bias. Exploring these dynamics would clarify the respective responsibilities of decision-makers and analysts, while enhancing the reliability and practical relevance of prescriptive frameworks in both individual and group contexts.

In Chapter 5, we examined the impact of payoff recurrence on discount rates, drawing primarily on the choice bundling literature. The findings provide empirical evidence for the importance of contextual factors in shaping time preferences. Notably, prompting participants to consider payoff recurrence significantly reduced discount rates, suggesting its potential as a debiasing strategy against present bias. Future research could build on this by testing different types of decision outcomes, recurrence patterns, and time delays to evaluate the robustness of this effect and advance its development into a systematic debiasing approach. In addition, while our experiment was based on monetary outcomes, the influence of recurrence on discount rate should be further explored using different alternatives, such as health-related outcomes. This type of research can provide insights into developing a promising debiasing strategy and refining the elicitation processes. In addition, since recurrent decisions are common in everyday life, future research that incorporates them more explicitly can also help bridge the gap between experimental findings and real-world decision-making.

While the early attempts investigated within this dissertation provide valuable groundwork, further research is essential to establish a more rigorous and nuanced understanding of time preference and time-related biases in decision analysis, and more specifically in the MADM context. Advancing this line of research not only leads to theoretical contributions but also provides numerous practical implications for decision-makers and analysts who are always faced with complex problems in real life.

## 6.4 Concluding remarks

This dissertation set out to examine the impact of time preferences and time-related biases on decision-making processes with a particular focus on Multi-Attribute Decision Making (MADM) contexts. Through systematic literature reviews, conceptual analyses, and experimental investigations, it demonstrated how judgments and preferences are formed, and how intertemporal

trade-off processes are navigated in both single and multi-objective decisions. From a theoretical perspective, this research lays the groundwork for further exploration of time preferences and related biases across diverse MADM methods and interactive decision-making settings. From a practical angle, it presents systematic methods to mitigate biases in various decision contexts by integrating the role of the analyst. By addressing an emerging topic, this dissertation sets the stage for continued investigation and methodological advancement in a developing area of inquiry.

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# Appendix

## A Appendix - Survey design for Chapter 4

This appendix presents the questionnaire used for data collection in Chapter 4.

**Informed consent:** You are being invited to participate in a research study that is being done by Ph.D. candidate Pelin Gülüm Taş from the TU Delft. The purpose of this research is to understand your preferences based on hypothetical decision-making problems, and it will take you approximately 20 minutes to complete. We will be asking you to identify and assign numerical values to the various questions. There are no correct answers and we are only interested in your personal preferences. The data will be used for scientific publication and application. As with any online activity, the risk of a breach is always possible. To the best of our ability, your answers in this study will remain confidential. We will minimize any risks by designing the survey anonymously; the IP addresses and other personal data will not be collected. The data will be stored in TU Delft Drive (Netherlands), and only the authors can get access to it. Your participation in this study is entirely voluntary, and you can withdraw at any time. Once you finish the survey, it will not be possible to remove the data as the survey is completely anonymous. If you have any questions, feel free to contact the corresponding and responsible author at P.GulumTas@tudelft.nl and J.Rezaei@tudelft.nl. You agree to this Opening Statement by clicking ‘Yes’.

**Base case scenario:** Imagine you’ve been feeling tired and dizzy, with disrupted sleep and brain fog for a few weeks. After consulting a doctor and undergoing several tests, a conclusive full-body Magnetic Resonance Imaging (MRI) is recommended to finalize your diagnosis and decide on a treatment plan. An MRI is a safe, non-invasive imaging test using magnetic fields and radio waves to capture detailed images of the body’s internal structures. Although painless, the MRI can be uncomfortable as it requires wearing a hospital gown, staying awake, and remaining perfectly still inside a tunnel-like, tight, noisy device throughout the procedure. Screening duration varies from 15 minutes to 90 minutes depending on machine type, and the cost for an MRI screening ranges from 197 to 706 Euros, which is not covered by insurance and must be paid out-of-pocket. The hospital provides three MRI options (A, B, and C), each varying in screening duration and cost. All other aspects of these options are identical. The details are outlined in the table below.

Alternatives	Cost (€)	Payment time	Screening duration (min.)	Screening starting time
A	627	immediately	20	immediately
B	434	immediately	50	immediately
C	283	immediately	80	immediately

**Q1:** Understanding the decision problem given above plays a crucial role for this questionnaire. Do you think you understand it fully?

- Yes
- No

If “No” was selected, participants were directed to reread the base case scenario to ensure full understanding before continuing.

**Preferential independence check**

**Q2:** Suppose that the duration of a screening procedure is 30 minutes and it costs 250 Euros. If the duration were decreased by 10 minutes (becomes 20 minutes), how much extra would you accept to pay for the screening procedure?

Euros

**Q3:** Now, suppose that the duration of a screening procedure is 70 minutes and it costs 550 Euros. If the duration were decreased by 10 minutes (becomes 60 minutes), how much extra would you accept to pay for the screening procedure?

Euros

**Q4:** Suppose that the duration of a screening procedure is 30 minutes and it costs 550 Euros. If the duration were decreased by 10 minutes (becomes 20 minutes), how much extra would you accept to pay for the screening procedure?

Euros

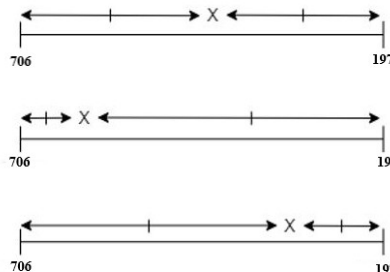
**Q5:** Suppose that the duration of a screening procedure is 70 minutes and it costs 250 Euros. If the duration were decreased by 10 minutes (becomes 60 minutes), how much extra would you accept to pay for the screening procedure?

Euros

**Mid-value splitting**

**Q6:** Now, we want to know how you value different screening costs. Suppose that you get a screening alternative that lasts 15 minutes. If you are offered a longer procedure, let us know X where you feel indifferent about a change in cost from 706 Euros to X Euros or from X Euros to 197 Euros.

The picture below shows an example of what is meant by the value of X. It can be seen that the value of X is defined such that the changes on both sides of X (decreasing the cost from 706 Euros to X Euros, and decreasing from X Euros to 197 Euros) are equally preferred.



X=

**Q7:** Suppose that you get a screening alternative that lasts 15 minutes. If you are offered a longer procedure, let us know Y where you feel indifferent about a change in cost from €706

to €Y or from €Y to €X (X = Piped answer from Q6) (Y is a number between X and 706).

Y=

**Q8:** Suppose that you get a screening alternative that lasts 15 minutes. If you are offered a longer procedure, let us know Z where you feel indifferent about a change in cost from €X to €Z or from €Z to €197. (Z is a number between 197 and X(X = Piped answer from Q6)).

Z=

**Q9:** Does X Euros (Piped answer from Q6) look like a good mid-value between Z Euros (Piped answer from Q8) and Y Euros (Piped answer from Q7) ?

Yes

No, I want to provide another mid-value point.

**Q10:** Now, we want to know how you value different screening durations. Suppose that you pay €706 for a screening procedure. If you are offered a lower cost, let us know about X, where you feel indifferent about a change in screening duration from 15 minutes to X minutes or from X minutes to 90 minutes. (X is a number between 15 and 90).

X=

**Q11:** Suppose that you pay €706 for a screening procedure. If you are offered a lower cost, let us know about Y where you feel indifferent about a change in screening duration from 15 minutes to Y minutes or from Y minutes to X minutes (X? ( Y is a number between 15 and X (X = Piped answer from Q10)).

Y=

**Q12:** Suppose that you pay €706 for a screening procedure .If you are offered a lower cost, let us know about Z where you feel indifferent about a change in screening duration from X minutes (X = Piped answer from Q10) to Z minutes or from Z minutes to 90 minutes. (Z is a number between X(X = Piped answer from Q10) and 90).

Z=

**Q13:** Does X minutes (Piped answer from Q10) look like a good mid-value between Z minutes (Piped answer from Q12) and Y minutes (Piped answer from Q11)?

Yes

No, I want to provide another mid-value point.

**Trade-off process****Q14:** Which pair would you prefer?

- 197 Euros screening cost (paid immediately) and 90 minutes screening duration (received immediately).
- 706 Euros screening cost (paid immediately) and 15 minutes screening duration (received immediately).

**Depending on the answer to Q14, participants were directed to one of the following trade-off questions.**

**Q15:** For which value of V are options 1 and 2 equally preferred for you? (Please enter a V value between 15 and 90).

Option 1	
Screening cost (paid immediately)	Screening duration (received immediately)
706 Euros	15 min

Option 2	
Screening cost (paid immediately)	Screening duration (received immediately)
197 Euros	V

V= 

**Q16:** For which value of T are options 1 and 2 equally preferred for you? (Please enter a T value between 197 and 706).

Option 1	
Screening cost (paid immediately)	Screening duration (received immediately)
197 Euros	90 min

Option 2	
Screening cost (paid immediately)	Screening duration (received immediately)
T	15 min

T= 

**The second part of the survey involves the same tasks—preferential independence check, mid-value splitting, and trade-off processes—applied to the time-related scenario. Therefore, these tasks are not repeated here, and we proceed directly to the demographic questions and the well-being assessment.**

**Demographic questions and EQ-5D-3L well-being test****Q17:** What is your gender?

- Male
- Female
- Non-binary/ Third gender
- Prefer not to say

**Q18:** What is your age?

- 17-22 years old
- 23-28 years old
- 29-34 years old
- 35-40 years old
- 41 and above

**Q19:** What is your highest completed level of education?

- No degree
- High school diploma
- Bachelor's degree
- Master's degree
- Doctoral degree

**Q20:** What is your country of origin?**Q21:** Have you ever had an MRI screening before?

- Yes
- No

**Q22:** Do you have claustrophobia ?

- Yes

- No

**Q23:** Do you have any chronic illness?

- Yes  
 No

**Under each heading, please tick the ONE box that best describes your health TODAY.**

**Q24:** MOBILITY (walking about)

- I have no problems walking about.  
 I have some problems walking about.  
 I have a lot of problems washing or dressing myself.

**Q25:** LOOKING AFTER MYSELF

- I have no problems washing or dressing myself.  
 I have some problems washing or dressing myself.  
 I have a lot of problems walking about.

**Q26:** DOING USUAL ACTIVITIES (for example, going to school, hobbies, sports, playing, doing things with family or friends)

- I have no problems doing my usual activities.  
 I have some problems doing my usual activities.  
 I have a lot of problems doing my usual activities.

**Q27:** HAVING PAIN OR DISCOMFORT

- I have no pain or discomfort.  
 I have some pain and discomfort.  
 I have a lot of pain or discomfort.

**Q28:** FEELING WORRIED, SAD OR UNHAPPY

- I am not worried, sad, or unhappy.

- I am a bit worried, sad, or unhappy.
- I am very worried, sad, or unhappy.

**Q29:** We would like to know how good or bad your health is TODAY. This line is numbered from 0 to 100. 100 means the best health you can imagine, and 0 means the worst health you can imagine.

**Please slide the indicator towards the number that best represents your health today and release it.**



**Q30:** Please let us know if you have any comments. For instance, tell us if you had difficulty answering some of the questions.

## B Appendix - Survey design for Chapter 5

This appendix presents the questionnaire used for data collection in Chapter 5. Each participant was randomly assigned to either the loss or gain condition and completed both one-off and recurring scenarios that varied in magnitude, while the remaining sections of the questionnaire were identical for all participants.

**Informed consent:** You are invited to participate in a research study conducted by TU Delft. The purpose of this research is to understand your preferences based on hypothetical decision-making problems, and it will take you approximately 6 minutes to complete. We will be asking you to read some decision scenarios and make evaluations. We are only interested in your personal preferences. The data will be used for scientific publication and application purposes. As with any online activity, the risk of a breach is always possible. To the best of our ability, your answers in this study will remain confidential. We will minimize any risks by designing the survey anonymously; the IP addresses and other personal data will not be collected. The data will be stored in TU Delft Drive (Netherlands), and only the authors can access it. Your participation in this study is entirely voluntary, and you can withdraw at any time. Once you finish the survey, it will not be possible to remove the data, as the survey is completely anonymous. You agree to this Opening Statement by clicking ‘Yes’.

**Training task:** In this experiment, you will encounter several decision scenarios and be asked questions about your personal preferences. There are no right or wrong answers. We aim to understand how you evaluate the given alternatives. You should read each scenario carefully and think about two alternatives that take place at different points in time. Next, you will be asked to determine a value at which these two options become equally preferable to you. **It is not about preferring one alternative over the other. The goal is to identify the missing value that makes both alternatives equally preferable to you.** Here’s an illustrative example:

**Decision scenario:** Imagine that you have just won a lottery which will immediately pay you €50 reward. Alternatively, you can wait a month and get a larger reward. How much extra money would make it worthwhile for you to delay the reward from today to one month later?

Your task is to specify this extra amount you want to receive for waiting and enter it in the given box. The extra money you are asking for should make these two options equally preferable for you.

**Answer:** If you demand €5 extra to get the reward next month instead of today, this means that receiving €50 immediately is equally preferable to receiving €55 next month for you. If you demand €0 extra, this means you are indifferent between receiving €50 today and €50 in a month, and the timing of the payment is not important to you.

To confirm that you have read the instructions so far and understood them, please write the word confirm in the box below.

**Loss condition**

**Q1:** Imagine you have been using the same health insurance package for the past five years, paying €100 each month. Your payment is always due on the 1<sup>st</sup> of the month. Your insurance provider is now offering a new option: You can change your payment date to the 30<sup>th</sup> of the month if you agree to a small increase in your monthly insurance cost. If you choose this option, the new monthly price you agree to will remain fixed for the next two years. How much more would you be willing to pay each month to change your insurance payment date from the 1<sup>st</sup> to the 30<sup>th</sup> of every month? (Assume a month is 30 days.)

**Your answer =**

**Q2:** Imagine that it is the 1<sup>st</sup> of the month, and you have just received an unexpected €1000 bill. You are given a choice between paying €1000 immediately or delaying the payment until the 30<sup>th</sup> of the same month but paying a larger amount. How much more would you be willing to pay to change the payment date of the bill from today (the 1<sup>st</sup> of the month) to the 30<sup>th</sup> of the same month? (Assume a month is 30 days.)

**Your answer =**

**Q3:** Imagine you have been living in the same apartment for the past five years, and your current rent is €1000. Your rent payment is always due on the 1<sup>st</sup> of the month. Your landlord is now considering changes to your payment schedule and offering a new option: You can change your rent payment date to the 30<sup>th</sup> of each month if you agree to a small increase in your monthly rent cost. If you choose this option, the new monthly rent you agree to will remain fixed for the next two years. How much more would you be willing to pay each month to change your rent payment date from the 1<sup>st</sup> to the 30<sup>th</sup> of every month? (Assume a month is 30 days.)

**Your answer =**

**Q4:** Imagine that it is the 1<sup>st</sup> of the month, and you have just received an unexpected €100 bill. You are given a choice between paying €100 immediately or delaying the payment until the 30<sup>th</sup> of the same month but paying a larger amount. How much more would you be willing to pay to change the payment date of the bill from today (the 1<sup>st</sup> of the month) to the 30<sup>th</sup> of the

same month? (Assume a month is 30 days.)

**Your answer =**

### Gain condition

**Q5:** Imagine that for the past five years, you have been receiving €1000 monthly interest income from a fixed deposit account with a bank. The interest payments are always deposited into your bank account on the 30<sup>th</sup> of each month. The bank is now considering changes to your payment schedule and offering a new option: You can receive your interest payments earlier, on the 1<sup>st</sup> of each month, if you agree to a small decrease in the monthly interest payment you receive. If you choose this option, the new monthly income you agree to will remain fixed for the next two years. How much less would you be willing to receive each month to change your interest payment date from the 30<sup>th</sup> to the 1<sup>st</sup> of every month? (Assume a month is 30 days.)

**Your answer =**

**Q6:** Imagine that it is the 1<sup>st</sup> of the month and you have just won an unexpected lottery which will pay you a €100 reward on the 30<sup>th</sup> of the same month. You are given a choice between receiving €100 on the 30<sup>th</sup> of the month or speeding the payment up to today (1<sup>st</sup> of the month) but receiving a smaller amount. How much less would you be willing to receive to change the payment date of the lottery from the 30<sup>th</sup> of the month to today (the 1<sup>st</sup>)? (Assume a month is 30 days.)

**Your answer =**

**Q7:** Imagine that for the past five years, you have been supplementing your income by writing short articles for an online content platform. Each month, you consistently earn €100 from your published stories. Payments are transferred to your bank account on the 30<sup>th</sup> of each month. The platform is now considering changes to your payment schedule and offering a new option: You can receive your earnings earlier, on the 1<sup>st</sup> of each month, if you agree to a small decrease in the monthly payment you receive. If you choose this option, the new monthly income you agree to will remain fixed for the next two years. How much less would you be willing to receive each month to change your earning payment date from the 30<sup>th</sup> to the 1<sup>st</sup> of every month? (Assume a month is 30 days.)

**Your answer =**

**Q8:** Imagine that it is the 1<sup>st</sup> of the month and you have just won an unexpected lottery which will pay you a €1000 reward on the 30<sup>th</sup> of the same month. You are given a choice between receiving €1000 on the 30<sup>th</sup> of the same month or speeding the payment up to today (1<sup>st</sup> of the month) but receiving a smaller amount. How much less would you be willing to receive to change the payment date of the lottery from the 30<sup>th</sup> of the month to today (the 1<sup>st</sup>)? (Assume a month is 30 days.)

**Your answer =**

### Demographic questions

**Q9:** How do you describe yourself?

Female

Male

- Other

**Q10:** How old are you?

**Your answer =**

**Q11:** What is your highest completed level of education?

- No degree
- High school diploma
- Bachelor's degree
- Master's degree
- Doctoral degree

**Q12:** What was your total household income in Euros after taxes during the past 12 months?

- Below €30.000
- €30.000 to €49.999
- €50.000 to €69.999
- €70.000 to €89.999
- €90.000 to €119.999
- €120.000 or more

**Q13:** How would you describe your current employment status? Please select the option that best describes your situation.

- Employed full-time
- Employed part-time
- Self-employed
- Unemployed
- Retired
- Homemaker

**Q14:** All things considered, do you now feel economically secure?

- Yes
- Unsure
- No



## About the author

Pelin Güllüm was born in 1995 in Antakya, Türkiye. She completed her undergraduate studies in Industrial Engineering at Çukurova University in 2018, graduating as the second-highest-ranking student in her department. She then obtained her master's degree in Industrial Engineering from Yıldız Technical University in Istanbul, focusing on risk analysis and decision-making using various Multi-Criteria Decision-Making (MCDM) methods. During this time, she gained academic experience as a research assistant for two and a half years, contributing to projects on decision analysis.

After completing her master's degree, Pelin was awarded the prestigious YLSY scholarship from the Republic of Türkiye Ministry of National Education, which enabled her to pursue her doctoral studies at Delft University of Technology in the Netherlands. Her PhD research focused on time preferences and time-related biases in decision-making, exploring how individuals evaluate outcomes occurring at different points in time within complex multi-attribute decision contexts. Her work lies at the intersection of behavioral economics, psychology, and decision analysis, aiming to improve understanding of how different factors shape human judgments and preferences and to inform policy design and practical decision support.




## Publications from this dissertation

1. **Gülüm Taş, P.**, Maknoon, Y., & Rezaei, J. (2025). Time's influence: A systematic review of biases in intertemporal decision-making. *Annual Review of Psychology*, 77, 223-254.
2. **Gülüm Taş, P.**, Maknoon, Y., & Rezaei, J. (Under review). Intertemporal judgments in multi-attribute decision-making: Biases and mitigation ideas. Manuscript submitted for publication in *Journal of Multi-Criteria Decision Analysis (MCDA)*.
3. **Gülüm Taş, P.**, Maknoon, Y., & Rezaei, J. Time preference in multi-attribute value theory: An experimental study. Manuscript submitted for publication in *European Journal of Operational Research (EJOR)*.
4. **Gülüm, P.**, Maknoon, Y., & Rezaei, J. Time preference in decisions with recurring payoffs. Manuscript submitted for publication in *Journal of Behavioral Decision Making*.

## Selected conference presentations

1. **Gülüm Taş, P.**, Maknoon, Y., & Rezaei, J. (2025, October). *Time preference in multi-attribute decision making: An experimental study*. 2025 INFORMS Annual Meeting, Atlanta, USA.
2. **Gülüm Taş, P.**, Maknoon, Y., & Rezaei, J. (2025, June). *Time preference in recurring payoffs*. 34th European Conference on Operational Research (EURO 2025), Leeds, United Kingdom.
3. **Gülüm Taş, P.**, Maknoon, Y., & Rezaei, J. (2024, July). *Time preference influences attribute weights and values in multi-attribute decision-making*. 33rd European Conference on Operational Research (EURO 2024), Copenhagen, Denmark.
4. **Gülüm Taş, P.**, Maknoon, Y., & Rezaei, J. (2023, September). *Time preference-related decision biases: A systematic literature review and research agenda*. Fall Workshop of the European Working Group on Behavioural OR, Delft, Netherlands.



This dissertation examines how time preferences and time-related biases influence judgments in intertemporal decision-making, with particular attention to multi-objective contexts. Using systematic reviews, conceptual frameworks, and controlled experiments, it reveals how temporal delays and multi-attribute trade-offs shape valuation and discounting behavior. By extending intertemporal choice theories to multi-attribute settings, the work advances behavioral decision theory and proposes strategies to mitigate biases. Overall, it provides theoretical and empirical insights to support more consistent and informed decision-making across individual and societal domains.