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Intertemporal Judgements in Multi-Attribute Decision-Making: Biases and Mitigation Ideas

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ABSTRACT

Intertemporal judgements 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 process. Drawing on evidence from behavioural economics, psychology, and decision analysis, we identify six time-related biases and analyse the vulnerabilities they can introduce at each step of the MADM procedure. We also outline preliminary ideas that may help analysts and decision-makers 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.

1 | Introduction

Many decisions require trade-offs between outcomes occurring at different time points. While making these trade-offs, decision-makers' judgements are generally affected by the resolution times of the outcomes (Fishburn and 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 judgements. They distort assessments and lead to undesirable outcomes such as poor financial decisions (Morton and Fasolo 2009) or procrastination (Fredrickson and Kahneman 1993).

Extensive research on biases is grounded in empirical investigations that adopt a descriptive approach[1] (Hardisty et al. 2013; Loewenstein et al. 2003). 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 judgements and related biases across various

fields, such as economics (Anderhub and Güth 2001; Fishburn and Rubinstein 1982), health (Fuchs 1980; Zhang and Rashad 2008), education (Finn and Miele 2016; Hoogerheide and Paas 2012), 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 judgements 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?***

Our approach to addressing this question involves three main steps. First, we identify time-related biases and understand their impact on judgement. 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 behavioural decision research, we outline practical suggestions to 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 and Raiffa 1975). MAVT is based on eliciting individual preferences, representing them through a value function, and performing multiple trade-offs. Because it relies heavily on eliciting judgements from decision-makers, this method 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 analysing the influence of such biases on complex decision-making within a prescriptive environment using MAVT may 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 2 reviews the concept of time preference and introduces six time-related biases. The methodology of MADM is detailed in Section 3, while Section 4 investigates the procedure through the lens of time preference and biases. Finally, Section 5 outlines the conclusions drawn from the study and suggests avenues for future research.

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 and Edwards 1986).

In the DU model, the total utility of a consumption stream from period t to period T is denoted by $U_t(c_t, \ldots, c_T)$. 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:

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

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:

$$D(k) = \left(\frac{1}{1+\rho}\right)^k, \tag{2}$$

with $\rho > 0$ as the discount rate, reflecting the degree of preference for present utility over future utility. In this formulation, t and T denote discrete time periods with $T \geq t$, so that $T-t$ is a non-negative integer. The index $k \in \{0, 1, \ldots, T-t\}$ denotes the number of periods from the present, so that $k=0$ corresponds to the current period t, and $k = T-t$ corresponds to the terminal period T. Throughout this section, indices such as j, k, and l denote non-negative integer delays from the present period and are assumed to lie within the relevant finite horizon. When two dated outcomes are compared, k and l may refer to any two distinct delays. If the comparison is intended to represent an earlier outcome versus a later outcome, we assume $0 \leq k < l \leq T-t$. 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 and 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 $U_t(\boldsymbol{c}_t)$ in Equation (1) is the sum of discounted instantaneous utilities, with the cardinal utility $u(c_{t+k})$ independent of consumption at

any other period c_{t+j}, for all $j \neq k$, where j and k are non-negative integer delays within the planning horizon. 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 (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, an outcome x received after k periods is preferred to an outcome y received after l periods, then the same preference ordering should hold when both outcomes are shifted forward by the same amount of time. Formally:

$$(x, t+k) \succ (y, t+l) \quad \Leftrightarrow \quad \left(x, t'+k\right) \succ \left(y, t'+l\right), \quad \forall t' \geq t, \tag{3}$$

where k and l are non-negative integer delays within the relevant finite horizon. No strict ordering between k and l is required in general; however, when the comparison concerns an earlier versus a later outcome, we assume $0 \leq k < l$. The shifted dates $t'+k$ and $t'+l$ are assumed to remain within the relevant planning horizon.

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 judgements 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 200 hundred decision biases (Manoogian and Benson 2017), considered seminal bias and time preference papers (Cooper and Meterko 2019; Ehrlinger et al. 2016; Loewenstein and Prelec 1992; Montibeller and von Winterfeldt 2015; Neal et al. 2022; Rambaud et al. 2023), and went through multiple bias taxonomies (Arkes 1991; Arnott 1998; Peón et al. 2017). By reaching definitions and working mechanisms of all reported biases in the literature, we identified the ones that directly influence individuals' intertemporal judgements 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 behaviour. To clarify the influences on judgements, 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 behavioural 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 behaviours such as prioritising 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 et al. 2003). It leads to a 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 behaviours 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 judgements may lead to regret or financial loss.

Recency bias is a behavioural 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 behaviours such as overreacting to short-term trends and making judgements 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

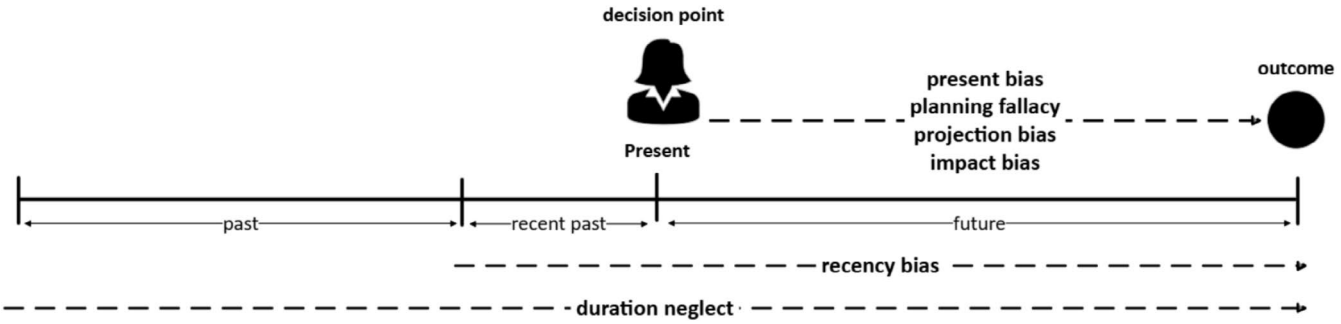

FIGURE 1 | Influence areas of the biases on the time axis.

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 and 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 and 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 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 judgements 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 and Rabin 2015). It causes strong devaluation behaviour 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 | 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 methods. Early stages—such as setting objectives, identifying attributes, and evaluating performance of alternatives—are largely consistent across different MADM 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 and 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 ($i = 1, 2, \ldots, m$).

Step 2—Identifying attributes related to objectives: This step is about identifying attributes, X_j, $(j = 1, 2, \ldots, n)$ 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 and 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 $\boldsymbol{a}_k$ can be represented as a vector of outcomes $a_k = (a_{k1}, a_{k2}, \ldots, a_{kn})$, where a_{kj} is the level achieved by the alternative $\boldsymbol{a}_k$ 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 λ_j, $(j = 1, 2, \ldots, n)$ to reflect their significance in the decision-making process (von Winterfeldt and Fischer 1975). 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 $v(\boldsymbol{a}_k)$ of an alternative $\boldsymbol{a}_k$ is computed as:

$$v(\boldsymbol{a}_k) = \sum_{j=1}^{n} \lambda_j v_j(a_{kj}), \tag{4}$$

where $v_j(a_{kj})$ is the normalized value of a_{kj}, λ_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) 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 and 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 and Sarin 1984; Dyer and 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 judgements throughout the process (Montibeller and von Winterfeldt 2015; Rezaei et al. 2022). Furthermore, this already complex evaluation process is further complicated when intertemporal dynamics are integrated. Therefore, analysing MADM steps through the lens of time preference can enhance awareness and foster the development of strategies to reduce biased judgements. Motivated by this, we offer a comprehensive analysis and present several promising ideas in the following section.

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 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.

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 and Burt 2008; Hadjichristidis et al. 2014; Rodon and Meyer 2012). 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 (Rezaei et al. 2022; Weber et al. 1988). 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 and 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 et al. 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.

TABLE 1 | Suggestions to reduce the impact of time-related biases in setting objectives and alternatives.

Time-related biases	Suggestions
Present bias	• Using scenario analysis techniques (Motoki et al. 2023) • Using problem structuring methods (Ackermann and Eden 2020; Eden 1988; Mingers and Rosenhead 2004) • Nominal Group Technique (Delbecq and van de Ven 1971)
Projection bias	• Value Focused Thinking (Keeney 1996) • Using problem structuring methods (Ackermann and Eden 2020; Eden 1988; Mingers and Rosenhead 2004) • Adopting perspective-taking (Kanten 2011)
Recency bias	• Using problem structuring methods (Ackermann and Eden 2020; Eden 1988; Mingers and Rosenhead 2004) • Nominal Group Technique (Delbecq and van de Ven 1971) • Keeping decision-makers accountable (Lau et al. 2016; Schillemans 2022)
Impact bias	• Using problem structuring methods (Ackermann and Eden 2020; Eden 1988; Mingers and Rosenhead 2004) • Using scenario analysis techniques (Motoki et al. 2023) • Using mental simulations (Buechel et al. 2017; Gilbert et al. 1998)
Duration neglect (the peak-end rule)	• Value Focused Thinking (Keeney 1996) • Using problem structuring methods (Ackermann and Eden 2020; Eden 1988; Mingers and Rosenhead 2004)
Planning fallacy	• Value Focused Thinking (Keeney 1996) • Using problem structuring methods (Ackermann and Eden 2020; Eden 1988; Mingers and Rosenhead 2004) • Keeping decision-makers accountable (Lau et al. 2016; Schillemans 2022) • Using mental simulations (Buechel et al. 2017; Gilbert et al. 1998)

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 and Yariv 2014; Sulistiawan and 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 and Kahneman 1993; Godovykh and Hahm 2020; Hands and 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 and 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 and Kolaska 2017; Conlin et al. 2007).

4.2 | Suggestions to Reduce the Impact of Biases in Setting Objectives and Alternatives

As illustrated in Table 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 and 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 overcommit 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 judgements (Bang and 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 and 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 and 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 and 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 and Thompson 2014).

Initiating mental simulations can help avoid unrealistic and redundant objective settings caused by planning fallacy and impact bias (Buechel et al. 2017; Finkenauer et al. 2007; Gilbert et al. 1998; Wang and Chiou 2022). 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 (Lau et al. 2016; Schillemans 2022; 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 a particular objective.

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 and 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

TABLE 2 | Suggestions to reduce the impact of time-related biases in identifying the attributes.

Time-related biases	Suggestions
Present bias	• Adopting neutral frames and using validated measurement units (Strijbosch et al. 2019; Weingarten et al. 2021) • Conducting the brainstorming sections systematically (Keeney 1996) • Sticking to the same salience level between the attributes (Carvalho et al. 2016; Guan et al. 2022) • Inviting multiple experts or decision-makers (Keeney 1996)
Projection bias	• Conducting the brainstorming sections systematically (Keeney 1996) • Inviting multiple experts or decision-makers (Keeney 1996) • Envisioning the future and imagining potential changes regarding the suggested attributes (Chanel et al. 2023)
Recency bias	• Envisioning the future and imagining potential changes regarding the suggested attributes (Chanel et al. 2023) • Conducting the brainstorming sections systematically (Keeney 1996) • Inviting multiple experts or decision-makers (Keeney 1996)
Impact bias	• Representing attributes with neutral and factual terms (Liersch and McKenzie 2009) • Adopting perspective taking methods (Buechel et al. 2017; Gilbert et al. 1998)
Duration neglect	• Increasing the familiarity of experts with the problem (C. Morewedge et al. 2005) • Using graphical information formats (when applicable) (Liersch and McKenzie 2009)
Planning fallacy	• Inviting multiple experts or decision-makers (Keeney 1996) • Encouraging decision-makers to examine past decisions and their attributes (Strijbosch et al. 2019) • Systematically listing all possible attributes (Strijbosch et al. 2019) • Envisioning the future and imagining potential changes regarding the suggested attributes (Chanel et al. 2023)

interpret or respond to it (Montibeller and von Winterfeldt 2015; Poulton 1982).

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 (Finkenauer 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 prioritising short-term gains. *Present bias* may also cause inclusion of criteria that focus excessively on immediate gains (Hunter et al. 2018; Kang and Ikeda 2016; Meier and Sprenger 2010; Millemaci and Waldmann 2016). Research shows that some individuals may have subjective time periods in mind, which distorts their temporal perceptions in judgement (Balakrishnan et al. 2020; Jang and 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 and 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 and 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.

4.4 | Suggestions to Reduce the Impact of Biases in Identifying the Attributes

Several strategies may reduce biases (Table 2), including increasing decision-makers' familiarity with the objective set (C. 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 (Charness and Sutter 2012; Keeney 1996). 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 judgements (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 and 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 2 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 1988; Loewenstein and Prelec 1992). 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 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 (Boltz and Yum 2010; Gilbert et al. 2002). 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 and 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.

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 and 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 et al. 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 and 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.

4.6 | Suggestions to Reduce the Impact of Biases in Evaluating the Performance of Alternatives

As summarized in Table 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 judgements in empirical evidence from past cases (Batselier and 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 judgements 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 (I. Fisher 1930; Mishan and 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 (reducing 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

TABLE 3 | Suggestions to reduce the impact of time-related biases in evaluating the performance of alternatives.

Time-related biases	Suggestions
Present bias	• Discounting future outcomes and using condensed values in performance evaluation (Mishan and Quah 2020) • Adopting Reference Class Forecasting (Batselier and Vanhoucke 2016; Flyvbjerg 2007) • Prompting reflections and considering full performance history (Isler et al. 2020; Yelbuz et al. 2022) • Using visual tools to show long-term performance trends (Eberhard 2023; Wall et al. 2021)
Projection bias	• Adopting Reference Class Forecasting (Batselier and Vanhoucke 2016; Flyvbjerg 2007) • Prompting reflections and considering full performance history (Isler et al. 2020; Yelbuz et al. 2022)
Recency bias	• Discounting future outcomes and using condensed values in performance evaluation (Mishan and Quah 2020) • Adopting Reference Class Forecasting (Batselier and Vanhoucke 2016; Flyvbjerg 2007) • Using visual tools to show long-term performance trends (Eberhard 2023; Wall et al. 2021)
Impact bias	• Using visual tools to show long-term performance trends (Eberhard 2023; Wall et al. 2021) • Prompting reflections and considering full performance history (Isler et al. 2020; Yelbuz et al. 2022)
Duration neglect	• Using visual tools to show long-term performance trends (Eberhard 2023; Wall et al. 2021) • Prompting reflections and considering full performance history (Isler et al. 2020; Yelbuz et al. 2022)
Planning fallacy	• Adopting Reference Class Forecasting (Batselier and Vanhoucke 2016; Flyvbjerg 2007) • Using visual tools to show long-term performance trends (Eberhard 2023; Wall et al. 2021)

their evaluations with data (Criado-Perez et al. 2024; Yelbuz et al. 2022). These suggestions primarily relate to Assumption 4 in the DU model, which posits that decision-makers can rationally evaluate performance over time.

4.7 | Eliciting Value/Utility Functions

Research consistently shows that temporal location significantly influences the value of alternatives (Ernst et al. 2018; Godovykh and Hahm 2020; Jang and Urminsky 2023; Krieger et al. 2021; Motoki et al. 2023; Weingarten et al. 2021). 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 and Zauberman 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 and 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 and 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 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 judgements about future preferences (Buchheim and Kolaska 2017; Chen et al. 2019; Loewenstein et al. 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 behavioural 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 and Zaremba 2023; Hao et al. 2016; Irani and 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.

4.8 | Suggestions to Reduce the Impact of Biases in Eliciting Value/Utility Functions

As summarized in Table 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

TABLE 4 | Suggestions to reduce time-related biases in eliciting value or utility functions.

Time-related biases	Suggestions
Present bias	• Providing a waiting period between information receiving and elicitation steps (Imas et al. 2022) • Group decision making (Delbecq and van de Ven 1971)
Projection bias	• Eliciting functions in a controlled environment (Buchheim and Kolaska 2017; Loewenstein et al. 2003) • Controlling for psychological drivers and visceral effects (G. Fisher and Rangel 2014; Haushofer et al. 2021)
Recency bias	• Performing multiple measurements (Strijbosch et al. 2019) • Group decision making and accountability (Delbecq and van de Ven 1971; Lau et al. 2016; Schillemans 2022)
Impact bias	• Motivating people to think about multiple time points (Lench et al. 2011; C. Morewedge et al. 2005) • Group decision making and accountability (Delbecq and van de Ven 1971; Lau et al. 2016; Schillemans 2022)
Duration neglect	• Performing multiple measurements (Strijbosch et al. 2019) • Using external information sources (Roy and Christenfeld 2007)
Planning fallacy	• Exercising episodic future thinking (Atance and O'Neill 2001; Schacter et al. 2017) • Considering empirical benchmarks from historical datasets (Shmueli et al. 2016)

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 judgements.

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 and Quah 2020). Defining these elements in advance makes the temporal assumptions of the analysis explicit and provides a clear frame for subsequent judgements. 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 the 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; C. 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 and Kolaska 2017; Chen et al. 2019; Conlin et al. 2007; Loewenstein et al. 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 et al. 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 judgements. 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 prescreening 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 judgements.

Risk preferences must be thoughtfully examined in relation to their underlying drivers, such as stress (Haushofer et al. 2021) and visceral influences (Briz et al. 2015; Fisher and Rangel 2014). 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 engage more and provide informed judgements.

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 judgements 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 and O'Neill 2001). The facilitator can prompt decision-makers to adopt EFT, enabling them to better anticipate potential obstacles and provide more realistic judgements 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 and 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 and 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.

Inviting multiple decision-makers with diverse viewpoints can help balance short- and long-term considerations (Charness and 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 and 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 judgements might be biased (relates to 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).

4.9 | Eliciting Attribute Weights

Time-related biases can distort decision-makers' preferences and judgements, 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 and 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 and 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 and Kuhbandner 2022; Hoogerheide and 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 assigning 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 and Rabin 2019; Briz et al. 2015; Chang et al. 2018; G. Fisher and 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 much positive. Suppose there is an attribute related to the duration of an experience in an MADM problem. In this case, the decision-maker may be unable to call memories correctly, which causes assigning distorted importance weights to these attributes (Hetou et al. 2021; Redelmeier et al. 2003). 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

TABLE 5 | Suggestions to reduce time-related biases in eliciting attribute weights.

Time-related biases	Suggestions
Present bias	• Using a systematic method instead of direct rating (Keeney and Raiffa 1975) • Using mental simulations (Buechel et al. 2017; Gilbert et al. 1998)
Projection bias	• Using social distance phenomenon (Bauckham et al. 2019; Buechel et al. 2014; Gilbert et al. 1998) • Using mental simulations (Buechel et al. 2017; Gilbert et al. 1998) • Using a systematic method instead of direct rating (Keeney and Raiffa 1975)
Receny bias	• Using time-reversal heuristic (Ernst et al. 2018) • Using social distance phenomenon (Bauckham et al. 2019; Buechel et al. 2014; Gilbert et al. 1998) • Using mental simulations (Buechel et al. 2014; Gilbert et al. 1998) • Adopting different perspectives (Boltz and Yum 2010; Thoma and Tytus 2018)
Impact bias	• Motivating people to think about multiple time points (Eastwick et al. 2008; Lench et al. 2011) • Using mental simulations (Buechel et al. 2017; Gilbert et al. 1998) • Using social distance phenomenon (Bauckham et al. 2019; Buechel et al. 2014; Gilbert et al. 1998)
Duration neglect	• Using external information sources (Kanten 2011; Katt et al. 2021; Peetz et al. 2010; Weick and Guinote 2010) • Encouraging retrospective reflection and increasing familiarity of decision-makers (C. K. Morewedge et al. 2009)
Planning fallacy	• Exercising episodic future thinking for the attributes (Atance and O'Neill 2001; Schacter et al. 2017) • Considering empirical benchmarks from historical datasets (Shmueli et al. 2016)

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 judgements (Katt et al. 2021; König et al. 2015).

4.10 | Suggestions to Reduce the Impact of Biases in Eliciting Attribute Weights

Table 5 illustrates a few useful strategies. Given the extensive research highlighting the differences in attribute weighting methods and their susceptibility to various biases (Montibeller and von Winterfeldt 2015; Pöyhönen and Hämäläinen 2001), preferring a well-structured elicitation method not only helps maintain consistency but also can mitigate present and projection biases. 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 judgements more deliberately rather than impulsively favouring 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 and Guinote 2010). For example, when evaluating a time-related attribute, providing decision-makers with information about the duration of a similar past incident can help reduce bias (Batselier and Vanhoucke 2016; Flyvbjerg 2007). When external sources are unavailable, a facilitator can encourage retrospective reflection and motivate decision-makers to rethink their past experiences (Isler et al. 2020; Morewedge et al. 2009; Yelbuz et al. 2022).

A facilitator can help decision-makers elicit attribute weights aligned with their values rather than biased judgements 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 judgements 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 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 and 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.

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 and 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 favour of one alternative or canceling each other's effects throughout the evaluation. While some biases distort intertemporal judgements, 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.

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 behavioural 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 investigations 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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Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Endnotes

[1] In this study, descriptive refers to understanding how people make decisions based on observed behaviours 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).

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