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The Future of Decisions From Experience: Connecting Real-World Decision Problems to Cognitive Processes

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Abstract
In many important real-world decision domains, such as finance, the environment, and health, behavior is strongly influenced by experience. Renewed interest in studying this influence led to important advancements in the understanding of these *decisions from experience* (DfE) in the last 20 years. Building on this literature, we suggest ways the standard experimental design should be extended to better approach important real-world DfE. These extensions include, for example, introducing more complex choice situations, delaying feedback, and including social interactions. When acting upon experiences in these richer and more complicated environments, extensive cognitive processes go into making a decision. Therefore, we argue for integrating cognitive processes more explicitly into experimental research in DfE. These cognitive processes include attention to and perception of numeric and nonnumeric experiences, the influence of episodic and semantic memory, and the mental models involved in learning processes. Understanding these basic cognitive processes can advance the modeling, understanding and prediction of DfE in the laboratory and in the real world. We highlight the potential of experimental research in DfE for theory integration across the behavioral, decision, and cognitive sciences. Furthermore, this research could lead to new methodology that better informs decision-making and policy interventions.

Keywords
decisions from experience, cognitive processes, uncertainty, learning, risk taking

People often learn the instrumental value of behavior through experiencing its outcomes directly. When we tell a joke, we cannot help but notice whether the audience laughs or not; when we choose a different route to our workplace, we experience whether this route was quicker or not; and when we place sport bets, we are even more curious than usual to find out the result of the associated sporting event. Understanding how people experience, learn, and act on feedback received as a consequence of their choices is at the center of *decisions from experience* (DfE) with widespread theoretical and practical implications. Here, we define DfE as actions that are based on one's preferences and are shaped by repeated feedback (i.e., through experiencing the consequences of choices).

In experimental research, DfE are mostly examined with a simplified choice task, in which participants repeatedly select between two options on the basis of samples of numeric feedback. This experimental simplification likely arose because the modern research program to understand DfE mostly involved comparisons to *decisions from description* (DfD). Unlike DfE, DfD tasks present complete information for different choice options as summary statistics; feedback and learning about one's choices are excluded. Such tasks have long been the primary mode of studying decision-making in psychology, economics, and other social sciences. Although research using DfD paradigms has usefully shaped the fields of judgment and decision-making and behavioral

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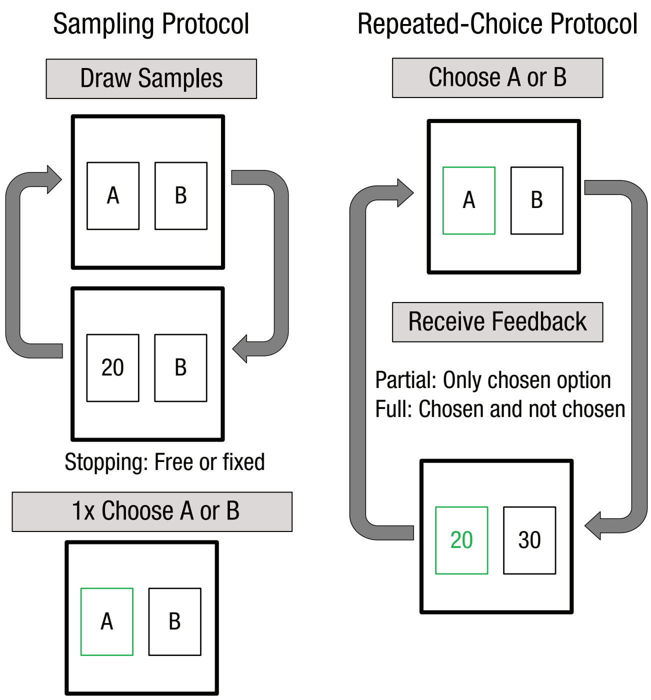

Fig. 1. Overview of different experimental protocols of decisions from experience (see also Hertwig & Erev, 2009). Sampling protocols vary in whether the participant (free) or experimenter (fixed) determines when sampling stops. Repeated-choice protocols vary in whether feedback from the unselected option is available (full) or not (partial). The figure depicts the full-feedback case.

economics, this article aims to (re)establish the broader scope of DfE research. To accomplish this goal, we will demonstrate the importance of DfE independently from DfD and highlight the relevance of DfE for real-life decision-making. For example, studies using the DfE methodology and tasks have examined real-world problems, including terrorist attacks (Yechiam, Barron, & Erev, 2005); emotional states (Frey et al., 2014); taxation, punishment, law enforcement, and safety enhancement (Spektor & Wulff, 2021; Teodorescu et al., 2021; Yakobi et al., 2020); pandemics and COVID-19 (Erev et al., 2020; Plonsky et al., 2021); aging (Frey et al., 2015); and clinical settings and populations (Teodorescu & Erev, 2014; Yechiam, Busemeyer, et al., 2005).

In this article, we lay out a road map for how research in DfE should be extended in research questions, experimental paradigms, and theories. Such extensions can increase understanding of long-lasting behavioral puzzles in important real-world settings, such as finance, the environment, and health. In all these settings, experiences are critical, and decision makers are required to cognitively process experiential information to understand, construct, and act upon these choice scenarios. These cognitive processes include how decision makers pay attention to and perceive those experiences they deem relevant, how they recall and weight past experiences from short- and long-term memory, and how they learn from different sources of feedback.

Unlike DfD tasks, in which many perceptual, learning, and memory processes are excluded, the experimental DfE paradigm can serve as a research platform in which attentional, perceptual, memory, and learning processes constitute an integral part of decision-making (see also Hertwig, 2016; Hogarth, 1981; Rakow & Newell, 2010). Accordingly, DfE research can build bridges from preferential economic behavior to research areas in cognitive psychology (e.g., number perception, memory, and reinforcement learning) and even more broadly to artificial intelligence and machine learning. Incorporating research from these areas into DfE research can provide process-level explanations of how preferences in DfE are formed. In return, DfE research can contribute to these research areas by positioning cognitive processes in a richer context, where people's motivations, preferences, and goals play a crucial role. This exchange of ideas and practices could lay the groundwork for findings from cognitive science to apply to real-life judgment and decision-making as well as to economic theories. In sum, this article aims to broaden the scope of experimental research in DfE to better account for real-world decision problems, and it highlights the role of cognitive processes in this endeavor.

Experimental Paradigms in DfE

In a typical DfE experiment, participants are presented with two options (e.g., geometrical squares) on a computer screen, and they are asked to make a choice by clicking one of the two squares. Selecting an option generates a random outcome according to a distribution unknown to the participant. The main instruction to participants is to choose the option they prefer. Most DfE studies have used one of two different experimental protocols (see Fig. 1): *sampling* or *repeated choice* (see Camilleri & Newell, 2011).

In the sampling protocol, participants draw outcome samples from the available options without consequence; that is, the outcomes drawn do not count toward participants' final payoff. Instead, when sampling has finished, participants indicate from which option they would like to take a single and consequential outcome draw. The number of samples drawn can either be freely determined by the participants or can be fixed by the experimenter.

In contrast, in the repeated-choice protocol, each sampling choice is (potentially) consequential, and the number of trials is usually fixed and not determined by the participant. That way, every sample in this protocol

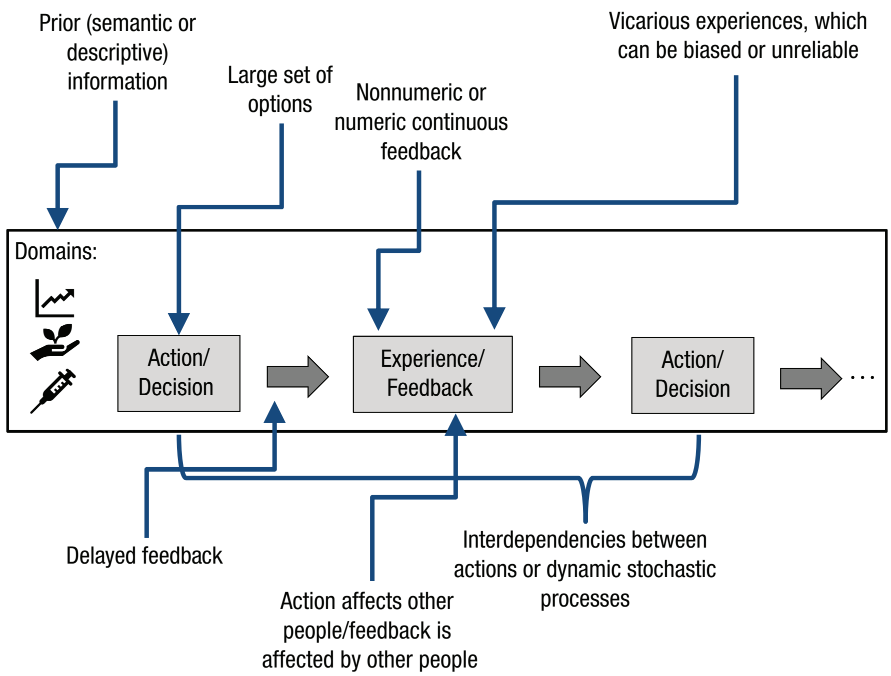

Fig. 2. Suggested extensions of the standard experimental decisions from experience paradigm to approach more complex real-world decision problems and to better study relevant cognitive processes.

also elicits a preference for the chosen option. This protocol shares many features with the multiarmed bandit tasks used extensively in reinforcement-learning research (e.g., Daw et al., 2006; Palminteri et al., 2015) as well as with multistage decision-making problems (Rapoport, 1967). There are two versions of this protocol: the *partial-feedback* version, in which participants receive feedback only from their chosen option, and the *full-feedback* version, in which feedback about what would have happened from the unselected option is also provided.

The sampling and the repeated-choice protocol have been successfully used to advance understanding about decision-making under (partial) uncertainty and have led to important discoveries, including the *description–experience gap*, in which choices from experience lead to different choice patterns than choices from description do (Barron & Erev, 2003; Hertwig et al., 2004; Ludvig & Spetch, 2011; Weber et al., 2004). Usually, choice patterns are similar between the sampling and the repeated-choice protocols, indicating a consistent effect of experience across experimental protocols and consistent differences from the effect of described information (Erev et al., 2017; Wulff et al., 2018; but see Erev et al., 2022). Furthermore, in the standard sampling and repeated-choice protocols, behavior has been explained by similar cognitive processes (Gonzalez & Dutt, 2011).

The implications of the gap between choice behavior from described versus experienced information for decision-making has already been the focus of multiple review articles and perspectives (e.g., Hertwig & Erev, 2009; Hertwig & Wulff, 2021). Moreover, this gap has been shown to play a major role in varying conclusions about the capability of human beings to execute logical statistical inferences and rational decisions (Lejarraga & Hertwig, 2021; Schulze & Hertwig, 2021). Despite these important developments, the focus on comparing DfE to DfD behavior has constrained the richness of mainstream experience-based paradigms. The current article thus builds on this past work in highlighting the importance of personal experience in decision-making, but it does this independent of comparisons with description.

Real-World Decision Problems

In everyday decisions involving experience, there are a variety of features that are lacking from the standard experimental paradigm in DfE. In this section we use examples from three decision domains—finance, the environment, and health—to highlight some of the missing features we believe are crucial for extending the experimental scope of DfE to better address the breadth of real-life DfE (see Fig. 2). These examples are not meant to be an exhaustive list of all the complexity that can exist in DfE; rather, these features involve the cognitive processes that are critical for the next step in studying DfE. Simultaneously, the ensuing new directions should help to make experimental DfE research more relevant as a tool for understanding and improving real-life decision-making.

Finance

Financial decisions, such as choosing to invest in the stock market, are often affected by personal experiences with assets (Andersen et al., 2019; Malmendier & Nagel, 2011). These effects have been explained by mechanisms of reinforcement learning going beyond the rational updating of beliefs both in the stock market (Choi et al., 2009; Kaustia & Knüpfer, 2008) and in financial-decision tasks in the laboratory (Heinke et al., 2022; Jiao, 2022). In experiments using real stock-market data, participants' investment decisions are more affected by experienced than by described information on returns (Lejarraga, Woike, & Hertwig, 2016). The structure of investment decisions provides one of the closest analogues to DfE as studied in experiments. Even investment decisions, however, involve many features and more complicated cognitive processes than typical DfE experiments.

First, unlike typical experiments, investment decisions are rarely between two available choice options with each of them having at most two possible outcomes. Instead, financial markets are characterized by the availability of a large number of different investment options, with feedback on these options generally ample, numeric, and continuous (rather than binary). The magnitude of the set of potential options requires an understanding of how selective attention processes narrow down these large item sets for consideration. The rich feedback requires an understanding of how people perceive, store, and subsequently recall this numeric information when making a decision. Moreover, return distributions are usually not static, as is often the case in experiments, but rather follow trends that may require the investor to develop more complicated mental models. As a direct consequence, stock-market returns can be perceived differently depending on other return information in investors' idiosyncratic portfolios. This also affects behavior: Researchers have found that the more extreme an experienced positive return is in the context of an investor's portfolio, the more likely it is that the investor will sell this asset (Antoniou et al., 2021).

Second, financial decision-making is characterized by the availability of different sources of information, such as statistical summaries of historical stock returns (i.e., descriptive information), personal experiences, and the experiences of peers or other investors. This wealth of information sources raises the question of how people integrate and evaluate these differing sources of information when considering an investment option. Experiments in DfE usually consider only direct personal experiences, sidestepping the issue of how learning takes place across multiple information sources (but see Erev et al., 2017). This difference might be the reason for some inconsistencies between laboratory findings and real-world regularities. For example, investors in the stock market seem to prefer lottery-type assets with a small probability of a high return (Bali et al., 2011; Kumar, 2009). Such a preference, however, is in contrast with choice behavior usually reported in DfE experiments, in which people avoid options with a small probability of a (relatively) high outcome (Wulff et al., 2018).

Finally, price movements in the stock market are the product of many agents. This gives investment decisions a social component (Lu & Tang, 2019), which is usually ignored in laboratory DfE tasks. As a result, prices in financial markets can deviate from fundamental values, with price bubbles that can exist for extensive periods (Abreu & Brunnermeier, 2003; Brunnermeier & Oehmke, 2013). Hence, *mentalizing*—that is, the ability to understand mental models, expectations, and buying and selling strategies of other agents—is an important aspect of successful financial investments (Corgnet et al., 2018; Hefti et al., 2018). Consequently, taking the behavior of others into account can lead to different investment strategies and subsequent observed behavior compared with situations that ignore social interdependencies.

Environment

In recent years, people have begun to experience the consequences of their environmental actions in terms of extreme weather events such as flooding, new temperature records, or shortened seasons (Broomell et al., 2015; Lewandowsky, 2021; Weber, 2010, 2016). As with financial decisions, this experiential component has clear parallels with existing experimental paradigms in DfE (e.g., Dutt & Gonzalez, 2012a), but there are also major differences. One important difference is that the outcomes of decisions are usually realized immediately in experiments, whereas in environmental decisions the consequences are often experienced years or even decades later. For instance, new regulations introduced today will lead to changes in the observed trajectories of temperatures or sea-level rise only with substantial delays, and any potential benefits are thus subject to temporal discounting. Research on how such time preferences affect risk taking has been conducted mainly in DfD (but see Dai et al., 2019), with some evidence that people take more risks when risky prospects are pushed into the future (Baucells & Heukamp, 2010; Konstantinidis et al., 2020; Luckman et al., 2017, 2020; Sagristano et al., 2002). The structure of delayed consequences could thus explain the discrepancy between behavior often interpreted as risk averse in laboratory settings and the apparent society-wide willingness to take massive environmental risks through wait-and-see approaches. Moreover, compared with the DfE design, describing delays in DfD tasks ignores the influence of long-term memory, where past actions and experiences need to be stored and recalled across long time horizons. Adding delayed feedback to experimental DfE tasks could thus help us understand how these memory processes interact with time preferences and how they might impact risk taking.

Another aspect not explored in the standard experimental DfE paradigm is that tackling environmental problems often requires multiple actions, and outcomes from different actions can be correlated with each other. This complexity makes it more difficult to assign credit to the causal actions taken than in typical experimental DfE tasks (see Gallistel et al., 2019; Sutton & Barto, 2018). Moreover, the multiplicity of actions opens up the possibility that people will create idiosyncratic causal models and find spurious patterns in the action-outcome sequences (Dutt & Gonzalez, 2012b; Newell et al., 2014). Besides experiences, these causal models can also be influenced by prior assumptions about the world derived from ideology or political orientation. Prior assumptions and mental models can explain why personal experiences do not always lead to behavioral change (Lewandowsky, 2021; McDonald et al., 2015; Myers et al., 2013; Whitmarsh, 2008; Wong-Parodi & Rubin, 2022). As an example, experiences of floodings affect climate-change-mitigation responses only when people attribute the flooding event to climate change (Ogunbode et al., 2019).

As with financial decisions, environmental decisions are often made on the basis of information from multiple sources, not just direct personal experience (Newell et al., 2016). Although we discussed above the importance of understanding how these multiple information sources are combined in the learning process, a key feature of environmental decisions is that the experiences of others are often, at least in part, caused by our own actions. However, unlike typical studies of social preferences (e.g., the dictator game), in environmental decisions (and in DfE more generally) there is often ambiguity in whether certain experiences have been made and can be recalled, and in how a certain action affects other people. For instance, driving rather than taking public transportation to work results in a positive outcome for yourself while (perhaps negligibly) contributing to a continually worsening situation for people living on islands vulnerable to rising sea levels. Recent research on social preferences points to the fact that the high levels of prosocial behavior often shown in decisions under certainty (Engel, 2011) cannot easily be transferred to decisions under (partial) ambiguity. Rather, ambiguity can make people behave more egoistically or even antisocially, when people use the ambiguity between their actions and the resulting outcomes as wiggle room to maintain a positive self-image (Dana et al., 2007; Mazar et al., 2008; Olschewski et al., 2019). Thus, opening the standard experimental DfE paradigm to incorporate other stakeholders can help researchers to better understand the processes driving preference formation in choice domains with social interdependencies.

Health

Decisions involving health, including decisions about whether to smoke or not, which vaccines to take, and which disease screenings to undertake, are affected by past experiences, just as financial and environmental decisions are (Betsch et al., 2011; Wegier et al., 2019; Wegier & Shaffer, 2017; Wegwarth et al., 2021). When health declines, people must decide between various medication and treatment options with different possible outcomes, including taking into account any potential side effects.

Unlike financial decisions, which differ from experimental DfE in the continuous nature of the numeric feedback received, health decisions are often defined by the nonnumeric nature of feedback. Both the side effects of medications, such as unpleasant bodily states or direct pain, and the relief provided by treatment are nonnumeric experiences. The ways in which people perceive nonnumeric stimuli differ greatly from numeric cognition, so behavior in such situations is not well approximated by making choices between numeric lotteries in experimental DfE paradigms (Lejarraga, Pachur, et al., 2016). In particular, decisions between affect-rich options, such as medications with harmful side effects, seem to be less impacted by probability information and more impacted by the affective response to the most harmful outcome (Pachur et al., 2014). The (imagined) bodily feedback in terms of not feeling well, having anxieties, or experiencing pain can also trigger episodic memories of past experiences, which in turn can affect behavior (Suter et al., 2015).

As in other real-world situations, health-related decisions are based on context-rich feedback that goes beyond the situation at hand but draws on other knowledge through semantic memory. An example is *vaccine* *hesitancy*, which is the unwillingness to take up an overall beneficial vaccine. In the case of influenza vaccines, perceptions of risk and benefit affect the likelihood that people will take the vaccine, which can be examined in standard experimental DfE tasks. But other psychological factors have been identified: perceived social norms, perceived behavioral control, trust in societal institutions, and misconceptions about vaccines and viruses (Schmid et al., 2017). This shows the importance of studying choice problems within the context of interest to examine how experiences are embedded into a semantic network that can then affect behavior.

Unlike the financial market, where the performance of stocks an investor has not purchased can nonetheless be observed, in health-related decision-making there is usually no chance to experience the consequences of the medical treatment option not chosen. This difference maps onto the distinction between the partial- and full-feedback versions of the repeated-choice protocol and can have direct consequences on behavior. One consequence is that health-related decision-making often relies on vicarious experience. For instance, when deciding whether to undertake a major surgery, decision makers are forced to rely on the experiences of others, either relayed through their doctor or directly from other patients (e.g., support groups). Vicarious experience introduces questions around the trustworthiness of information and considerations of social preferences, as people can decide which experiences to communicate. In the context of the recent COVID-19 pandemic, van Bavel et al. (2020) identified misinformation as one of the major behavioral challenges—for example, in the form of reported personal experiences with alternative means to prevent the disease or treat an infection. When correct and false information can be sampled, open questions in DfE arise as to how people can learn to identify false information, how they can unlearn false information, and how they themselves can be prevented from spreading false information. Consequently, decision makers not only have to integrate vicarious experiences with their own but must also evaluate the motives of the information source; they must also attempt to compensate for bias and give unreliable information appropriate weight.

Toward a Better Understanding of Cognitive Processes in DfE

Although the real-world decision problems discussed above suggest that the standard experimental paradigms in DfE are perhaps oversimplified, we still believe that controlled experiments are a powerful method to study real-world DfE. Rather, these examples should motivate researchers to extend established experimental paradigms to broaden the impact of DfE research on topical societal problems of decision-making. The real-world decision problems we identified all had in common that the cognitive processes required to frame and solve them were more complicated than in standard experimental DfE paradigms. We argue that these additional cognitive processes are crucial to understanding and predicting choice behavior. Therefore, the field should more thoroughly examine the underlying cognitive processes in DfE with new experimental paradigms, new dependent variables, and new theoretical connections. Figure 3 depicts how the cognitive processes we deem most important can be grouped into three broader categories: attention and perception, memory, and learning. For each category we continue by showcasing innovative research into exploring cognitive processes in DfE and pointing to unresolved research questions and future directions.

Attention and perception

Attention. In real-world decision problems, the decider usually faces a multitude of possible options and experiences. Under these circumstances, attentional processes are likely to mediate which options will be considered and which experiences will be heeded. In contrast, experiments in DfE usually restrict choices to only two options and implicitly assume that participants pay full attention to all available experiences. Yet even under these simplified circumstances, experimental manipulations, eye tracking, and cognitive modeling have shown that attention processes can affect preferential choices in the sampling protocol (Ashby & Rakow, 2016; Glickman et al., 2018; Glöckner et al., 2016; Vanunu et al., 2021; Zilker & Pachur, 2021). In particular, the saliency of an experience in terms of its significance or visual features can capture the attention of the decider and thereby influence behavior. Experiments and choice modeling have shown that relatively high numbers in a stream of experiences receive more weight in subsequent decisions (Spitzer et al., 2017; Vanunu et al., 2020). This in turn can lead to choice tendencies for high-variance options (Tsetsos et al., 2012). Moreover, when increasing the visual saliency of numbers by using a dot or a different color, participants' choices were consistent with overweighting these salient numbers (Glickman et al., 2018; Kunar et al., 2017).

Few studies have explored instances of structural complexity, for example, by increasing the number of available choice options in experiments. In these situations, participants choose risky options more frequently (Hills et al., 2013; Noguchi & Hills, 2016). This effect can be explained by participants paying more attention to the highest outcomes, which come from the

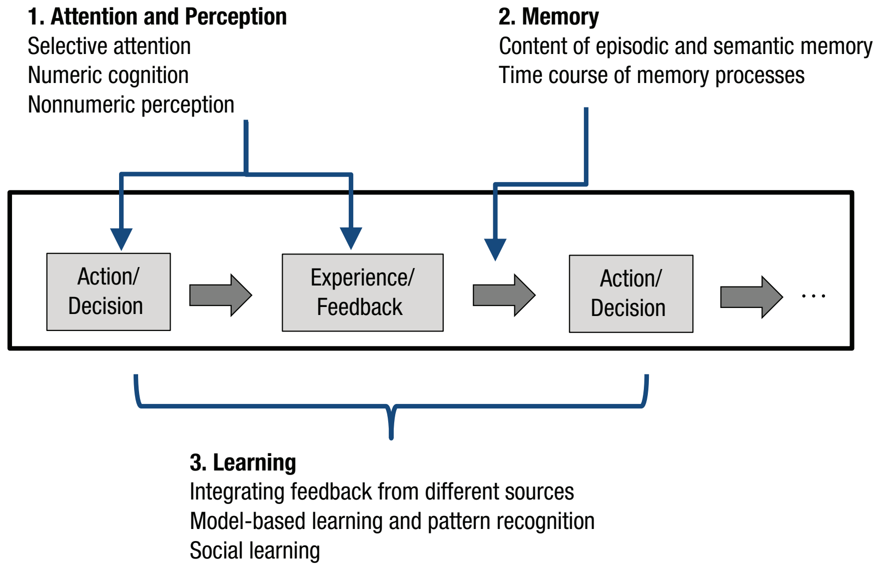

Fig. 3. Overview of the cognitive processes involved in decisions from experience with a focus on the cognitive processes that should be studied more closely in future experimental work.

high-variance options and makes them thus appear more favorably. Beyond this effect, more research in DfE should explore how the number of available options or experiences affect decision and search strategies. This expansion could extend results from DfD by finding that people can switch strategies—that is,changing which attributes they heed, how many of them to take into account, and which order to employ in examining them (Fiedler & Glöckner, 2012; Krajbich et al., 2010; Meissner et al., 2020; Mullett & Stewart, 2016; Payne et al., 1988).

Furthermore, attention can also be influenced by additional cues in the environment. When investors check their portfolios to learn about the performance of their assets, they look more often when the market goes up, which in turn leads to more trading (Quispe-Torreblanca et al., 2022). Relatedly, prices of certain assets have been shown to be overvalued because these assets have received a lot of attention in social media (Bali et al., 2021). These findings have the potential to relate observational real-world data to experimental research in DfE and hence to extend research questions by examining factors that make people pay attention to experiences more broadly.

Numeric cognition. Many real-world decision problems, most notably in finance, require decision makers to deal with substantial numeric feedback—for example, in terms of returns on investment. Often, researchers assume that decision makers have perfect perception and representation of this numeric information. Consequently, in DfE experiments behavior is usually assessed with respect to the characteristics of the theoretical underlying distribution of the samples or with characteristics of the actual samples (e.g., the sample mean). People, however, perceive and represent numeric information imprecisely and in a biased fashion, which then can influence preferential choices (Khaw et al., 2021; Schley & Peters, 2014; Woodford, 2020). In numeric cognition, numerosity representation is often described as a compressed mental number line with a logarithmic function (Dehaene, 2003; Dehaene et al., 2008; Longo & Lourenco, 2007). Though this line of research deals with processes relevant to choosing and learning from numeric experience, it is not usually connected with DfE (e.g., Cheyette & Piantadosi, 2019; Whalen et al., 1999).

Numerosity information can be provided symbolically (e.g., Arabic numerals) or nonsymbolically (e.g., bars or dots representing quantity). Large amounts of numerosity information must often be perceived, weighted, and integrated in DfE. Thus, even when numeric information is available symbolically, the representation and integration of these numeric values may become imprecise and compressed because of capacity limitations (Khaw et al., 2021). In domains such as healthy food choices, however, experiences usually consist of nonsymbolic magnitudes, such as the amount of food one is served in a restaurant. These representations also provide a link to the animal-cognition literature, in which nonsymbolic magnitudes are the default presentation format (Pisklak et al., 2019; Shafir et al., 2008). Nonsymbolic numerosity information could lead to less precise representations than symbolic numerosity information. Thus, modeling number perception explicitly and understanding how numeric cognition might differ between symbolic and nonsymbolic presentations (Duffy et al., 2021; Garcia et al., 2022; Zeigenfuse et al., 2014) can help us to better understand preferential behavior from experiences.

A limitation of examining choices in experimental DfE research is that observed choices can only reveal ordinal relative judgments; they do not provide information about the absolute values participants assign to individual options. In a financial-investment context, choice problems can be framed differently, for example, when deciding at what price to buy or sell a given asset. This problem requires a more precise estimate of the value of the asset (e.g., Golan & Ert, 2015; Pachur & Scheibehenne, 2017). Preceding the renewed interest in DfE, a long tradition in psychology examined numerosity judgments about the mean of number sequences. These studies usually concluded that people were accurate, intuitive statisticians (Peterson & Beach, 1967). More recently, however, mean or sum estimates from experienced samples have been found to be slightly downward biased (Brezis et al., 2015; McGowan et al., 2022; Scheibehenne, 2019). This difference can be explained by the fact that earlier studies had smaller sample sizes and focused more on noise rather than on systematic deviations from the true sample mean. Directly comparing mean estimates and preferential valuations of number streams suggests that answers deviating from the sample mean could be partly due to a compressed mental number line in the perception of numbers, rather than to risk or skewness preferences (Olschewski, Newell, et al., 2021).

Finally, the context in which people perceive numerosity information matters in DfD: For example, the range and the distribution of numeric values shape choice consistency and risk taking (Frydman & Jin, 2022; Stewart et al., 2015). Some recent results point toward the impact of context when experiencing numeric feedback (Bavard et al., 2021; Hayes & Wedell, 2023; Madan et al., 2021; Palminteri & Lebreton, 2021; Prat-Carrabin & Woodford, 2022). Hence, taking the context into account—such as the range of expected or experienced outcomes—can lead to a better understanding of individual and societal choice patterns (e.g., selling decisions regarding assets from idiosyncratic portfolios; Antoniou et al., 2021).

When experiences are not directly consequential, such as when observing other people, an important question is when to stop sampling information and make a final decision (Glickman et al., 2022). This problem is experimentally examined in the free-sampling version of the sampling protocol (Hills & Hertwig, 2010). This protocol has also been used as a simulation tool to educate retail investors (Bradbury et al., 2015; Kaufmann et al., 2013). Several studies concluded that in this protocol, participants sample too little information when sampling bears no monetary costs (Hertwig et al., 2004; Wulff et al., 2018). These analyses, however, usually did not take the costs of information acquisition (in terms of opportunity costs or cognitive effort) into account (Fiedler et al., 2021; Vul et al., 2014). Furthermore, they also did not measure the subjective value of additional information, which could be low if experiences are perceived imprecisely (Olschewski & Scheibehenne, 2023). Thus, future research could improve understanding of search processes by measuring additional variables such as confidence, precision of number representation, or cognitive effort (Xiang et al., 2021).

One way to measure the subjective value of additional information is to manipulate the number of sampled experiences exogenously. Studies with this design showed that participants in choice tasks became more accurate in picking the higher expected-value option with a larger sample size (Tsetsos et al., 2012). In another study, estimation accuracy decreased from four to eight samples, but increased again from eight to sixteen samples (Brezis et al., 2015). The latter finding was explained by a dual-systems approach, in which a few samples were integrated analytically but more samples were processed according to the imprecise number system. Thus, additional information might not always be valuable with respect to a more veridical representation of a choice problem. Cognitive processes (such as the representation of numerosity) and conscious strategies to integrate experiences can affect the value of information and should be taken into account to better understand search behavior.

Nonnumeric perception. There are many instances in people's daily lives in which feedback is nonnumeric—for example, when forming impressions about other people (Prager et al., 2018). Other examples include the side effects of medications, food choices, and climate-change consequences, which are mostly experienced through nonnumeric feedback. So far, there has been little research about nonnumeric feedback in DfE experiments. There is an adjacent line of research, however, that has dealt with nonnumeric stimuli, namely ensemble perception (Whitney & Yamanashi Leib, 2018). This line of research examines how participants develop summary evaluations of stimuli, such as line orientation, color hues, or facial expressions. This research has also demonstrated that higher-level concepts such as average economic value can be estimated quite precisely from sets of images of consumer products (Yamanashi Leib et al., 2020).

These nonnumeric experiences are processed differently than numeric ones. For example, when asked to provide summary judgments separately for clusters of visual and numeric stimuli, participants' accuracy decreased as a function of cluster size for numeric, but not for visual, stimuli (Rosenbaum et al., 2021). Importantly, research in ensemble perception usually uses different experimental designs than DfE (Whitney & Yamanashi Leib, 2018). First, in ensemble perception research stimuli are presented simultaneously and not sequentially, as in DfE. Second, the choice in ensemble-perception research is usually perceptual with an objectively correct answer, whereas DfE research examines preferential decisions. Including stimuli sets and theories on ensemble perceptions into experimental DfE could be a promising avenue for future study of nonnumerical experiences.

Finally, when examining information search, experimental DfE research usually studies only numeric experiences. These experiments present only a limited number of search options and thus constrain information search. In real-world decision problems, however, there are many experiences to consider, including nonnumeric ones—for example, on social-media sites on the Internet. An understudied aspect of the information-search issue concerns when people actively search for this nonnumeric information (perhaps, for example, with respect to other people's experiences with medical side effects or climate change), to overcome potential misinformation (see Pennycook & Rand, 2021), and when they are satisfied with the status quo of their own experiences and look no further. This decision could also depend on people's subjective confidence in the current state of knowledge, which in turn could be determined by the underlying cognitive processing of these nonnumeric experiences. Hence, by broadening the experimental paradigms to include nonnumeric and context-rich stimuli, research in DfE can help to tackle the pervasive problem of fake news and misinformation.

Memory

When choosing between a healthy or unhealthy meal in a restaurant or when deciding to trust or mistrust a potential business partner, people necessarily draw on information from previous experiences stored in memory. There are two key factors in how memory influences real-world choices: The first is what people remember, and this relates to the content of their memories; the second is when the memories were formed, and this relates to the time course of the memory processes. An example of the importance of what people remember is how extreme events (i.e., the best or the worst outcome available) are both better remembered and more heavily weighted in DfE (Madan et al., 2014; Madan et al., 2021). People thus more frequently choose risky options that have led to the highest experienced outcomes and less frequently choose those that have led to the lowest experienced outcomes (Ludvig et al., 2014). Similarly, in terms of when memories are formed, people are more likely to remember recent outcomes and more likely to overweight these outcomes in choice (Plonsky et al., 2015).

Content of memory. In standard DfE experiments, memory processes are usually not the focus of analysis. Implicitly, it is assumed that participants only take the information sampled immediately prior to the decision into account (e.g., Kopsacheilis, 2018). Decisions, however, can also be affected by episodic memory (Duncan & Shohamy, 2016; Madan et al., 2014), such as when people prefer options they recall better (Weilbächer et al., 2020). One unresolved topic is how these episodic memories are represented in DfE. For example, do people recall specific past episodes (e.g., when milk cost £1.12) to inform their choices or do they learn less concrete properties of the environment (e.g., when milk costs between £0.80 and £1.50)? This distinction between different types of memory representations is also reflected in computational models of memory and decision-making. Instance-based episodic models assume that people have precise representations of individual experiences (e.g., Gonzalez et al., 2003; Hotaling et al., 2019; Lengyel & Dayan, 2007), whereas gist models assume that people have highly abstracted representations of past experiences (Brainerd et al., 1999; Steyvers & Griffiths, 2008). These differences in representation are important when designing practical intervention strategies. For example, if the goal is to reduce problematic behavior such as speeding or gambling, reminders of concrete past experiences would be more effective when people precisely recall specific past experiences compared with when they base their decisions on a general gist representation.

To better understand the memory representations that influence choice, we need to update the paradigms used in DfE research. To date, many experimental paradigms in DfE have used a limited set of outcomes per decision problem, often only three (see Wulff et al., 2018). This reduces the memory demands of the task and makes it difficult to assess people's memory for individual samples or episodes. Thus, an emerging area of research is how memory supports decision-making when continuous outcomes are used (e.g., Mason et al., 2022; Olschewski, Newell, et al., 2021; Spektor et al., 2019). Continuous outcomes can also build bridges to the fields of retrospective evaluations and numeric cognition (discussed above). Using continuous outcomes as well as nonnumeric stimuli in DfE tasks will allow researchers to better understand the types of memory representations used and to distinguish between instance-based or gist-based samples.

Similarly, stochastic processes in experimental DfE tasks are usually stationary, rather than nonstationary, which is likely to impact the types of memory representations used to guide choices. In contrast, nonstationary or dynamic task environments would better reflect the real-world contexts in which people learn about investment returns or social interactions, where both the rate of return and the behavior of people, respectively, can change over time. In such nonstationary environments, episodic learning models that incorporate individual samples, rather than simply running averages, can explain choices better (Bornstein et al., 2017; Gershman & Daw, 2017). Therefore, more work examining nonstationary environments can help researchers to better understand how memory representations affect DfE (see also Konstantinidis et al., 2022).

From a theoretical perspective, an important future advancement is to integrate models of memory representations of real-world experiences with models of choice in DfE. As an example, *decision by sampling* (DbS; Stewart et al., 2006) specifies what people store in long-term memory when making decisions. By doing so, the theory provides a process account of how the subjective value of a choice option is constructed by comparing the rank position of a target item within a small subset of samples retrieved from long-term memory. The distribution of items in long-term memory is assumed to reflect real-world frequencies. In principle, if DbS were combined with a process detailing how that store of information is formed and updated with new experiences, the resulting theory could be applied to DfE to explain the influence of long-term memory processes on DfE. A challenge to this approach, however, is that exactly how people represent the distribution of past experiences in memory is not known (Szollosi et al., 2022; Tran et al., 2017).

Time course. In the standard DfE experimental paradigm, feedback from a given action is usually provided immediately and is based on a single action. This feedback structure contrasts with real-world problems, such as climate change or healthy eating, in which outcomes are the result of a series of decisions and feedback is often delayed. One approach to study these environments has been microworld experiments, in which participants are presented with a simulated world where they can make decisions over multiple in-experiment years or seasons, getting repeated feedback in a manner similar to DfE tasks (Dörner & Güss, 2022; Gonzalez et al., 2005; Kumar & Dutt, 2018; Liang et al., 2019; Meyer, 2012; Newell et al., 2016). Whereas these studies capture some of the complexity of real-world decisions, introducing long time delays between actions and outcomes, which require long-term memory processes, was beyond the scope of these studies (but see Lejarraga, 2010). Thus, a future direction could be to examine learning in DfE over longer periods of time, perhaps using multiweek studies in which participants are invited to submit decisions and receive feedback each week through online or smartphone applications; this method has been fruitfully used to study spatial cognition or mental health (see Coutrot et al., 2018; Gillan & Rutledge, 2021). This extended timeline could allow researchers to study how decision makers consolidate memories of experiences over longer time periods and how this affects decisions and attitudes in DfE.

If experiences from across a longer time scale affect behavior in DfE, an important open question is how these experiences are integrated with more immediate feedback. This issue is an extension of the general problem of integrating prior information with new incoming data. In context-rich domains, such as health- or environment-related decisions, semantic memories, which represent general knowledge about the world, can be conceptualized as prior information. For example, when trying to evaluate the risk associated with nuclear power plants, people may be more likely to recall general information about concepts such as nuclear technology, chemistry, or atoms as opposed to direct (episodic) experiences. Recent research in risk perception could help pave the way to combining semantic information with DfE. For example, researchers have examined how the structure of word distributions in the natural language, extracted from Internet databases, influences individuals' risk perception of events such as nuclear war (Bhatia et al., 2019). Relatedly, aspect listing of risk associations has been shown to affect overall self-reported risk preferences (Steiner et al., 2021). Moreover, research in probability judgment has used Bayesian inference models to combine prior information sampled from memory with information sampled directly from the immediate environment (Zhu et al., 2020). A similar approach could be adopted in DfE research to probe how semantic memory representations influence behavior when the interpretation of feedback depends on semantic networks. Furthermore, taking prior beliefs more thoroughly into account in DfE could improve understanding in settings where ideological beliefs might lead to individual differences in the semantic networks of deciders. This in turn might lead to different behaviors, even when deciders encounter the same experiences in the immediate environment (e.g., Hahnel et al., 2020).

Learning

Learning in DfE refers to the change in option valuations as new feedback is experienced and integrated. The way learning processes affect decision-making is at the center of interest in associative and reinforcement learning (Sutton & Barto, 2018) and was also examined in early DfE research (e.g., Barron & Erev, 2003; Busemeyer, 1985; Erev & Barron, 2005; Erev & Roth, 1998; Yechiam & Busemeyer, 2005, 2006). For example, different solutions to the trade-off between exploring new options and exploiting knowledge about rewarding options in the partial-feedback version of the repeated-choice protocol have been modeled with reinforcement learning (Gershman, 2018, 2019; Speekenbrink & Konstantinidis, 2015; Wu et al., 2018). Here we propose extensions that take other, more complex learning processes into account to form behavior.

Integrating feedback. In many real-life scenarios, such as in finance, making choices requires considering different types of information from different sources, including one's own previous experience (as in DfE) and descriptive summaries of the choice options (e.g., outcomes and probabilities, as in DfD). Recently, experimental studies have investigated how introducing descriptions in a typical DfE task affects choice behavior (e.g., Barron et al., 2008; Hertwig et al., 2018; Jessup et al., 2008). An early study found that descriptions are neglected when available in a DfE task (Lejarraga & Gonzalez, 2011). Further research has shown that descriptive information can have an impact on choice, but mostly at the early stages of the task, when there is little experience and descriptive summaries offer valuable information about the choice options; as more experience is accumulated, this influence of description diminishes (Weiss-Cohen et al., 2016). Another factor is a high number of available choice options, which makes learning from experiences harder (Ashby et al., 2017; Frey et al., 2015; Konstantinidis et al., 2015). Thus, when choice options increase, descriptive information can help participants to maximize rewards, but an even higher number of choice options can make participants neglect descriptive information because of information overload (Jacoby et al., 1974; Weiss-Cohen et al., 2018).

Though there seems to be a general tendency for weighting experienced information higher than described information in experimental paradigms, the reason for this is not clear. One possibility is that experiences are more salient. Another is that sequential experiences can be more easily integrated into existing valuations than described outcomes and associated probabilities can (see Busemeyer & Townsend, 1993; Erev et al., 2017; Glöckner et al., 2012). In a contrary finding, however, participants seemed to prefer descriptive over experienced information (Lejarraga, 2010) when they can choose between them, and participants were more confident about decisions based on described information than experienced information (Lejarraga & Lejarraga, 2020).

Further, the influence of descriptive information may depend on other characteristics of the choice environment. For example, the type of experience, whether nonconsequential (as in the sampling) or consequential (as in the repeated-choice protocol), may allow for different degrees of influence of descriptive information. In the studies conducted thus far, experience was usually consequential (e.g., Weiss-Cohen et al., 2016, 2018). A possible hypothesis is that nonconsequential experiences might have less influence on choices than consequential ones, because of lower emotional involvement. Furthermore, descriptive information can have different epistemic content. Descriptions can offer information about the underlying stochastic processes (as in casino games) or summaries of empirical observations (as in the stock market or sport bets). In principle, descriptions about stochastic processes are more informative than descriptions of empirical observations, which could be subject to sampling error or temporal trends—but how this distinction influences choice behavior is not known.

Another important aspect of real-world decision-making is the reliability and trustworthiness of information. In other domains, such as sensorimotor learning (e.g., Körding & Wolpert, 2004) or spatial cognition (e.g., Chen et al., 2017), people approximate the Bayesian ideal when integrating multiple information sources. In DfE research, however, explicitly manipulating these factors is rare, and little is known about how people integrate information varying in reliability. One possibility is that descriptive summaries may be perceived as unreliable because they are usually provided by someone else. Personal and situational factors can determine how trustworthy descriptive information is perceived to be, and this evaluation can affect its impact on choice. For example, advertisements provide summary information only to increase product sales, which suggests that this information is highly unreliable. In contrast, experiences are often directly observed as a consequence of one's actions. Vicarious experiences, however, can be unreliable. For example, observing the efficacy of a diet or medical treatment in someone else's life cannot be considered reliable information concerning the potential impact of those approaches on the observer, because the impact of those treatments may depend on unobserved situational and physical heterogeneity. Moreover, when experiences are communicated, these experiences can be biased: Extreme events, for example, are more likely to be passed on between people (Plonsky & Teodorescu, 2020a; see also Fiedler, 2000). Understanding how people deal with perceptions of the reliability of feedback can have applications into policy implementations. For example, warning labels often convey descriptive information about gambling, health, or security risks in order to improve decision-making. Because people combine information from different sources to make judgments and decisions, effective design and development of descriptive communication should also take into account people's personal experience with a situation (e.g., Weiss-Cohen et al., 2021).

Mental models and pattern recognition. In addition to learning from direct experience, the processes of information integration can be influenced by people's assumptions about the underlying stochastic process that generates rewards. These assumptions are particularly relevant in context-rich domains, such as climate change, where people have additional theories about how the world works. The impact of these additional assumptions on learning and behavior relates to the distinction in reinforcement learning between *model-free learning*, which is based on trial and error, and *model-based learning*, which incorporates a model of how actions and outcomes are connected in an environment (Daw et al., 2011). Most analyses in DfE have assumed that participants do not incorporate such higher-order representations about the stochastic process. For example, when the underlying odds of winning or losing in a DfE task are stationary, participants have been assumed to also treat the task as stationary. Yet recent evidence suggests that participants behave as if the environment is dynamic, and they develop higher-order mental models and concepts about upcoming outcomes, resulting in identifiable search and choice patterns (Barron & Leider, 2010; Clotfelter & Cook, 1993; Cohen & Teodorescu, 2021; Oskarsson et al., 2009; Szollosi et al., 2019; but see the discussion in Ashby et al., 2017; Plonsky & Teodorescu, 2020b; Yechiam et al., 2020). Expectations about upcoming rewards can originate from identifying certain regularities in the environment, such as that larger rewards are less likely to be received than smaller rewards (the *risk-reward regularity*; see Pleskac & Hertwig, 2014). There is evidence of the use of such heuristics: Leuker et al. (2019) found that when lotteries are atypical (i.e., do not follow this risk-reward regularity), participants take longer to make choices and show higher levels of attention (measured by eye tracking) in a DfD task. Similarly, probability judgments and search patterns in DfE have shown that people assume a negative relation between probability and reward (Hoffart et al., 2019).

If participants construct such mental models in controlled experiments, these mental models are likely to also affect behavior in, for example, debates about the right policies to fight climate change, a topic to which people bring their own lay theories. Studying and integrating these expectations into learning models can thus improve explanations of behavior (see also Leuker et al., 2018). Moreover, real-world decision problems often contain complex interdependencies, such as when climate-change policies affect important outcome measures or restrict future choice options. Future studies could incorporate these interdependencies into experimental DfE research by including choices between multiple actions with complex causal relations or allowing for sequential decisions that can change the composition of a future decision environment (see Brehmer, 1992; Liang et al., 2019; Meyer, 2012). Also, little research has examined whether (and how) people learn and represent correlations between choice options from experience (Kareev, 2000; Laudenbach et al., 2022; Olschewski, Diao, & Rieskamp, 2021). In this context, it matters whether feedback from options that are not chosen is available or not (i.e., full vs. partial feedback; Ben Zion et al., 2010; Grosskopf et al., 2006). When feedback of forgone options is available in a large set of uncorrelated options, people sometimes chase risky options that provided a huge reward most recently. Finally, it is important to understand whether people can transfer experiences in one environment to other environments when these environments share critical, model-based features in an adaptive way (Juechems et al., 2022). These learning transfers, for example, could depend on similarity functions between experiences, options, or environments, and more research could explore under what circumstances such similarity is used to guide learning (Spektor et al., 2019).

Another behavioral observation that may originate from participants trying to recognize and exploit patterns in sequentially occurring experiences is *recency*. Recency means that recent events have a higher influence on choice behavior than normatively warranted, assuming a stationary generating stochastic process (see, e.g., Hogarth & Einhorn, 1992; Murdock, 1962). The effect of recency on choice, however, could depend on whether experiences are consequential or not, as recency has more consistently been reported with consequential experiences (e.g., Madan et al., 2014). In contrast, in the sampling protocol, recency effects are stronger when participants self-determine their number of samples but are less consistently found when the number of samples is externally determined (Wulff et al., 2018). In the former case, recency might not be due to pattern recognition but rather could follow from strategic information search (i.e., people stop sampling when they see a good outcome from the preferred option or a bad outcome from the nonpreferred option).

In contrast to this positive recency, a *wavy-recency* effect has been reported when rare events are present (Plonsky et al., 2015, Plonsky & Erev, 2017; Szollosi et al., 2019). The wavy-recency effect emerges after a rare, extreme outcome occurs amid a sequence of smaller, more common outcomes. In this case, people initially respond to this large deviation with negative recency and are less likely (after a rare win) or more likely (after a rare loss) to select the option that yielded that rare event. Within a few trials, however, people quickly reverse themselves and go back to selecting the option that yielded the large win and avoiding the option that yielded the large loss (showing positive recency)—even more than baseline levels.

These sequential effects of experiences can depend on subtle differences in mental accounting. Imas (2016) showed that experienced losses can increase risk taking when losses are not realized but can decrease risk taking when losses are realized. This distinction could be connected to consequential and nonconsequential experiences in DfE and has the potential to identify interventions that can change the influence of recent experiences. For example, in gambling, players could be nudged to repeatedly realize their gains and losses during a visit to a casino. Similarly, nudging a patient to change doctors during a medical treatment might make patients conclude a series of experiences and “realize” the overall gain or loss of a past treatment. As a consequence, the experience of treatment success or failure could affect subsequent risk taking in health-related decisions differently depending on whether the patient changed doctors or not play a larger role in real-world behavior.

In general, recency can be helpful for adapting to changing environments (Konstantinidis et al., 2022). In important societal problems, such as vaccine uptake to prevent the spread of a disease, however, conspiracy theories or ideological reasons may prevent some people from taking recent experiences into account (Jennings et al., 2021; Pertwee et al., 2022). Consequently, future research in DfE should also examine circumstances in which recent information is ignored, either because people have a strong prior conviction or because motivated cognition biases people’s learning processes to underweight certain experiences.

Social learning. Learning often happens in social environments, interactions, and contexts; an important question is how learning in social contexts differs from learning in nonsocial contexts. Social decision-making has been extensively studied with strategic games in which a payoff matrix of possible actions and rewards for all players is explicitly described, and participants receive information about the actions of other players. Such action-feedback schemes closely resemble DfE, and substantial research has documented that feedback about other players’ actions affects individual behavior and group outcomes of cooperation (e.g., Bereby-Meyer & Roth, 2006; Fischbacher & Gächter, 2010). Much less is known, however, about how people learn in social interactions when descriptions of the consequences of their actions are not available.

In the prisoner’s dilemma, where cooperation leads to higher social welfare but is dominated by defecting under pure self-interest, participants can learn to cooperate when the full payoff matrix is described (e.g., Andreoni & Miller, 1993). If no description is provided and people only experience outcomes from their interaction with other players, cooperation diminishes (Martin et al., 2014). This decline shows how experiencing outcomes (as examined in DfE) may not be enough to promote cooperation in situations where the social interactions are complex. This finding dovetails with the idea that in complex or partly ambiguous situations, such as those in which people learn from individual experiences, people can interpret information self-servingly and behave less prosocially (Dana et al., 2007; Olschewski et al., 2019) compared with decisions under certainty (Engel, 2011) or in DfD (Polman & Wu, 2020). Relatedly, participants in the prisoner’s dilemma are less responsive to information about the cooperation rates of their fellow participants when that information is presented through experiences rather than through descriptions (Isler et al., 2022).

Another question about social processes is how people learn from experience when uncertainty is generated by the behavior of other humans, rather than stochastic processes. This uncertainty can be studied with the ultimatum game (Güth et al., 1982), which gives one participant (the proposer) the possibility to distribute a certain amount of money while the other participant (the responder) can decide whether to accept the proposal or reject it; rejecting the proposal results in both participants receiving nothing. In this scenario, the proposer can reduce uncertainty about what the responder will do by referring to social norms. One such social norm is that splitting an outcome equally between two players is always acceptable. Consequently, social norms can replace learning through feedback and in that way reduce information search and impact behavior (Fleischhut et al., 2021). Experiments in DfE can be extended to take social interactions into account to study how beliefs about social norms and fairness interact with personal experiences to shape cooperation and trust, or the opposite.

Summary cognitive processes in DfE

In this section we reviewed innovative research about exploring cognitive processes involved in DfE and suggested avenues for future directions. As depicted in Figure 3, we conceptualized the cognitive processes as attention and perception, memory, and learning. All these cognitive processes have in common that they provide explanations for observed behavior without recurring to subjective preferences. With our examples and the cited initial evidence, we hope to convince the reader that how people distribute attention to experiences and how they represent numeric as well as nonnumeric experiences can substantially impact behavior in DfE. Similarly, the way experiences are stored in memory and how recent experiences interact with episodic memory and the semantic network is an important determinant of how experiences relate to behavior. Finally, the integration of information from different sources, mental models about the environment, and social aspects of learning are equally important determinants of behavior.

We argue that these cognitive processes are likely to mediate the relation between experiences and subsequent behavior in nontrivial ways. Therefore, they should be studied more explicitly to better understand behavior in experimental tasks and, especially, in real-world behavior. As we explained in the real-world decision-making section, cognitive processes are likely to even play a larger role in real-world behavior in domains such as finance, the environment, and health because in these domains choice situations are usually more complex, are embedded in a broader semantic network, and often include social interactions. This makes understanding the role of cognitive processes in such choice scenarios an important objective.

Conclusion

Experimental research in DfE is a growing field in judgment and decision-making. These experiments provide a rich context allowing for the simultaneous investigation of information processing and preferential choice. Because many real-world decision problems share the same properties of information search and evaluation followed by action, DfE experiments offer substantial potential for external and ecological validity. Nearly two decades of successful research with what has become the standard experimental paradigms in DfE open the door for these exciting possibilities (Hertwig et al., 2004; Hertwig & Wulff, 2021). Now is the time to broaden experimental DfE paradigms to fully unleash their potential. Therefore, we advocate expanding the experimental DfE paradigm to better match real-world scenarios. The extensions we have discussed include larger sets of choice options, nonnumeric experiences, delayed feedback, a richer choice context, multiple sources of information, or social interactions. These extensions can contribute to the understanding of societal problems, such as promoting a healthy lifestyle, taking effective measures against climate change, and fostering a cooperative community. Therefore, following the suggestions in this perspective, future research in DfE can generate impact beyond the borders of its empirical field by, for example, providing behavioral insights for policy interventions to improve decision-making.

We have further argued that many of the real-world decision problems are complex situations that usually involve extensive cognitive processing of previous experiences before reaching a decision. These cognitive processes were attention and perception, memory, and learning. They are crucial to understand and predict behavior in real-world scenarios but remain understudied in DfE experiments. We believe that behavioral experiments are the appropriate setting to study cognitive processes once the experimental paradigms are extended to incorporate them more explicitly. The proposed focus on cognitive processes can also establish connections to cognitive science, neuroscience, and computer science. For example, implementing core constructs from associative and reinforcement learning in DfE (e.g., model-based learning) can create links to cognitive neuroscience and animal learning. The advent of new analytical tools, such as machine-learning techniques, could help foster this interdisciplinary work by connecting cognitive models with analyses of large-scale data sets (e.g., Erev et al., 2017; Peterson et al., 2021). Moreover, eliciting recall data from past experiences or using refined cognitive models of memory processes in experimental DfE can connect to memory research. Finally, comparing preferential to perceptual or judgment tasks can elucidate the influence of attention and perception on DfE and connect to areas of mathematical cognition and visual science.

Together, the inclusion of theories and concepts from learning, memory, perception, and attention into DfE research can help develop broader classes of models that incorporate preferential as well as nonpreferential tasks. Examining basic cognitive processes to understand preferential behavior is a topical agenda and relates to similar approaches to link economic behavior (usually in DfD) to cognitive psychology (see Bordalo et al., 2012; Frydman & Jin, 2022; Khaw et al., 2021; Lieder et al., 2018; Rakow & Newell, 2010; Schley & Peters, 2014; Summerfield & Tsetsos, 2012). In addition, using the DfE paradigm as an experimental method to understand real-world problems makes it possible to use insights from basic cognitive research to improve policy interventions and training for high-stakes decision-making. We look forward to even more interdisciplinary research and even more design creativity in DfE in the future.

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