Universität Basel

Fakultät für
Psychologie

The cognitive and neural dynamics of memory-based decisions

Inauguraldissertation zur Erlangung der Würde eines Doktors der Philosophie
vorgelegt der Fakultät für Psychologie der Universität Basel von

Peter Maximilian Kraemer

aus München, Deutschland

Basel, 2022

Universität
Basel

Fakultät für
Psychologie

Genehmigt von der Fakultät für Psychologie auf Antrag von

Prof. Dr. Sebastian Gluth &

Prof. Dr. Jörg Rieskamp

Datum des Doktoratsexamen:

DekanIn der Fakultät für Psychologie

Universität
Basel

Fakultät für
Psychologie

Erklärung zur wissenschaftlichen Lauterkeit

Ich erkläre hiermit, dass die vorliegende Arbeit ohne die Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel selbstständig verfasst habe. Zu Hilfe genommene Quellen sind als solche gekennzeichnet. Die veröffentlichten oder zur Veröffentlichung in Zeitschriften eingereichten Manuskripte wurden in Zusammenarbeit mit den Koautoren erstellt und von keinem der Beteiligten an anderer Stelle publiziert, zur Publikation eingereicht, oder einer anderen Prüfungsbehörde als Qualifikationsarbeit vorgelegt. Es handelt sich dabei um folgende Manuskripte:

- Kraemer, PM, Weilbächer, RA, Mechera-Ostrovsky, T, & Gluth, S (2022). Cognitive and neural principles of a memory bias on preferential choices. *Current Research in Neurobiology*. 3. 100029.
- Kraemer, PM, Fontanesi, L, Spektor, MS, & Gluth, S (2021). Response time models separate single- and dual-process accounts of memory-based decisions. *Psychonomic Bulletin & Review*, 28: 304-323.
- Kraemer, PM, & Gluth, S (submitted). Episodic memory retrieval affects the onset and dynamics of evidence accumulation during value-based decisions. Submitted to *The Journal of Neuroscience*.
- Kraemer, PM, Wulff, DU, & Gluth, S (2021). A sequential sampling account of semantic relatedness decisions. *Proceedings of the 43th Annual Meeting of the Cognitive Science Society*. 1788-1794.

Bamberg, 30.05.2022

Peter Maximilian Kraemer

To my dad,

whose perseverance and critical mind

have always accompanied me

during this odyssey.

Acknowledgments

Much time goes by while obtaining a doctorate. Numerous hours have been spent in the office, in the lab, and other places, with no one around but myself, some might even say, in solitude. Thereby, it is easy to forget that I never were alone. I was lucky enough to have a lot of people around me who inspired my thoughts, altered my perspectives, and with whom I just had a good time. What a pity that memory is so imperfect that I run in danger to forget one or the other person here; people who affected my life and work during these times of conducting my dissertation. While I hope for forgiveness from the forgotten, I will do my best – of course, adopting the well-proven recall strategy of clustering – to thank the people I owe deep gratitude.

First and foremost, I would like to thank Sebastian. Your exceptional supervision allowed me to grow as an independent researcher. Your empathic understanding of my individual circumstances gave me happiness and inner peace. It has been a delighting experience to work with you. Further, I would like to thank Jörg for valuable comments on my work. Your feedback during lab meetings and PhD conferences helped to improve every single project of this dissertation. Together with the PhD program (on this note, thanks to Mariela, Rui and Rainer) you contributed to a space for PhD students to develop new skills and to orient themselves in a scientific environment. Many thanks for these efforts.

I would like to thank Laura, Mikhail, Dirk, Tehilla, and Regina for great collaboration within the presented projects. Regina deserves a bonus-thank for teaching me important lessons about Switzerland and administratory realities at the university. This helped me

a lot while reorienting in Basel. Moreover, thanks to all other members of the groups of Economic Psychology and Decision Neuroscience, namely Dimitris, Janine, Ash, Nathaniel, Hanna, Jana, Doron, Steve, Markus, Sebastian, Annina, Florian, Nives, Kevin, and Rebecca as well as the student researchers Maria, Sarah, Carmina, Noëlle, Gregory, and Marie for your immense support.

I was very privileged to travel to many conferences and workshops where I met numerous smart and kind people – too many to count them all. Just to name a few: Thanks to Prnay and Alina for a beautiful time in Amsterdam; to Johannes for knowing the best quotes; to Blair for granting me the flair of student life at an American University; and to Zhiwei for some of the most inspiring conversations I ever had.

Last but not least, I would like to thank my family. Gifted with the perseverance of my dad and the curiosity of my mum, I was able to pursue and finalise this work. I was always assured of your support. Further, my parents-in-law were not only invaluable as they helped me moving several times, they also granted me precious timeouts during the holidays allowing me to regenerate. Special thanks go to Leon for keeping a critical eye on me while I am writing this thesis. Finally, my deepest gratitude goes to Carmen, who carried the burdens of these upsetting times together with me. I couldn't hope for a better partner to walk down this road with.

Table of Contents

Abstract

The recent years have seen the rise of neuroeconomics, a scientific discipline investigating the cognitive and neural principles of value-based decision making. While neuroeconomists made significant progress in characterizing basic computations of value-based decision making, the critical role of memory has all-too-often been neglected. Within this cumulative dissertation thesis, I present four manuscripts, which address the relation of memory and decision making. Manuscript 1 reviews empirical evidence which demonstrates that memory-based decisions are biased in favor of choice options which can be recalled from memory. Adopting cognitive process models, Manuscript 2 demonstrates that this memory bias is rather due to a single decision process, as compared to a dual-process account of memory-based decisions. Manuscript 3 focuses on the temporal dynamics of memory retrieval and choice formation, outlining altered evidence accumulation dynamics of memory-based versus standard value-based decisions. Finally, Manuscript 4 takes the first steps toward a cognitive process model which accounts for the temporal dynamics of both, memory retrieval and decision making. While every manuscript can be approached individually, the synopsis part of this dissertation thesis discusses them in a broader perspective, drawing on the neuroeconomic framework by Rangel et al. (2008). All in all, this dissertation thesis advocates for neuroeconomics to take memory processes more seriously. Future research will especially profit from a deeper understanding of the temporal dynamics of memory retrieval and its relation to decision making.

Chapter 1

Introduction

"The aim of life is an action,

not a thought."

Charles S Sherrington

(1940/2009, p.201)

1.1 The problem of decision making

As humans, we are gifted with a highly adaptive behavioral repertoire, which arose by evolutionary means of natural selection (Saveliev, 2010). While our ancestors may have faced existential choices such as fighting a predator or fleeing from it, modern life often comes with less relentless, yet difficult concerns such as what job to take, whom to get married to, or where to have lunch. Although these decisions greatly differ in their significance, they all require an agent to solve a *decision problem*, that is to select among several potential courses of action, given the individual goals and the current situation.

Decision making is studied from a variety of different viewpoints (e.g., Johnson & Busemeyer, 2010). While many researchers ask for the *normative* principles that should guide decision making, others have a *descriptive* agenda, aiming to describe and predict the actual choices of an agent. Yet a third perspective focuses on the underlying *computational* processes, which result in observable behavior. The computational approach thus asks, how do decisions come about? Although all approaches have their justification, in this dissertation I adopt a perspective from neuroeconomics, an interdisciplinary research area comprising the cognitive neurosciences, psychology and economics (Camerer et al., 2005; Glimcher & Fehr, 2013), to focus mostly on the computational principles of decision making.

1.2 Computations in economic decision making

Whereas some decision scientists focus on decisions about the temporal, perceptual, or semantic properties of presented stimuli (e.g., Balci & Simen, 2014; Britten et al., 1992; Lucas, 2000), neuroeconomists concentrate on *economic* decisions, hence decisions which depend on the value, accredited to objects or actions (Camerer et al., 2005). Thereby, neuroeconomic inquiry strongly relies on the information processing paradigm, according to which the brain is treated as an information processing system, which collects perceptual information, forms internal representations of the outside world, and directs appropriate actions (Cisek & Kalaska, 2010; Oppenheimer & Kelso, 2015). The involved computations have been structured in a popular framework of economic decision making (Rangel et al., 2008). The authors identified five basic computations: Representation, valuation, action selection, evaluation of choice outcome, and learning (see, Fig. 1.1).

Before describing the cognitive and neural underpinnings of these computations, I would like to consider the example of restaurant choice, which comprises relevant aspects of economic decision making. In this example, an agent sits in her office at noon and senses an upcoming feeling of hunger. Considering to have lunch either at the university canteen or a close-by cafeteria, she faces a decision problem. She weighs the advantages and disadvan-

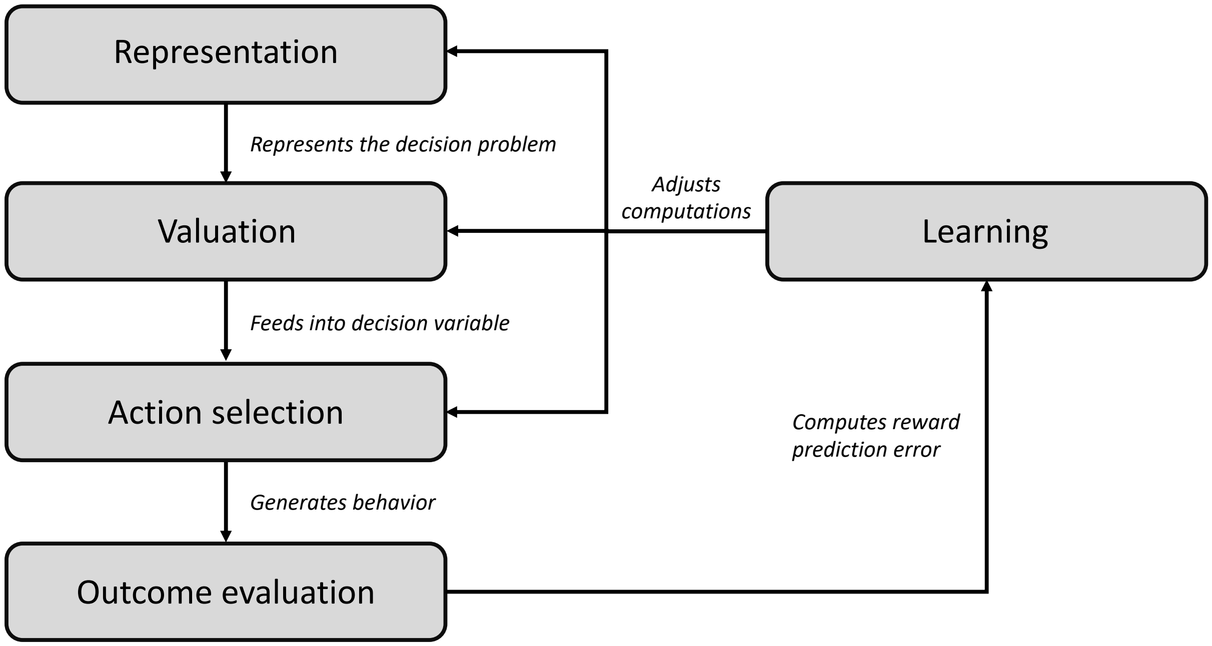


Figure 1.1: Schematic overview of the basic computations of the neuroeconomic framework by Rangel et al. (2008). Grey boxes represent the computations, italic texts indicate the function of the preceding computations.

tages of the alternatives and decides to have lunch at the seemingly favorable cafeteria. After arriving there, she orders a dish but quickly realizes the food to be rather flavorless, lacking spices and herbs almost completely. Disappointed, she plans to take this into account for future restaurant choices. This example of an everyday episode contains all computations suggested by Rangel et al. (2008), further described in the following paragraphs.

1.2.1 Representation

As an entry step to the decision process, a representation of the decision problem at hand is computed to set grounds for further processing. Potential action plans (e.g., eating at the canteen; eating at the cafeteria) need to be identified alongside with external (e.g., it is lunch time) and internal (e.g., sensing upcoming hunger) states.

Unfortunately, Rangel et al. (2008) remain rather vague about the mechanisms of this computation. It is still unclear, how action plans are identified (see, Chapter 6 for a discussion) and how the external and internal states are computed. Due to its complex nature, it can be assumed that the neural realization of the representation is not confined to a particular brain region but is rather wide-spread over the nervous system. Once the cognitive system can draw on the representation of the decision problem, each action plan can be valuated. Note, however, that the framework does not explicitly assume a strict sequentiality of the computations.

1.2.2 Valuation

In the course of valuation, positive (e.g., because canteen is cheap) or negative (e.g., because canteen has a long waiting line) values, which are associated with potentially rewarding or punishing outcomes (i.e., saving money; losing time), are assigned to each action plan under consideration. This process involves the integration of relevant attributes (e.g. money, time, taste) of choice options into unitary subjective value signals, as assumed by established theories in judgment and decision making, reenforcement learning, and economics (Kahneman & Tversky, 1979; Sutton & Barto, 1998; von Neumann & Morgenstern, 1947). Valuation processes integrate signals from different systems, factoring in basic evolutionary needs (Pavlovian systems), repeated stimulus-response associations (habit systems), and high-level computations of action-outcome associations (goal-directed systems). Importantly, valuation processes are modulated by the context, in which decisions are made (e.g., the delay of a payoff) or individual behavioral tendencies, such as attitudes towards risk and uncertainty.

On the neural level, valuation signals are found in several brain regions including the striatum and prefrontal structures (Kable & Glimcher, 2009; Platt & Plassmann, 2013; Rushworth et al., 2011). Especially the orbitofrontal cortex (oFC) of the macaque monkey and its human homologue, the ventromedial prefrontal cortex (vmPFC), have been shown to accomodate neurons which represent different choice options and encode their respective subjective value (Bartra et al., 2013; Clithero & Rangel, 2014; Padoa-Schioppa & Assad, 2006, 2008). Accompanied with evidence from lesion studies (e.g., Camille et al., 2011;

Fellows & Farah, 2005; Noonan et al., 2010; Peters & D'Esposito, 2016; Vaidya & Fellows, 2020) it can be assumed that the oFC/vmPFC computes and represents subjective value in economic choices.

1.2.3 Action selection

As each of the action plans is associated with a value, a preference is formed for one of them by processes of action selection. A large body of evidence suggests that action selection draws on the principles of *evidence accumulation* (Heekeren et al., 2008; Ratcliff et al., 2016; Shadlen & Kiani, 2013). According to this view, a *decision variable* represents the momentary preference for either action plan. Over time, the decision variable samples and integrates *evidence* (e.g. subjective value of the action plans) to update its level of preference. When a certain threshold level of evidence is reached, the process is terminated and the preferred action plan is executed. In economic decisions, the decision variable is often thought to depend on the valuation of the considered action plans (Busemeyer et al., 2019; Clithero, 2018; Fehr & Rangel, 2011).

The idea of evidence accumulation is largely appreciated in decision neuroscience since the brain appears to implement action selection in a comparable way (Cisek & Kalaska, 2010; Gold & Shadlen, 2007; Smith & Ratcliff, 2004). Several frontal and parietal areas seem to represent action plans with the neural activity of effector-specific neurons[1]. These neurons receive affarent signals from various brain regions, including valuation signals of the vmPFC (e.g., Basten et al., 2010; Gluth et al., 2012; Hare et al., 2011). Over time, the relative activity level for corresponding action plans varies as a function of incoming valuation signals (Cisek, 2012; Gluth et al., 2013). As the activity level for one action plan outweighs the others, the initiation of corresponding actions is caused via efferent connections with the motor system (Rizzolatti & Kalaska, 2013; Thura & Cisek, 2014).

---

[1] Note that there is an ongoing debate of whether action selection is performed in brain regions that code for value versus regions that code for action (Cisek & Kalaska, 2010; Fine & Hayden, 2022; Levy & Glimcher, 2012; Padoa-Schioppa, 2011; Rangel & Hare, 2010; Rushworth et al., 2011). However, the principle of response competition, which is the central point of action selection, apply to both perspectives.

1.2.4 Outcome evaluation and learning

After an action is selected and performed (i.e., being at the cafeteria having lunch), an agent processes the consequences of her action (i.e., food is flavorless) and the desirability of her new state (i.e., disappointed). This evaluation can be used to adjust the computations of representation, valuation, and action selection via learning mechanisms, so that future decisions can take advantage of prior experiences.

The role of learning is mainly discussed for the adjustment of valuation processes, emphasizing the adaptation of habits via reenforcement learning. A well-studied concept is the reward-prediction error, where expected and actual reward are compared to readjust stimulus-response associations (Sutton & Barto, 1998). Such computations have been attributed to dopamine neurons in mid brain nuclei (Bayer & Glimcher, 2005; D'Ardenne et al., 2008; Fontanesi et al., 2019a; Schultz et al., 1997) as well as the ventral striatum (O'Doherty et al., 2003). Rangel et al. (2008) assume that reward prediction error-like computations may also be relevant for other computations such as representation and action selection. While the latter gained some traction recently as threshold parameters in evidence accumulation models have been discussed to depend on mechanisms of reenforcement learning (Fontanesi et al., 2019b; Pedersen et al., 2017), the role of learning for representation remains elusive.

Overall, the framework by Rangel et al. (2008) offers a coarse structuring of the computations, which are required for a neuro-cognitive system to solve value-based decision problems. While building on narrower proposals, which mainly focus on valuation and action selection (Kable & Glimcher, 2009; Platt & Plassmann, 2013), the framework broadened the perspectives to consider the computations of representation and learning. It has been welcomed by the neuroeconomic community and stimulated new research in the area, both being evident from the high citation numbers since its publication (1,194 citations in Web of Knowledge on May fourth, 2022). The framework however, similar to other contemporary discussions in neuroeconomics (Kable & Glimcher, 2009; Konovalov & Krajbich, 2019; Rushworth et al., 2011), misses to consider a crucial point: Decision making heavily depends on memory.

1.3 The function of memory in decision making

Memory constitutes an umbrella term, covering a range of different systems such as declarative, non-declarative, and prospective memory, each with their respective neural basis and cognitive specifications (Cohen & Squire, 1980; Milner et al., 1998; Squire & Wixted, 2011). As the nervous system's capability to store skills and knowledge, memory makes relevant information accessible when needed (Gazzaniga et al., 2011). Imagine the agent of our restaurant example without having access to memory. How would she, sitting in her office, even consider different restaurants which are out of her sight? How would she integrate relevant attributes such as price or expected waiting time without consulting prior experiences? How would she, given her disappointment, avoid to make the same mistake to go to the cafeteria next time? From this example, one can infer that all computations of decision making, as outlined by Rangel et al. (2008), strongly depend on memory processes. However, research on the role of memory for economic decision making is still in its infancy.

Psychologists and behavioral economists have been addressing the problem of memory-based decision making for a long time (Alba & Hutchinson, 1987; Lynch & Srull, 1982; Weber et al., 1995), leading to the development of theories of memory-based judgment and decision making (Johnson et al., 2007; Stewart et al., 2006). However, the consideration of memory only recently made its way to the neuroeconomic literature (Shohamy & Daw, 2015). An important reason for this were emerging findings that the hippocampus, a brain region traditionally related to memory processes, is involved in economic choices (see, Palombo et al., 2015; Weilbächer & Gluth, 2017, for reviews). Furthermore, theoretic advances on action selection and learning necessitated a closer look on memory processes (Gershman & Daw, 2017; Shadlen & Shohamy, 2016). These developments opened a door for a new perspective in neuroeconomics, to investigate the precise neuro-cognitive principles behind memory-based decision making. In this dissertation thesis, I present four manuscripts, reporting progress in this endeavour. To illustrate the relations between the manuscripts, they are embedded within the neuroeconomic framework by Rangel et al. (2008).

1.4 The foci of this dissertation

In Manuscript 1 (M1, Chapter 2), my colleagues and I reviewed evidence for a *memory bias*, a tendency of people to prefer options they can recall from memory over options they cannot recall. We discuss the neural and cognitive basis for this bias, suggesting that it affects valuation processes to a large extent. While the neural foundations are to be found in the connectivity of the hippocampus and vmPFC, on the cognitive level, meta-cognitive beliefs and aversion to uncertainty seem to drive the memory bias. We formulated new hypotheses for future research and discussed a cognitive modeling framework, namely, the evidence accumulation framework, as a promising approach to study memory-based decisions.

In the second manuscript (M2, Chapter 3), we tested an alternative hypothesis stating that the memory bias does not arise from a biased valuation process (*single process account*), but instead, from a mixture of action-selection processes with different decision policies (*dual-process account*). Both accounts can, in principle, explain similar behavioral choice data but, as we show, differ with respect to expected response times. Using evidence accumulation modeling, we derived qualitative predictions for the response time patterns and tested them empirically. Based on our results, we found clear support that the single process account is to be preferred, since it matched with the qualitative predictions and provided a more parsimonious explanation for the data.

Having gained some insight on the effect of memory on valuation in M1 and M2, the third manuscript (M3, Chapter 4) was centered around the question how action selection processes depend on memory retrieval. More specifically, using cognitive modeling and electro-encephalography (EEG), we investigated the temporal dynamics of memory retrieval and action selection. Our results suggested that the retrieval of memories is associated with a delayed onset of the evidence accumulation process. Moreover, when decisions required memory retrieval, participants accumulated evidence for a longer time as reflected by a higher decision threshold and lower rate of evidence accumulation. Finally, although we did not identify a neural signature reflecting memory retrieval, the latency of action selection onset suggests that memory retrieval and action selection progress in parallel for some time. This finding asks for the formulation of cognitive process models which can account for parallel memory retrieval and action selection.

We approached this challenge in the fourth manuscript (M4, Chapter 5). By modeling the retrieval dynamics with help of memory structure models from natural language processing, we tested different sequential sampling models to account for behavioral benchmarks in semantic decision making. We simulated data under a set of plausible parameter values and showed that different sequential sampling models can account for the benchmarks with different cognitive mechanisms. In particular, the leaky competing accumulator model accounted for all benchmarks and made predictions for a new benchmark which we verified empirically. The model provided a parallel account of memory retrieval and action selection.

In the final chapter, I briefly summarize the main findings of this dissertation and discuss potential directions of future research.

Chapter 2

How memory affects valuation

2.1 Manuscript 1: Cognitive and neural principles of a memory bias on preferential choices

Kraemer, P. M., Weilbächer, R. A., Mechera-Ostrovsky, T., & Gluth, S. (2022). Cognitive and neural principles of a memory bias on preferential choices. *Current Research in Neurobiology, 3*. https://doi.org/10.1016/j.crneur.2022.100029.

2.2 The Memory bias

The neuroeconomic framework posits that valuation computes *stimulus values* for each action plan (Rangel et al., 2008; Rangel & Hare, 2010). Stimulus values represent the expected desirability of a decision outcome and are computed by integrating over basic attributes (e.g., tastiness, healthiness) of the choice options. On the neural level, stimulus attributes are encoded in several brain regions (depending on the respective attribute quality) and feed into the oFC/vmPFC to allow the computation of stimulus values. Importantly, attributes can have positive or negative effects on stimulus values, implying the expectation of reward or punishment. The magnitude of this effect is governed by the corresponding *attribute values*, which are either externally provided (e.g., in decisions from description) or retrieved from memory as samples of information (Johnson et al., 2007; Stewart et al., 2006; Zhao et al., 2021).

Acknowledging that valuation draws on memory, an obvious question is whether the imperfection of memory introduces bias to valuation and subsequent action selection processes (Weber & Johnson, 2006). One such bias is the *memory bias*, a tendency to prefer choice options which can be recalled from memory over options which cannot be recalled. The memory bias was identified by Gluth et al. (2015) in a remember-and-decide task. Participants learned the association of snacks with locations and later, being cued with locations, had to retrieve the corresponding snack identities to make preferential decisions between the options. Sometimes, participants recalled the snack identities and were able to make informed value-based choices. Other times, memory recall failed and participants' access to attribute values were at least diminished, if not absent. Interestingly, when participants compared a recalled with a not-recalled option, they preferred the former one, even if that option was relatively unattractive (i.e., its subjective value measure was below the average value of all snacks used in the experiment). Fitting a logistic regression model to the choice data revealed that participants behaved as if they compared the subjective value of the recalled option with a *reference value*. This reference value substituted the value of the not-recalled option, since attribute values were likely not accessible. This finding stimulated a systematic research program to outline the cognitive and neural principles that underlie the memory bias.

In Manuscript 1 (Kraemer et al., 2022), we reviewed the major outcomes of this endeavour. In brief, Gluth et al. (2015) investigated the brain's functional circuitry, showing that effective connectivity between the hippocampus and the vmPFC drove memory-based choices. The connectivity was particularly enhanced, when the memory bias likely had an effect on choice behavior. On the cognitive level, Mechera-Ostrovsky and Gluth (2018) found that the memory bias can partially be explained by meta-cognitive beliefs about the relation of the ability to recall an item and its value. The fact that an item could not be recalled suggested it to be neither immensely valuable nor exceptionally valueless. This is seemingly factored in the valuation of the not-recalled option. Meta-cognitive beliefs alone, however, were not sufficient to explain the magnitude of the memory bias. Another attempt by Weilbächer, Kraemer, and Gluth (2020) asked, whether the memory bias resembles behavioral tendencies known from decisions under uncertainty. More specifically, we showed that the memory bias is domain dependent, causing a preference for recalled (hence, certain) options in the gain domain but not in the loss domain. Two further studies ruled out that the memory bias was due to, either attentional biases (Weilbächer et al., 2021), or a dual-process account, drawing on a recognition-heuristic like process (Kraemer et al., 2021a, also discussed in Chapter 3). Overall the research program around the memory bias illuminated the neuro-cognitive underpinnings of this phenomenon and proposed new directions for future research.

2.3 Is the memory bias a valuation bias?

Although the memory bias has been described as affecting valuation processes (Kraemer et al., 2022), this notion has not been explicitly discussed in the paper. Since this dissertation thesis adopts a holistic approach to value-based decision making, it is imperative to discuss the memory bias with respect to the neuroeconomic framework by Rangel et al. (2008). Despite the relative vagueness of the framework, one can derive at least two characteristics that qualify the memory bias as a result of valuation processes.

First, valuation should depend on brain regions which represent value. While these brain regions mainly comprise the ventral striatum for habit systems, Pavlovian and goal-directed systems depend largely on oFC/vmPFC (Rangel et al., 2008). Since the memory bias does not draw on repeated learning of stimulus-response associations, one can assume a subordinate role of habit systems. Therefore, Pavlovian and/or goal-directed systems are the main candidates to foster the memory bias, spotlighting the role of the vmPFC. Gluth et al. (2015) found that the representation of value in the vmPFC is better explained by a model which takes the likelihood of remembering a choice option into account. Hence, recalling the identity of an item has an effect on the value representation for chosen and unchosen options. In addition, the elevated connectivity between hippocampus and vmPFC may modulate value representations in vmPFC, offering a mechanistic explanation for the memory bias.

Second, Rangel et al. (2008) propose that valuation is susceptible to modulations. The memory bias may arise from a biased reference value which dominates the valuation of the not-recalled choice option, when the item identity, and thus, the attribute values, are inaccessible. As the reference value seems to depend on meta-cognitive beliefs (Mechera-Ostrovsky & Gluth, 2018) and is domain sensitive (Weilbächer, Kraemer, & Gluth, 2020), it was revealed that the bias is adaptive to the respective decision scenarios, which substantiates diverse modulations of value representations and suggests the memory bias to depend on valuation processes.

Apart from these two points arguing for valuation, there are also arguments that speak against the memory bias to depend on representation or action selection. By definition, representation concerns internal and external states (i.e., the sensation of hunger, experimental procedures) as well as potential action plans (i.e., pressing one or another button to indicate a decision and have the chance of eventually receiving a snack). One can determine that all computations of representation can be performed, even if the snack identity is not being recalled. Hence, the minimum requirements for valuation are fulfilled and a decision variable can be informed. In neuroeconomics, the decision variable is often defined as a difference in subjective value of the considered choice options (Busemeyer et al., 2019; Fehr & Rangel, 2011; Krajbich et al., 2010), a practice also applied to study the memory bias by adhering to a reference value (Gluth et al., 2015; Kraemer et al., 2021a; Weilbächer et al., 2021). While the decision variable depends on the outcome of valuation processes (see, Section 2.4) it appears conceivable that alternative mechanisms of action selection such as value-difference-independent decision policies (e.g., a recognition heuristic) or *a priori* biases may explain the memory bias. However, both explanations have been found to provide a less parsimonous explanation for empirical data (Kraemer et al., 2021a, Chapter 3), rendering it unlikely that the memory bias is a phenomenon, predominantly driven by valuation-independent action selection mechanisms.

Finally, the role of learning remains an open question. It is currently unknown, whether the memory bias constitutes a general behavioral tendency or emerges during the performance of the (cognitively demanding) remember-and-decide task. It is possible that participants face their cognitive limitations and adapt by developing value-dependent encoding and decision strategies to increase task performance (Bays & Dowding, 2017; Madan & Spetch, 2012). Consequently, the memory bias may follow principles of bounded rationality (Lieder & Griffiths, 2019; Simon, 1956). Nonetheless, the empirical and theoretical arguments point to the direction that the memory bias is largely a phenomenon to originate in biased valuation processes. A potential role of learning does not compromise these arguments but rather has the potential to offer new explanations for the occurrence of this phenomenon.

2.4 The application of evidence accumulation models in memory-based decisions

The research program on the memory bias exemplified the utility of evidence accumulation models in memory-based decision making (Gluth et al., 2015; Kraemer et al., 2021a; Weilbächer et al., 2021). As mentioned in Chapter 1, these models mimic the process of action selection as they assume the accumulation of evidence over time until a threshold is reached (Bogacz et al., 2006; Ratcliff et al., 2016; Shadlen & Kiani, 2013). In a neuroeconomic context, evidence often depends on a decision variable, composed of the value difference of the considered choice options (Clithero, 2018; Fehr & Rangel, 2011; Krajbich et al., 2010). The decision variable can thus be understood as reflecting the valuation of individual action plans, which are subject to momentary noise akin to sampling information from attribute value distributions in memory (Polanía et al., 2019; Stewart et al., 2006). Consequently, evidence accumulation models cover central aspects of valuation and action selection, both being crucial computations in the neuroeconomic framework by Rangel et al. (2008) and similar accounts (Kable & Glimcher, 2009; Platt & Plassmann, 2013).

Apart from offering a mathematical framework for neuroeconomic choice, evidence accumulation models have further advantages which are leveraged in the other manuscripts of this dissertation thesis. First, as they jointly model choice and response time data (Bogacz et al., 2006; Wilson & Collins, 2019), evidence accumulation models allowed a rigorous empirical test of an alternative account of the memory bias (M2, Chapter 3). Second, their account of the temporal progression of action selection (Gluth et al., 2013; Polanía et al., 2014) helped to identify differences in the cognitive and neural dynamics of memory-based versus value-based decision processes (M3, Chapter 4). Finally, the application of evidence accumulation to memory retrieval (Kumar, 2020; Ratcliff, 1978) inspired the examination of models that consider the dynamics of memory retrieval and action selection (M4, Chapter 5).

2.5 Conclusions

In sum, our review outlined important neural and computational mechanisms that underlie the memory bias. I have argued that, based on the current evidence, the memory bias is to be understood as a biased valuation process. Finally, evidence accumulation models have proven useful to gain a deeper understanding of the memory bias. The remaining manuscripts will heavily draw on the evidence accumulation framework to investigate the cognitive and neural mechanisms of memory-based decisions.

Chapter 3

Process models of memory-based decisions

3.1 Manuscript 2: Response time models separate single- and dual-process accounts of memory-based decisions

Kraemer, P. M., Fontanesi, L., Spektor, M. S., & Gluth, S. (2021a). Response time models separate single- and dual-process accounts of memory-based decisions. *Psychonomic Bulletin and Review*, *28*, 304–323. https://doi.org/10.3758/s13423-020-01794-9.

3.2 A dual-process account of the memory bias

It is a long cultivated research strategy in the decision sciences to study the deviation of economic concepts of rationality from actual human behavior (Camerer et al., 2003; Rieskamp et al., 2006; Simon, 1956; Tversky & Kahneman, 1974). A popular set of theories propose that behavioral biases are the result of fast and erroneous judgment processes, whereas economically rational behavior arises from slow and effortful processing (Evans, 2008; Kahneman &

Frederick, 2002). These *dual-process theories* gained wide popularity across judgment and decision making and behavioral economics in the recent years (Huettel, 2010; Kahneman, 2011; Melnikoff & Bargh, 2018). We therefore wondered, whether a dual-process theory may explain the memory bias and, if so, whether this would put the theoretic concept of a reference value to dispute.

How could a dual-process account of the memory bias be envisioned? Mechera-Ostrovsky and Gluth (2018) discussed that the preference for recalled options, which constitutes the memory bias, to some extent resembles the recognition heuristic. The recognition heuristic is a fast and frugal choice rule, which states that, given only one of two options can be recognized, the recognized option is inferred to have a higher value (Goldstein & Gigerenzer, 2002). Mechera-Ostrovsky and Gluth (2018) further argued that the recognition heuristic alone cannot explain the memory bias sufficiently because recalled options were not exclusively preferred, violating the assumption of a noncompensatory choice rule. It is, however, conceivable that participants sometimes relied on a heuristic process, independent of the value comparison, and other times on economically rational valuation, comparing the value of the recalled option with a reference value representing the expected value of all snacks used in the experiment. Such a dual-process account can be modeled adopting the dual-process diffusion model (DPDM, Alós-Ferrer, 2018). In brief, this model assumes two independent evidence accumulation processes, the heuristic process and the utility process. While both processes select their respectively preferred action, a central executive decides, which of the two finally triggers the corresponding action. In M2 (Kraemer et al., 2021a), we derived qualitative predictions of the DPDM indicating that the model produces choice behavior markedly similar to the memory bias.

3.3 Comparing single- and dual-process accounts

The dual-process account constitutes an alternative to the concept of a biased reference value which explains the memory bias as a result of a single valuation process. As both accounts make comparable predictions with respect to choice data, we resorted to the capability of evidence accumulation models to make additional predictions about a different behavioral measure, namely response times (Bogacz et al., 2006; Wilson & Collins, 2019). Both accounts can be implemented as diffusion models which describe the process of decision making as relative evidence accumulation between two decision boundaries (Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998). These models jointly predict choices and response times as originating from the same evidence accumulation process. In our study, we derived qualitative predictions from the single-process diffusion model (SPDM, comparable to Gluth et al., 2015) and the DPDM (implemented, as described above Alós-Ferrer, 2018).

We found that the models make different predictions with respect to response times. The SPDM expected the longest response times for decisions where the subjective value of the recalled option was equivalent to the reference value. The DPDM, on the other hand, expected longest response times for decisions where the subjective value of the recalled option was equivalent to the average value of all snacks in the experiment. We tested these predictions with a regression model on an empirical data set by Mechera-Ostrovsky and Gluth (2018). We found decisive evidence in favor of the SPDM. Further, we implemented SPDM and DPDM in a hierarchical Bayesian framework (Lee, 2011; Lee & Wagenmakers, 2013) and performed quantitative model comparison. Again, we found clear support for the SPDM as it provided a more parsimonious fit to the data.

We also tested, whether the memory bias can be explained as an *a priori* preference for recalled snacks. A priori preferences have been implemented as a bias of the starting point of the evidence accumulation process (Edwards, 1965; Ratcliff & Rouder, 1998; Voss et al., 2004). From a dual-process perspective, this *starting point bias* can be interpreted as the result of a heuristic-like process of a default-interventionalist model (Chen & Krajbich, 2018; Evans, 2008). If the memory bias manifests as a starting point bias in favor of the recalled snack, one can expect corresponding differences in the response time distributions of recalled versus non-recalled snacks (Ratcliff & Rouder, 1998). We tested this account by estimating the *memory-bias-as-starting-point-bias* model, where, in contrast to the SPDM, the decision boundaries represented the choice for recalled versus not-recalled options. Although the starting point bias was allowed to explain the memory bias the results still suggest a biased reference value. Thus, the bias was confined to the drift-rate (Krajbich, 2021; Mulder et al., 2012) instead of the starting point.

3.4 Conclusions

Overall, in this study we used cognitive modeling to rule out two potential dual-process accounts of the memory bias. As discussed in Section 2.3, the dual-process accounts tested here could be interpreted as value-difference-independent action selection processes in the neuroeconomic framework (Rangel et al., 2008). However, neither the parallel-competitive account by Alós-Ferrer (2018), nor the default-interventionalist account of the memory-bias-as-starting-point-bias model yielded a superior explanation of the memory bias as compared to the single-process account. These findings not only affirm critique on lacking empirical support of dual-process theories (Keren & Schul, 2009; Kruglanski & Gigerenzer, 2011; Melnikoff & Bargh, 2018; Smith & Huettel, 2010), they also substantiate the notion that the memory bias depends on a biased valuation process.

The study makes a strong case for the utility of cognitive process models which not only describe behavior but also its underlying computations. Based on our findings, we decided to retain a single-process diffusion model for our efforts to investigate the temporal dynamics of memory-based decision making, described in M3 (Chapter 4).

Chapter 4

The dynamics of memory-based decisions

4.1 Manuscript 3: Episodic memory retrieval affects the onset and dynamics of evidence accumulation during value-based decisions

Kraemer, P. M., & Gluth, S. (submitted). Episodic memory retrieval affects the onset and dynamics of evidence accumulation during value-based decisions. *Submitted to The Journal of Neuroscience*. https://doi.org/10.1101/2022.04.26.489332.

4.2 Studying the temporal dynamics of memory-based decisions

The previous chapters focused on the effect of memory on valuation processes, which drive human choice behavior. While we took advantage of the dynamics of decision processes to test alternative accounts of the memory bias (M2), still little is known about how memory-based decisions emerge over time. In this study, we were interested in the temporal progression of memory retrieval and action selection processes, as well as their putative interactions. We asked two essential questions. First, do memory retrieval and action selection occur in a sequential or parallel manner? Second, what effect does memory retrieval have on the dynamics of action selection?

We investigated these questions with an adaptation of the remember-and-decide task, with which we got extensive experience in past projects (M1). In contrast to previous studies though, we did not concentrate on the memory bias but on basic temporal properties of memory retrieval and action selection. During an encoding period, participants learned the association of snacks with abstract symbols (identicons). Importantly, the snacks were presented either in the left or right visual hemifield so that their visual properties were encoded in the contralateral visual cortices. Later, during the decision period, participants made incentivized preferential choices between money amounts and snacks. We presented the snacks either visually (value trials) or as identicons (memory trials) so that participants had to retrieve the snacks from memory to make informed decisions. While participants performed this task, we collected temporally precise EEG data to measure the neural dynamics of memory retrieval and action selection.

4.3 Do memory retrieval and action selection progress in sequence or in parallel?

Although the neuroeconomic framework by Rangel et al. (2008) covers several computations that are based on one another, the authors do not discuss the question whether these processes occur in a sequential manner or in parallel. It is therefore unclear, whether valuation processes have to be completed so that action selection can be initiated or whether both processes may occur in parallel with a continuous flow of information. The perpetual question of sequential versus parallel processes has been proven difficult to answer with mathematical modeling alone, since both mechanisms can mimic each other to a substantial degree (Townsend, 1972). Addressing this question usually requires a researcher to articulate a number of rigid assumptions which apply to the computational level of an information processing system (Marr, 1982; Townsend & Wenger, 2004). In an effort to pursue a neurocognitive perspective, we took an alternative route that relied on the identification of neural signatures of memory retrieval and action selection. We hoped to measure these signatures with high temporal precision to make reliable statements about their temporal appearance and their functional connectivity.

We chose the lateralized readiness potential (LRP, Coles & Gratton, 1988) as a neural marker for action selection. The LRP is recorded over the motor areas and is defined as the relative difference of left and right movement-related activity. Although the LRP is sometimes treated as a pure motor component, it is often considered to reflect properties of cognitive and neural processes beyond motor activity (Coles, 1989). Importantly, the LRP has been implicated with the onset (Gluth et al., 2013) and progression (Polanía et al., 2014) of evidence accumulation in value-based decision making, rendering it a viable candidate component for action selection in the remember-and-decide task. Although its exact relationship with evidence accumulation was not as straightforward as expected, the LRP suggested that action selection was initiated at about 235 milliseconds (in memory trials) after the presentation of the identicon and progressed until a decision was executed.

To identify a neural signature for memory retrieval, we aimed to exploit the bi-hemispheric organisation of the visual system. When visual information is encoded in one hemisphere, its recall will likely produce a reactivation of the corresponding brain regions (Gratton, 1998). Studies on memory retrieval have indicated that such reactivation is reflected in the desynchronisation of alpha and beta frequency bands, recorded over posterior areas (Waldhauser et al., 2016; Waldhauser et al., 2012). Although we found electrode clusters which yielded the expected alpha and beta desynchronisation during the encoding period, such desynchronisation patterns were absent during memory retrieval in the decision period (M3, Appendix

1). We thus were unable to identify a neural signature of memory retrieval. Based on our data, it was therefore not possible to give a definitive answer to the question of whether memory retrieval and action selection occured in sequence or in parallel. Still, our results allowed to draw some limited conclusions. A body of recent literature on cued recall paradigms (sharing relevant features with the remember-and-decide task) suggests that the reinstatement of memories is controlled by a hippocampal process that operates between 500 and 1,500 milliseconds after exposure to a retrieval cue (see, Staresina & Wimber, 2019, for a review). Since the LRP onset in our study was found at 235 milliseconds after the exposure to an identicon, it is reasonable to assume that the action selection process started before memories were reinstated, hence, before the memory retrieval process was terminated. Thus, memory retrieval and action selection likely proceed in parallel for some time. The precise interactions and properties of information flow, however, are yet to be discovered in future research.

4.4 How memory retrieval affects action selection

For our second question, we asked how memory affects the dynamics of action selection. Several recent studies contrasted perceptual and value-based decisions with respect to evidence accumulation dynamics and highlighted important similarities and differences between both types of decisions (Bakkour et al., 2019; Dutilh & Rieskamp, 2016; Polanía et al., 2014). In our study, however, we were interested in the differences between classic consumer choices, where goods are visually accessible, and memory-based decisions that rely on internal memory representations. While it has been shown that memory-based decisions rely on different fixation patterns than value-based decisions (Weilbächer et al., 2021), it is unclear how evidence accumulation dynamics are affected.

Thus, we contrasted value trials and memory trials from the remember-and-decide task of our study. We found no difference between both trial types regarding the coherence of choices with respect to independent subjective value ratings, which were collected in advance to the remember-and-decide task. However, participants exhibited considerably longer response times in memory-based decisions. From the perspective of a drift-diffusion process, this finding can be explained by a delayed onset of evidence accumulation, and/or by increased decision thresholds paired with a lower accumulation rate. Estimating a drift-diffusion model, which was based on our modeling experience in M2, we found clear evidence for both hypotheses. Thus, evidence accumulation was initiated with a delay and continued for a longer time until a decision was made. Analyzing the LRP data, we found that former finding was supported by a delayed LRP onset in memory trials which was related to the time consumed by non-decisional processes. Contrary to our initial predictions, however, the slope and amplitude of the LRP were unrelated to the accumulation rate and the boundary separation of the cognitive model.

An important finding of this study is that value-based and memory-based choices are equally coherent with subjective value ratings. Thus, participants did not develop biased preferences for money offers in memory trials as reflected in the absence of a drift-rate and starting point biases. This finding suggests that valuation processes yielded similar outcomes for both trial types. However, the accumulation rate seemed decreased in memory trials (mind, however, the diverging interpretation of evidence between highest density intervals and Bayes Factors). There were no decreases in coherence though, because the boundary separation was increased in memory trials. However, we speculated that the decreased accumulation rate may be due to reduced informativeness of individual evidence samples. This argument is congruent with recent findings describing memory reenstatement as a hippocampal process with rhythmically increasing fidelity (Kerrén et al., 2018; Staresina & Wimber, 2019; Treder et al., 2021). In other words, memories are not instantaneously accessible to the system but get more vivid over time, orchestrated by the hippocampus. As the hippocampus seems to be particularly relevant for valuation from memory (M1, Gluth et al., 2015), it is conceivable that valuation underlies such retrieval dynamics in the remember-and-decide task. If so, it would be advantageous to formulate evidence accumulation models which account for the dynamic nature of memory retrieval. In Manuscript 4, I describe our first steps toward such models.

4.5 Conclusions

In this study, we investigated the temporal dynamics of memory retrieval and action selection. For both of our research questions, we faced complications. Our attempt to identify a neural signature of memory retrieval failed. Moreover, only the LRP onset but not the slope or peak amplitude revealed insights into the process of evidence accumulation. While these complications limited the explanatory power of this study, we were nevertheless able to draw some conclusions. Our findings suggested that memory retrieval and action selection likely progress in parallel for some time and that memory-based decisions are associated with a delayed onset and altered evidence accumulation dynamics concerning the drift-rate and boundary separation. Future research may learn from the complications we faced and develop new approaches to give definitive answers to the questions we could not address here.

An important issue was the rather narrow scope of this study. The cognitive modeling aspect was restricted to the dynamics of action selection in the hope to study the temporal dynamics of memory retrieval via neural measures. However, our results highlighted the importance of accounting for the dynamics of memory retrieval in the evidence accumulation framework. In Manuscript 4 (Chapter 5) we outlined a promising approach to this endeavour.

Chapter 5

The value of memory structure

Kraemer, P. M., Wulff, D. U., & Gluth, S. (2021b). A sequential sampling account of semantic relatedness decisions. *Proceedings of the 43rd Annual Meeting of the Cognitive Science Society*, 1788–1794. https://doi.org/10.31234/osf.io/ksa2g.

5.1 An evidence accumulation model for memory retrieval and action selection

The previous chapters approached memory-based decisions by studying the effects of memory on valuation and action selection processes. For reasons of simplicity, memory was treated as a boolean variable that indicated whether snacks were recallable (M1, M2) or whether participants were situated in a memory trial or a value trial (M3). This practice however neglects the dynamics of memory retrieval and leads to an insufficient description of memory-based decisions. In this final manuscript, we addressed the question of how the dynamics of memory retrieval and action selection can be jointly accounted for within the evidence accumulation framework.

To study mechanisms of memory, it is often useful to assume a representational basis of knowledge, also denoted as memory representation or *memory structure* (Kahana, 2020).

Memory structure has been of particular importance in research on semantic memory, where concepts are represented in accordance to their relative meaning. Drawing on the concept of semantic relatedness (hence, the relatedness of concepts in their meaning), researchers have developed different memory structures such as semantic networks, feature lists and vector spaces (see, Jones et al., 2015; Kumar, 2020, for reviews). Such structures are suitable to model retrieval dynamics such as spreading activation, provided an adequate process model is chosen to link semantic relatedness to realistic behavior (Jones et al., 2018; Siew et al., 2019).

Here, we tested if evidence accumulation models can be designed to model action selection and memory retrieval by drawing on a memory structure. We focused on semantic relatedness decisions, where participants judge whether two concepts are semantically related or not. We simulated data for three evidence accumulation models, which depended on semantic relatedness scores from a semantic vector space model. We showed how these models can account for different behavioral benchmarks, and partly made valid predictions for phenomena, not yet described in the literature.

Our findings highlighted the leaky competing accumulator model (LCA). The LCA not only accounted for all behavioral benchmarks, it also modeled the dynamics of memory retrieval and action selection within the same process. On the one hand, the lateral inhibition between the accumulators $I_{related}$ and $I_{unrelated}$ represented the competitive nature of action selection, guiding the race toward a ”related” versus ”unrelated” response. On the other hand, the dynamics of memory retrieval were covered by the accumulation rate of the $I_{related}$ accumulator. The shorter the semantic distance between two concepts, the faster the accumulator approached the decision threshold. This dynamic may mimic the activation level of a memory trace between both concepts in a semantic network (Anderson, 1983; Collins & Loftus, 1975; van Maanen et al., 2012). Taken together, we demonstrated that the LCA can be implemented to account for the parallel nature of memory retrieval and action selection as we assumed in M3. It is, however, yet to be established how modeling attempts of value-based decisions could profit from this possibility.

5.2 Relating semantic relatedness and value

As outlined in Chapter 2, the neuroeconomic framework posits that the neural implementation of valuation processes depends on the integration of attribute values (Rangel & Hare, 2010). This qualifies multi-attribute value theories (e.g., Keeney & Raiffa, 1976) as a cognitive model to valuation on the computational level. To study valuation, some researchers pre-specify attributes and attribute values of choice options and present them in a structured matrix (see e.g., Ettlin et al., 2015, for a discussion). However, this practice is not only relatively artificial as it neglects the role of internal memory representations (M3, Lynch & Srull, 1982), it is also fairly directive since it remains unclear, which attributes an agent would take into account in realistic scenarios (Bhatia & Stewart, 2018). Many neuroeconomists omit this issue by adhering to independently measured value ratings (such as liking or willingness-to-pay) which serve as surrogates of the outcomes of valuation processes. These proxy values are then used to inform cognitive action selection models (e.g., M3, Bakkour et al., 2019; Krajbich et al., 2010; Polanía et al., 2014). Often, the implicit assumption is that valuation occurs by sampling attribute values from latent distributions in memory (Noguchi & Stewart, 2018; Polanía et al., 2019; Stewart et al., 2006). It is needless to say, that this approach not only neglects the memory retrieval dynamics that are relevant for value computation, it also remains uninformative about what attributes are relevant for a specific decision problem. Thus, both, the pre-specifying and the omitting approach, exhibit substantial limitations and therefore can only be seen as interim solutions to model valuation until more sophisticated approaches are developed. Here, I argue that memory structures might provide an useful approach to represent attributes and attribute values in memory-based decisions.

Memory structures are typically constructed by the organizational principle of semantic relatedness or similarity (Jones et al., 2015). Whereas similarity has been shown to affect multi-attribute choice in decisions from experience (e.g., Jarecki & Rieskamp, 2022), it is conceivable that these principles can also be exploited to model one-shot decisions like consumer choices. Based on the domain of the decision problem (e.g., food choice), people may adhere to semantically related attributes (e.g. healthiness or tastiness). Semantic space models may be suited to compute a representational basis for these attributes for instance by using vector arithmetics (Levy et al., 2015; Mikolov et al., 2013; Pennington et al., 2014) or dimensionality reduction (Bhatia & Stewart, 2018). One could then compute the semantic relatedness of individual choice options (e.g., broccoli, chocolate) with the attributes to obtain information about attribute values. Say for example, a semantic space model predicts broccoli to highly relate with healthiness whereas chocolate scores low on healthiness but high on tastiness. Semantic space models may thus be helpful to assess relevant attributes and to obtain information about attribute values without the necessity to pre-specify the attribute dimensions. Still, however, there is the need to transform the mnemonic properties of choice options into preference related values to drive action selection (Bhatia et al., 2019), leaving room for extensive research in this area.

On the other hand, modeling the retrieval dynamics may help to gain a deeper understanding of well-known neuroeconomic phenomena. For instance, the tastiness of food items has been found to be processed earlier than healthiness (Sullivan et al., 2015). While the authors offered different levels of abstractness between healthiness and tastiness, Maier et al. (2020) suggested this difference to be due to memory retrieval. In line with query theory, attributes may be recalled at at different time points (Johnson et al., 2007). It is thus possible, that, analogously to the findings of this simulation study, tastiness is recalled faster due to a shorter semantic distance of foods and taste, as compared to snacks and healthiness. Future studies may profit from the information of semantic distance embedded in vector space and network models, offering mnemonic quantities to explain the different time points, at which these attributes enter the action selection process (see also, van Maanen et al., 2012).

5.3 Conclusions

In this simulation study, we have explored evidence accumulation models which draw on memory retrieval dynamics associated with semantic distance on the one hand and the competitive nature of action selection on the other hand. These models can account for established response time effects in semantic relatedness decisions and make valid predictions for phenomena which were not described in the literature record. While these findings underline the utility of evidence accumulation models for memory-based decisions more generally, it is an important future research question, how the memory structure and retrieval processes can be used to study preferential decisions.

Chapter 6

Summary and perspectives

6.1 Summary

In this dissertation, I investigated the diverse roles of memory in economic choice. Reviewing literature on memory-based decision making, me and my colleagues argued that insufficient memory recall results in biased valuation processes which we have examined on the neural and behavioral level (M1, Chapter 2). We pinpointed meta-cognitive beliefs and uncertainty aversion as psychological explanations for this phenomenon. Additionally, we reasoned that cognitive modeling, and the evidence accumulation framework in particular, is suited to study the neural and cognitive processes of memory-based decision making.

Using evidence accumulation models, we eliminated an alternative account of the memory bias, which attributed the bias to different decision policies during action selection (M2, Chapter 3). The memory bias appears to be rather the result of a single process than a dual process as conceptualized here. While this project contributed to a pertinent characterization of the memory bias as a valuation bias, it also highlighted the importance of a closer inspection of the temporal dynamics of action selection during memory-based decisions.

Investigating the temporal profile of these decisions in another experiment (M3, Chapter 4), we found that memory-based decisions consume considerably more time than common consumer choices. By combining temporally-precise EEG technology with neuro-cognitive modeling, we attributed the additional time to a delayed action selection onset as well as altered evidence accumulation dynamics in memory-based choice formation. In addition, these findings suggested that memory recall and action selection operated largely in parallel.

While these findings highlighted key features of memory-based decisions, it remained unknown how the temporal profile of memory retrieval affects action selection. To study this in more detail, I tested the suitability of different cognitive models to integrate the dynamics of memory retrieval into the action selection process (M4, Chapter 5). As a main finding, the leaky competing accumulator model, in conjunction with a semantic memory structure, exhibited high potential to explain established behavioral findings and predict new phenomena.

All in all, the conducted research established several effects of memory on decision processes with a particular focus on valuation and action selection. This dissertation thereby contributed to the growing understanding of memory-based decision making in neuroeconomics. The developed cognitive models and approaches will hopefully stimulate present and future research.

6.2 Future directions

In the presented manuscripts, we pointed out several future directions in decision making research. New brain imaging studies may unravel the role of meta-cognitive beliefs and uncertainty aversion to explain the memory bias on the neural level (M1). Further, there is the need to use mathematically formulated dual-process models to test their validity over a large set of decision problems (M2). More research is needed to characterize EEG markers of memory retrieval and action selection and to study the neural (co-)dynamics of these signals (M3). Finally, the sheer complexity of memory-based decision problems asks for more inclusive models which jointly consider memory structure, memory retrieval and decision processes (M4). All these points are – in my opinion – valid and can lead to new advances in the field. However, here I would like to discuss a problem, which I hold worthwhile to approach at this state: Generating choice sets from memory.

To specify this problem, I would like to revisit the neuroeconomic framework of value-based decision making (Rangel et al., 2008). According to this framework, approaching and avoiding choice options is represented by action plans. Most experimental paradigms expose participants to a decision problem, where the choice options are exogenously provided by the experimenter. Of course, this scenario constitutes a simplification of ecologically valid decisions. To take the example of restaurant choice: It is unlikely that, while an agent considers where to have lunch, a stranger shows up and says something like ”Tell me, do you want to go to the canteen or to the cafeteria? No other option allowed!”. Instead, many – if not most – decision problems in the wild require agents to autonomously generate a set of *endogenous* choice options (e.g., italian restaurant, indian restaurant, fast food restaurant etc.) and to decide among them. To be clear, the use of exogenous choice options is justifiable under a reductionist research strategy. However, this practice obscures that memory does not only serve to sample attribute values of choice options – as mainly investigated in this dissertation – but also to generate the choice options themselves using memory recall. While behavioral economists have identified this issue in the last century (Lynch & Srull, 1982; Roberts & Lattin, 1997), it has only recently made its way into the neuroeconomic literature (e.g., Bhatia, 2019; Zhang et al., 2021). In the following, I will address two potentially impactful directions, which should be pursued to set a research agenda for this problem.

First, in judgment and decision making, it is a common research strategy to identify deviations from economically rational behavior (Rieskamp et al., 2006). So far, research on decisions with endogenous choice sets has not systematically investigated choice biases but has identified several effects, which give strong grounds for further investigation. When agents generate options from semantic memory, their memory search has been shown to underlie classic phenomena such as semantic clustering (Bhatia, 2019) and priming (Nedungadi, 1990). It is plausible that, due to such memory effects, agents generate options from semantic fields which are ill-suited to meet the current task demands. Hence, the resulting choice set may be biased in a way that the agent misses to consider highly valuable choice options, likely leading to unfit decision outcomes. Another potential source of bias is the tendency to recall desirable items early (Aka & Bhatia, 2021; Bhatia, 2019). Effects of serial position of recall have been demonstrated in the context of memory-based decisions (Li & Epley, 2009) and are coherent with accounts of bounded rationality, which suggest that options which are recalled early are likely favorable (Johnson & Raab, 2003). Analogously to the meta-cognitive beliefs that partly give rise to the memory bias (Mechera-Ostrovsky & Gluth, 2018), it is possible that meta-cognitive beliefs also play a role in endogenous decisions, favoring options which are recalled early. Future research should follow a systematic research program, comparable to the one presented in M1, to develop adequate experimental paradigms and to test for the existence of the predicted effects.

Second, since recall of choice options depends on a process of memory search, it is reasonable to assume that choice options are recalled at different points in time (e.g., Hills et al., 2012; Jones & Mewhort, 2007). Consequently, action plans may be initiated at different time points (e.g., van Maanen et al., 2012). Thus, some early recalled options may have a temporal advantage as their action selection process can progress (and even terminate), while other options are not even yet considered, requiring further retrieval time to be represented in the decision problem. A potential direction for future research is to formulate a cognitive model which accounts for these properties of a temporal advantage. As I showed in M4, the LCA constitutes a promising starting point for such an purpose. Each action plan could be represented as a separate accumulator on the decision corridor with mutual inhibition governing the competitive nature of action selection. The initiation time of an accumulator might depend on a separate accumulation-to-bound process which reflects memory retrieval from semantic structures. Favorably, the rate parameters of the accumulators would depend on a valuation function, which transforms memory contents to units of subjective value

(Chapter 5). To validate such a model, real-time neural markers such as the LRP onset may be helpful to identify time points at which a new option is being considered (M3).

Since the composition of choice sets has a profound effect on our decisions (e.g., Berkowitsch et al., 2014; Spektor et al., 2019), it is remarkable that the question of how we generate endogenous choice sets has received so little attention. One reason may lie in the required additional assumptions which complicate the investigation of decision making. However, recent developments in the fields of natural language processing facilitate the study of memory for judgment and decision making (Bhatia et al., 2019; Kumar, 2020). Combined with advances in model-based cognitive neuroscience (Turner et al., 2017) one can be reasonably optimistic that more complex decision problems can be addressed in the future (Busemeyer et al., 2019), contributing to an elevated ecological validity of experimental decision making research.

6.3 Final remarks

This dissertation thesis began with a quote by Nobel Laureate Sir Charles S Sherrington, recognizing that it is action, which is the most important function of mind and brain, as it ensures our survival and evolutionary success. We have seen that the selection of appropriate action depends on complex and intertwined computations, performed by our nervous system. Thereby, researchers often neglect that action needs memory to fulfill its purpose. The research conducted in this dissertation spent a close look to the relation of the involved cognitive processes. I focused especially on the temporal dynamics of memory retrieval and decision making, as they yield valuable insights of how decisions come about. This dissertation hopefully makes a contribution for the field to recognize the pivotal role of memory for decision making. After all, as Nobel Laureate Eric R Kandel put it: ”Without memory, we would be nothing.” (in Seeger, 2009, 00:01:54).

Bibliography

Aka, A., & Bhatia, S. (2021). What I Like Is What I Remember: Memory Modulation and Preferential Choice. *Journal of Experimental Psychology: General*, *150*(10), 2175–2184. https://doi.org/10.31234/osf.io/3uyfz

Alba, J. W., & Hutchinson, J. W. (1987). Dimensions of Consumer Expertise. *Journal of Consumer Research*, *13*(4), 411. https://doi.org/10.1086/209080

Alós-Ferrer, C. (2018). A Dual-Process Diffusion Model. *Journal of Behavioral Decision Making*, *31*(2), 203–218. https://doi.org/10.1002/bdm.1960

Anderson, J. R. (1983). A Spreading Activation Theory of Memory. *Journal of Verbal Learning and Verbal Behavior*, *22*, 0–00.

Bakkour, A., Palombo, D. J., Zylberberg, A., Kang, Y. H., Reid, A., Verfaellie, M., Shadlen, M. N., & Shohamy, D. (2019). The hippocampus supports deliberation during value-based decisions. *eLife*, *8*, 1–28. https://doi.org/10.7554/eLife.46080

Balci, F., & Simen, P. (2014). Decision processes in temporal discrimination. *Acta Psychologica*, *149*, 157–168. https://doi.org/10.1016/j.actpsy.2014.03.005

Bartra, O., McGuire, J. T., & Kable, J. W. (2013). The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. *NeuroImage*, *76*, 412–427. https://doi.org/10.1016/j.neuroimage.2013.02.063

Basten, U., Biele, G., Heekeren, H. R., & Fiebach, C. J. (2010). How the brain integrates costs and benefits during decision making. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(50), 21767–21772. https://doi.org/10.1073/pnas.0908104107

Bayer, H. M., & Glimcher, P. W. (2005). Midbrain dopamine neurons encode a quantitative reward prediction error signal. *Neuron*, *47*(1), 129–141. https://doi.org/10.1016/j.neuron.2005.05.020

Bays, P. M., & Dowding, B. A. (2017). Fidelity of the representation of value in decision-making. *PLoS Computational Biology*, *13*(3), 1–16. https://doi.org/10.1371/journal.pcbi.1005405

Berkowitsch, N. A., Scheibehenne, B., & Rieskamp, J. (2014). Rigorously testing multialternative decision field theory against random utility models. *Journal of Experimental Psychology: General*, *143*(3), 1331–1348. https://doi.org/10.1037/a0035159

Bhatia, S. (2019). Semantic processes in preferential decision making. *Journal of Experimental Psychology: Learning Memory and Cognition*, *45*(4), 627–640. https://doi.org/10.1037/xlm0000618

Bhatia, S., Richie, R., & Zou, W. (2019). Distributed semantic representations for modeling human judgment. *Current Opinion in Behavioral Sciences*, *29*, 31–36. https://doi.org/10.1016/j.cobeha.2019.01.020

Bhatia, S., & Stewart, N. (2018). Naturalistic multiattribute choice. *Cognition*, *179*(May), 71–88. https://doi.org/10.1016/j.cognition.2018.05.025

Bogacz, R., Brown, E., Moehlis, J., Holmes, P., & Cohen, J. D. (2006). The physics of optimal decision making: A formal analysis of models of performance in two-alternative forced-choice tasks. *Psychological Review*, *113*(4), 700–765. https://doi.org/10.1037/0033-295X.113.4.700

Britten, K. H., Shadlen, M. N., Newsome, W. T., & Movshon, J. A. (1992). The Analysis of Visual Motion: A Comparison of Neuronal and Psychophysical Performance. *The Journal of Neuroscience*, *12*(12), 4745–4765. https://doi.org/10.1109/TPWRD.2006.877077

Busemeyer, J. R., Gluth, S., Rieskamp, J., & Turner, B. M. (2019). Cognitive and Neural Bases of Multi-Attribute, Multi-Alternative, Value-based Decisions. *Trends in Cognitive Sciences*, *23*(3), 251–263. https://doi.org/10.1016/j.tics.2018.12.003

Camerer, C., Issacharoff, S., Loewenstein, G., O'Donoghue, T., & Rabin, M. (2003). Regulation for Conservatives : Behavioral Economics and the Case for "Asymmetric Paternalism". *University of Pennsylvania Law Review*, *151*(3), 1211–1254.

Camerer, C., Loewenstein, G., & Prelec, D. (2005). Neuroeconomics: How neuroscience can inform economics. *Journal of Economic Literature*, *43*(1), 9–64. https://doi.org/10.1257/0022051053737843

Camille, N., Griffiths, C. A., Vo, K., Fellows, L. K., & Kable, J. W. (2011). Ventromedial frontal lobe damage disrupts value maximization in humans. *Journal of Neuroscience*, *31*(20), 7527–7532. https://doi.org/10.1523/JNEUROSCI.6527-10.2011

Chen, F., & Krajbich, I. (2018). Biased sequential sampling underlies the effects of time pressure and delay in social decision making. *Nature Communications*, *9*(1), 1–10. https://doi.org/10.1038/s41467-018-05994-9

Cisek, P. (2012). Making decisions through a distributed consensus. *Current Opinion in Neurobiology*, *22*(6), 927–936. https://doi.org/10.1016/j.conb.2012.05.007

Cisek, P., & Kalaska, J. F. (2010). Neural mechanisms for interacting with a world full of action choices. *Annual Review of Neuroscience*, *33*, 269–298. https://doi.org/10.1146/annurev.neuro.051508.135409

Clithero, J. A. (2018). Response times in economics : Looking through the lens of sequential sampling models. *Journal of Economic Psychology*, *69*(October 2016), 61–86. https://doi.org/10.1016/j.joep.2018.09.008

Clithero, J. A., & Rangel, A. (2014). Informatic parcellation of the network involved in the computation of subjective value. *Social Cognitive and Affective Neuroscience*, *9*(9), 1289–1302. https://doi.org/10.1093/scan/nst106

Cohen, N. J., & Squire, L. R. (1980). Preserved learning and retention of pattern-analyzing skill in amnesia: Dissociation of knowing how and knowing that. *Science*, *210*(4466), 207–210. https://doi.org/10.1126/science.7414331

Coles, M. G. (1989). Modern mind-brain reading: Psychophysiology, physiology, and cognition. *Psychophysiology*, *26*(3), 251–269. https://doi.org/10.1111/j.1469-8986.1989.tb01916.x

Coles, M. G. H., & Gratton, G. (1988). Detecting early communication: Using measures of movement-related potentials to illuminate human information processing. *Biological Psychology*, *26*, 69–89.

Collins, A. M., & Loftus, E. F. (1975). A Spreading Activation Theory of Semantic Processing. *Psychological Review*, *82*(6), 407–428. https://doi.org/10.1037//0033-295X.82.6.407

D'Ardenne, K., McClure, S. M., Nystrom, L. E., & Cohen, J. D. (2008). BOLD responses reflecting dopaminergic signals in the human ventral tegmental area. *Science*, *319*(5867), 1264–1267. https://doi.org/10.1126/science.1150605

Dutilh, G., & Rieskamp, J. (2016). Comparing perceptual and preferential decision making. *Psychonomic Bulletin and Review*, *23*(3), 723–737. https://doi.org/10.3758/s13423-015-0941-1

Edwards, W. (1965). Optimal strategies for seeking information: Models for statistics, choice reaction times, and human information processing. *Journal of Mathematical Psychology*, *2*(2), 312–329. https://doi.org/10.1016/0022-2496(65)90007-6

Ettlin, F., Bröder, A., & Henninger, M. (2015). A new task format for investigating information search and organization in multiattribute decisions. *Behavior Research Methods*, *47*(2), 506–518. https://doi.org/10.3758/s13428-014-0482-y

Evans, J. S. B. T. (2008). Dual-Processing Accounts of Reasoning , Judgment , and Social Cognition. *Annu. Rev. Psychol.*, *59*, 255–78. https://doi.org/10.1146/annurev.psych.59.103006.093629

Fehr, E., & Rangel, A. (2011). Neuroeconomic foundations of economic choice-recent advances. *Journal of Economic Perspectives*, *25*(4), 3–30. https://doi.org/10.1257/jep.25.4.3

Fellows, L. K., & Farah, M. J. (2005). Different underlying impairments in decision-making following ventromedial and dorsolateral frontal lobe damage in humans. *Cerebral Cortex*, *15*(1), 58–63. https://doi.org/10.1093/cercor/bhh108

Fine, J. M., & Hayden, B. Y. (2022). The whole prefrontal cortex is premotor cortex. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, *377*(1844), 20200524. https://doi.org/10.1098/rstb.2020.0524

Fontanesi, L., Gluth, S., Rieskamp, J., & Forstmann, B. (2019a). The role of dopaminergic nuclei in predicting and experiencing gains and losses: A 7T human fMRI study. *bioRxiv*, (14017). https://doi.org/10.1101/732560

Fontanesi, L., Gluth, S., Spektor, M., & Rieskamp, J. (2019b). A reinforcement learning diffusion decision model for value-based decisions. *Psychonomic Bulletin and Review*. https://doi.org/https://doi.org/10.3758/s13423-018-1554-2

Gazzaniga, M. S., Heatherton, T. F., & Halpern, D. F. (2011). *Psychological Science*. W. W. Norton Company.

Gershman, S. J., & Daw, N. D. (2017). Reinforcement Learning and Episodic Memory in Humans and Animals: An Integrative Framework. *Annual Review of Psychology*, *68*(1), 101–128. https://doi.org/10.1146/annurev-psych-122414-033625

Glimcher, P. W., & Fehr, E. (2013). *Neuroeconomics: Decision Making and the Brain*. Academic Press.

Gluth, S., Rieskamp, J., & Buchel, C. (2012). Deciding When to Decide: Time-Variant Sequential Sampling Models Explain the Emergence of Value-Based Decisions in the

Human Brain. *Journal of Neuroscience*, *32*(31), 10686–10698. https://doi.org/10.1523/JNEUROSCI.0727-12.2012

Gluth, S., Rieskamp, J., & Büchel, C. (2013). Classic EEG motor potentials track the emergence of value-based decisions. *NeuroImage*, *79*, 394–403. https://doi.org/10.1016/j.neuroimage.2013.05.005

Gluth, S., Sommer, T., Rieskamp, J., & Büchel, C. (2015). Effective Connectivity between Hippocampus and Ventromedial Prefrontal Cortex Controls Preferential Choices from Memory Article Effective Connectivity between Hippocampus and Ventromedial Prefrontal Cortex Controls Preferential Choices from Memory. *Neuron*, 1078–1090. https://doi.org/10.1016/j.neuron.2015.04.023

Gold, J. I., & Shadlen, M. N. (2007). The Neural Basis of Decision Making. *Annual Review of Neuroscience*, *30*(1), 535–574. https://doi.org/10.1146/annurev.neuro.29.051605.113038

Goldstein, D. G., & Gigerenzer, G. (2002). Models of Ecological Rationality : The Recognition Heuristic. *Psychological Review*, *109*(1), 75–90. https://doi.org/10.1037//0033-295X.109.1.75

Gratton, G. (1998). The contralateral organization of visual memory: a theoretical concept and a research tool. *Psychophysiology*, *35*(6), 638–647. https://doi.org/10.1017/S0048577298980453

Hare, T. A., Schultz, W., Camerer, C. F., O'Doherty, J. P., & Rangel, A. (2011). Transformation of stimulus value signals into motor commands during simple choice. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(44), 18120–18125. https://doi.org/10.1073/pnas.1109322108

Heekeren, H. R., Marrett, S., & Ungerleider, L. G. (2008). The neural systems that mediate human perceptual decision making. *Nature Reviews Neuroscience*, *9*(6), 467–479. https://doi.org/10.1038/nrn2374

Hills, T. T., Jones, M. N., & Todd, P. M. (2012). Optimal foraging in semantic memory. *Psychological Review*, *119*(2), 431–440. https://doi.org/10.1037/a0027373

Huettel, S. A. (2010). Ten challenges for decision neuroscience. *Frontiers in Neuroscience*, *4*(SEP), 1–7. https://doi.org/10.3389/fnins.2010.00171

Jarecki, J. B., & Rieskamp, J. (2022). Comparing attribute-based and memory-based preferential choice. *Decision*, *49*(March), 65–90. https://doi.org/10.1007/s40622-021-00302-9

Johnson, E. J., Häubl, G., & Keinan, A. (2007). Aspects of Endowment: A Query Theory of Value Construction. *Journal of Experimental Psychology: Learning Memory and Cognition*, *33*(3), 461–474. https://doi.org/10.1037/0278-7393.33.3.461

Johnson, J. G., & Busemeyer, J. R. (2010). Decision making under risk and uncertainty. *Wiley Interdisciplinary Reviews: Cognitive Science*, *1*(5), 736–749. https://doi.org/10.1002/wcs.76

Johnson, J. G., & Raab, M. (2003). Take the first: Option-generation and resulting choices. *Organizational Behavior and Human Decision Processes*, *91*(2), 215–229. https://doi.org/10.1016/S0749-5978(03)00027-X

Jones, M. N., Willits, J., & Dennis, S. Models of Semantic Memory (J. R. Busemeyer, Z. Wang, J. T. Townsend, & A Eidels, Eds.). In: In *The oxford handbook of computational and mathematical psychology* (J. R. Busemeyer, Z. Wang, J. T. Townsend, & A Eidels, Eds.). Ed. by Busemeyer, J. R., Wang, Z., Townsend, J. T., & Eidels, A. New York, NY, US: Oxford University Press, 2015, pp. 232–254.

Jones, M. N., Gruenenfelder, T. M., & Recchia, G. (2018). In defense of spatial models of semantic representation. *New Ideas in Psychology*, *50*, 54–60. https://doi.org/10.1016/j.newideapsych.2017.08.001

Jones, M. N., & Mewhort, D. J. (2007). Representing word meaning and order information in a composite holographic lexicon. *Psychological Review*, *114*(1), 1–37. https://doi.org/10.1037/0033-295X.114.1.1

Kable, J. W., & Glimcher, P. W. (2009). The Neurobiology of Decision: Consensus and Controversy. *Neuron*, *63*(6), 733–745. https://doi.org/10.1016/j.neuron.2009.09.003

Kahana, M. J. (2020). Computational models of memory search. *Annual Review of Psychology*, *71*, 107–138. https://doi.org/10.1146/annurev-psych-010418-103358

Kahneman, D. (2011). *Thinking, fast and slow.* Farrar, Straus; Giroux.

Kahneman, D., & Frederick, S. Representativeness revisited : Attribute substitution in intuitive judgment (T. Gilovich, D. Griffin, & D. Kahneman, Eds.). In: In *Heuristics of intuitive judgment: Extensions and applications* (T. Gilovich, D. Griffin, & D. Kahneman, Eds.). Ed. by Gilovich, T., Griffin, D., & Kahneman, D. New York: Cambridge University Press, 2002, pp. 49–81.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263–292. https://doi.org/10.2307/1914185

Keeney, R. L., & Raiffa, H. (1976). *Decisions with Multiple Objectives: Preferences and Value Tradeoffs.* Wiley. https://books.google.de/books?id=k%5C_x9AAAAIAAJ

Keren, G., & Schul, Y. (2009). Two Is Not Always Better Than One - A Critical Evaluation of Two-System Theories. *Perspectives on Psychological Science*, *4*(6), 533–550.

Kerrén, C., Linde-Domingo, J., Hanslmayr, S., & Wimber, M. (2018). An Optimal Oscillatory Phase for Pattern Reactivation during Memory Retrieval. *Current Biology*, *28*(21), 3383–3392.e6. https://doi.org/10.1016/j.cub.2018.08.065

Konovalov, A., & Krajbich, I. (2019). Over a Decade of Neuroeconomics: What Have We Learned? *Organizational Research Methods*, *22*(1), 148–173. https://doi.org/10.1177/1094428116644502

Kraemer, P. M., Fontanesi, L., Spektor, M. S., & Gluth, S. (2021a). Response time models separate single- and dual-process accounts of memory-based decisions. *Psychonomic Bulletin and Review*, *28*, 304–323. https://doi.org/10.3758/s13423-020-01794-9

Kraemer, P. M., & Gluth, S. (submitted). Episodic memory retrieval affects the onset and dynamics of evidence accumulation during value-based decisions. *Submitted to The Journal of Neuroscience*. https://doi.org/10.1101/2022.04.26.489332

Kraemer, P. M., Weilbächer, R. A., Mechera-Ostrovsky, T., & Gluth, S. (2022). Cognitive and neural principles of a memory bias on preferential choices. *Current Research in Neurobiology*, *3*. https://doi.org/10.1016/j.crneur.2022.100029

Kraemer, P. M., Wulff, D. U., & Gluth, S. (2021b). A sequential sampling account of semantic relatedness decisions. *Proceedings of the 43rd Annual Meeting of the Cognitive Science Society*, 1788–1794. https://doi.org/10.31234/osf.io/ksa2g

Krajbich, I. (2021). Multi-parameter utility and drift-rate functions conflate attribute weights and choice consistency. *psyArXiv*.

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–1298. https://doi.org/10.1038/nn.2635

Kruglanski, A. W., & Gigerenzer, G. (2011). Intuitive and Deliberate Judgments Are Based on Common Principles. *Psychological Review*, *118*(1), 97–109. https://doi.org/10.1037/a0020762

Kumar, A. A. (2020). Semantic memory: A review of methods, models, and current challenges. *Psychonomic Bulletin and Review*. https://doi.org/10.3758/s13423-020-01792-x

Lee, M. D. (2011). How cognitive modeling can benefit from hierarchical Bayesian models. *Journal of Mathematical Psychology*, *55*(1), 1–7. https://doi.org/10.1016/j.jmp.2010.08.013

Lee, M. D., & Wagenmakers, E.-J. (2013). *Bayesian cognitive modeling: A practical course*. Cambridge University Press. https://doi.org/https://doi.org/10.1017/CBO9781139087759

Levy, D. J., & Glimcher, P. W. (2012). The root of all value: A neural common currency for choice. *Current Opinion in Neurobiology*, *22*(6), 1027–1038. https://doi.org/10.1016/j.conb.2012.06.001

Levy, O., Goldberg, Y., & Dagan, I. (2015). Improving Distributional Similarity with Lessons Learned from Word Embeddings. *Transactions of the Association for Computational Linguistics*, *3*, 211–225. https://doi.org/10.1162/tacl_a_00134

Li, Y, & Epley, N. (2009). When the Best Appears to Be Saved for Last: Serial Position Effects on Choice. *Journal of Behavioral Decision Making*, *22*, 378–389. https://doi.org/10.1002/bdm

Lieder, F., & Griffiths, T. L. (2019). Resource-rational analysis: Understanding human cognition as the optimal use of limited computational resources. *Behavioral and Brain Sciences*. https://doi.org/10.1017/S0140525X1900061X

Lucas, M. (2000). Semantic priming without association: A meta-analytic review. *Psychonomic Bulletin and Review*, *7*(4), 618–630. https://doi.org/10.3758/BF03212999

Lynch, J. G., & Srull, T. K. (1982). Memory and Attentional Factors in Consumer Choice: Concepts and Research Methods. *Journal of Consumer Research*, *9*(1), 18. https://doi.org/10.1086/208893

Madan, C. R., & Spetch, M. L. (2012). Is the enhancement of memory due to reward driven by value or salience? *Acta Psychologica*, *139*(2), 343–349. https://doi.org/10.1016/j.actpsy.2011.12.010

Maier, S. U., Raja Beharelle, A., Polanía, R., Ruff, C. C., & Hare, T. A. (2020). Dissociable mechanisms govern when and how strongly reward attributes affect decisions. *Nature Human Behaviour*, *4*(9), 949–963. https://doi.org/10.1038/s41562-020-0893-y

Marr, D. (1982). *Vision: A computational investigation into the human representation and processing ofvisual information*. Freeman.

Mechera-Ostrovsky, T., & Gluth, S. (2018). Memory beliefs drive the memory bias on value-based decisions. *Scientific Reports*, *8*(1), 1–10. https://doi.org/10.1038/s41598-018-28728-9

Melnikoff, D. E., & Bargh, J. A. (2018). The Mythical Number Two. *Trends in Cognitive Sciences*, *22*(4), 280–293. https://doi.org/10.1016/j.tics.2018.02.001

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. *1st International Conference on Learning Representations, ICLR 2013 - Workshop Track Proceedings*, 1–12.

Milner, B., Squire, L. R., & Kandel, E. R. (1998). Cognitive neuroscience and the study of memory. *Neuron*, *20*(3), 445–468. https://doi.org/10.1016/S0896-6273(00)80987-3

Mulder, M. J., Wagenmakers, E.-J., Ratcliff, R., Boekel, W., & Forstmann, B. U. (2012). Bias in the Brain: A Diffusion Model Analysis of Prior Probability and Potential Payoff. *Journal of Neuroscience*, *32*(7), 2335–2343. https://doi.org/10.1523/JNEUROSCI.4156-11.2012

Nedungadi, P. (1990). Recall and Consumer Consideration Sets: Influencing Choice without Altering BrandEvaluations. *Journal of Consumer Research*, *17*(3), 263–276.

Noguchi, T., & Stewart, N. (2018). Multialternative decision by sampling: A model of decision making constrained by process data. *Psychological Review*, *125*(4), 512–544. https://doi.org/10.1037/rev0000102

Noonan, M. P., Walton, M. E., Behrens, T. E., Sallet, J., Buckley, M. J., & Rushworth, M. F. (2010). Separate value comparison and learning mechanisms in macaque medial and lateral orbitofrontal cortex. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(47), 20547–20552. https://doi.org/10.1073/pnas.1012246107

O'Doherty, J. P., Dayan, P., Friston, K., Critchley, H., & Dolan, R. J. (2003). Temporal difference models and reward-related learning in the human brain. *Neuron*, *38*(2), 329–337. https://doi.org/10.1016/S0896-6273(03)00169-7

Oppenheimer, D. M., & Kelso, E. (2015). Information processing as a paradigm for decision making. *Annual Review of Psychology*, *66*, 277–294. https://doi.org/10.1146/annurev-psych-010814-015148

Padoa-Schioppa, C. (2011). Neurobiology of economic choice: A good-based model. *Annual Review of Neuroscience*, *34*, 333–359. https://doi.org/10.1146/annurev-neuro-061010-113648

Padoa-Schioppa, C., & Assad, J. A. (2006). Neurons in the orbitofrontal cortex encode economic value. *Nature*, *441*(7090), 223–226. https://doi.org/10.1038/nature04676

Padoa-Schioppa, C., & Assad, J. A. (2008). The representation of economic value in the orbitofrontal cortex is invariant for changes of menu. *Nature Neuroscience*, *11*(1), 95–102. https://doi.org/10.1038/nn2020

Palombo, D. J., Keane, M. M., & Verfaellie, M. (2015). How does the hippocampus shape decisions? *Neurobiology of Learning and Memory*, *125*, 93–97. https://doi.org/10.1016/j.nlm.2015.08.005

Pedersen, M. L., Frank, M. J., & Biele, G. (2017). The drift diffusion model as the choice rule in reinforcement learning. *Psychonomic Bulletin and Review*, *24*(4), 1234–1251. https://doi.org/10.3758/s13423-016-1199-y

Pennington, J, Socher, R, & Manning, C. (2014). Glove: global vectors for word representation. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing*, 1532–1543. https://doi.org/10.1080/02688697.2017.1354122

Peters, J., & D'Esposito, M. (2016). Effects of Medial Orbitofrontal Cortex Lesions on Self-Control in Intertemporal Choice. *Current Biology*, *26*(19), 2625–2628. https://doi.org/10.1016/j.cub.2016.07.035

Platt, M. L., & Plassmann, H. (2013). *Multistage Valuation Signals and Common Neural Currencies*. Elsevier Inc. https://doi.org/10.1016/B978-0-12-416008-8.00013-9

Polanía, R., Krajbich, I., Grueschow, M., & Ruff, C. C. (2014). Neural Oscillations and Synchronization Differentially Support Evidence Accumulation in Perceptual and Value-Based Decision Making. *Neuron*, *82*(3), 709–720. https://doi.org/10.1016/j.neuron.2014.03.014

Polanía, R., Woodford, M., & Ruff, C. C. (2019). Efficient coding of subjective value. *Nature Neuroscience*, *22*(1), 134–142. https://doi.org/10.1038/s41593-018-0292-0

Rangel, A., Camerer, C., & Montague, P. R. (2008). A framework for studying the neurobiology of value-based decision making. *Nature Reviews Neuroscience*, *9*(7), 545–556. https://doi.org/10.1038/nrn2357

Rangel, A., & Hare, T. (2010). Neural computations associated with goal-directed choice. *Current Opinion in Neurobiology*, *20*(2), 262–270. https://doi.org/10.1016/j.conb.2010.03.001

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108.

Ratcliff, R., & McKoon, G. (2008). The Diffusion Decision Model: Theory and data. *Neural Computation*, *20*(4), 873–922.

Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science*, *9*(5), 347–356.

Ratcliff, R., Smith, P. L., Brown, S. D., & Mckoon, G. (2016). Diffusion Decision Model : Current Issues and History. *Trends in Cognitive Sciences*, *20*(4), 260–281. https://doi.org/10.1016/j.tics.2016.01.007

Rieskamp, J., Busemeyer, J. R., & Mellers, B. A. (2006). Extending the bounds of rationality: Evidence and theories of preferential choice. *Journal of Economic Literature*, *44*(3), 631–661. https://doi.org/10.1257/jel.44.3.631

Rizzolatti, G., & Kalaska, J. F. Voluntary Movement: The Parietal and Premotor Cortex (E. R. Kandel, J. H. Schwarz, T. M. Jessell, S. A. Siegelbaum, & A. J. Hudspeth, Eds.). In: In *Principles of neural science* (E. R. Kandel, J. H. Schwarz, T. M. Jessell, S. A. Siegelbaum, & A. J. Hudspeth, Eds.). Ed. by Kandel, E. R., Schwarz, J. H., Jessell, T. M., Siegelbaum, S. A., & Hudspeth, A. J. New York: McGraw-Hill Education LLC, 2013, pp. 865–893.

Roberts, J. H., & Lattin, J. M. (1997). Consideration : Review of Research and Prospects for Future Insights. *Journal of Marketing Research*, *34*, 406–410.

Rushworth, M. F., Noonan, M. A. P., Boorman, E. D., Walton, M. E., & Behrens, T. E. (2011). Frontal Cortex and Reward-Guided Learning and Decision-Making. *Neuron*, *70*(6), 1054–1069. https://doi.org/10.1016/j.neuron.2011.05.014

Saveliev, S. V. (2010). Natural selection in brain evolution of early hominids. *Paleontological Journal*, *44*(12), 1589–1597. https://doi.org/10.1134/S0031030110120130

Schultz, W., Dayan, P., & Montague, P. R. (1997). A neural substrate of prediction and reward. *Science*, *275*(5306), 1593–1599. https://doi.org/10.1126/science.275.5306.1593

Seeger, P. (2009). In search of memory. Universal.

Shadlen, M. N., & Kiani, R. (2013). Decision making as a window on cognition. *Neuron*, *80*(3), 791–806. https://doi.org/10.1016/j.neuron.2013.10.047

Shadlen, M. N., & Shohamy, D. (2016). Decision Making and Sequential Sampling from Memory. *Neuron*, *90*(5), 927–939. https://doi.org/10.1016/j.neuron.2016.04.036

Shohamy, D., & Daw, N. D. (2015). Integrating memories to guide decisions. *Current Opinion in Behavioral Sciences*, *5*, 85–90. https://doi.org/10.1016/j.cobeha.2015.08.010

Siew, C. S. Q., Wulff, D. U., Beckage, N. M., & Kenett, Y. N. (2019). Cognitive Network Science : A Review of Research on Cognition through the Lens of Network Representations , Processes , and Dynamics. *Complexity*, *2019*. https://doi.org/https://doi.org/10.1155/2019/2108423

Simon, H. (1956). Rational choice and the structure of the environment. *Psychological Review*, *63*(2).

Smith, D. V., & Huettel, S. A. (2010). Decision neuroscience: Neuroeconomics. *Wiley Interdisciplinary Reviews: Cognitive Science*, *1*(6), 854–871. https://doi.org/10.1002/wcs.73

Smith, P. L., & Ratcliff, R. (2004). Psychology and neurobiology of simple decisions. *Trends in Neurosciences*, *27*(3), 161–168. https://doi.org/10.1016/j.tins.2004.01.006

Spektor, M. S., Gluth, S., Fontanesi, L., & Rieskamp, J. (2019). How similarity between choice options affects decisions from experience: The accentuation-of-differences model. *Psychological Review*, *126*(1), 52–88. https://doi.org/10.1037/rev0000122

Squire, L. R., & Wixted, J. T. (2011). The cognitive neuroscience of human memory since H.M. *Annual Review of Neuroscience*, *34*, 259–288. https://doi.org/10.1146/annurev-neuro-061010-113720

Staresina, B. P., & Wimber, M. (2019). A Neural Chronometry of Memory Recall. *Trends in Cognitive Sciences*, *23*(12), 1071–1085. https://doi.org/10.1016/j.tics.2019.09.011

Stewart, N., Chater, N., & Brown, G. D. (2006). Decision by sampling. *Cognitive Psychology*, *53*(1), 1–26. https://doi.org/10.1016/j.cogpsych.2005.10.003

Sullivan, N., Hutcherson, C., Harris, A., & Rangel, A. (2015). Dietary Self-Control Is Related to the Speed With Which Attributes of Healthfulness and Tastiness Are Processed. *Psychological Science*, *26*(2), 122–134. https://doi.org/10.1177/0956797614559543

Sutton, R. S., & Barto, A. G. (1998). *Reenforcement Learning: An Introduction*. The MIT Press.

Thura, D., & Cisek, P. (2014). Deliberation and commitment in the premotor and primary motor cortex during dynamic decision making. *Neuron*, *81*(6), 1401–1416. https://doi.org/10.1016/j.neuron.2014.01.031

Townsend, J. T. (1972). Some results concerning the identifiability of parallel and serial processes. *Br. J. math. statist. Psychol.*, *25*, 168–199.

Townsend, J. T., & Wenger, M. J. (2004). The serial – parallel dilemma : A case study in a linkage of theory and method. *Psychonomic Bulletin and Review*, *11*(3), 391–418.

Treder, M. S., Charest, I., Michelmann, S., Martín-Buro, M. C., Roux, F., Carceller-Benito, F., Ugalde-Canitrot, A., Rollings, D. T., Sawlani, V., Chelvarajah, R., Wimber, M., Hanslmayr, S., & Staresina, B. P. (2021). The hippocampus as the switchboard between perception and memory. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(50). https://doi.org/10.1073/pnas.2114171118

Turner, B. M., Forstmann, B. U., Love, B. C., Palmeri, T. J., & Van Maanen, L. (2017). Approaches to analysis in model-based cognitive neuroscience. *Journal of Mathematical Psychology*, *76*, 65–79. https://doi.org/10.1016/j.jmp.2016.01.001

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Judgment Under Uncertainty: Heuristics and Biases*, *185*, 1124–1131. https://doi.org/10.4324/9781912282562

Vaidya, A. R., & Fellows, L. K. (2020). Under construction: Ventral and lateral frontal lobe contributions to value-based decision-making and learning. *F1000Research*, *9*, 1–8. https://doi.org/10.12688/f1000research.21946.1

van Maanen, L., van Rijn, H., & Taatgen, N. (2012). RACE/A: An architectural account of the interactions between learning, task control, and retrieval dynamics. *Cognitive Science*, *36*(1), 62–101. https://doi.org/10.1111/j.1551-6709.2011.01213.x

von Neumann, J, & Morgenstern, O. (1947). *Theory of games and economic behavior* (2nd ed.). Princeton University Press.

Voss, A., Rothermund, K., & Voss, J. (2004). Interpreting the parameters of the diffusion model: An empirical validation. *Memory and Cognition*, *32*(7), 1206–1220. https://doi.org/10.3758/BF03196893

Waldhauser, G. T., Braun, V., & Hanslmayr, S. (2016). Episodic Memory Retrieval Functionally Relies on Very Rapid Reactivation of Sensory Information. *Journal of Neuroscience*, *36*(1), 251–260. https://doi.org/10.1523/JNEUROSCI.2101-15.2016

Waldhauser, G. T., Johansson, M., & Hanslmayr, S. (2012). Alpha/Beta Oscillations Indicate Inhibition of Interfering Visual Memories. *Journal of Neuroscience*, *32*(6), 1953–1961. https://doi.org/10.1523/JNEUROSCI.4201-11.2012

Weber, E. U., Goldstein, W. M., & Barlas, S. (1995). And let us not Forget Memory: The Role of Memory Processes and Techniques in the Study of Judgment and Choice. *Psychology of Learning and Motivation - Advances in Research and Theory*, *32*(100), 33–81. https://doi.org/10.1016/S0079-7421(08)60307-2

Weber, E. U., & Johnson, E. J. Constructing Preferences from Memory (S. Lichtenstein & P. Slovic, Eds.). In: In *The construction of preference* (S. Lichtenstein & P. Slovic, Eds.). Ed. by Lichtenstein, S., & Slovic, P. New York: Cambridge University Press, 2006, pp. 397–410.

Weilbächer, R. A., & Gluth, S. (2017). The interplay of hippocampus and ventromedial prefrontal cortex in memory-based decision making. *Brain Sciences*, *7*(1). https://doi.org/10.3390/brainsci7010004

Weilbächer, R. A., Kraemer, P. M., & Gluth, S. (2020). The Reflection Effect in Memory-Based Decisions. *Psychological Science*, *31*(11), 1439–1451. https://doi.org/10.1177/0956797620956315

Weilbächer, R. A., Krajbich, I., Rieskamp, J., & Gluth, S. (2021). The influence of visual attention on memory-based preferential choice. *Cognition*, *215*(August 2020). https://doi.org/10.1016/j.cognition.2021.104804

Wilson, R. C., & Collins, A. G. E. (2019). Ten simple rules for the computational modeling of behavioral data. *eLife*, 1–33.

Zhang, Z., Wang, S., Good, M., Hristova, S., Kayser, A. S., & Hsu, M. (2021). Retrieval-constrained valuation: Toward prediction of open-ended decisions. *Proceedings of the National Academy of Sciences*, *118*(20), e2022685118. https://doi.org/10.1073/pnas.2022685118

Zhao, W. J., Richie, R, & Bhatia, S. (2021). Process and content in decisions from memory. *Psychological Review*. https://doi.org/10.31234/osf.io/nwxs2

Appendix A

Manuscripts

A.1 Manuscript 1: Cognitive and neural principles of a memory bias on preferential choices

Current Research in Neurobiology 3 (2022) 100029

Contents lists available at ScienceDirect

Current Research in Neurobiology

journal homepage: www.sciencedirect.com/journal/current-research-in-neurobiology

Cognitive and neural principles of a memory bias on preferential choices

Peter M. Kraemer[a], Regina A. Weilbächer[a], Tehilla Mechera-Ostrovsky[b], Sebastian Gluth[c,*]

[a] Department of Psychology, University of Basel, Switzerland
[b] Department of Psychology, University of New South Wales, Australia
[c] Department of Psychology, University of Hamburg, Germany

ARTICLE INFO

Keywords:
Value-based decision making
Episodic memory
Ventromedial prefrontal cortex
Hippocampus
fMRI
Cognitive modeling

ABSTRACT

Value-based decisions depend on different forms of memory. However, the respective roles of memory and valuation processes that give rise to these decisions are often vaguely described and have rarely been investigated jointly. In this review article, we address the problem of memory-based decision making from a neuroeconomic perspective. We first describe the neural and cognitive processes involved in decisions requiring memory processes, with a focus on episodic memory. Based on the results of a systematic research program, we then spotlight the phenomenon of the memory bias, a general preference for choice options that can be retrieved from episodic memory more successfully. Our findings indicate that failed memory recall biases neural valuation processes as indicated by altered effective connectivity between the hippocampus and ventromedial prefrontal cortex. This bias can be attributed to meta-cognitive beliefs about the relationship between subjective value and memory as well as to uncertainty aversion. After summarizing the findings, we outline potential future research endeavors to integrate the two research traditions of memory and decision making.

1. Introduction

Most of our daily decisions rely on past experiences. Be it what food we prefer, whether to invest in stocks or what pictures we like on social media, we never face these decisions with a clean sheet. Instead, we are influenced by our past learning, semantic knowledge, or autobiographical background. In other words: Decision making strongly depends on information that we obtain from memory. But how do we make decisions when memory recall is impaired? How do we decide when we do not recall how a specific food tastes, how well a stock has performed in the past, or what content a picture shows? How do our decision processes adapt to such situations when memory fails?

In this review article, we first give a neuroeconomic perspective on value-based decision processes and how they relate to memory on a cognitive and neural level. Second, we review the literature on how people make decisions when significant information about the potential choice options cannot be made available by memory processes. Third, we spotlight the *memory bias*, a human tendency to prefer even relatively unattractive choice options over uncertain options that cannot be adequately recalled. Fourth, we summarize the current state of research regarding the memory bias and connect it to recent literature on the interplay of memory and decision making. Finally, we describe future avenues and challenges for studying the cognitive neuroscience of memory-based decision making.

2. Decision making and memory

2.1. A neuroeconomic perspective on decision making

How do we decide between different alternatives? Over centuries, mathematicians, economists, and later on also psychologists and neuroscientists have been concerned with this question. The dominant view nowadays comes from expected utility theory, proposing that decision-makers decide between different options as if they seek to maximize the utility they derive from doing so (von Neumann and Morgenstern, 1953). An alternative term for utility is *subjective value*, defined as a latent variable that describes the personal preference for a choice option (Menger, 1871). We will use the term subjective value for the remainder of this review. For decades, researchers treated subjective value as a black box that cannot be observed but only inferred from choice behavior (Samuelson, 1937). However, the relatively young discipline of neuroeconomics draws on theory and methodology from economics, cognitive psychology, and neuroscience to gain a deeper understanding of how subjective value is computed and used for decision making

---

* Corresponding author. Von-Melle-Park 11, 20146, Hamburg, Germany.
E-mail address: sebastian.gluth@uni-hamburg.de (S. Gluth).

https://doi.org/10.1016/j.crneur.2022.100029
Received 25 August 2021; Received in revised form 31 January 2022; Accepted 31 January 2022

(Camerer et al., 2005; Glimcher and Fehr, 2013).

A popular model to study value-based choice is the two-stage model (e.g., Platt and Plassmann, 2013), according to which decision making occurs essentially in the two stages of *valuation* and *action selection*. During valuation, decision-makers attribute subjective value to the choice options they consider, thereby forming a neural representation of value. Converging evidence from neurophysiological and lesion studies, some of which date back to the 1980s (for overviews, see Montague and Berns, 2002; Rolls, 2000), as well as from ensuing brain imaging studies (Bartra et al., 2013; Clithero and Rangel, 2014) suggest frontal brain regions, particularly the ventromedial prefrontal cortex (vmPFC), to show an activity profile that matches the idea of a representation of subjective value. vmPFC seems to construct and integrate value signals (Bault et al., 2019; Chib et al., 2009; Vaidya and Fellows, 2020) and contribute to the comparison between value-based choice options (Boorman et al., 2009; Rushworth et al., 2011).

During action selection, decision-makers consider alternative action plans (e.g., approaching one or another choice option) and select among them to achieve a current goal (e.g., maximize subjective value). Several cortical regions such as the posterior parietal cortex, the frontal eye fields, or the supplementary motor area have been associated with the representation and selection of action plans (see, Cisek and Kalaska, 2010; Gold and Shadlen, 2007, for reviews). As association areas, these regions receive afferent inputs from various brain areas involved in perception, cognition, and valuation and have efferent connections with motor areas that initiate the potential actions (Shadlen and Shohamy, 2016). Neurons in the association areas are effector-specific and tuned to particular actions (Cisek, 2007). Action selection can be understood as the competitive activation of these neurons over time. When the activation level of one action plan outweighs that of all others by some margin, the respective behavior is triggered, much like in an accumulation-to-bound process (Shadlen and Kiani, 2013). While in perceptual decisions, action selection draws on sensory inputs, in value-based decisions, regions that code for subjective value affect action selection (Busemeyer et al., 2019; Hunt and Hayden, 2017; Shadlen and Shohamy, 2016).

The two-stage model states that valuation and action selection are two critical processes for value-based decision making (Platt and Plassmann, 2013; Rangel et al., 2008). Choice options need to be evaluated to represent subjective value. Further, the subjective value of different options needs to be compared to select an appropriate action. It is debated whether the process of comparing subjective values of different options is executed in regions such as vmPFC that code for the value of choice options (Padoa-Schioppa, 2011; Rushworth et al., 2012) or in regions that code for actions (Cisek and Kalaska, 2010; Gold and Shadlen, 2007). While the solution of this debate is not directly relevant to our work, it highlights the importance of a detailed understanding of how subjective value is assessed and computed in the neuro-cognitive system. We argue that valuation crucially depends on memory processes, as discussed below.

2.2. *Why memory is important for decision making*

There is consensus that value signals in the brain are constructed with the support of memory (Hunt and Hayden, 2017; Shadlen and Shohamy, 2016; Shohamy and Daw, 2015). Although the interplay of memory and value-based decision processes was recognized decades ago in the literature (Lynch and Srull, 1982; Nedungadi, 1990), the two cognitive functions have been studied largely in separation. This, however, has changed recently, as neuroeconomists have become increasingly interested in understanding the role of memory-related brain regions such as the hippocampus in value-based choice tasks (Shohamy and Daw, 2015). At the same time, psychological research developed more integrative models of judgment and decision making (Johnson et al., 2007; Stewart et al., 2006; Suri et al., 2020; Zhao et al., 2021). Also, behavioral economics started to integrate memory processes into their theories in order to explain relevant contextual biases on consumer and investment behavior (Bordalo et al., 2020; Gödker et al., 2019).

Importantly, memory is not a homogeneous cognitive function but an umbrella term that comprises several, loosely connected mechanisms and systems. To elaborate on how value is constructed from memory, it is necessary to understand what form of memory is under consideration. Classically, cognitive psychology distinguishes between two major long-term memory systems: declarative and non-declarative memory (Cohen and Squire, 1980). Non-declarative memory describes implicit memory processes which cannot be verbalized, such as procedural memory (skills and habits), priming, classical conditioning, and non-associative learning. On the other hand, the declarative memory system circumscribes semantic memory for facts about the world and episodic memory for past experienced events (Milner et al., 1998). Retrieval of episodic memories is characterized by a conscious recollection of the events alongside the context in which they took place. Although episodic memory covers autobiographical episodes, it is not to be confused with autobiographical memory, which focuses on autobiographical contents without a conscious recollection of context (Wheeler et al., 1997) and has a partly different neural basis (Gilboa, 2004).

Traditionally, neuroeconomists focused on the impact of non-declarative memory processes and, in particular, reinforcement learning on decision making (see Dayan and Niv, 2008; Dolan and Dayan, 2013, for a review). This framework is concerned with how decision-makers learn action-dependent habits, which can affect the probabilities of specific responses without an explicit representation of value (Mishkin et al., 1984). In recent years, however, the field has become more and more interested in how decision-makers weigh in mnemonic information from episodic memory (Biderman et al., 2020; Shadlen and Shohamy, 2016; Weilbächer & Gluth, 2017). Accordingly, people retrieve specific episodes from past rewarding or punishing events and integrate these into their valuation processes when making new decisions. Notably, episodic memory has also been implicated in reinforcement learning (Bornstein et al., 2017; Gershman and Daw, 2017) and decisions from experience (Hertwig et al., 2004), both being prominent research directions in neuroeconomics.

On the neural level, a long tradition of lesion and neuroimaging studies identified the hippocampus and the surrounding medial temporal lobe as key players in episodic memory (see Milner et al., 1998; Squire and Wixted, 2011, for reviews). In value-based decisions from memory, it seems that the hippocampus engages with the vmPFC to affect valuation processes, as shown by electrophysiological and brain imaging studies (see Palombo et al., 2015; Weilbächer & Gluth, 2017, for reviews). Thus, during a decision between several options, episodic memories that are associated with those options are being recalled and affect their valuation (Bakkour et al., 2019; Murty et al., 2016), which in turn drives the action selection process (Biderman et al., 2020; Shadlen and Shohamy, 2016).

On the other hand, the hippocampus and the surrounding medial temporal lobe are not the only brain regions involved in episodic memory, and the vmPFC has not only been associated with decision-making but also with memory-related processes. For example, patients with vmPFC lesions construct past and future events only with low episodic detail (Bertossi et al., 2016), and lesions to the mPFC in rats lead to impairments of recalling place-reward associations (Seamans et al., 1995). Furthermore, brain imaging studies have identified the parietal lobe as another critical brain region that is regularly involved in episodic memory tasks (Wagner et al., 2005). An interesting suggestion concerning this area's role in episodic memory is that it may implement an accumulation-to-bound process for memory retrieval, given that activity in the lateral posterior parietal cortex is tightly coupled with accuracy and response times in recognition tasks (Sestieri et al., 2014; Wagner et al., 2005). In other words, neurons in the parietal lobe may accumulate evidence for identifying an object as recognized or novel. Given all of these findings, the neural circuitry that mediates value-based decisions from memory is arguably much more complex than the mere assumption of a hippocampus-to-vmPFC axis, in which the former region would strictly represent mnemonic processes, and the latter would be solely associated with choice-related mechanisms.

3. When memory fails to inform decisions

The relationship of memory and decision making can be better understood by adopting the view of humans as bounded-rational decision makers (Kahneman and Tversky, 1979; Simon, 1956) who have to adapt their choice strategies to meet the challenges of limited knowledge and cognitive capacities. From this perspective, it is reasonable to assume that some violations of classic economic theory originate from limits associated with the cognitive process of memory retrieval (Weber and Johnson, 2006).

For example, the impact of memory retrieval on decisions from experience has been examined extensively (Hertwig et al., 2004). In these tasks, people learn about the potential outcomes of choice options by receiving feedback for chosen options. Many of those decisions are affected by the accessibility of information in memory. For instance, the serial position of information affects memory retrieval and choice. First presented information (i.e., primacy effect) and most recently learned information (i.e., recency effect) have been shown to have a greater likelihood to be remembered and to influence choice (Hertwig et al., 2004; Shteingart et al., 2013). Madan et al. (2014) showed that associative priming (Ludvig et al., 2015), which describes the increased likelihood of retrieving items associated with extreme outcomes (positive or negative), exerts an effect on risky choices. Similarly, St-Amand et al., 2018 showed that, in decision from experience, people become more risk averse when episodic memory is attenuated, that is, they choose the option that always offered the same amount of reward more frequently.

A further pervasive role of memory was shown in consumer choices. Nedungadi (1990) showed that priming affects information retrieval and biases brand choices. Food choices are affected by the neurological decline of memory-related brain regions due to age (Levin et al., 2019) and brain damage (Bakkour et al., 2019; Enkavi et al., 2017). Taken together, these studies emphasize the importance of accessibility of information in memory-based decision making.

3.1. The memory bias

The role of accessibility of memory content becomes evident when people fail to access memory during choice formation. Empirical work has shown that decision makers adapt to such situations by shifting their preferences towards the options they can remember better. This is true even if the (better) remembered options are comparatively unattractive (Gluth et al., 2015). Thus, people are willing to accept relatively bad options as long as they have good memory for them. To give an everyday

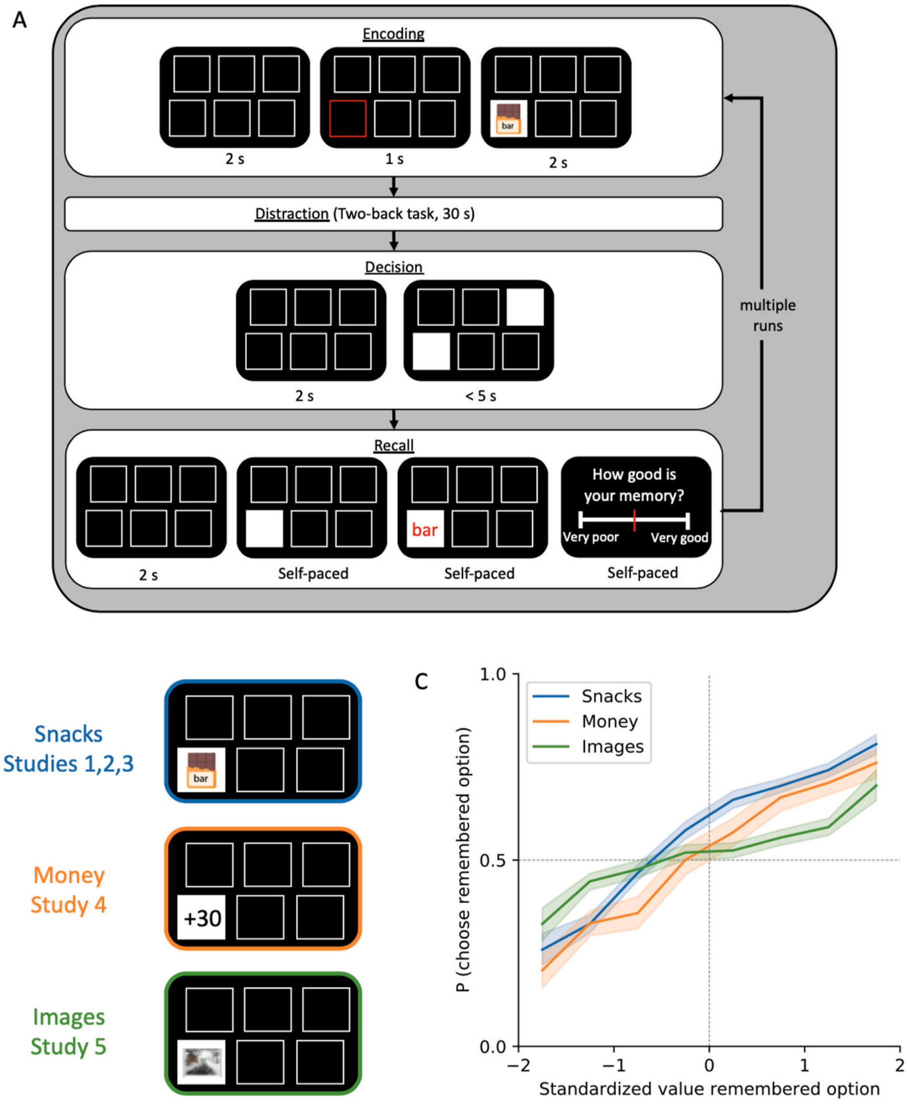


Fig. 1. Remember-and-decide task. **A)** Task structure with periods Encoding, Distraction, Decision and Recall. The core element of the task is the requirement to recall the options when making decisions. **B)** Different stimulus categories used in the experiments. **C)** Choice data, showing the memory bias. The curves show the probability of choosing the remembered option (as a function of its standardized subjective value) when the other option cannot be recalled. The memory bias is evident by the fact that the psychometric curves cross the indifference line (P = 0.5) at a standardized value below 0, reflecting an elevated preference for the remembered option. It has been replicated in multiple experiments and across different stimulus categories.

example, people may choose to eat at an arguably unattractive fast-food restaurant instead of an alternative one, because they might recall less details from their previous visits of the latter compared to the former. Although chances are that the alternative restaurant is preferable, people tend to prefer the unattractive option which is associated with more detailed memory recall. Gluth et al. (2015) termed this effect the *memory bias*.

The phenomenon was established using the *remember-and-decide* task (Fig. 1A). This task comprises several rounds, each consisting of four phases: encoding, distraction, decision and cued recall. During the *encoding phase*, participants learn the association between a number of items (e.g., food snacks, images, monetary rewards) and their location on the screen. Next, a *distraction phase* prevents participants from maintaining the encoded item-location associations in their working memory. In the *decision phase*, participants face a two-alternative forced choice task. In each decision trial, two locations from the encoding phase are highlighted and participants decide which item they prefer. Importantly, the items are “hidden” so that the items’ identities need to be recalled from memory. After performing a number of these decision trials, participants enter the recall phase in which their ability to retrieve the items behind each location is tested. For each of these items, participants then rated the memory strength, that is, they reported their subjective estimation of vividness of the snack in memory.

The core feature of the remember-and-decide task is that, in the

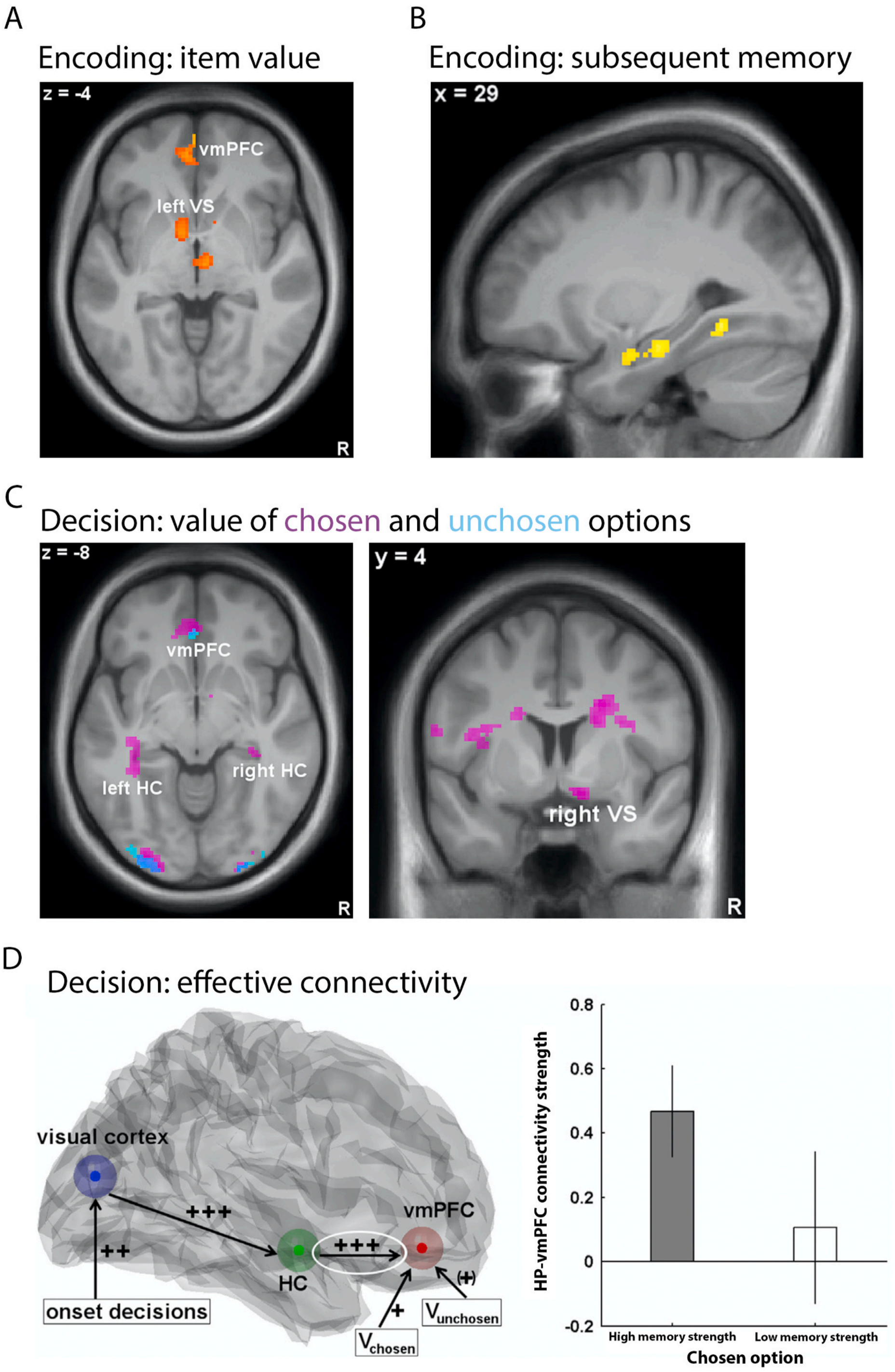


Fig. 2. Neural mechanisms of memory-based decisions (Gluth et al., 2015). **A** and **B)** During encoding of future choice options, vmPFC (together with ventral striatum; VS) represents the subjective value of the options, and hippocampus predicts which item will be remembered later on. **C)** During memory-based decisions, both vmPFC and hippocampus (HC) represent the value of chosen options, but only vmPFC encodes unchosen option values as well. **D)** A significantly positive coupling from HC to vmPFC was only observed in trials, in which the better remembered option was chosen, suggesting that this connectivity mediates the memory bias.

decision period, participants need to retrieve item-specific information from memory to make informed preferential choices. Obviously, choices depend heavily on whether the item can be retrieved or not. When both items are recalled, choice probability is a probabilistic function of the value difference between the two options, just as in regular value-based decisions (McFadden, 2001). When none of the items is recalled, participants are forced to guess. Most importantly, when only one option, but not the other, can be recalled, participants must solely rely on the value of the remembered option to make an informed decision. In this case, we observed a biased choice behavior as participants did not only choose remembered options of average and above-average but also of below-average subjective value. Only remembered options of extremely low subjective value were rejected. This *memory bias* can be visualized as a shift in the choice curve that links the standardized subjective value of the remembered option to its probability of being chosen (Fig. 1C).

Across five studies, we investigated the cognitive and neural mechanisms that mediate the memory bias. After identifying the hippocampus and vmPFC as key brain regions (Gluth et al., 2015), we assessed to what extent the memory bias is driven by subjective beliefs in memory strength (Mechera-Ostrovsky and Gluth, 2018), visual attention (Weilbächer et al., 2021), and whether the memory bias resembles decisions under uncertainty (Weilbächer et al., 2020). Finally, we tested whether the bias is better accounted for by a single evaluation process or by dual processes involving heuristics and utility maximization (Kraemer et al., 2020). In the next section, we revisit this work and draw connections from it to related recent literature on memory-based decision making.

3.2. *The neural basis of the memory bias (Study 1)*

Gluth et al. (2015) discovered the memory bias in a fMRI study with three groups of participants (two memory groups, one control group) performing the remember-and-decide task with food snacks as choice options. While the two memory groups exhibited the memory bias, the control group –which did not have to recall but saw the snacks during the decision phase– did not show a tendency to choose the options they could recall in the ensuing recall period.

As participants encoded the snack-location associations, ventral striatum and vmPFC activity was correlated with the subjective value of the snacks (Fig. 2A). Both areas are projection areas of the dopaminergic reward system and encode subjective value (Bartraet al., 2013). While the hippocampus was not sensitive to subjective value during encoding, its activity predicted whether a snack was recalled during decision and recall phases, in line with subsequent memory effects (Kim, 2011) (Fig. 2B). During the decision phase, the snack values of chosen options, modulated by their memory strength, were present in vmPFC and anterior hippocampus, but the value of unchosen options were only correlated with vmPFC activity (Fig. 2C). These results suggest that the hippocampus was partially co-activated with the valuation system during memory-based decisions, in line with previous evidence for representations of subjective value in the hippocampus (Lebreton et al., 2009; H. Lee et al., 2012). When testing for a neural correlate of the memory bias, an increased hippocampus-vmPFC connectivity was found when participants chose the better remembered option (Fig. 2D). Thus, the hippocampus-vmPFC axis appears to be more involved when memory strength has an effect on choice. This could implicate that the hippocampus affects valuation processes in vmPFC in a way which biases action selection in favor of remembered options (Shadlen and Shohamy, 2016). This is in line with converging literature on the role of the hippocampus in deliberation (Bakkour et al., 2019; Biderman et al., 2020; Bornstein and Norman, 2017).

These findings suggest that valuation processes in vmPFC depend on hippocampus when episodic memories affect deliberation. Interestingly, a recent study by Zhang et al. (2021) found functional coupling of vmPFC and antero-lateral prefrontal cortex when semantic memory is used, presumably for choice set generation and semantic retrieval. It is an open question whether such decisions would also be affected by a memory bias. For instance a memory bias could play out as a brand effect, where people choose brands that they know, even if the product quality may be arguably low. This could be due to a higher association of a brand with its related features as compared to a retrieved alternative.

3.3. *The role of meta-cognitive beliefs about memory (Study 2)*

Having gained insight on its neural mechanisms, further questions arose pertaining to the exact psychological mechanisms that drive the memory bias. First, we examined whether meta-cognitive beliefs about memory strength play a role in the memory bias. According to this rationale, when participants can only remember one option they may discount the other (not-remembered) option for the very reason that they do not remember it. Psychologically speaking, one could think of this mechanism as an “if it’s not remembered, it must be bad” heuristic. Hence, we derived the hypothesis that a stronger belief in the value-dependency of memory strength should correlate positively with the memory bias.

To test this hypothesis, we conducted a preregistered experiment that included not only the remember-and-decide task but also a second task that assessed participants’ beliefs about their performance in the remember-and-decide task (Mechera-Ostrovsky and Gluth, 2018). In this *estimate-your-memory task*, participants indicated for every snack how often they were able to recall it. In addition to replicating the memory bias, we found that snacks of high subjective value were indeed estimated to be recalled more often. Most importantly and as predicted, there was a significantly positive correlation between this value-dependency of beliefs and the memory bias on choice. This suggests that meta-cognitive beliefs about the relationship between subjective value and memory contribute to our preference for better-remembered alternatives. Future work should investigate the neural mechanisms that underlie this contribution. In particular, it would be interesting to know whether the connectivity between hippocampus and vmPFC in memory-based decisions is modulated by regions such as the rostrolateral prefrontal cortex, which has been linked to meta-cognitive assessments in perceptual and value-based choice (De Martino et al., 2013; Fleming et al., 2012).

Beyond this effect of subjective value on (subjective) beliefs, a non-linear relationship between value and (objective) memory performance was found. That is, participants showed a higher recall probability for items with very high values but also (to a lesser extent) for items with very low values. Intriguingly, it has been shown that both confidence judgments in value-based decisions (Lebreton et al., 2015) and meta-cognitive judgments of mnemonic performance (Hebscher et al., 2016) exhibit similar U-shaped relationships with subjective value and recognition accuracy, respectively. Taken together, these results seem to indicate that the memory bias is tightly linked to the notion of confidence on both the cognitive and the neural level. More specifically, when choosing between a remembered and a forgotten option, people may take into account whether they have sufficient memory strength for choosing an option. Because this memory strength (or confidence) appears to be lowest for options that are slightly below average in terms of subjective value, as seen in this study, the decision is most difficult at this point, which is in line with people being indifferent between the two options.

3.4. *The role of attention (Study 3)*

Recent research suggests that overt visual attention affects value comparisons in value-based choice (Krajbich, 2019). Although it is currently debated whether value or choice is modulated (Mormann and Russo, 2021), there is a robust empirical effect that people tend to choose options they have looked at longer (Fiedler & Glöckner, 2012; Gluth et al., 2020; Krajbich et al., 2010; Pärnamets et al., 2015; Stewart et al., 2016; Westbrook et al., 2020). On the other hand, looking behavior is also linked to memory retrieval processes (see, Lai et al., 2013, for a review). In experimental situations, it is established that people look at the locations of previously presented options while they retrieve information from memory (Renkewitz and Jahn, 2012; Scholz et al., 2015). Since overt attention is related to retrieval and to decision processes, we asked whether overt attention contributes to the memory bias.

To investigate this, Weilbächer et al. (2021) used eye tracking to record gaze patterns in the remember-and-decide task. Once more, we replicated the behavioral effect of the memory bias. In line with the studies mentioned above, we also found that chosen options received significantly more attention than unchosen options. However, remembered options were not looked at longer or more often than not-remembered options. Thus, both an attention bias and a memory bias were present, but they did not influence each other. More generally, the study allowed us to compare decisions with visually presented options (value trials) against decisions that required options to be recalled from memory (memory trials). We found that the influence of attention on choice was stronger in memory trials compared to value trials. We speculate that in the case of memory-based decisions, attention is likely to be relevant for the retrieval process itself, potentially facilitating information retrieval (Richardson and Spivey, 2000; Scholz et al., 2011). As a consequence, people may exhibit an even stronger preference for attended options in these kind of decisions. Additionally, we found that decisions involving episodic memory were less consistent with subjective value ratings. This higher stochasticity likely depends on the fact that information needs to be retrieved from episodic memory. Some theories of decision making suggest that subjective values are sampled or retrieved from internal value representations (Polanía et al., 2019; Stewart et al., 2006). It seems plausible that the greater stochasticity is due to uncertain success of the memory retrieval or sampling processes. If this is true, then choice consistency should be tightly coupled to memory strength. Future studies may further look into this relationship, for instance, by varying memory strength in a parametric way.

3.5. *The role of uncertainty (Study 4 and 5)*

Arguably the most obvious cognitive mechanism underlying the memory bias is uncertainty. Specifically, we reasoned that people dislike choosing an option they have no or only little memory of, because they are uncertain about that option's subjective value. Given this rationale, memory-based decisions share conceptual similarities with decisions under uncertainty. The latter are typically studied with lottery gambles and can entail both risk (when the probability of an outcome is known) and ambiguity (when the probability is unknown). As discussed in the introduction, economists and behavioral scientists have studied decision making under risk and ambiguity extensively (Oppenheimer and Kelso, 2015) and have identified many puzzling behavioral effects. One of these effects is the *reflection effect*, the finding that people are less willing to accept uncertainty when facing potential gains compared to potential losses (Kahn and Sarin, 1988; Kahneman and Tversky, 1979; Tversky and Kahneman, 1981; Viscusi and Magat, 1992). Connecting memory- and uncertainty-based decisions, we thus predicted that the tendency to prefer better-remembered options (i.e., the memory bias) should be less pronounced in the loss as compared to the gain domain. In Weilbächer et al. (2020), we ran two preregistered experiments in which participants performed the remember-and-decide task in the gain as well as the loss domain. The two experiments differed in terms of stimulus material (positive and negative monetary values; appetitive and aversive pictures). Confirming our prediction and thus the link between decisions from memory and decisions under uncertainty, we found that the memory bias was less pronounced in the loss domain compared to the gain domain. In other words, when facing potential gains, people stick to better-remembered options and avoid the risk of choosing what they do not recall well, but when it comes to potential losses, people take the risk and are more likely to choose the unknown. A potential explanation may be linked to the above-mentioned finding that the memory bias depends on hippocampal-vmPFC connectivity (Fig. 2D). Assuming that the hippocampus biases valuation in vmPFC, this bias may be less relevant in the loss domain since the vmPFC seems to be less sensitive to negative values (Bartra et al., 2013). Another possibility is that regions known to mediate framing effects and uncertainty in value-based decisions such as the amygdala and the orbitofrontal cortex (De Martino et al., 2006; Hsu et al., 2005) modulate the connection between hippocampus and vmPFC to promote the memory bias.

3.6. *Decision processes underlying the memory bias*

In the previous sections, we demonstrated that the memory bias is a robust empirical finding, which generalizes over several stimulus domains and can at least partially be attributed to subjective beliefs about memory strength as well as to uncertainty-related preferences. While these factors outline potential reasons for the occurrence of the memory bias, the computational mechanisms which give rise to this phenomenon remain unknown. For instance, it is conceivable that people exhibit the memory bias because they may rely on a heuristic choice process that favors choosing remembered options (note that the underlying cognitive process, such as a memory-dependent heuristic, is not to be confused with the empirical phenomenon of the memory bias itself). Analogous to the recognition heuristic, according to which people make judgements simply based on whether they recognize an option or not (Goldstein and Gigerenzer, 2002), participants in our studies may sometimes have decided simply based on whether they have remembered an option or not. In the section on subjective beliefs (see above), we argued that a heuristic process alone cannot explain the memory bias, because people rejected remembered options with very low values. However, heuristic processes have been suggested to be used adaptively from a wider repertoire of decision processes (Marewski and Link, 2014; Pachur, 2011). From a perspective of dual-process theories, people may thus alternate between fast and erroneous heuristic decisions and slower but more accurate decision processes that entail higher cognitive effort (Alós-Ferrer, 2018; Evans, 2008; Kahneman, 2011). In terms of memory-based choices, people may resort sometimes to a recognition-like heuristic and at other times to a utility-maximizing but cognitively costly process. Such a dual-process account would result in a general tendency to choose remembered options while giving the flexibility to reject very low-valued options.

In contrast to dual-process theories, Gluth et al. (2015) suggested that a single choice mechanism is sufficient to explain the memory bias. According to this single-process account, people accumulate preference by comparing the subjective value of the remembered option with a reference value, which acts as a replacement of the unavailable value of the not-remembered option. This reference value is biased so that participants tend to prefer remembered options. In Kraemer et al. (2020), we tested whether this single-process model or a dual-process account that alternates between a heuristic and a utility mechanism explains the memory bias best. The challenge here was that both, single- and dual-process accounts predicted a choice pattern which resembled the behavior of the memory bias. Yet, we were able to show that the two accounts differ with respect to their response time (RT) predictions. Resorting to the data by Mechera-Ostrovsky and Gluth (2018), we adopted hierarchical Bayesian modeling techniques (M. D. Lee and Wagenmakers, 2013) to compare the two accounts. Qualitative as well as quantitative model comparisons provided strong support for the single-process account, as it was more in line with the RT predictions. Thus, we conclude that the memory-bias depends on a single biased evaluation process rather than an alternation between heuristic and utility-maximizing strategies.

As a summary of the current state of knowledge and the open questions surrounding the memory bias, Fig. 3 provides a schematic overview of what we currently know and still do not know about the neural and cognitive mechanisms underlying this influence of memory

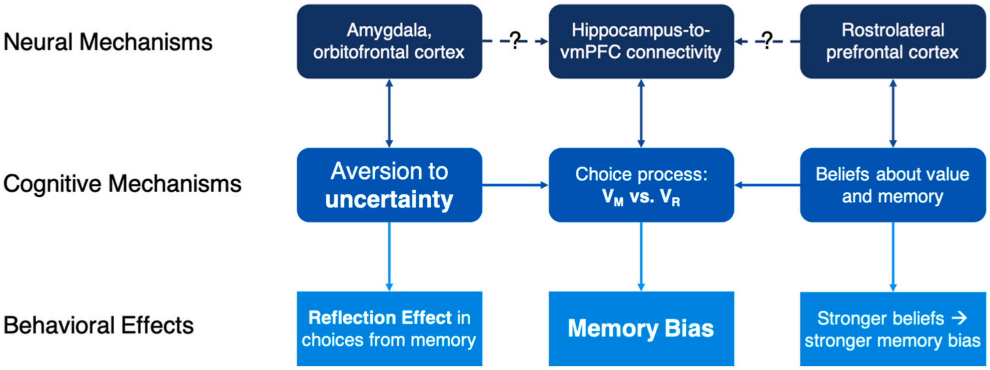


Fig. 3. The knowns and unknowns of the neural and cognitive mechanisms underlying the memory bias. Cognitively, the memory bias arises from a (biased) comparison process between the value of the memorized option (V_M) and and a reference value (V_R) that replaces the value of the not-remembered option. We have shown that the phenomenon is related to an increased hippocampus-to-vmPFC connectivity, and that uncertainty and beliefs about memory contribute to it. What is currently unknown, however, are the neural mechanism underling these influences of uncertainty and beliefs.

on value-based decisions.

4. Perspectives

In the previous sections, we have argued that valuation processes often depend on episodic memory which is consequential for value-based decision making. This relation becomes particularly critical when memory processes fail. In such cases, the neural and cognitive systems adapt to allow us to make informed decisions that are biased towards better-memorized options due to meta-cognitive beliefs and uncertainty aversion. In this concluding chapter, we outline future important research endeavors of memory-based decision making more generally.

4.1. *Neural basis of the influence of beliefs and uncertainty*

As discussed above and depicted in Fig. 3, the neural basis of the memory bias' modulation by meta-cognitive beliefs about value, memory, and uncertainty aversion remains to be discovered. In our view, a plausible assumption is that regions that are known to be involved in meta-cognitive assessments (e.g., rostrolateral prefrontal cortex, rlPFC; De Martino et al., 2013; Fleming et al., 2012) on the one hand and decisions under uncertainty (e.g., amygdala and orbitofrontal cortex, OFC; De Martino et al., 2006; Hsu et al., 2005) on the other hand modulate memory bias by acting on the choice-related processes in the vmPFC directly or by affecting the connectivity between hippocampus and vmPFC that we have linked to the memory bias (Gluth et al., 2015).

Concerning meta-cognitive beliefs, the rlPFC has been linked to the ability to make meta-cognitive judgments about one's own performance (Fleming et al., 2010). Further, De Martino et al. (2013) have reported an increased functional connectivity between this region and the vmPFC when decisions were made with high confidence. Thus, believing in a strong relationship between subjective value and memory strength could enhance a decision-maker's confidence when choosing well-remembered options. This may be reflected in increased activity in rlPFC but also in a stronger influence of this region's activity on the choice dynamics of vmPFC.

Regarding uncertainty, activity in the amygdala appears to be higher when decisions are in alignment with the above-discussed reflection effect (i.e., choosing safe options in the gain domain but risky options in the loss domain). At the same time, activity in OFC scales with the ability to overcome this tendency (De Martino et al., 2006). Thus, a tentative hypothesis could be that these regions exert different influences on the hippocampus-vmPFC connectivity, which mediates the memory bias. The amygdala may strengthen the hippocampus-vmPFC connectivity for decisions in the gain domain but weaken it for decisions in the loss domain. On the other hand, the OFC may weaken the relationship between the hippocampus-vmPFC connectivity and the behavioral phenomenon of the memory bias in general, leading to more rational decisions (in a strictly economic understanding of rationality). These hypotheses could be investigated with neuroimaging studies that make use of Dynamic Causal Modeling (Friston et al., 2003), which allows testing whether a third region's activity modulates the connectivity between two other regions.

Additionally, it has been shown that reward-related brain regions such as the ventral striatum are more activated in the case of successful and highly confident memory retrieval (Clos et al., 2015; Schwarze et al., 2013) and when identifying previously seen items as "old" in recognition tasks compared to identifying novel items as "new" (Han et al., 2010). This has been interpreted as reflecting the pleasure of being able to retrieve information accurately. Hence, it is tempting to speculate that the joy of retrieving an option is mingled with the estimation of that option's subjective value, which should promote the memory bias. Similarly, higher confidence and associated joy in remembering snacks may activate the brain's reward system, and these reward signals could be mingled with the option's subjective value representation. As a result, the brain may overestimate the subjective value of well-remembered options, resulting in the memory bias phenomenon.

4.2. *Sequential sampling modeling of choices from memory*

Memory-based decision-making is a challenging topic to study because it involves understanding several cognitive processes (i.e., memory and decision formation). Moreover, cognitive processes are latent variables that cannot be observed directly but must be inferred from behavior and brain function. To study these processes, mathematical and computational models of cognition are useful tools (Farrell and Lewandowsky, 2018). In neuroeconomics, the sequential sampling framework appears to become the dominant paradigm to model value-based decision making and economic choice (Clithero, 2018; Fehr and Rangel, 2011). As briefly mentioned above, the core idea of this framework is that decisions arise from a noisy process of sampling or accumulating pieces of evidence in a sequential manner, which is terminated as soon as the desired level of evidence or confidence about the most appropriate choice option has been collected. In several of our own studies (Gluth et al., 2015; Kraemer et al., 2020; Weilbächer et al., 2021), we adopted the sequential sampling framework to gain valuable insights into the underlying cognitive and neural processes of memory-based decisions. For example, we have learned that the memory bias arises from a single comparison process that is biased towards more vividly remembered options rather than from a mixture of two separate choice strategies (Kraemer et al., 2020). Similarly, by modeling the dynamics of memory-based decisions with an attention-based sequential sampling model (Thomas et al., 2019), we provided evidence that the influence of attention is enhanced when decisions require memory retrieval (Weilbächer et al., 2021). We argue that adopting this framework will remain critical for future research that seeks to close the gap between memory and decision making even further.

One reason for our view is that the framework is compatible with dominant psychological theories of memory-based decision making.

Although some scholars have proposed relatively simple decision rules which depend on recognition (Gigerenzer and Gaissmaier, 2011), the information processing paradigm is gaining more and more traction in psychology and neuroscience (Oppenheimer and Kelso, 2015). This paradigm suggests that decision-making draws on fundamental processes of memory, attention, and perception. Decision-relevant information is retrieved (sampled) from an internal representation of the choice options and used to generate a decision outcome. Notably, prominent approaches like Query theory (Johnson et al., 2007) and Decision by Sampling (Stewart et al., 2006) implement this sampling idea, where informative samples drive the decision process towards an eventual decision. Hence, the link to the sequential sampling framework is obvious, and adopting it will be critical to advance the field as it offers a robust mathematical foundation.

Importantly, sequential sampling models are theoretically closely related to action selection processes (Cisek, 2012; Shadlen and Kiani, 2013) and have been related to neural processes in related brain regions such as the frontal eye fields, the pre-supplementary motor area and the posterior parietal cortex in monkeys (Cisek and Kalaska, 2010; Gold and Shadlen, 2007) and human homologues (Gluth et al., 2012, 2013; Hare et al., 2011; Pisauro et al., 2017). Nevertheless, how does value-based evidence accumulation depend on memory processes? While brain imaging studies identified vmPFC and hippocampus as key regions in memory-based decisions (Bakkour et al., 2019; Gluth et al., 2015; Shadlen and Shohamy, 2016), a mechanistic understanding of how information is integrated from memory requires a more nuanced investigation, including real-time observations of how decision processes unfold. Future research may combine sequential sampling models with neuroscientific methods that offer a high temporal resolution such as electro- and magnetoencephalography (EEG/MEG) to identify the relative components of memory retrieval and action selection, allowing a thorough investigation of the underlying cognitive and neural processes.

4.3. *Memory representation*

Up until now, most research has been focused on how decision making is affected by memory processes. Thereby, the clear focus of this research line has been on decision processes, studying how deliberation or valuation works. To understand, however, how memory and decision making interact, we need a better understanding of the involved memory processes. This applies not only to encoding and retrieval processes but also to the representation of information in memory, or *memory structure* (Kahana, 2020). With regard to this question of memory representation, we see two trends gaining more attention in the field of decision making. First, from a connectionist perspective, decision making can be modeled as activation in a neural network with a decision scenario as input and a response as output (Bhatia, 2013; Hunt and Hayden, 2017; Suri et al., 2020). In such a network, memory can be conceptualized as hidden units that have a relatively stable effect on action generating units. While this perspective delivers a memory structure, it does not model a retrieval process with retrieval dynamics. This account holds that value does not need to be represented explicitly but emerges from the activation of the network structure (Yoo and Hayden, 2018).

Another account of memory-based decisions comes from research that uses semantic memory representations such as semantic networks (Siew et al., 2019) or high-dimensional vector spaces (Bhatia et al., 2019). In these accounts, retrieval processes draw on these memory structures and use their information to generate actions. Zhao et al. (2021) and Kraemer et al. (2021) followed this line, demonstrating their applicability to different decision contexts. However, more research in this direction is needed to understand the implications for valuation processes.

4.4. *Constructing value from memory*

While episodic memory often focuses on the retrospective nature of memory, prospective aspects and their potential role in decision-making gained more traction recently (Biderman et al., 2020). It is important to note that the hippocampus and adjacent medial temporal lobe structures do not only enable us to retrieve past episodes, but they also allow us to use such episodes (or parts of them) to construct and envision future states of the world flexibly. In particular, the hippocampus has been shown to be involved in associative value learning (Gerraty et al., 2014; Wimmer and Shohamy, 2012), constructing novel representations of value (Barron et al., 2013) and deliberation during value-based decisions (Bakkour et al., 2019; Bornstein and Daw, 2013).

Importantly, value-based decision making itself has been described as a constructive process (e.g., Lichtenstein and Slovic, 2006). Choice behavior of humans (and other animals) appears to be highly dependent on the context in general and on the available choice set in particular (Busemeyer et al., 2019; Spektor et al., 2021). These findings contradict the idea that people have stable preferences which they need to retrieve in a given choice context. Thus, the neuroeconomic view of decision making as a two-stage process of valuation and action selection is challenged. Instead models that assume preferences to be constructed on the fly so that another, currently available alternative can influence the estimation of an option's value, appear to provide a more complete account of the cognitive process of decision making. At first glance, one could think that the rejection of a simple value-retrieval mechanism may speak against an essential role of memory in decision making. In our view, however, the above-mentioned ability of the brain's memory system to recombine past events for creating future prospects of the world suggests that memory-based processes are also involved in the context-depended formation of preferences. Thus, once more, memory and decision-making processes seem to be intertwined and should be investigated jointly in the future.

CRediT authorship contribution statement

Peter M. Kraemer: Conceptualization, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Regina A. Weilbächer:** Conceptualization, Writing – original draft, Writing – review & editing. **Tehilla Mechera-Ostrovsky:** Conceptualization, Writing – original draft, Writing – review & editing. **Sebastian Gluth:** Conceptualization, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Some of the work discussed here was supported by the Swiss National Science Foundation (SNSF Grant No. 172761 to Sebastian Gluth) and the Research Fund of the University of Basel (Grant No. 3PE1049 to Peter Kraemer). Sebastian Gluth also acknowledges support from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (Grant agreement No. 948545).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crneur.2022.100029.

References

Alós-Ferrer, C., 2018. A dual-process diffusion model. J. Behav. Decis. Making 31 (2), 203–218. https://doi.org/10.1002/bdm.1960.

Bakkour, A., Palombo, D.J., Zylberberg, A., Kang, Y.H., Reid, A., Verfaellie, M., Shadlen, M.N., Shohamy, D., 2019. The hippocampus supports deliberation during value-based decisions. Elife 8, 1–28. https://doi.org/10.7554/eLife.46080.

Barron, H.C., Dolan, R.J., Behrens, T.E., 2013. Online evaluation of novel choices by simultaneous representation of multiple memories. Nat. Neurosci. 16 (10), 1492–1498. https://doi.org/10.1038/nn.3515.

Bartra, O., McGuire, J.T., Kable, J.W., 2013. The valuation system: a coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. Neuroimage 76, 412–427. https://doi.org/10.1016/j.neuroimage.2013.02.063.

Bault, N., di Pellegrino, G., Puppi, M., Opolczynski, G., Monti, A., Braghittoni, D., Thibaut, F., Rustichini, A., Coricelli, G., 2019. Dissociation between private and social counterfactual value signals following ventromedial prefrontal cortex damage. J. Cognit. Neurosci. 31 (5), 639–656. https://doi.org/10.1162/jocn{_}a{_}01372.

Bertossi, E., Tesini, C., Cappelli, A., Ciaramelli, E., 2016. Ventromedial prefrontal damage causes a pervasive impairment of episodic memory and future thinking. Neuropsychologia 90, 12–24. https://doi.org/10.1016/j.neuropsychologia.2016.01.034.

Bhatia, S., 2013. Associations and the accumulation of preference. Psychol. Rev. 120 (3), 522–543. https://doi.org/10.1037/a0032457.

Bhatia, S., Richie, R., Zou, W., 2019. Distributed semantic representations for modeling human judgment. Curr. Opin. Behav. Sci. 29, 31–36. https://doi.org/10.1016/j.cobeha.2019.01.020.

Biderman, N., Bakkour, A., Shohamy, D., 2020. What are memories for? The Hippocampus bridges past experience with future decisions. Trends Cognit. Sci. 24 (7), 542–556. https://doi.org/10.1016/j.tics.2020.04.004.

Boorman, E.D., Behrens, T.E., Woolrich, M.W., Rushworth, M.F., 2009. How green is the grass on the other side? Frontopolar cortex and the evidence in favor of alternative courses of action. Neuron 62 (5), 733–743. https://doi.org/10.1016/j.neuron.2009.05.014.

Bordalo, P., Nicola, G., Shleifer, A., 2020. Memory, attention, and choice. Q. J. Econ. 135 (3), 1399–1442. https://doi.org/10.1093/qje/qjaa007 (Advance).

Bornstein, A.M., Daw, N.D., 2013. Cortical and hippocampal correlates of deliberation during model-based decisions for rewards in humans. PLoS Comput. Biol. 9 (12) https://doi.org/10.1371/journal.pcbi.1003387.

Bornstein, A.M., Khaw, M.W., Shohamy, D., Daw, N.D., 2017. Reminders of past choices bias decisions for reward in humans. Nat. Commun. 8 (May), 1–9. https://doi.org/10.1038/ncomms15958.

Bornstein, A.M., Norman, K.A., 2017. Reinstated episodic context guides sampling-based decisions for reward. Nat. Neurosci. 20 (7), 997–1003. https://doi.org/10.1038/nn.4573.

Busemeyer, J.R., Gluth, S., Rieskamp, J., Turner, B.M., 2019. Cognitive and neural bases of multi-attribute, multi-alternative, value-based decisions. Trends Cognit. Sci. 23 (3), 251–263. https://doi.org/10.1016/j.tics.2018.12.003.

Camerer, C., Loewenstein, G., Prelec, D., 2005. Neuroeconomics: how neuroscience can inform economics. J. Econ. Lit. 43 (1), 9–64. https://doi.org/10.1257/0022051053737843.

Chib, V.S., Rangel, A., Shimojo, S., O'Doherty, J.P., 2009. Evidence for a common representation of decision values for dissimilar goods in human ventromedial prefrontal cortex. J. Neurosci. 29 (39), 12315–12320. https://doi.org/10.1523/JNEUROSCI.2575-09.2009.

Cisek, P., 2007. Cortical mechanisms of action selection: the affordance competition hypothesis. Phil. Trans. Biol. Sci. 362 (1485), 1585–1599. https://doi.org/10.1098/rstb.2007.2054.

Cisek, P., 2012. Making decisions through a distributed consensus. Curr. Opin. Neurobiol. 22 (6), 927–936. https://doi.org/10.1016/j.conb.2012.05.007.

Cisek, P., Kalaska, J.F., 2010. Neural mechanisms for interacting with a world full of action choices. Annu. Rev. Neurosci. 33, 269–298. https://doi.org/10.1146/annurev.neuro.051508.135409.

Clithero, J.A., 2018. Response times in economics : looking through the lens of sequential sampling models. October 2016 J. Econ. Psychol. 69, 61–86. https://doi.org/10.1016/j.joep.2018.09.008.

Clithero, J.A., Rangel, A., 2014. Informatic parcellation of the network involved in the computation of subjective value. Soc. Cognit. Affect Neurosci. 9 (9), 1289–1302. https://doi.org/10.1093/scan/nst106.

Clos, M., Schwarze, U., Gluth, S., Bunzeck, N., Sommer, T., 2015. Goal- and retrieval-dependent activity in the striatum during memory recognition. Neuropsychologia 72, 1–11. https://doi.org/10.1016/j.neuropsychologia.2015.04.011.

Cohen, N.J., Squire, L.R., 1980. Preserved learning and retention of pattern-analyzing skill in amnesia: dissociation of knowing how and knowing that. Science 210 (4466), 207–210. https://doi.org/10.1126/science.7414331.

Dayan, P., Niv, Y., 2008. Reinforcement learning: the good, the bad and the ugly. Curr. Opin. Neurobiol. 18 (2), 185–196. https://doi.org/10.1016/j.conb.2008.08.003.

De Martino, B., Fleming, S.M., Garrett, N., Dolan, R.J., 2013. Confidence in value-based choice. Nat. Neurosci. 16 (1), 105–110. https://doi.org/10.1038/nn.3279.

De Martino, B., Kumaran, D., Seymour, B., Dolan, R.J., 2006. Decision-making in the human brain. Science 313 (August), 684–688.

Dolan, R.J., Dayan, P., 2013. Goals and habits in the brain. Neuron 80 (2), 312–325. https://doi.org/10.1016/j.neuron.2013.09.007.

Enkavi, A.Z., Weber, B., Zweyer, I., Wagner, J., Elger, C.E., Weber, E.U., Johnson, E.J., 2017. Evidence for hippocampal dependence of value-based decisions. Sci. Rep. 7 (1), 1–9. https://doi.org/10.1038/s41598-017-18015-4.

Evans, J.S.B.T., 2008. Dual-processing accounts of reasoning , judgment , and social cognition. Annu. Rev. Psychol. 59, 255–278. https://doi.org/10.1146/annurev.psych.59.103006.093629.

Farrell, S., Lewandowsky, S., 2018. Computational Modeling of Cognition and Behavior. Cambridge University Press.

Fehr, E., Rangel, A., 2011. Neuroeconomic foundations of economic choice-recent advances. J. Econ. Perspect. 25 (4), 3–30. https://doi.org/10.1257/jep.25.4.3.

Fiedler, S., Glockner, A., 2012. The dynamics of decision making in risky choice: an eye-tracking analysis. Front. Psychol. 3 (OCT), 1–18. https://doi.org/10.3389/fpsyg.2012.00335.

Fleming, S.M., Weil, R.S., Nagy, Z., Dolan, R.J., Rees, G., 2010. Relating introspective accuracy to individual differences in brain structure. Science 329, 1541–1543. https://doi.org/10.1126/science.336.6082.670.

Fleming, S.M., Huijgen, J., Dolan, R.J., 2012. Prefrontal contributions to metacognition in perceptual decision making. J. Neurosci. 32 (18), 6117–6125. https://doi.org/10.1523/JNEUROSCI.6489-11.2012.

Friston, K.J., Harrison, L., Penny, W., 2003. Dynamic causal modelling. Neuroimage 19 (4), 1273–1302. https://doi.org/10.1016/S1053-8119(03)00202-7.

Gerraty, R.T., Davidow, J.Y., Wimmer, G.E., Kahn, I., Shohamy, D., 2014. Transfer of learning relates to intrinsic connectivity between hippocampus, ventromedial prefrontal cortex, and large-scale networks. J. Neurosci. 34 (34), 11297–11303. https://doi.org/10.1523/JNEUROSCI.0185-14.2014.

Gershman, S.J., Daw, N.D., 2017. Reinforcement learning and episodic memory in humans and animals: an integrative framework. Annu. Rev. Psychol. 68 (1), 101–128. https://doi.org/10.1146/annurev-psych-122414-033625.

Gigerenzer, G., Gaissmaier, W., 2011. Heuristic decision making. Annu. Rev. Psychol. 62, 451–482. https://doi.org/10.1146/annurev-psych-120709-145346.

Gilboa, A., 2004. Autobiographical and episodic memory - one and the same? Evidence from prefrontal activation in neuroimaging studies. Neuropsychologia 42 (10), 1336–1349. https://doi.org/10.1016/j.neuropsychologia.2004.02.014.

Glimcher, P.W., Fehr, E., 2013. Neuroeconomics: Decision Making and the Brain. Academic Press.

Gluth, S., Kern, N., Kortmann, M., Vitali, C.L., 2020. Value-based attention but not divisive normalization influences decisions with multiple alternatives. Nat. Human Behav. 4 (6), 634–645. https://doi.org/10.1038/s41562-020-0822-0.

Gluth, S., Rieskamp, J., Buchel, C., 2012. Deciding when to decide: time-variant sequential sampling models explain the emergence of value-based decisions in the human brain. J. Neurosci. 32 (31), 10686–10698. https://doi.org/10.1523/JNEUROSCI.0727-12.2012.

Gluth, S., Rieskamp, J., Buchel, C., 2013. Classic EEG motor potentials track the emergence of value-based decisions. Neuroimage 79, 394–403. https://doi.org/10.1016/j.neuroimage.2013.05.005.

Gluth, S., Sommer, T., Rieskamp, J., Buchel, C., 2015. Effective connectivity between Hippocampus and ventromedial prefrontal cortex controls preferential choices from memory article effective connectivity between Hippocampus and ventromedial prefrontal cortex controls preferential choices from memory. Neuron 1078–1090. https://doi.org/10.1016/j.neuron.2015.04.023.

Godker, K., Jiao, P., Smeets, P., 2019. Investor Memory, 016. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3348315.

Gold, J.I., Shadlen, M.N., 2007. The neural basis of decision making. Annu. Rev. Neurosci. 30 (1), 535–574. https://doi.org/10.1146/annurev.neuro.29.051605.113038.

Goldstein, D.G., Gigerenzer, G., 2002. Models of ecological rationality: the recognition heuristic. Psychol. Rev. 109 (1), 75–90. https://doi.org/10.1037//0033-295X.109.1.75.

Han, S., Huettel, S.A., Raposo, A., Adcock, R.A., Dobbins, I.G., 2010. Functional significance of striatal responses during episodic decisions: recovery or goal attainment? J. Neurosci. 30 (13), 4767–4775. https://doi.org/10.1523/JNEUROSCI.3077-09.2010.

Hare, T.A., Schultz, W., Camerer, C.F., O'Doherty, J.P., Rangel, A., 2011. Transformation of stimulus value signals into motor commands during simple choice. Proc. Natl. Acad. Sci. U. S. A. 108 (44), 18120–18125. https://doi.org/10.1073/pnas.1109322108.

Hebscher, M., Barkan-Abramski, M., Goldsmith, M., Aharon-Peretz, J., Gilboa, A., 2016. Memory, decision-making, and the ventromedial prefrontal cortex (vmPFC): the roles of subcallosal and posterior orbitofrontal cortices in monitoring and control processes. Cerebr. Cortex 26, 4590–4601. https://doi.org/10.1093/cercor/bhw220.

Hertwig, R., Barron, G., Weber, E.U., Erev, I., 2004. Decisions from experience and the effect of rare events in risky choice. Psychol. Sci. 15 (8), 534–539.

Hsu, M., Bhatt, M., Adolphs, R., Tranel, D., Camerer, C.F., 2005. Neuroscience: neural systems responding to degrees of uncertainty in human decision-making. Science 310 (5754), 1680–1683. https://doi.org/10.1126/science.1115327.

Hunt, L.T., Hayden, B.Y., 2017. A distributed, hierarchical and recurrent framework for reward-based choice. Nat. Rev. Neurosci. 18 (3), 172–182. https://doi.org/10.1038/nrn.2017.7.

Johnson, E.J., Haubl, G., Keinan, A., 2007. Aspects of endowment: a Query theory of value construction. J. Exp. Psychol. Learn. Mem. Cognit. 33 (3), 461–474. https://doi.org/10.1037/0278-7393.33.3.461.

Kahana, M.J., 2020. Computational models of memory search. Annu. Rev. Psychol. 71, 107–138. https://doi.org/10.1146/annurev-psych-010418-103358.

Kahn, B.E., Sarin, R.K., 1988. Modeling ambiguity in decisions under uncertainty. J. Consum. Res. 15 (2), 265. https://doi.org/10.1086/209163.

Kahneman, D., 2011. Thinking, Fast and Slow. Farrar, Straus; Giroux.

Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica 47, 263–292. https://doi.org/10.2307/1914185.

Kim, H., 2011. Neural activity that predicts subsequent memory and forgetting: a meta-analysis of 74 fMRI studies. Neuroimage 54 (3), 2446–2461. https://doi.org/10.1016/j.neuroimage.2010.09.045.

Kraemer, P.M., Weilbacher, R.A., Fontanesi, L., Gluth, S., 2020. In: Zaleskiewicz, InT., Traczyk, T. (Eds.), Neural Bases of Financial Decision Making: From Spikes to Large-Scale Brain Connectivity, Psychological Perspectives on Financial Decision Making. Springer, pp. 3–19.

Kraemer, P.M., Wulff, D.U., Gluth, S., 2021. A Sequential Sampling Account of Semantic Relatedness Decisions. https://doi.org/10.31234/osf.io/ksa2g.

Krajbich, I., 2019. Accounting for attention in sequential sampling models of decision making. Curr. Opin. Psychol. 29, 6–11. https://doi.org/10.1016/j.copsyc.2018.10.008.

Krajbich, I., Armel, C., Rangel, A., 2010. Visual fixations and the computation and comparison of value in simple choice. Nat. Neurosci. 13 (10), 1292–1298. https://doi.org/10.1038/nn.2635.

Lai, M.-l., Tsai, M.-j., Yang, F.-y., Hsu, C.-y., Liu, T.-c., Lee, S.W.-y., Lee, M.-h., Chiou, G.-l., Liang, J.-c., Tsai, C.-c., 2013. A review of using eye-tracking technology in exploring learning from 2000 to 2012. Educ. Res. Rev. 10 (88), 90–115. https://doi.org/10.1016/j.edurev.2013.10.001.

Lebreton, M., Abitbol, R., Daunizeau, J., Pessiglione, M., 2015. Automatic integration of confidence in the brain valuation signal. Nat. Neurosci. 18 (8), 1159–1167. https://doi.org/10.1038/nn.4064.

Lebreton, M., Jorge, S., Michel, V., Thirion, B., Pessiglione, M., 2009. An automatic valuation system in the human brain: evidence from functional neuroimaging. Neuron 64 (3), 431–439. https://doi.org/10.1016/j.neuron.2009.09.040.

Lee, H., Ghim, J.W., Kim, H., Lee, D., Jung, M.W., 2012. Hippocampal neural correlates for values of experienced events. J. Neurosci. 32 (43), 15053–15065. https://doi.org/10.1523/JNEUROSCI.2806-12.2012.

Lee, M.D., Wagenmakers, E.-J., 2013. Bayesian Cognitive Modeling: A Practical Course. Cambridge University Press. https://doi.org/10.1017/CBO9781139087759.

Levin, F., Fiedler, S., Weber, B., 2019. The influence of episodic memory decline on value-based choice. Aging Neuropsychol. Cognit. 26 (4), 599–620. https://doi.org/10.1080/13825585.2018.1509939.

Lichtenstein, S., Slovic, P., 2006. In: Lichtenstein, S., Slovic, P. (Eds.), The Construction of Preference. Cambridge University Press.

Ludvig, E.A., Madan, C.R., Spetch, M.L., 2015. Priming memories of past wins induces risk seeking. J. Exp. Psychol. Gen. 144 (1), 24–29. https://doi.org/10.1037/xge0000046.

Lynch, J.G., Srull, T.K., 1982. Memory and attentional factors in consumer choice: concepts and research methods. J. Consum. Res. 9 (1), 18. https://doi.org/10.1086/208893.

Madan, C.R., Ludvig, E.A., Spetch, M.L., 2014. Remembering the best and worst of times: memories for extreme outcomes bias risky decisions. Psychon. Bull. Rev. 21 (3), 629–636. https://doi.org/10.3758/s13423-013-0542-9.

Marewski, J.N., Link, D., 2014. Strategy selection: an introduction to the modeling challenge. Wiley Interdiscipl. Rev.: Cognit. Sci. 5 (1), 39–59. https://doi.org/10.1002/wcs.1265.

McFadden, D., 2001. Economic choices. Am. Econ. Rev. 91 (3), 351–378.

Mechera-Ostrovsky, T., Gluth, S., 2018. Memory beliefs drive the memory bias on value-based decisions. Sci. Rep. 8 (1), 1–10.

Menger, C., 1871. Grundsätze der Volkswirtschaftslehre. Braumüller.

Milner, B., Squire, L.R., Kandel, E.R., 1998. Cognitive neuroscience and the study of memory. Neuron 20 (3), 445–468. https://doi.org/10.1016/S0896-6273(00)80987-3.

Mishkin, M., Malamut, B., Bachevalier, J., 1984. Memories and habits: two neural systems. In: Lynch, G., McGaugh, J.L., Weinberger, N.M. (Eds.), Neurobiology of Human Learning and Memory. Guilford Press, pp. 65–77.

Montague, P.R., Berns, G.S., 2002. Neural economics and the biological substrates of valuation. Neuron 36 (2), 265–284. https://doi.org/10.1016/S0896-6273(02)00974-1.

Mormann, M., Russo, J.E., 2021. Does attention increase the value of choice alternatives? Trends Cognit. Sci. 305–315. https://doi.org/10.1016/j.tics.2021.01.004.

Murty, V.P., FeldmanHall, O., Hunter, L.E., Phelps, E.A., Davachi, L., 2016. Episodic memories predict adaptive Value-Based Decision-Making. J. Exp. Psychol. Gen. 145 (5), 1–11. https://doi.org/10.1037/xge0000158.

Nedungadi, P., 1990. Recall and consumer consideration sets: influencing choice without altering BrandEvaluations. J. Consum. Res. 17 (3), 263–276.

Oppenheimer, D.M., Kelso, E., 2015. Information processing as a paradigm for decision making. Annu. Rev. Psychol. 66, 277–294. https://doi.org/10.1146/annurev-psych-010814-015148.

Pachur, T., 2011. The limited value of precise tests of the recognition heuristic. Judgment Decis. Mak. 6 (5), 413–422.

Padoa-Schioppa, C., 2011. Neurobiology of economic choice: a good-based model. Annu. Rev. Neurosci. 34, 333–359. https://doi.org/10.1146/annurev-neuro-061010-113648.

Palombo, D.J., Keane, M.M., Verfaellie, M., 2015. How does the hippocampus shape decisions? Neurobiol. Learn. Mem. 125, 93–97.

Parnamets, P., Johansson, P., Hall, L., Balkenius, C., Spivey, M.J., Richardson, D.C., 2015. Biasing moral decisions by exploiting the dynamics of eye gaze. Proc. Natl. Acad. Sci. U. S. A. 112 (13), 4170–4175. https://doi.org/10.1073/pnas.1415250112.

Pisauro, M.A., Fouragnan, E., Retzler, C., Philiastides, M.G., 2017. Neural correlates of evidence accumulation during value-based decisions revealed via simultaneous EEG-fMRI. Nat. Commun. 8, 15808 https://doi.org/10.1038/ncomms15808.

Platt, M.L., Plassmann, H., 2013. Multistage Valuation Signals and Common Neural Currencies. Elsevier Inc. https://doi.org/10.1016/B978-0-12-416008-8.00013-9.

Polanía, R., Woodford, M., Ruff, C.C., 2019. Efficient coding of subjective value. Nat. Neurosci. 22 (1), 134–142. https://doi.org/10.1038/s41593-018-0292-0.

Rangel, A., Camerer, C., Montague, P.R., 2008. A framework for studying the neurobiology of value-based decision making. Nat. Rev. Neurosci. 9 (7), 545–556. https://doi.org/10.1038/nrn2357.

Renkewitz, F., Jahn, G., 2012. Memory indexing : a novel method for tracing memory processes in complex cognitive tasks. J. Exp. Psychol. Learn. Mem. Cognit. 38 (6), 1622–1639.

Richardson, D.C., Spivey, M.J., 2000. Representation, space and Hollywood Squares: looking at things that aren't there anymore. Cognition 76 (3), 269–295. https://doi.org/10.1016/S0010-0277(00)00084-6.

Rolls, E.T., 2000. The orbitofrontal cortex and reward. Cerebr. Cortex 10 (3), 284–294. https://doi.org/10.1093/cercor/10.3.284.

Rushworth, M.F., Kolling, N., Sallet, J., Mars, R.B., 2012. Valuation and decision-making in frontal cortex: one or many serial or parallel systems? Curr. Opin. Neurobiol. 22 (6), 946–955. https://doi.org/10.1016/j.conb.2012.04.011.

Rushworth, M.F., Noonan, M.A.P., Boorman, E.D., Walton, M.E., Behrens, T.E., 2011. Frontal cortex and reward-guided learning and decision-making. Neuron 70 (6), 1054–1069. https://doi.org/10.1016/j.neuron.2011.05.014.

Samuelson, P.A., 1937. A note on measurement of utility. Rev. Econ. Stud. 4 (2), 155–161. https://doi.org/10.2307/2967612.

Scholz, A., Helversen, B.V., Rieskamp, J., 2015. Eye movements reveal memory processes during similarity- and rule-based decision making. Cognition 136, 228–246. https://doi.org/10.1016/j.cognition.2014.11.019.

Scholz, A., Mehlhorn, K., Bocklisch, F., Krems, J., 2011. Looking at nothing diminishes with practice. Proc. Ann. Meet. Cognit. Sci. Soc. 33 (33).

Schwarze, U., Bingel, U., Badre, D., Sommer, T., 2013. Ventral striatal activity correlates with memory confidence for old- and new-responses in a difficult recognition test. PLoS One 8 (3), 2–8. https://doi.org/10.1371/journal.pone.0054324.

Seamans, J.K., Floresco, S.B., Phillips, A.G., 1995. Functional differences between the prelimbic and anterior cingulate regions of the rat prefrontal cortex. Behav. Neurosci. 109 (6), 1063–1073. https://doi.org/10.1037/0735-7044.109.6.1063.

Sestieri, C., Tosoni, A., Mignogna, V., Mcavoy, M.P., Shulman, G.L., Corbetta, M., Romani, G.L., 2014. Memory accumulation mechanisms in human cortex are independent of motor intentions. J. Neurosci. 34 (20), 6993–7006. https://doi.org/10.1523/JNEUROSCI.3911-13.2014.

Shadlen, M.N., Kiani, R., 2013. Decision making as a window on cognition. Neuron 80 (3), 791–806. https://doi.org/10.1016/j.neuron.2013.10.047.

Shadlen, M.N., Shohamy, D., 2016. Decision making and sequential sampling from memory. Neuron 90 (5), 927–939. https://doi.org/10.1016/j.neuron.2016.04.036.

Shohamy, D., Daw, N.D., 2015. Integrating memories to guide decisions. Curr. Opin. Behav. Sci. 5, 85–90. https://doi.org/10.1016/j.cobeha.2015.08.010.

Shteingart, H., Neiman, T., Loewenstein, Y., 2013. The role of first impression in operant learning. J. Exp. Psychol. Gen. 142 (2), 476–488. https://doi.org/10.1037/a0029550.

Siew, C.S.Q., Wulff, D.U., Beckage, N.M., Kenett, Y.N., 2019. Cognitive Network Science : A Review of Research on Cognition through the Lens of Network Representations, Processes, and Dynamics. Complexity, 2019.

Simon, H., 1956. Rational choice and the structure of the environment. Psychol. Rev. 63 (2).

Spektor, M.S., Bhatia, S., Gluth, S., 2021. The elusiveness of context effects in decision making. Trends Cognit. Sci. https://doi.org/10.1016/j.tics.2021.07.011.

Squire, L.R., Wixted, J.T., 2011. The cognitive neuroscience of human memory since H. M. Annu. Rev. Neurosci. 34, 259–288. https://doi.org/10.1146/annurev-neuro-061010-113720.

St-Amand, D., Sheldon, S., Otto, A.R., 2018. Modulating episodic memory alters risk preference during decision-making. J. Cognit. Neurosci. 30 (10), 1433–1441. https://doi.org/10.1162/jocn_a_01253.

Stewart, N., Chater, N., Brown, G.D., 2006. Decision by sampling. Cognit. Psychol. 53 (1), 1–26. https://doi.org/10.1016/j.cogpsych.2005.10.003.

Stewart, N., Gachter, S., Noguchi, T., Mullett, T.L., 2016. Eye movements in strategic choice. J. Behav. Decis. Making 29 (2–3), 137–156. https://doi.org/10.1002/bdm.1901.

Suri, G., Gross, J.J., McClelland, J.L., 2020. Value-Based decision making: an interactive activation perspective. Psychol. Rev. 127 (2), 153–185. https://doi.org/10.1037/rev0000164.

Thomas, A.W., Molter, F., Krajbich, I., Heekeren, H.R., Mohr, P.N.C., 2019. Gaze bias differences capture individual choice behaviour. Nat. Human Behav. 3, 625–635. https://doi.org/10.1038/s41562-019-0584-8.

Tversky, A., Kahneman, D., 1981. The framing of decisions and the psychology of choice. Science 211 (4481), 453–458. https://doi.org/10.1126/science.7455683.

Vaidya, A.R., Fellows, L.K., 2020. Under construction: ventral and lateral frontal lobe contributions to value-based decision-making and learning. F1000Research 9, 158. https://doi.org/10.12688/f1000research.21946.1.

Viscusi, W.K., Magat, W.A., 1992. Bayesian decisions with ambiguous belief aversion. J. Risk Uncertain. 5 (4), 371–387. https://doi.org/10.1007/BF00122576.

von Neumann, J., Morgenstern, O., 1953. Theory of Games and Economic Behavior, third ed. Princeton University Press.

Wagner, A.D., Shannon, B.J., Kahn, I., Buckner, R.L., 2005. Parietal lobe contributions to episodic memory retrieval. Trends Cognit. Sci. 9 (9), 445–453. https://doi.org/10.1016/j.tics.2005.07.001.

Weber, E.U., Johnson, E.J., 2006. Constructing preferences from memory. In: Lichtenstein, InS., Slovic, P. (Eds.), The Construction of Preference. Cambridge University Press, pp. 397–410.

Weilbacher, R.A., Gluth, S., 2017. The interplay of hippocampus and ventromedial prefrontal cortex in memory-based decision making. Brain Sci. 7 (1) https://doi.org/10.3390/brainsci7010004.

Weilbacher, R.A., Kraemer, P.M., Gluth, S., 2020. The reflection effect in memory-based decisions. Psychol. Sci. 31 (11), 1439–1451. https://doi.org/10.1177/0956797620956315.

Weilbacher, R.A., Krajbich, I., Rieskamp, J., Gluth, S., 2021. The influence of visual attention on memory-based preferential choice. Cognition 215 (August 2020), 104804. https://doi.org/10.1016/j.cognition.2021.104804.

Westbrook, A., van den Bosch, R., Maatta, J.I., Hofmans, L., Papadopetraki, D., Cools, R., Frank, M.J., 2020. Dopamine promotes cognitive effort by biasing the benefits versus costs of cognitive work. Science 367 (6484), 1362–1366. https://doi.org/10.1126/science.aaz5891.

Wheeler, M.A., Stuss, D.T., Tulving, E., 1997. Toward a Theory of Episodic Memory: the Frontal Lobes and Autonoetic Consciousness. https://doi.org/10.1037//0033-2909.121.3.331.

Wimmer, G.E., Shohamy, D., 2012. Preference by association: how memory mechanisms in the hippocampus bias decisions. Science 338 (6104), 270–273.

Yoo, S.B.M., Hayden, B.Y., 2018. Economic choice as an untangling of options into actions. Neuron 99 (3), 434–447. https://doi.org/10.1016/j.neuron.2018.06.038.

Zhang, Z., Wang, S., Good, M., Hristova, S., Kayser, A.S., Hsu, M., 2021. Retrieval-constrained valuation: toward prediction of open-ended decisions. Proc. Natl. Acad. Sci. Unit. States Am. 118 (20), e2022685118 https://doi.org/10.1073/pnas.2022685118.

Zhao, W.J., Richie, R., Bhatia, S., 2021. Process and Content in Decisions from Memory. https://doi.org/10.31234/osf.io/nwxs2. *Preprint*.

A.2 Manuscript 2: Response time models separate single- and dual-process accounts of memory-based decisions

Psychonomic Bulletin and Review (2021) 28:304–323
https://doi.org/10.3758/s13423-020-01794-9

BRIEF REPORT

Response time models separate single- and dual-process accounts of memory-based decisions

Peter M. Kraemer[1] · **Laura Fontanesi**[1] · **Mikhail S. Spektor**[2,3] · **Sebastian Gluth**[1]

Abstract

Human decisions often deviate from economic rationality and are influenced by cognitive biases. One such bias is the *memory bias* according to which people prefer choice options they have a better memory of—even when the options' utilities are comparatively low. Although this phenomenon is well supported empirically, its cognitive foundation remains elusive. Here we test two conceivable computational accounts of the memory bias against each other. On the one hand, a single-process account explains the memory bias by assuming a single biased evidence-accumulation process in favor of remembered options. On the contrary, a dual-process account posits that some decisions are driven by a purely memory-driven process and others by a utility-maximizing one. We show that both accounts are indistinguishable based on choices alone as they make similar predictions with respect to the memory bias. However, they make qualitatively different predictions about response times. We tested the qualitative and quantitative predictions of both accounts on behavioral data from a memory-based decision-making task. Our results show that a single-process account provides a better account of the data, both qualitatively and quantitatively. In addition to deepening our understanding of memory-based decision-making, our study provides an example of how to rigorously compare single- versus dual-process models using empirical data and hierarchical Bayesian parameter estimation methods.

Keywords Judgment · Decision making

Introduction

Many decisions in our daily lives, such as where to go on holiday or what to buy in a grocery store, rely on information from memory. Although the role of memory processes in judgements and decision-making has been neglected for a long time, researchers have recently put more emphasis on the relation of these two domains (Shadlen & Shohamy, 2016; Weilbächer & Gluth, 2017). For example, recent studies focused on how memory, by playing a role in the evaluation process, can contribute to violations of standard economic theories of decision-making (Weber & Johnson, 2006).

Gluth et al. (2015) showed one of such violations in a decision-making task in which the subjective value (utility) of the options had to be recalled from memory. In this paradigm, individuals first learn to associate different snacks with specific locations. Afterward, they choose between two locations and therefore need to remember to which snacks the two locations were associated with (see Fig. 1). The authors reported that participants tended to prefer remembered snacks over forgotten snacks, even when the subjective value of the former was lower than average (and thus more likely to be lower than the forgotten option's subjective value). The authors referred to this effect as the *memory bias*. Using functional magnetic resonance imaging (fMRI), Gluth et al. (2015) further showed that this tendency was mediated by an increased effective connectivity from the hippocampus to the ventromedial prefrontal cortex. Since these areas are typically associated with memory and value-based decisions, respectively, the fMRI results supported the idea that memory processes exert a biasing influence on valuation and choice processes. Follow-up studies replicated the memory bias and found that it was partly driven by beliefs about the dependency of memory

---

✉ Peter M. Kraemer
peter.kraemer@unibas.ch

[1] Department of Psychology, University of Basel, Missionsstrasse 62a, 4055 Basel, Switzerland

[2] Universitat Pompeu Fabra, Ramon Trias Fargas, 25, Barcelona 08005, Spain

[3] Barcelona Graduate School of Economics, Ramon Trias Fargas, 25, Barcelona, 08005, Spain

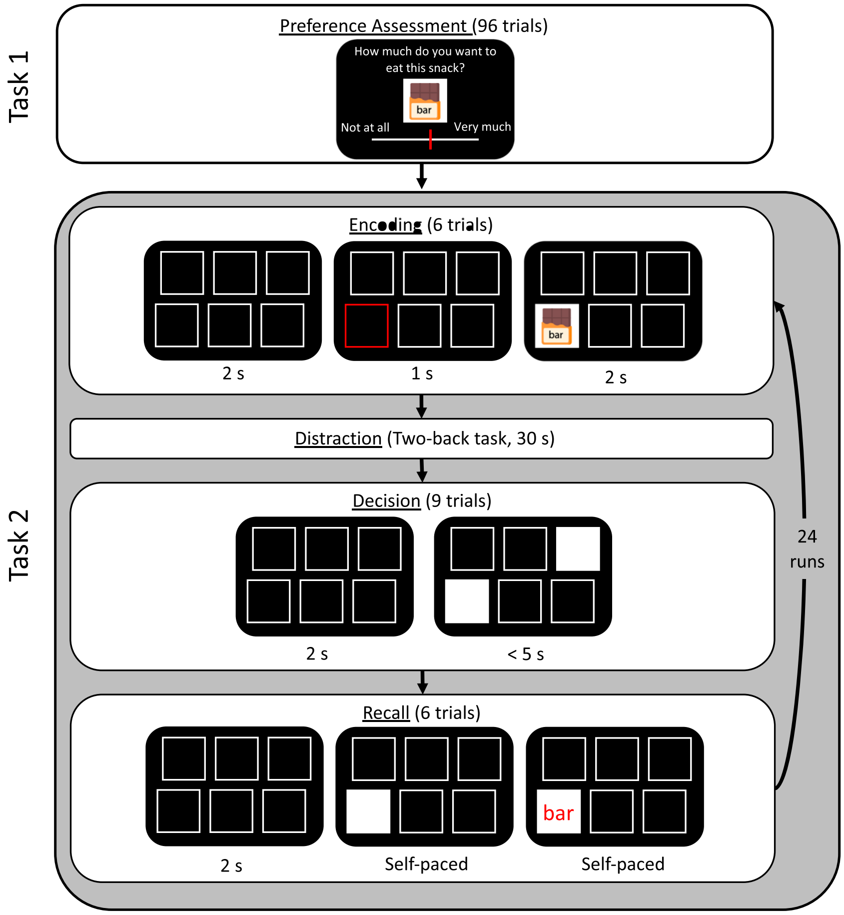


Fig. 1 Experiment on memory-based decision-making. During task 1, participants rated their subjective value for all snacks. Task 2 was the remember-and-decide task which comprised four phases: encoding, distraction, decision and recall. Here, we show one example trial per phase. During encoding, participants associated snacks with individual locations. The distraction phase contained a 2-back task with integers. In the decision phase, they retrieved snack-location associations from memory and made preferential choices between snacks. During recall, participants indicated which snack they associated with each location. Note that this is a simplified depiction of the experiment. For a full overview, see Mechera-Ostrovsky and Gluth (2018)

strength on utility (Mechera-Ostrovsky & Gluth, 2018), and that it exhibited typical characteristics of decisions under uncertainty (Weilbächer et al., in press).

Gluth et al. (2015) proposed a computational model that assumes people to choose between a remembered and a forgotten option by comparing the remembered option's value against a reference value. If this reference value is below the average snack value, the model predicts that people are more likely to choose remembered options, leading to the memory bias. Critically, this account assumes that all decisions between a remembered and a forgotten option result from the very same comparison-against-reference-value process. Therefore, it is a *single-process account* of the memory bias. Gluth et al. (2015)'s account of the memory bias is thus in stark contrast to dual-process theories (Kahneman & Frederick, 2002; Evans, 2008). Dual-process models assume that decisions are driven by two independent processes (so-called "type 1" and "type 2" processes) (Evans & Stanovich, 2013). Type 1 processes are described as intuitive processes that lead to relatively fast, automatic, and uncontrollable choices. Type 2 processes, on the other hand, are controlled, deliberate processes that lead to slower responses that are closer to normative predictions. Type 2 processes are thus viewed as rational processes (but see Oaksford & Hall, 2016). Such a *dual-process account* explains the memory bias as follows: In some cases, people make a decision based on a type 1 process which leads them to choose the option they remember better–intuitively and independently of its subjective value. In other cases, they make a decision based on a type 2 process. The type 2 process implements an unbiased choice, based on a cognitively demanding decision process that takes the subjective value of the remembered option into account in a rational (i.e., utility-maximizing) way.

As we will show, both single- and dual-process accounts can produce the memory bias on choice. Thus, we face a model-selection problem: Two models can account for the same behavioral phenomenon, but the assumed underlying cognitive processes are fundamentally different. To find out which model is more suitable to explain the memory bias, we consider an additional data dimension, namely response times (RTs). The consideration of RTs has a rich tradition in psychological research, since they contain information about the underlying cognitive processes (Luce, 1986). Additionally, RTs can aid model selection (Ballard & McClure, 2019; Gluth & Meiran, 2019; Wilson & Collins, 2019). Critically, we will show that although the single- and dual-process accounts can make similar predictions on choice behavior, they differ with respect to RTs. Therefore, considering both dimensions, choices and RTs, aids to resolve the present model-selection problem.

Joint modeling of choices and RTs is often done in the framework of sequential-sampling (or evidence-accumulation) models (Bogacz et al., 2006). A popular sequential-sampling model is the diffusion decision model (DDM) (Ratcliff, 1978; Ratcliff & Rouder, 1998). In a nutshell, the DDM describes a decision between two options as an accumulation of noisy, relative evidence over time (see also Fig. 2). Evidence, in the current task, represents the information regarding an option's subjective value that is recalled from memory. The accumulation process ends when the relative evidence for one or the other option surpasses a certain threshold. At that point, the decision is made. The accumulation process can also be biased towards one of the two options already at the beginning of a trial. The rate of evidence accumulation is referred to as the drift rate of the decision process. The higher the drift rate towards a specific option, the more often that option is chosen and the faster the decision. On the other side, the threshold controls how cautiously decisions are made. The higher the threshold, the slower and more consistent the decisions are.

Over the years, the DDM has been applied successfully to processes of memory retrieval and perceptual decision-making (Ratcliff et al., 2016), but researchers also adapted it to value-based decisions (for recent overviews see Busemeyer et al., (2019) and Clithero, 2018). Importantly, Gluth et al. (2015) used the DDM as the basis of their single-process account of memory-based decisions. Within their model,the memory bias results from abiased reference value for forgotten options, which influences the drift rate of the decision process. In recent years, novel evidence-accumulation models were developed to reflect ideas from dual-process theories of decision-making (Diederich & Trueblood, 2018; Alós-Ferrer, 2018). In particular, the dual-process diffusion model by Alós-Ferrer provided a suitable account of a range of phenomena from judgment and decision-making tasks. The model assumes two independent decision processes: a type 1-like heuristic process and a type 2-like utility-maximizing process. Since both the single- and dual-process accounts operate within the same framework (i.e., the DDM), it is possible to rigorously evaluate which of the two accounts better explains the memory bias.

In the present study, we first derived choice and RT predictions of a single- and a dual-process DDM in the context of memory-based decisions. Next, we compared the different qualitative predictions of these models with the actual RT data from a comparatively large sample of participants who performed the remember-and-decide task (Mechera-Ostrovsky & Gluth, 2018). Finally, we conducted a quantitative model comparison within a hierarchical Bayesian parameter estimation framework. Both our qualitative and quantitative comparisons lend consistent support for the single-process account, thus strengthening our knowledge of the computational cognitive basis of value-based decisions from memory.

Methods

Participants

We analyzed data from a previously published study (Mechera-Ostrovsky & Gluth, 2018). In total, 96 participants (67 female, mean age = 23.5, age range: [19, 35]) took

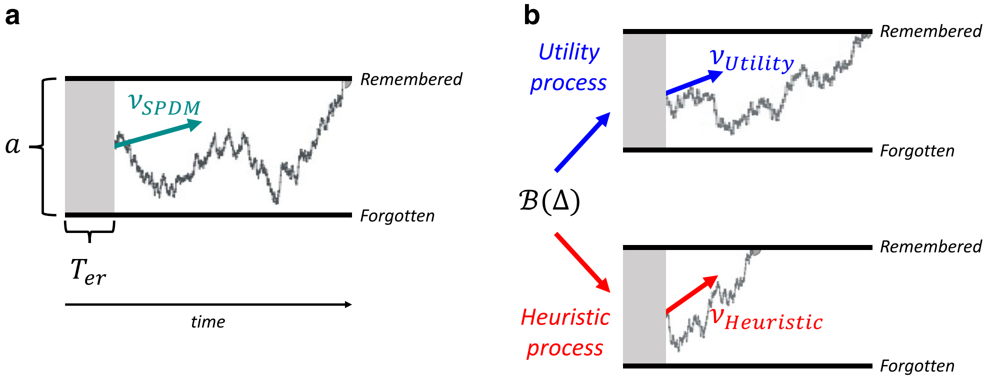


Fig. 2 Diffusion decision models. **a** Diffusion process of the single-process account. Evidence for an option accumulates over time with a rate of ν_{SPDM} until the threshold (boundary) for one choice option (remembered or forgotten) is reached. The boundary separation depends on the parameter a, and T_{er} depicts the non-decision time. **b** The dual-process account assumes two diffusion processes with different drift rates ($\nu_{Utility}$ and $\nu_{Heuristic}$). A Bernoulli trial based on the parameter Δ selects either the utility or the heuristic diffusion process

part in that study. Due to early termination and age restrictions, the data from six participants were not analyzed. The participants were students who took part in the study for course credits. The procedure was approved by the ethics committee of the University of Basel and all participants gave written informed consent.

Procedures

The full experimental procedure is described in Mechera-Ostrovsky and Gluth (2018). Here, we summarize the procedures relevant to the present research question. Participants were required to fast for four hours before the experiment started. They familiarized themselves with a set of 48 snacks. For each snack, they learned intuitive three-letter abbreviations (e.g., “sni” for “Snickers”) until they reached 100% accuracy. Participants’ subjective valuation of each snack was assessed on a continuous rating scale (Fig. 1). This evaluation was incentivized by selecting two snacks randomly at the end of the experiment and giving the higher-rated snack to the participant to eat.

After eliciting subjective valuations, participants faced the remember-and-decide task which consisted of the four periods encoding, distraction, decision, and recall (in that order). During encoding, participants saw empty squares at six different locations on the screen. One after another, each location was highlighted, and a snack image appeared in the respective square. Participants had to associate and remember which snack was located in which square. During the distraction period, participants performed a 2-back working memory task that prevented them from rehearsing the information obtained in the encoding phase. During the decision period, the six squares were presented again and, in each trial, two squares were highlighted. Participants picked one of the two snacks hidden behind the empty squares. Since the snack identity was not visually accessible, they had to retrieve it from memory to make an informed choice. During recall, the snack-location associations were probed to assess memory strength for each snack location.

Data preprocessing

First, we excluded trials that were unlikely to originate from a deliberate process: In particular, we excluded trials in which no choice was made (2.0%) and in which RTs were lower than 200 ms (1.4%). We then excluded trials that do not help to discriminate between single- and dual-process accounts: In particular, both accounts make the same predictions for behavior in trials in which both options are remembered or both options are forgotten. Therefore, we restricted our analyses to trials where one snack was remembered and the other was forgotten. This resulted in a total of 8031 trials (on average 89.2 trials per participant, $SD = 15.80$, range: [39, 118]). See Appendix A1 for more information on the trial types and Appendix B3 for analyses including all trial types.

Cognitive models

The diffusion decision model

In its original form, the DDM predicts choices and RTs using four parameters (Ratcliff, 1978). First, the boundary separation a determines the (relative) amount of evidence required to terminate the deliberation process. This parameter is responsible for speed–accuracy tradeoffs. Second, the starting-point bias z determines the amount of relative evidence at the beginning of the deliberation process. This parameter reflects prior information or a bias in favor of one of the options. Third, the drift rate ν determines the speed of evidence accumulation. In value-based decision-making, the drift rate is often directly proportional to the value difference between the two available options (e.g., Krajbich et al., 2010). The stronger the value difference, the higher the drift rate, making choices both faster and more frequently in favor of the option the drift rate is directed to. Analogously, small differences of values imply a low drift rate and thus higher RTs and less frequent choices in the direction of the drift rate. Finally, the non-decision time T_{er} absorbs every process that is not part of the deliberation process, such as the time it takes to execute the button press or to visually encode the stimuli.

Single-process account

According to Gluth et al. (2015)’s model of the memory bias, participants compare the subjective value of the remembered snack with a reference value. Thus, the drift rate depends on a comparison process such that

$$\nu_{SPDM} = V_{rem} - \gamma, \tag{1}$$

where ν_{SPDM} is the drift rate, V_{rem} is the subjective value of the remembered option and γ is the reference value. Here, a single evaluation process gives rise to the memory bias in every trial. This is why we refer to the model as a single-process diffusion model (SPDM). An example of a diffusion process is depicted in Fig. 2a.

Importantly, Gluth et al. (2015) argued that—assuming that memory strength is independent of value—this reference value should be unbiased (i.e., equal to the mean of all options) in order to maximize utility. When estimating it as a free parameter, however, the reference value was found to be biased such that remembered options appeared to be more valuable, even if they were comparatively unattractive.

Dual-process account

To model the dual-process account, we adopted the dual-process diffusion model (DPDM) by Alós-Ferrer (2018). The DPDM assumes that people vary between two types of choice strategies across trials (see Fig. 2b). In some trials, people use a *utility process* which captures "computational-normative aspects of decision-making" (p. 203). In other trials, a *heuristic process* favors "intuitive-affective attributes" (ibid) of a choice option with a relatively high drift rate, leading to fast and more consistent responses. The selection of a process in a given trial is supposedly governed by the central executive. It selects the utility process with the probability Δ and the heuristic process with $1 - \Delta$. The drift rate of the DPDM in a given trial is given by

$$\nu_{DPDM} = \begin{cases} \nu_{Utility}, & \text{if } k = 1 \\ \nu_{Heuristic}, & \text{if } k = 0 \end{cases} \tag{2}$$

where k is the outcome of a Bernoulli trial $\mathcal{B}(\Delta)$.

In the context of memory-based decisions in the remember-and-decide task, we propose that $\nu_{Utility}$ reflects the utility-maximizing process in which V_{rem} is compared to the (unbiased) average snack value of all possible snacks V_{avg}. Thus, the cognitively demanding utility process tends to select the option with the higher subjective utility without a bias towards the remembered option. If individuals do not follow the utility-maximizing process, they rely on a simple decision rule to make a choice. In the context of memory-based decisions, they can use recognition as a cue for value, much in line with the recognition heuristic in judgment tasks (Goldstein & Gigerenzer, 2002) (see also Discussion). In the diffusion-model framework, $\nu_{Heuristic}$ reflects the drift rate of the heuristic process that favors the choice of a snack, because it can be recalled correctly. Importantly, $\nu_{Heuristic}$ is independent of the snack's subjective value.

Qualitative predictions

The SPDM and DPDM can make very similar predictions regarding choices, but they differ significantly with respect to their predictions of RTs.

Previous research (e.g., Bogacz et al., 2006) showed that, in a simplified version of the DDM (i.e., without the starting-point bias and without across-trial variability in any of the parameters), choices of option A over B are related to the DDM parameters as

$$P(\text{choose A}|\nu, a, \sigma) = 1 - \frac{1}{1 + e^{\frac{2\nu a}{\sigma^2}}}, \tag{3}$$

where ν is the drift rate, a is the boundary separation, and σ is the noise of the drift process. If $\nu \to \infty$, participants are more likely to select option A and, conversely, if $\nu \to -\infty$, participants are more likely to choose option B. If $\nu = 0$, participants are indifferent between A and B.

The expected RTs under the DDM are given by

$$\begin{aligned} RT &= T_{er} + DT, \\ DT(\nu, a, \sigma) &= \frac{a}{\nu} \tanh\left(\frac{\nu a}{\sigma^2}\right), \end{aligned} \tag{4}$$

where T_{er} is the non-decision time and DT is the mean decision time as a function of the diffusion parameters (Bogacz et al., 2006). The DDM typically predicts an inverted U-shaped curve of the average RTs as a function of the drift: The expected RTs are slow when the speed of evidence accumulation is low ($\nu = 0$) and fast when the speed of evidence accumulation is high ($\nu \to \pm\infty$).

In the SPDM, the drift rate depends on V_{rem} and on the reference value γ (see Eq. 1), such that $\nu = 0$ when $V_{rem} = \gamma$. Accordingly, the SPDM assumes participants to be indifferent between choice options whenever $V_{rem} = \gamma$. This is reflected in a sigmoidal choice-probability curve with its indifference point at a negative V_{rem} value (Fig. 3b, green, continuous line). Such a curve was shown to reflect the memory bias (Gluth et al., 2015) and was found in the choice data used in the present study (see Mechera-Ostrovsky & Gluth, 2018). Furthermore, the SPDM assumes that the RTs follow an inverted U-shape with its peak at a negative V_{rem} value (Fig. 3d, green, continuous line).

The DPDM assumes two drift rates of two independent diffusion processes, only one of which is selected in a given trial. On utility trials, individuals use a utility-maximizing strategy so that $\nu_{Utility} = V_{rem} - V_{avg}$, leading to $\nu_{Utility} = 0$ when $V_{rem} = V_{avg}$. This is illustrated in Fig. 3a (blue, dashed line), where the sigmoidal choice curve of the utility process has its indifference point at a $V_{rem} = 0$, which corresponds to the average value of all snacks. Accordingly, the RT curve follows an inverted U-shape with its maximum at $V_{rem} = V_{avg}$ (Fig. 3c, blue, dashed line). In heuristic trials, the heuristic process accumulates evidence in favor of the remembered option, independently of its actual value. Since $\nu_{Heuristic}$ is independent of V_{rem}, the choices and RTs are also independent of V_{rem} (Fig. 3a/c, red, dotted lines). The full predictions of the DPDM (Fig. 3b/d, purple, dash-dotted lines) will be a mixture of the predictions of its two sub-processes, depending on the mixture parameter Δ.

Crucially, the DPDM is virtually indistinguishable from the SPDM on the level of choices alone: The choice curves are shifted to the left, such that its indifference point is at a negative V_{rem} value. However, since the expected RT curve of the heuristic process is independent of V_{rem}, the peak of the RT curve across all trials only depends on the utility process. Therefore, the RT curve of the DPDM follows an inverted U-shape with its peak expected RT at $V_{rem} = V_{avg}$ (for a mathematical proof, see Appendix A2). In sum, while

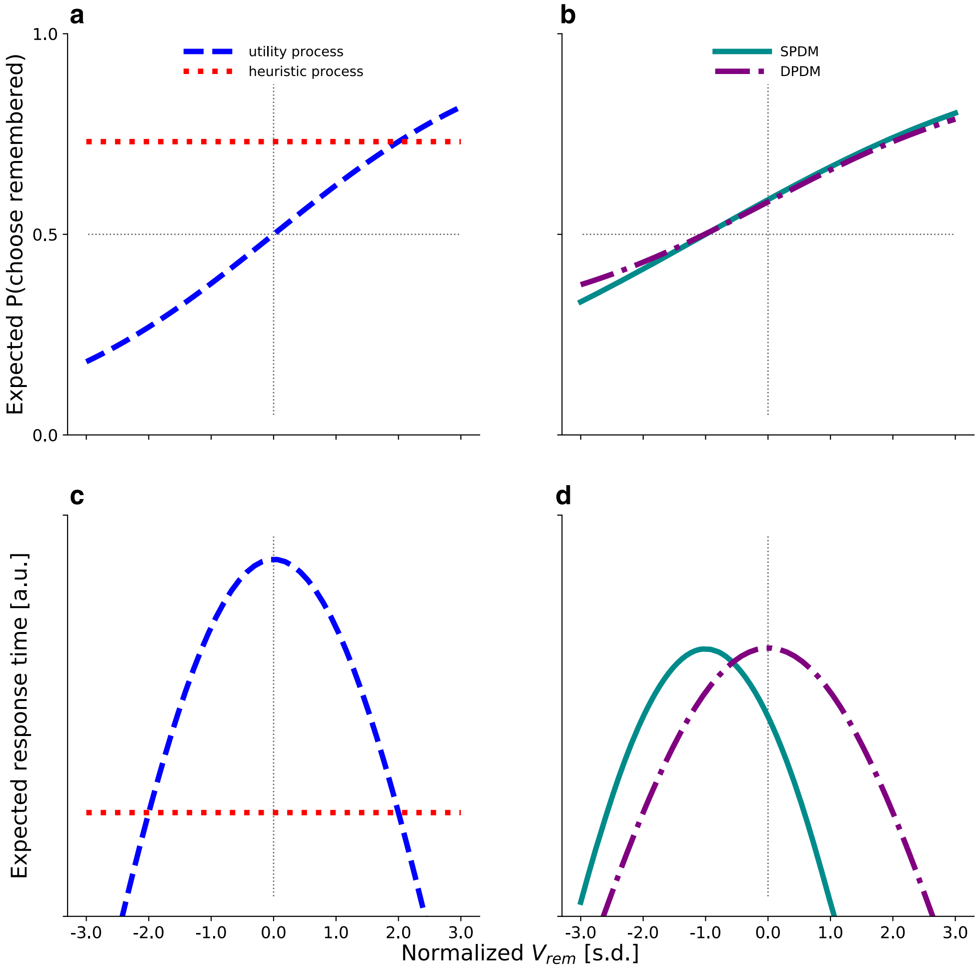


Fig. 3 Qualitative predictions. **a** Expected choice curves of the utility process (*blue*, *dashed*) and the heuristic process (*red*, *dotted*) as a function of the value of the remembered snack V_{rem}. **b** The weighted average of the two curves in **A** results in the expected choice curve of the DPDM (*purple*, *dashed-dotted*), which is depicted along with the expected curve for the SPDM (*cyan*, *solid*). **c** Expected RT curves for the utility and heuristic process. **d** Expected RT curves for the SPDM and DPDM

the SPDM and the DPDM cannot be distinguished based on the choice patterns, they can be distinguished based on their different predictions of RTs.

Testing qualitative predictions

As outlined in the previous section, single- and dual-process accounts predict different RTs patterns. More specifically, the DPDM assumes that the RT curve peaks at $V_{rem} = V_{avg}$, whereas the SPDM peaks at $V_{rem} = \gamma$, where $\gamma < V_{avg}$. To test which of these assumptions is supported by the data, we fitted a quadratic function to the RT data:

$$RT(V_{rem}) = \beta_0 + \beta_1 \times (V_{rem} + \beta_2)^2 \qquad (5)$$

This regression model describes a quadratic function with intercept β_0 and slope β_1. The term $(V_{rem} + \beta_2)^2$ shifts the maximum RT along the x-axis. If β_2 equals zero, the curve is symmetrical around V_{avg} which matches the RT predictions of the DPDM. If β_2 is larger than 0, the RT curve is shifted to the left, in line with the SPDM.

To estimate the β_2 parameter, we fitted a hierarchical Bayesian regression model to the log-transformed and z-standardized RTs. RTs of every trial were predicted using V_{rem_t}, individual β parameters, and Gaussian noise. The individual-level β parameters (denoted by subscript s) were drawn from group-level normal distributions:

$$\begin{aligned}
\beta_{0,s} &\sim \mathcal{N}(\mu_{\beta_0}, \sigma_{\beta_0}),\\
\beta_{1,s} &\sim \mathcal{N}(\mu_{\beta_1}, \sigma_{\beta_1}),\\
\beta_{2,s} &\sim \mathcal{N}(\mu_{\beta_2}, \sigma_{\beta_2}). \qquad (6)
\end{aligned}$$

At the group-level, all prior distributions were standard normal (for the μ parameters) and standard half-normal (for the σ parameters) distributions.

We leveraged the fact that, in case of the qualitative RT model, the DPDM's prediction is nested within the SPDM's prediction with the restriction $\mu_{\beta_2} = 0$. We applied a

Gaussian kernel density estimation (with a bandwidth of .1) to the posterior samples of μ_{β_2} and obtained a Bayes factor using the Savage–Dickey density ratio test (e.g., Lee & Wagenmakers, 2013).

Importantly, the SPDM does not only predict a shift to the left in both the choice and the RT curves (see Fig. 3b and d), but it also assumes that these shifts arise from the same process. Therefore, these two shifts of choice and RT curves should be related to each other. To test this relationship, we quantified the *memory bias on choice* as the intercept parameter of a hierarchical logistic regression model. When this parameter is larger than 0, the choice curve shifts in favor of the remembered option. Analogously, we interpret the β_2 parameter as *memory bias on response times*. To assess whether participants who exhibit a larger memory bias on choices also show a larger memory bias on RTs, we performed a Bayesian correlation analysis on the individual-level posterior medians of the intercept and β_{2_s} parameters.

Quantitative model comparison via hierarchical Bayesian modeling

In addition to comparing their qualitative predictions, we performed a quantitative model comparison using a hierarchical Bayesian approach. This comparison offers a more precise evaluation of the validity of the assumed cognitive processes. To the best of our knowledge, the DPDM (Alós-Ferrer, 2018) has only been used to derive qualitative predictions so far. Therefore, we consider our model comparison as providing a principled way of gauging the DPDM's quantitative adequacy.

SPDM

In the SPDM, choice and RT data come from a diffusion process that results in a Wiener distribution:

$$y \sim Wiener(a, z, T_{er}, \nu). \tag{7}$$

In the hierarchical model, the subject-specific parameters (denoted by subscript s) are drawn from normal group-level distributions with respective group-level parameters μ and σ (hyper priors are listed in Appendix B1). Boundary separation a_s, starting point bias z_s and non-decision time T_{er_s} were estimated as

$$\begin{aligned} a_s &\sim e^{\mathcal{N}(\mu_a, \sigma_a)}, \\ z_s &\sim \Phi(\mathcal{N}(\mu_z, \sigma_z)), \\ T_{er_s} &\sim e^{\mathcal{N}(\mu_{T_{er}}, \sigma_{T_{er}})}, \end{aligned} \tag{8}$$

where Φ denotes the cumulative distribution function of the standard normal. The drift rate parameter ν varies from trial to trial (subscript t) as follows:

$$\begin{aligned} \nu_{s,t} &= d_{SPDM_s}[Rem_{right_{s,t}} \times (V_{right_{s,t}} - \gamma_s) - Rem_{left_{s,t}} \\ &\quad \times (V_{left_{s,t}} - \gamma_s)], \\ d_{SPDM_s} &\sim e^{\mathcal{N}(\mu_{d_{SPDM}}, \sigma_{d_{SPDM}})}, \\ \gamma_s &\sim \mathcal{N}(\mu_\gamma, \sigma_\gamma), \end{aligned} \tag{9}$$

where $Rem_{right_{s,t}}$ ($Rem_{left_{s,t}}$) are dummy variables, indicating whether the right (left) snack was remembered, and $V_{right_{s,t}}$ ($V_{left_{s,t}}$) indicating the subjective value of the right (left) snack. d_{SPDM_s} is a free parameter which scales value differences to the speed of evidence accumulation. γ was the parameter which acts as reference value, indicating the biased value comparison in the SPDM.

DPDM

The DPDM is a mixture model, where the choices and RTs come from two different diffusion processes:

$$\begin{aligned} & y \sim \Delta \times Wiener(a, z, T_{er}, \nu_{Utility}) + (1 - \Delta) \\ & \times Wiener(a, z, T_{er}, \nu_{Heuristic}), \\ & \Delta_s \sim \Phi(\mathcal{N}(\mu_\Delta, \sigma_\Delta)). \end{aligned} \tag{10}$$

The mixing parameter Δ indicates the proportion of trials in which the response was generated by the utility process.

While both processes share the same parameters a, z and T_{er}, they differ with respect to their drift rates $\nu_{Utility}$ and $\nu_{Heuristic}$. $\nu_{Utility}$ is the same as in the SPDM but compares V_{rem} to the average snack value (V_{avg_s}) instead of γ.

$$\begin{aligned} \nu_{Utility_{s,t}} &= d_{Utility_s}[Rem_{right_{s,t}} \times (V_{right_{s,t}} - V_{avg_s}) \\ &\quad - Rem_{left_{s,t}} \times (V_{left_{s,t}} - V_{avg_s})], \\ &\quad d_{Utility_s} \sim e^{\mathcal{N}(\mu_{d_{Utility}}, \sigma_{d_{Utility}})}. \end{aligned} \tag{11}$$

The drift rate of the heuristic process is a free parameter:

$$\begin{aligned} \nu_{Heuristic_{s,t}} &= d_{Heuristic_s}[Rem_{right_{s,t}} - Rem_{left_{s,t}}], \\ d_{Heuristic_s} &\sim e^{\mathcal{N}(\mu_{d_{Heuristic}}, \sigma_{d_{Heuristic}}}. \end{aligned} \tag{12}$$

Note that the exponential transformation enforces a positive drift rate in the direction of the remembered option.

Model fitting and model comparison

We estimated the parameters of both hierarchical models with *Stan* (Stan-Development-Team, 2018) using a No-U-Turn sampler (Hoffman & Gelman, 2014). Each model was estimated with four chains of 10,000 iterations each (50% of which were warm-up iterations that were discarded). To ensure model convergence using the $\hat{R}$ statistic (Gelman & Rubin, 1992), we checked that $\hat{R} <= 1.01$ for all parameters. We compared the penalized-for-complexity fit of both models using the widely applicable information criterion (WAIC; Watanabe, 2013).

As all model comparison procedures are relative measures of fit (i.e., they can only assess the model performance relative to other models), we generated posterior predictive distributions for choice rates and RTs as a function of V_{rem} to evaluate absolute model performance (i.e., the degree to which they are able to capture quantitative and qualitative patterns in the empirical data). To do so, we simulated 500 experiments using virtual agents who behaved according to the model equations. Note that in the DPDM simulations, each trial was either a heuristic or utility trial, determined by the outcome of a Bernoulli trial with probability Δ_s. Each agent's parameter vector was drawn randomly from the posterior distribution obtained during model fitting. We aggregated the choices and RTs across trials and participants into 8 bins and calculated the respective 95% highest-density interval (HDI; Kruschke, 2015). Using parameter- and model-recovery analyses we confirmed that both models were able to recover data-generating parameters and that the models make different predictions with respect to behavior such that a data-generating model can be correctly identified (see Appendix B2 for details).

Results

Qualitative results

Our first approach to compare a single- and a dual-process account of memory-based decisions making was to evaluate the qualitative predictions of the respective approaches by fitting a regression model (5) to the RT data. As outlined in the Method section, the single-process account predicts that the RT curve follows an inverted U-shape (as a function of value difference) with its peak at a negative value of V_{rem}. This shift is quantified by the parameter μ_{β_2} (see Eq. 5). In line with this prediction, the posterior distribution of μ_{β_2} was positive and the 95% HDI excluded zero ($M =$ .62, 95% HDI: [.30,.98]). The individual-level means were

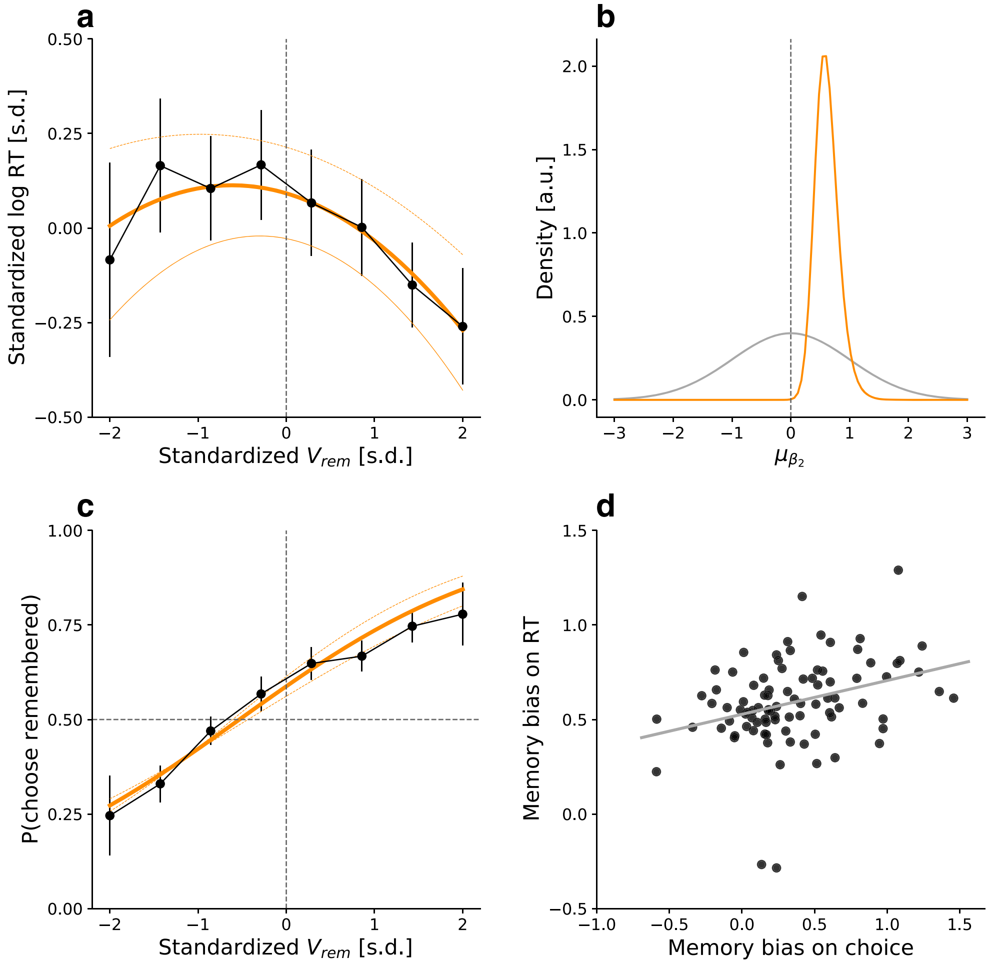


Fig. 4 Qualitative results. **a** Average RTs depending on V_{rem} in *black*. *Error bars* depict the empirical 95% CIs. The *orange curve* yields the predicted RT curves from the RT Model, using the posterior mean. The *dotted curves* indicate the predicted RTs of a 95% highest density interval of the posterior distributions. **b** Prior (*grey*) and posterior (*orange*) parameter distributions of $\mu_{\beta 2}$. **c** Empirical choices (*black*) and the estimated choice curve (*orange*). **d** Correlation of the individual estimates of memory bias on choice, and the memory bias on RT

distributed around the posterior μ_{β_2} with a σ_{β_2} (M = .49, 95% HDI: [.17,.86]). The RT model predicted the empirical RT data very well (Fig. 4a). To directly compare the predictions of the SPDM and the DPDM, we obtained a Bayes factor using the Savage–Dickey density ratio that tested whether μ_{β_2} is different from 0. We obtained very strong evidence in favor of the alternative hypothesis that μ_{β_2} is not 0, with a Bayes factor of 128.9, providing further support for the SPDM model.

Because the single-process account predicts that the memory bias on RT and the memory bias on choice arise from the same underlying process, we also fitted a hierarchical logistic regression model to the individual choice data. The group-level intercept indicated a shift of the choice curve in line with the memory bias on choice (M = .35, 95% HDI: [.25,.46]) and reproduces the non-Bayesian results reported by Mechera-Ostrovsky and Gluth (2018). Figure 4c depicts the predicted choice curve as a function of V_{rem}.

We correlated the medians of the participant level intercept parameter distributions (which reflect the memory bias on choice of each participant) with the β_{2s} parameters of the RT-model (which reflect the memory bias on RT). As predicted, the individual intercepts from the regression model correlated positively with the β_{2s} estimates from the RT-Model (r = .315, 95% HDI: [.12,.49], Fig. 4d). Thus, the shift in the RT curve is associated with the shift in the choice curve, suggesting a common underlying mechanism.

Table 1 Group-level parameter estimates for the single- and dual-process diffusion models.

Model	Parameter	M	95% HDI
SPDM	μ_a	1.77	[1.68, 1.88]
	σ_a	1.30	[1.25, 1.35]
	$\mu_{T_{er}}$	0.29	[0.27, 0.32]
	$\sigma_{T_{er}}$	1.46	[1.38, 1.57]
	μ_z	0.52	[0.51, 0.52]
	σ_z	1.05	[1.03, 1.08]
	$\mu_{d_{SPDM}}$	0.36	[0.31, 0.41]
	$\sigma_{d_{SPDM}}$	1.70	[1.51, 1.93]
	μ_γ	−0.54	[−0.70, −0.39]
	σ_γ	1.82	[1.58, 2.10]
DPDM	μ_a	1.82	[1.73, 1.93]
	σ_a	1.31	[1.26, 1.36]
	$\mu_{T_{er}}$	0.29	[0.26, 0.31]
	$\sigma_{T_{er}}$	1.48	[1.38, 1.57]
	μ_z	0.52	[0.51, 0.52]
	σ_z	1.06	[1.04, 1.09]
	$\mu_{d_{Utility}}$	0.70	[0.55, 0.85]
	$\sigma_{d_{Utility}}$	1.54	[1.30, 1.86]
	$\mu_{d_{Heuristic}}$	0.29	[0.17, 0.48]
	$\sigma_{d_{Heuristic}}$	3.03	[2.03, 4.62]
	μ_Δ	0.55	[0.44, 0.66]
	σ_Δ	1.84	[1.49, 2.32]

Note. M represents the posterior mean. The 95%-HDI depicts the boundaries of the 95% highest-density interval. Note that these values are transformed with respective transformation functions (see main text)

Quantitative results

In addition to the qualitative analysis, we compared the SPDM and the DPDM on a quantitative level by a model comparison within a hierarchical Bayesian framework. Summary statistics of the posterior distributions of all group-level parameters are provided in Table 1.

We relied on the WAIC for model comparison. The SPDM had a lower WAIC than the DPDM (17,394 vs. 17,468), with

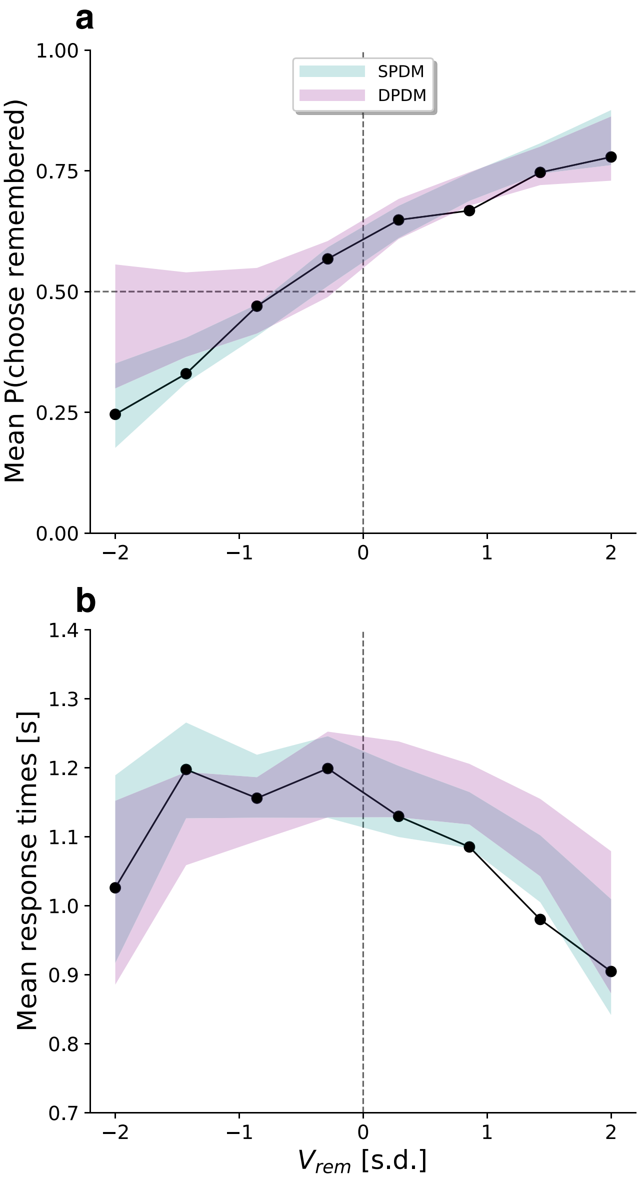


Fig. 5 Posterior predictives. **a** shows the 95% HDI of the means of simulated data sets, based on the estimated posterior parameter distributions of the SPDM (*cyan*) and DPDM (*purple*). The *black dots* indicate the empirical means. **b** shows the same for response times

a difference in WAICs of 74.34 ($SE = 24.74$), resulting in a strong standardized effect size of $\frac{\Delta \text{WAIC}}{SE} = 3.01$.

We performed posterior predictive checks to assess absolute model performance. Both models are capable to produce a shift in the choice curve (see Fig. 5a). However, whereas the SPDM predicts most data points well (i.e., within the 95% HDI), the empirical data often lie outside the 95% HDI of the DPDM, particularly when V_{rem} is low. With respect to RTs, this difference is even stronger (Fig. 5b). Specifically, when V_{rem} was below average, the DPDM underestimated the RTs. When it was above average, it overestimated them. This result is in line with the notion that the DPDM is unable to account for a shifted U-shaped RT curve, as it is forced to predict a curve that is symmetrical around zero. In contrast, the SPDM provides an accurate account of the empirical RT curve. Taken together, both the relative and the absolute model comparisons confirm the qualitative results and provide additional support for a single- and against a dual-process account of memory-based decisions.

Discussion

The present study compared a single- with a dual-process account of memory-based decisions. The single-process account assumes that memory affects the valuation of options, such that better-remembered options are perceived as more valuable. In contrast, the dual-process account assumes that each decision is made by one of two processes, where a rational process competes with a heuristic-based process which ignores value and uses memory-strength information only. While the single-process account was already tested before (Gluth et al., 2015), the dual-process account, implemented on the basis of the DPDM as proposed by Alós-Ferrer (2018), has never been tested in the current context. This study thus provides a first empirical test of these opposing theories on memory-based decisions. We found that both models can make similar predictions with respect to choices but differ regarding their predictions of RTs. Using previously published data from a memory-based choice task (Mechera-Ostrovsky & Gluth, 2018), we found consistent support for the single-process account in both qualitative and quantitative analyses.

Our results bear strong analogies to a debate on the use of the recognition heuristic in inference tasks. The recognition heuristic states that people judge recognized items as being more important / frequent / larger than unrecognized items (Goldstein & Gigerenzer, 2002). Originally, the heuristic was not conceptualized in the framework of dual-process accounts. However, to account for the fact that people do not always go with the recognized cue, it has been argued that the heuristic is applied in some but not all trials (Pachur, 2011). Yet, this proposal was refuted by a recent study that–similar to our approach–relied on RT data to dissociate between the recognition heuristic and competing theories of inferential judgements (Heck & Erdfelder, 2017).

Despite being very popular in judgment and decision-making and other psychological disciplines (Evans, 2008), dual-process theories often became a target of fundamental criticism for conceptual issues but also for the lack of empirical support (Keren & Schul, 2009; Kruglanski & Gigerenzer, 2011; Melnikoff & Bargh, 2018). One shortcoming of many dual-process theories is their poor formalization which impedes quantitative model comparison (Diederich & Trueblood, 2018). This is especially true, when between-trial dynamics which account for choice and RT differences are ignored (Krajbich et al., 2015). In this study, we outlined a principled way to test a dual-process against a single-process account by means of quantitative and qualitative model comparison. Our approach is based on a recently developed formal model of a dual-process account (Alós-Ferrer, 2018) with suitable assumptions for testing our particular hypothesis. Apart from model comparison, estimation of the model also offers a deeper understanding of the underlying processes, such as the relative proportion of the two presumed processes (e.g., Δ), or their within-trial dynamics (e.g., drift rates). We believe the field of judgment and decision-making is well advised to formalize the proposed dual-process models and to test their empirical content. This approach has the potential to move the debate on dual-process models forward by adhering to empirical findings and methodological rigor.

Within the dual-process framework, there are two types of conceptualization which specify how the two processes can be implemented (Evans, 2008). According to the *parallel-competitive* structure, type 1 and type 2 processes run in parallel and a potential conflict between them has to be resolved to determine which process is applied in a given decision. The DPDM of Alós-Ferrer (2018) can be assigned to this group of models. The second influential dual-process architecture comprises the *default-interventionist* models. These models assume that a type 1 process is activated to generate an intuitive default response but may be overcome by the reflective type 2 process. From a diffusion model perspective, such a process could be reflected in a starting point bias in favor of the intuitive option (e.g., Chen and Krajbich, 2018). Hence, we also tested whether the assumption of a starting point bias towards the remembered option could account for the present data, but found that it cannot (see Appendix C1). An alternative implementation of a default-interventionist model was proposed by Diederich and Trueblood (2018), who investigated risky choices, drawing on prospect theory (Kahneman & Tversky, 1979) and expected utility theory (Neumann & Morgenstern, 1953). In our study, however, we were interested in value-based decisions, which are directly covered by the DPDM of Alós-Ferrer (2018) but not by Diederich and Trueblood (2018).

The scientific process of model selection is based on the principle of parsimony (Occam's razor). According to this principle, we should prefer hypotheses that can account for a complex phenomenon drawing on a few (rather than many) assumptions. In this study, we found empirical support that a single decision process provides a more parsimonious explanation of memory-based choices compared to a dual-process account. This parsimony is supported both by the Bayes factors and information criteria analyses, established methods to compare models in terms of fit and parsimony (Vandekerckhove et al., 2015). On a more conceptual level, the single-process account could be said to draw on fewer assumptions than the dual-process account. On the one hand, the single-process account can account for the data assuming a single comparison process, between remembered option and a biased reference value. On the other hand, the dual-process account assumes a computationally demanding utility maximizing process, a heuristic process depending on recognition of an item, and a central executive which selects among these processes.

In sum, our results clearly indicate that a single decision process in which the evaluation process is biased by memory describes the memory bias better than a dual-process account that assumed two independent processes (i.e., a memory-heuristic and a utility process). We fit both models in a hierarchical Bayesian modeling framework and outlined a rigorous procedure to empirically test single- and dual-process accounts of decision-making.

Acknowledgements This work was supported by a grant from the Swiss National Science Foundation (SNSF Grant 100014_172761) to S. Gluth. The authors declare no conflicts of interest. We would like to thank Jennifer Trueblood and Simon Farrell for practical advice in the early stages of this project. The snack icon in Fig. 1 was made by Freepik from www.flaticon.com under creative commons licence.

Funding Open access funding provided by University of Basel.

Open Practices The data and code are available at (https://osf.io/kbyas/. The experiment was preregistered but was conducted for a different purpose.

Appendix

A1 Trial types

In the remember-and-decide task, there are three types of trials, based on the number of snacks remembered (i.e., both remembered; both forgotten; one remembered, one forgotten). For this study, only the last trial type was of interest, as the memory bias (i.e., the tendency to prefer remembered over forgotten options) can only be tested with these kinds of trials. Table 2 summarizes the trial numbers for each trial type.

Table 2 Numbers of different trial types

Trial type	Total	*M*	*SD*	Range
Both forgotten	5651	62.8	32.9	13-163
One remembered, one forgotten	8031	89.2	15.8	39-118
Both remembered	5468	60.8	30.0	7-142

Note. Total: Number of trials in the data set; *M*: mean trial number per participant; *SD*: standard deviation; Range: range of trials between participants

A2 Analytical derivation of expected mean response times

In the main text, we illustrate the RT predictions of the DPDM (and the SPDM) using simulations. Predictions for the expected RT (and for the symmetry of the predicted RT curve around 0; see Fig. 1) can also be derived analytically. Here, we report these derivations.

The DPDM describes the expected RTs (eRT) as the weighted sum of mean RTs of the heuristic and the utility process. It can be described as

$$\begin{aligned} eRT_{\Delta V} = \; & p(H) \times p(R|H) \times eRT(R|H) + p(H) \\ & \times [1 - p(R|H)] \times eRT(F|H) + [1 - p(H)] \\ & \times p(R|U, \Delta V, \gamma) \times eRT(R|U, \Delta V, \gamma) \\ & + [1 - p(H)] \times [1 - p(R|U, \Delta V, \gamma)] \\ & \times eRT(F|U, \Delta V, \gamma) \end{aligned} \tag{13}$$

where $eRT_{\Delta V}$ is the expected RT for the value difference ΔV, $p(H)$ is the probability of the heuristic process, $p(R)$ [$p(F)$] is the probability of remembering [forgetting] a snack, and $eRT(R)$ [$eRT(F)$] is the mean RT for

Table 3 Prior distributions for group parameters.

Group parameter	SPDM	DPDM
μ_a	$\mathcal{N}(0,3)$	$\mathcal{N}(0,3)$
σ_a	$\mathcal{HN}(0,3)$	$\mathcal{HN}(0,3)$
μ_z	$\mathcal{N}(0,1)$	$\mathcal{N}(0,1)$
σ_z	$\mathcal{HN}(0,1)$	$\mathcal{HN}(0,1)$
$\mu_{T_{er}}$	$\mathcal{N}(-1,1)$	$\mathcal{N}(-1,1)$
$\sigma_{T_{er}}$	$\mathcal{HN}(0,3)$	$\mathcal{HN}(0,3)$
$\mu_{d_{SPDM}}$	$\mathcal{N}(0,3)$	–
$\sigma_{d_{SPDM}}$	$\mathcal{HN}(0,3)$	–
μ_γ	$\mathcal{N}(0,1)$	–
σ_γ	$\mathcal{HN}(0,3)$	–
$\mu_{d_{Utility}}$	–	$\mathcal{N}(0,3)$
$\sigma_{d_{Utility}}$	–	$\mathcal{HN}(0,2)$
$\mu_{d_{Heuristic}}$	–	$\mathcal{N}(0,3)$
$\sigma_{d_{Heuristic}}$	–	$\mathcal{HN}(0,2)$
μ_Δ	–	$\mathcal{N}(0,3)$
σ_Δ	–	$\mathcal{HN}(0,3)$

remembered [forgotten] snacks. The probability of a utility process is $1 - p(H)$, the probability and mean RT of remembered and forgotten choices in utility trials depend on ΔV and the reference value γ which is equal to V_{avg} in the DPDM.

Since we assume that the RTs come from a diffusion process, such that $eRT(chooseR) = eRT(chooseF)$, Eq. 13 can be simplified to

$$eRT_{\Delta V} = p(H) \times eRT(R|H) + [1 - p(H)] \\ \times eRT(R|U, \Delta V, \gamma). \tag{14}$$

Because the utility process is the only one that depends on V_{rem} and assumes the lowest drift rate when $V_{rem} = V_{avg}$, the predicted peak of the RT is at V_{avg}.

The same logic and equation can be applied to the SPDM by setting $p(H)$ to 0 and allowing the reference value γ to be a free parameter. Then, the predicted peak RT in the single-process account is at γ.

B1 Prior distributions of group parameters

In our hierarchical models, the individual model parameters were all drawn from normal distributions at the group level. Thus, for each model parameter, we estimated a group mean

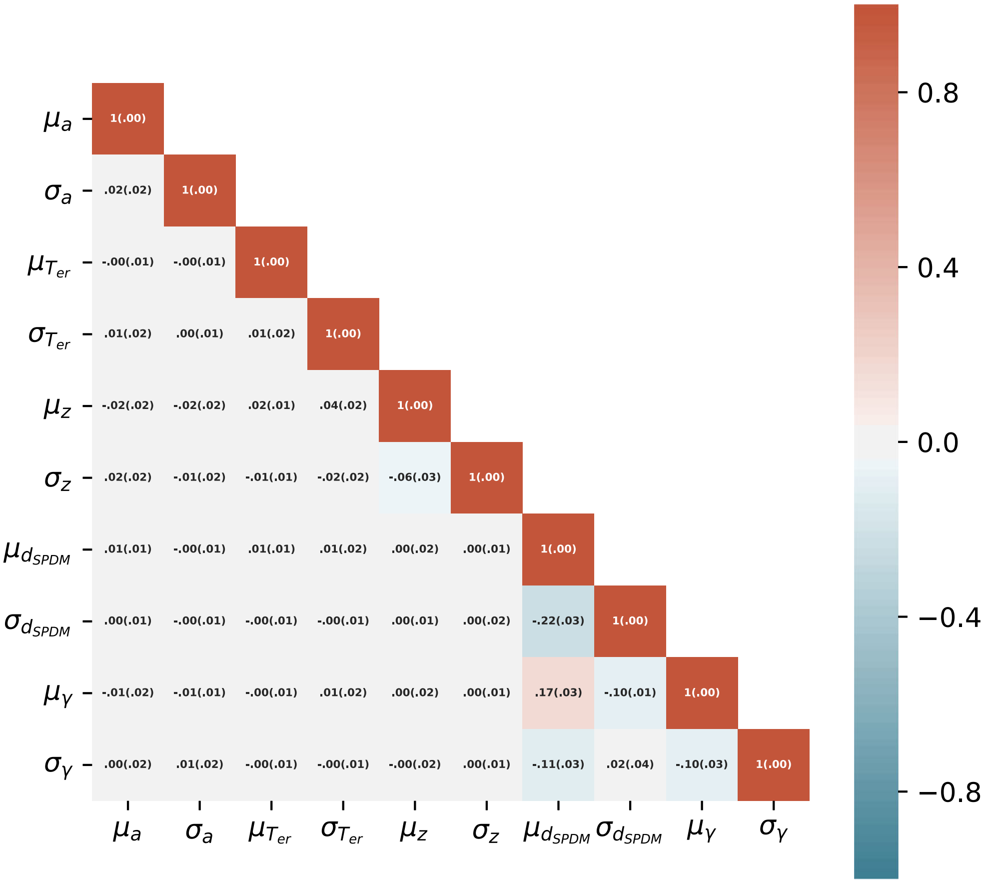


Fig. 6 Correlations of group parameter posterior samples of the SPDM. Each cell shows the mean correlation coefficients (using Fisher's transformation) with the corresponding standard deviation in brackets

and a group standard deviation, on top of the individual parameters themselves. All group means were given a weakly-informative normal prior, and all group standard deviations were given a weakly-informative half-normal prior. The prior distributions for the group-level parameters are listed in Table 3.

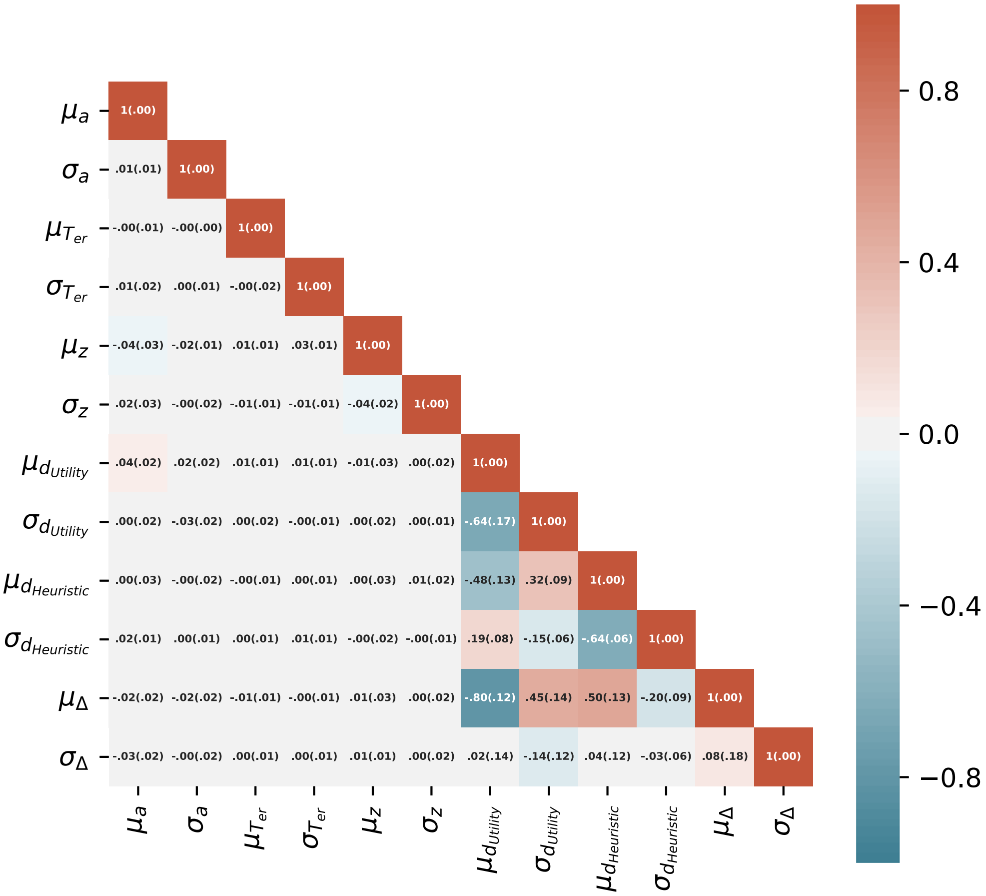
B2 Parameter and model recovery analyses

Parameter recovery

We performed a parameter-recovery analysis for both models. For each model, we chose the ten group-level parameter estimates from the respective models' posteriors that had the highest log-likelihood. From these group-level distributions, we drew 90 independent samples that determined individual-level behavior of the artificial agents. As inputs for the agents, we used the same inputs that we used for model fitting. For the DPDM, each trial was simulated to be either a heuristic or utility trial, based on independent Bernoulli trials $\mathcal{B}(\Delta_s)$. We re-fitted each of these generated datasets with the respective models to assess the degree to which parameters could be recovered.

Following an analysis approach implemented in Fontanesi et al. (2019), we addressed three questions in this analysis: 1) Do parameter values trade off during the estimation procedure (i.e., to which degree do models suffer from sloppiness)? 2) Are the models able to correctly identify the group-level parameters? 3) Are the models able to correctly identify the individual-level parameters?

To address question 1, we calculated Pearson correlation coefficients between the posterior samples of all group parameters of each of the ten fitted artificial data sets. Subsequently, the ten correlation coefficients were Fisher-transformed and subsequently averaged and their standard distribution was calculated. Note that group parameters were drawn independently from each other. Therefore, there should be no correlation between the posterior samples. Figure 6 shows the mean correlations between the parameters. Overall, we only observed weak correlations between μ_{dSPDM} and σ_{dSPDM}, and μ_{dSPDM} and μ_{γ}. The DPDM suffered from stronger sloppiness, especially between $\mu_{d_{Utility}}$, $\mu_{d_{Heuristic}}$ and μ_{Δ} (Fig. 7).



	μ_a	σ_a	$\mu_{T_{er}}$	$\sigma_{T_{er}}$	μ_z	σ_z	$\mu_{d_{Utility}}$	$\sigma_{d_{Utility}}$	$\mu_{d_{Heuristic}}$	$\sigma_{d_{Heuristic}}$	μ_{Δ}	σ_{Δ}
μ_a	1(.00)											
σ_a	.01(.01)	1(.00)										
$\mu_{T_{er}}$	-.00(.01)	-.00(.00)	1(.00)									
$\sigma_{T_{er}}$	.01(.02)	.00(.01)	-.00(.02)	1(.00)								
μ_z	-.04(.03)	-.02(.01)	.01(.01)	.03(.01)	1(.00)							
σ_z	.02(.03)	-.00(.02)	-.01(.01)	-.01(.01)	-.04(.02)	1(.00)						
$\mu_{d_{Utility}}$	.04(.02)	.02(.02)	.01(.01)	.01(.01)	-.01(.03)	.00(.02)	1(.00)					
$\sigma_{d_{Utility}}$	.00(.02)	-.03(.02)	.00(.02)	-.00(.01)	.00(.02)	.00(.01)	-.64(.17)	1(.00)				
$\mu_{d_{Heuristic}}$	.00(.03)	-.00(.02)	-.00(.01)	.00(.01)	.00(.03)	.01(.02)	-.48(.13)	.32(.09)	1(.00)			
$\sigma_{d_{Heuristic}}$	.02(.01)	.00(.01)	.00(.01)	.01(.01)	-.00(.02)	-.00(.01)	.19(.08)	-.15(.06)	-.64(.06)	1(.00)		
μ_{Δ}	-.02(.02)	-.02(.02)	-.01(.01)	-.00(.01)	.01(.03)	.00(.02)	-.80(.12)	.45(.14)	.50(.13)	-.20(.09)	1(.00)	
σ_{Δ}	-.03(.02)	-.00(.02)	.00(.01)	.00(.01)	.01(.01)	.00(.02)	.02(.14)	-.14(.12)	.04(.12)	-.03(.06)	.08(.18)	1(.00)

Fig. 7 Correlations of group parameter posterior samples of the DPDM. Each cell shows the mean correlation coefficients (using Fisher's transformation) with the corresponding standard deviation in brackets

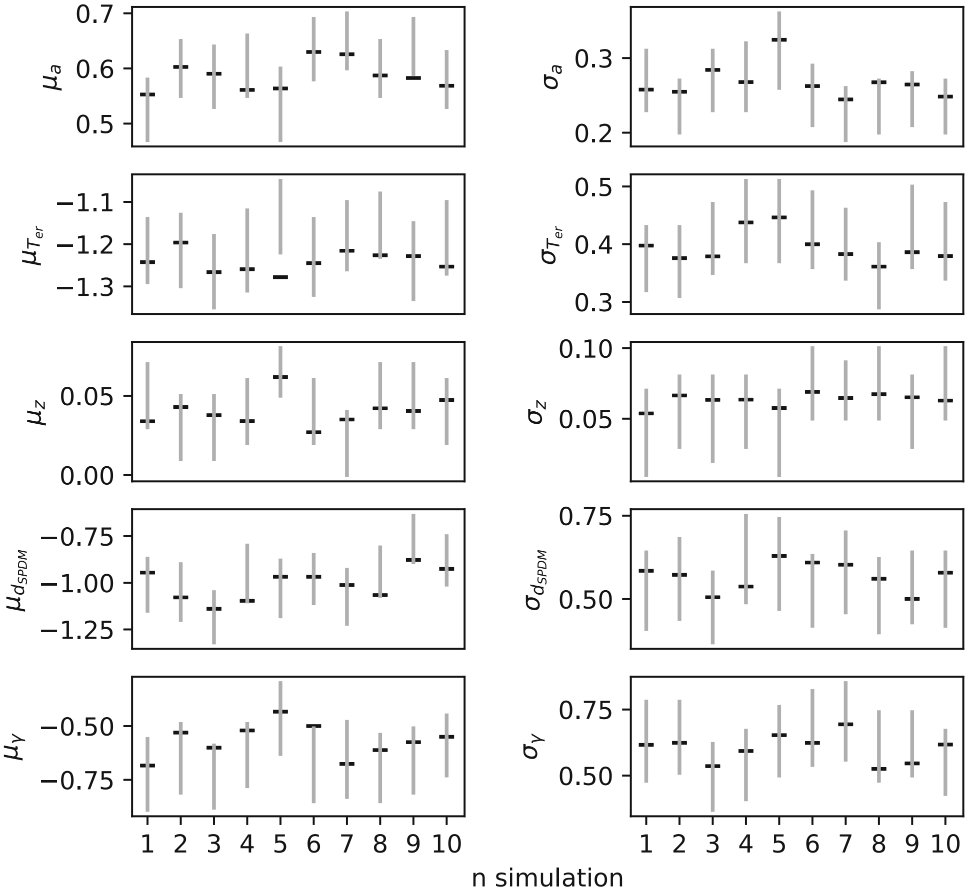


Fig. 8 Identifiability of the SPDM group parameters. *Horizontal black lines* indicate the generating parameter values for the ten simulations. *Vertical lines* indicate the 95% HDI of the estimated parameter distributions

To address question 2, we calculated the 95% HDIs of the posterior group-level parameter distributions. If the parameters are identifiable, the 95% HDI of should include the true data-generating parameter value (see also Spektor and Kellen, 2018). We observed good identifiability of the group-level parameters for both models (Figs. 8, 9, 10 and 11).

To address question 3, we correlated the true data-generating parameters on the individual level with the estimated means of the posterior distributions. For this analysis, the means were transformed back to the space of the group-level parameters. For both models, we observed very good recovery of the a and T_{er} parameters. The recoverability of z was lower but still fair which may be due to the low explanatory power of this parameter. The parameters which specified the drift rate were recovered well for the SPDM, and fairly well for the DPDM. Overall, we judge the recoverability to be good for the SPDM and relatively good for the DPDM, and sufficient for both models.

Model recovery

We performed a model-recovery analysis to assess whether both models could in principle be identified as the winning model, given that the data are generating by the respective model. From the parameter recovery analysis, we used the 20 simulated set of data of which ten were generated by each of the models. We fitted both models to each set of data separately and calculated the WAICs of the fits. The critical test for the model recovery was whether a model from which the data was generated wins the comparison against the competing model on that data. In other words, given the data were generated with the SPDM, the WAIC of the SPDM should be lower than the WAIC of the DPDM (and vice versa for the DPDM). The SPDM outperformed the DPDM on data which was generated under the SPDM (Fig. 12). The DPDM, on the other hand, won the model comparison against the SPDM in all sets of data that came from the DPDM, showing good model recovery.

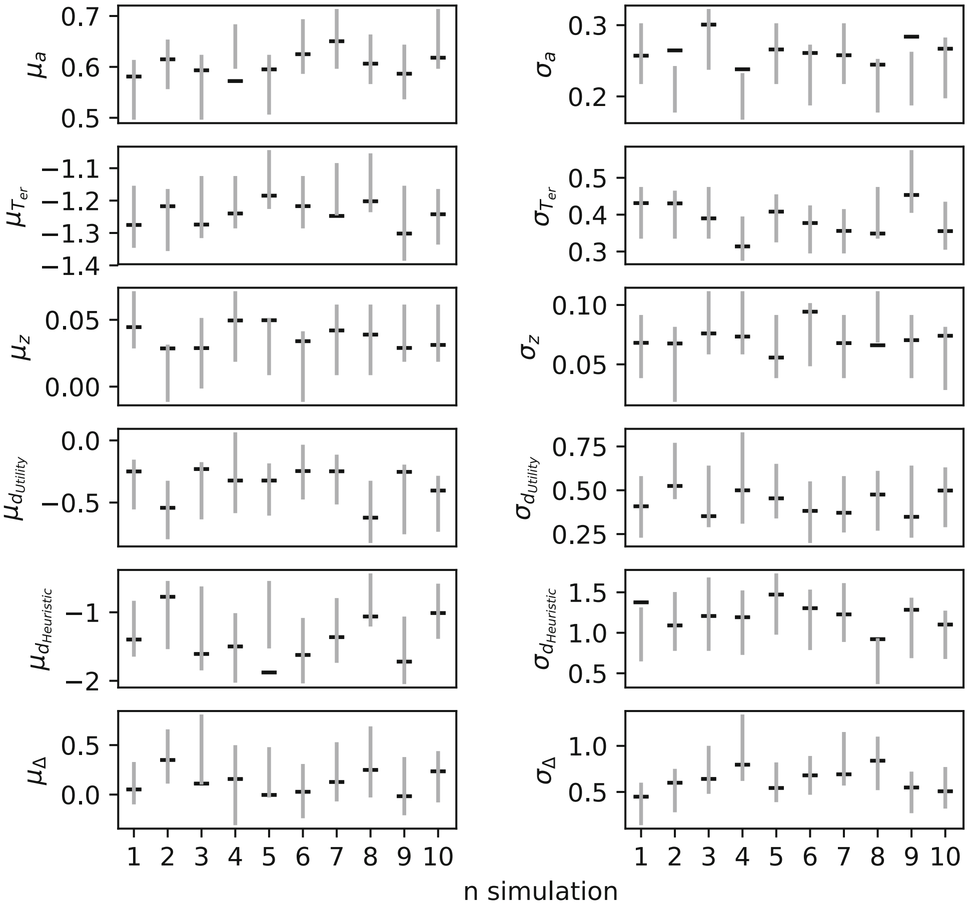


Fig. 9 Identifiability of the DPDM group parameters. *Horizontal black lines* indicate the generating parameter values for the ten simulations. *Vertical lines* indicate the 95% HDI of the estimated parameter distributions

B3 Analyses on all trial types

The main text focused on trials in which participants remembered one option but forgot the other one. These are the only trials in which the memory bias has an influence on participants' behavior. In trials in which both options are remembered, the SPDM assumes a purely utility-driven choice process (see Eq. 9) because the bias parameter γ_s is cancelled out from the drift rate $\nu_{s,t}$. When both options are remembered, the DPDM would also solely rely on the utility process, since the assumed recognition heuristic is not applicable. In trials in which both options are forgotten, the drift rate of both the SPDM and the DPDM equals zero (again, the DPDM's heuristic process is not applicable). In sum, both models make the same predictions for trials in which no option and both options are remembered.

Nonetheless, we fitted both models to data from all three trial types to check whether our results would still hold. Apart from including all trials, we followed the same procedures as in the main text. The posterior parameter distributions are summarized in Table 4. For the SPDM, the parameters were similar to those reported in the main text. On the other hand, the parameters affecting the drift rate in the DPDM differed when fitting the model to all trial types. $mu_{d_{Utility}}$ was estimated to be lower, $mu_{d_{Heuristic}}$ was estimated to be higher, and Δ increased substantially, indicating a higher proportion of utility trials.

As in the main text, quantitative model comparison favored the SPDM (WAIC = 44,465) over the DPDM (WAIC = 44,645) with a difference in WAICs of 179.98 and a standardized effect size of $\frac{\Delta \text{WAIC}}{SE} = 5.97$.

The posterior predictives yielded very similar predictions for both models (see Fig. 13a–c). Notably, while both models accounted relatively well for the "one remembered, one forgotten" and "both remembered" trial types, they made inaccurate predictions for the "both forgotten" trials. This results from the drift rate being zero in the "both forgotten" trials, which implies the prediction of slow RTs and random choices. In contrast to these predictions, the observed choices yielded a slight tendency to choose the right option (explained by a starting point bias $\mu_z > .5$) and

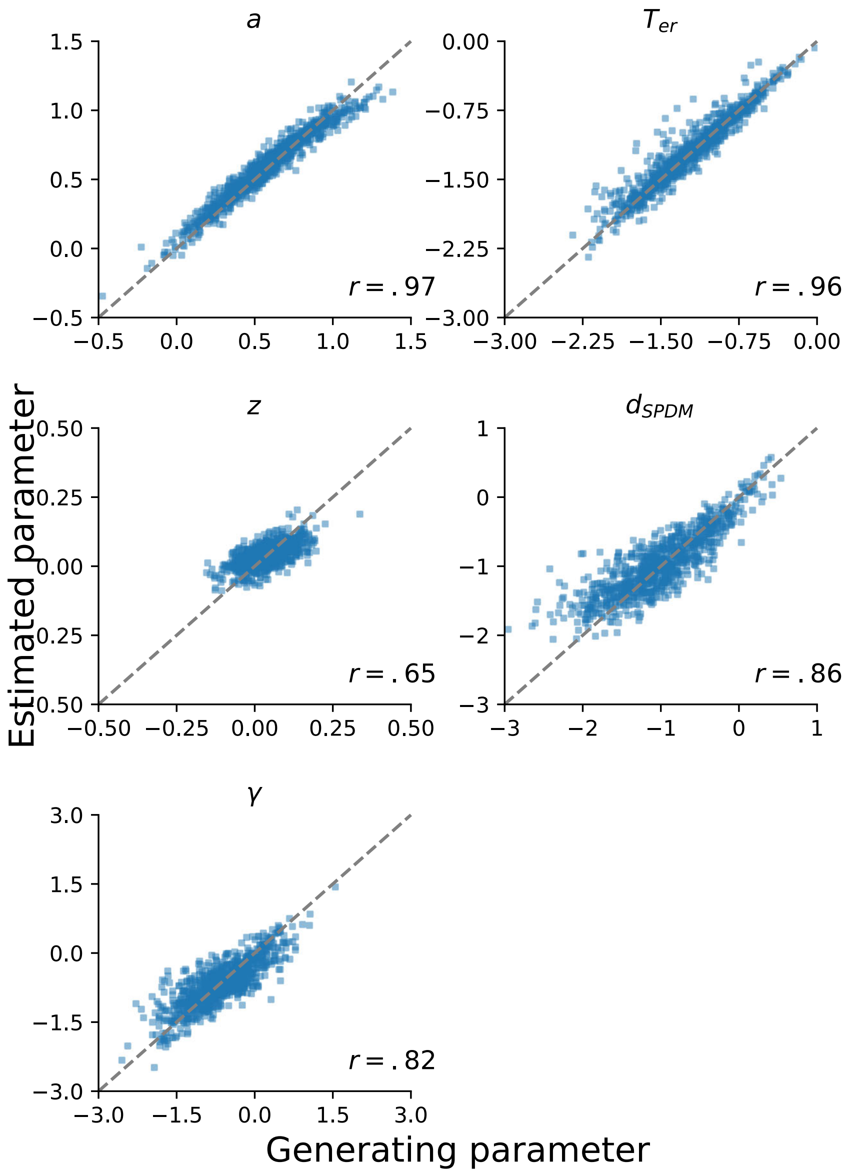


Fig. 10 Identifiability of the SPDM individual level parameters, pooled over all ten simulations. The position on the X-axes indicate generating parameter value, the Y-position show the estimated posterior mean. Values around the *dashed grey identity line* yield good recovery. The Pearson's correlation coefficients of generated and estimated parameters are indicated on the lower left for each parameter

the RTs were not slower than those of the other trial types. We would argue that participants may have simply guessed, when they knew that they could not remember either of the two options.

In sum, both models can be fitted and account all trial types apart from the "both forgotten" trials. In line with the results reported in the main text, the SPDM provides a better account of the data than the DPDM. Moreover, the parameter estimates of the SPDM remain stable, whereas those of the DPDM change substantially, reflecting the robustness of the SPDM, and the rather low robustness of the DPDM.

C1 Does a default-interventionist process explain the memory bias?

Apart from the parallel-competitive dual-process account of Alós-Ferrer (2018), it is conceivable that a default-interventionist account could explain the memory bias. Such an approach assumes that during each decision, rapid pre-conscious processes either approve of the type 1 decision, or intervene by initiating the rational type 2 process (Evans, 2008). From a diffusion model perspective, a default-interventionist account resembles a biased starting point z (Chen & Krajbich, 2018). More specifically, assuming

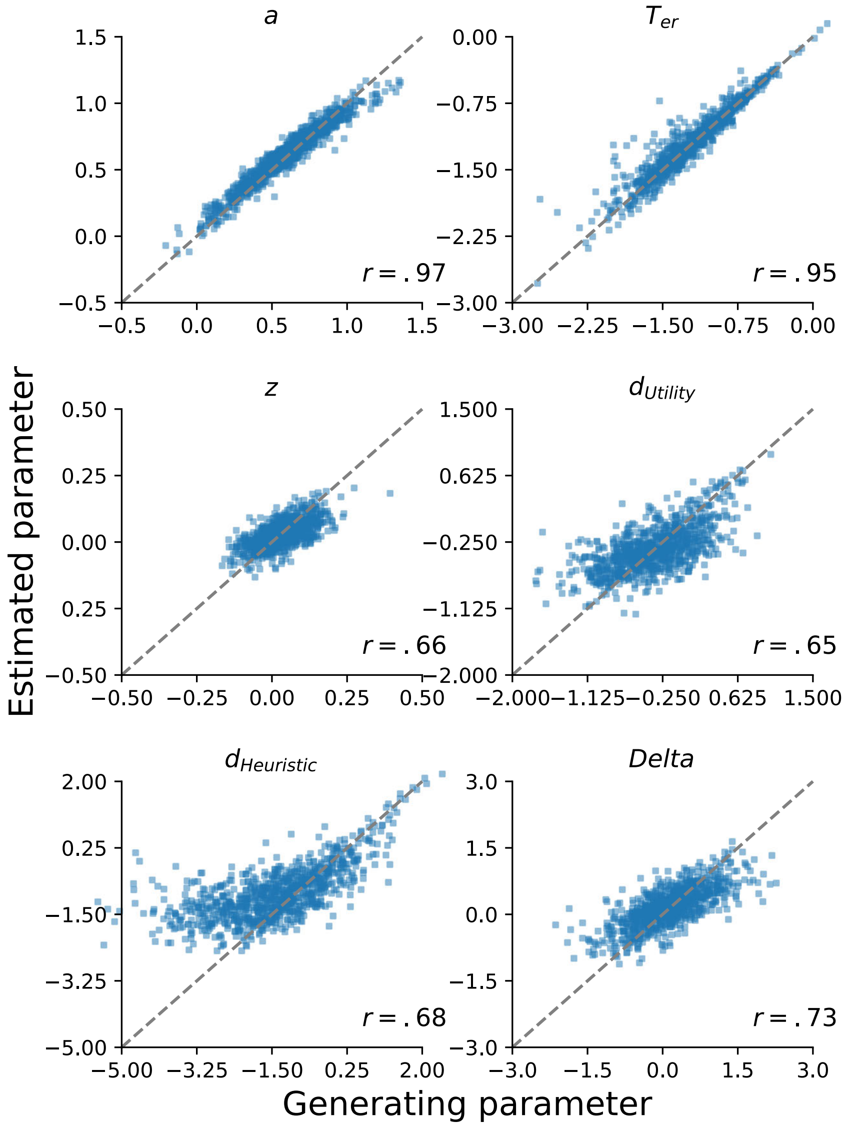


Fig. 11 Identifiability of the DPDM individual level parameters, pooled over all ten simulations. The position on the *X*-axes indicate generating parameter value, the *Y*-position show the estimated posterior mean. Values around the *dashed grey identity line* yield good recovery. The Pearson's correlation coefficients of generated and estimated parameters is indicated on the lower left for each parameter

that the default response would be implemented as a starting-point bias, the diffusion process would be biased so that the intuitive option would be selected quicker and more often than the non-intuitive one. Technically, this would still be a single-process account because the default option cannot finalize the decision process (there is some deliberation necessary), but its predictions resemble a default-interventionist dual-process model (e.g., fast errors).

With respect to the remember-and-decide task, this means that the starting point bias should favor the remembered option. If a biased starting point provided a better explanation for the memory bias, the memory bias parameter should be affected when a model is estimated with a free starting point which can favor the remembered option.

To evaluate this, we fitted another diffusion model to the data. We refer to this model as "memory-bias-as-starting-point-bias model". In order to fit the starting-point bias parameter, we reparameterized the DDM so that the upper boundary would represent choices in favor of the remembered option, and the lower boundary would represent choices against it. Other than that, the model was parameterized similarly to the SPDM (see Eq. 8)

$$\begin{aligned} v_{s,t} &= d_s(V_{rem_{s,t}} - \gamma_s), \\ d_s &\sim e^{\mathcal{N}(\mu_{d_{SPDM}}, \sigma_{d_{SPDM}})}, \\ \gamma_s &\sim \mathcal{N}(\mu_\gamma, \sigma_\gamma), \end{aligned} \tag{15}$$

where $V_{rem_{s,t}}$ is the value of the remembered option, d_s is the scale parameter and γ_s the memory bias parameter.

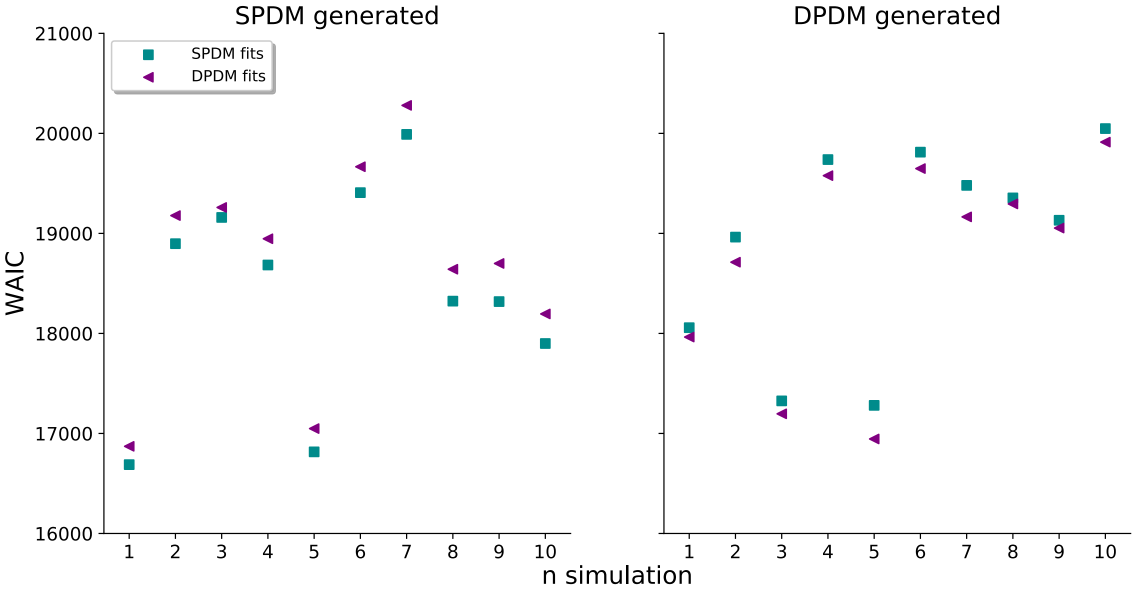


Fig. 12 Model recovery. The plot shows the WAIC values for the parameter fits of the SPDM (*cyan rectangles*), and the DPDM (*purple triangles*) for each simulated data set. The *left panel* shows the datasets generated from the SPDM, the *right panel* shows those from the DPDMx

Table 4 Group-level parameter estimates for the single- and dual-process diffusion models, considering all trial types

Model	Parameter	*M*	95% HDI
SPDM	μ_a	1.80	[1.70, 1.90]
	σ_a	1.28	[1.25, 1.34]
	$\mu_{T_{er}}$	0.26	[0.24, 0.29]
	$\sigma_{T_{er}}$	1.51	[1.42, 1.62]
	μ_z	.52	[.51, .52]
	σ_z	1.05	[1.03, 1.06]
	$\mu_{d_{SPDM}}$	0.31	[0.27, 0.35]
	$\sigma_{d_{SPDM}}$	1.70	[1.52, 1.92]
	μ_γ	−0.62	[−0.79, −0.44]
	σ_γ	1.97	[1.70, 2.34]
DPDM	μ_a	1.80	[1.72, 1.90]
	σ_a	1.28	[1.25, 1.34]
	$\mu_{T_{er}}$	0.26	[0.24, 0.28]
	$\sigma_{T_{er}}$	1.51	[1.40, 1.60]
	μ_z	.52	[.51, .52]
	σ_z	1.05	[1.04, 1.07]
	$\mu_{d_{Utility}}$	0.32	[0.27, 0.36]
	$\sigma_{d_{Utility}}$	1.75	[1.57, 1.99]
	$\mu_{d_{Heuristic}}$	1.00	[0.84, 1.16]
	$\sigma_{d_{Heuristic}}$	1.21	[1.00, 1.42]
	μ_Δ	.93	[.84, .97]
	σ_Δ	3.60	[2.41, 5.70]

Note. *M* = posterior mean. HDI = highest-density interval. Note that these values are reported after applying their respective transformations (see main text)

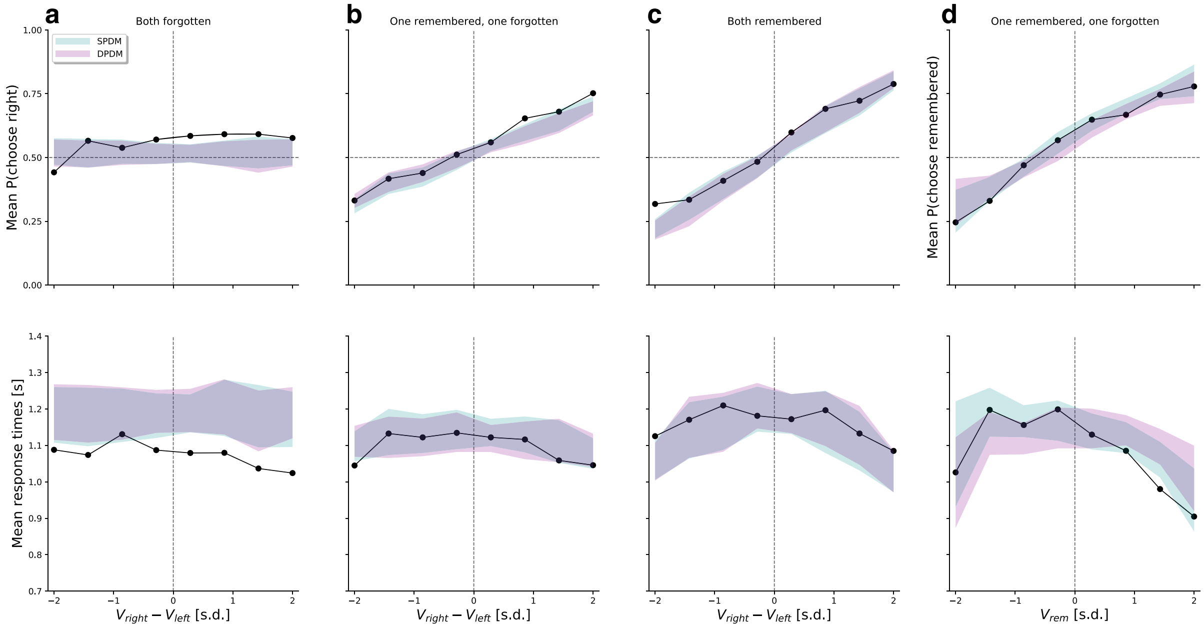


Fig. 13 Posterior simulations for all trial types. The *black dots* indicate the empirical means for choices (*upper panels*) and response times (*lower panels*). The *colored areas* indicate the 95% HDI of the means of simulated data sets based on the estimated posterior parameter distributions of the SPDM (*cyan*) and DPDM (*purple*). **a**, **b**, and **c** indicate the posterior simulations for “both forgotten”, “one remembered, one forgotten”, and “both remembered” trials, respectively. Note that these simulations depend on the value differences between the right and the left snack items, and the choices indicate the mean proportions of choices that favored the right option. **d** shows the posterior simulations for “one remembered, one forgotten” trials as a function of V_{rem} analogously to Fig. 5

Note that the starting point bias $f(z)$ is scaled between zero and one. A value of .5 yields that there is no starting point bias. A value $>$ .5 indicates that there was a bias in favor of the remembered option, a value $<$ .5 indicates that the starting point bias was favoring the forgotten option.

After fitting the model, the posterior distributions revealed that the starting point bias parameter $f(\mu_z)$ did not bias decisions in favor of the remembered option (see Table 5). From the posterior estimates it is evident that, if anything, there was a small starting point bias in favor of the forgotten option.

The model yielded a WAIC of 17,425 which was higher than the WAIC of the SPDM.

Table 5 Group parameter estimates of the memory-bias-as-starting-point-bias model

Parameter	*M*	95%-HDI
μ_a	1.77	[1.68, 1.88]
σ_a	1.30	[1.25, 1.35]
$\mu_{T_{er}}$	0.29	[0.27, 0.31]
$\sigma_{T_{er}}$	1.46	[1.38, 1.57]
μ_z	0.49	[0.48, 0.50]
σ_z	1.05	[1.00, 1.08]
$\mu_{d_{SPDM}}$	0.36	[0.31, 0.41]
$\sigma_{d_{SPDM}}$	1.70	[1.51, 1.93]
μ_γ	−0.62	[−0.78, −0.45]
σ_γ	1.82	[1.58, 2.10]

Note. *M* represents the posterior mean. The 95%-HDI depicts the boundaries of the 95% highest-density interval. Note that these values are transformed with respective transformation functions (see main text)

References

Alós-Ferrer, C. (2018). A dual-process diffusion model. *Journal of Behavioral Decision Making*, *31*(2), 203–218.

Ballard, I. C., & McClure, S. M. (2019). Joint modeling of reaction times and choice improves parameter identifiability in reinforcement learning models. *Journal of Neuroscience Methods*, *317*(2018), 37–44.

Bogacz, R., Brown, E., Moehlis, J., Holmes, P., & Cohen, J. D. (2006). The physics of optimal decision-making: A formal analysis of models of performance in two-alternative forced-choice tasks. *Psychological Review*, *113*(4), 700–765.

Busemeyer, J. R., Gluth, S., Rieskamp, J., & Turner, B. M. (2019). Cognitive and neural bases of multi-attribute, multi-alternative, value-based decisions. *Trends in Cognitive Sciences*, *23*(3), 251–263.

Chen, F., & Krajbich, I. (2018). Biased sequential sampling underlies the effects of time pressure and delay in social decision-making. *Nature Communications*, *9*(1), 1–10.

Clithero, J. A. (2018). Response times in economics : Looking through the lens of sequential sampling models. *Journal of Economic Psychology*, *69*, 61–86.

Diederich, A., & Trueblood, J. S. (2018). A dynamic dual process model of risky decision-making. *Psychological Review*, *125*(2), 270–292.

Evans, J. S. B. T. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annual Review of Psychology*, *59*, 255–78.

Evans, J. S. B. T., & Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspectives on Psychological Science*, *8*(3), 223–241.

Fontanesi, L., Gluth, S., Spektor, M., & Rieskamp, J. (2019). A reinforcement learning diffusion decision model for value-based decisions. *Psychonomic Bulletin and Review*.

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, *7*(4), 457–511.

Gluth, S., Sommer, T., Rieskamp, J., & Büchel, C. (2015). Effective connectivity between hippocampus and ventromedial prefrontal cortex controls preferential Choices from Memory, *Neuron*, 1078–1090.

Gluth, S., & Meiran, N. (2019). Leave-one-trial-out, LOTO, a general approach to link single-trial parameters of cognitive models to neural data. *eLife*, *8*, e42607.

Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: The recognition heuristic. *Psychological Review*, *109*(1), 75–90.

Heck, D. W., & Erdfelder, E. (2017). Linking process and measurement models of recognition-based decisions. *Psychological Review*, *124*(4), 442–471.

Hoffman, M. D., & Gelman, A. (2014). The no-U-turn sampler: Adaptively setting path lengths in Hamiltonian Monte Carlo. *Journal of Machine Learning Research*, *15*, 1593–1623.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263–292.

Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. In Gilovich, D., Griffin, T., & Kahneman, D. (Eds.) *Heuristics of intuitive judgment: Extensions and applications*, (pp. 49–81). New York: Cambridge University Press.

Keren, G., & Schul, Y. (2009). Two is not always better than one - A critical evaluation of two-system theories. *Perspectives on Psychological Science*, *4*(6), 533–550.

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–1298.

Krajbich, I., Bartling, B., Hare, T. A., & Fehr, E. (2015). Rethinking fast and slow based on a critique of reaction-time reverse inference. *Nature Communications*, 1–9.

Kruglanski, A. W., & Gigerenzer, G. (2011). Intuitive and deliberate judgments are based on common principles. *Psychological Review*, *118*(1), 97–109.

Kruschke, J. K. (2015). *Doing Bayesian data analysis, a tutorial with R, JAGS and Stan*. London: Academic Press.

Lee, M. D., & Wagenmakers, E. J. (2013). *Bayesian cognitive modeling: A practical course*. Cambridge: Cambridge University Press.

Luce, R. D. (1986). *Response times*. New York: Oxford University Press.

Mechera-Ostrovsky, T., & Gluth, S. (2018). Memory beliefs drive the memory bias on value-based decisions. *Scientific Reports*, *8*, 1–10.

Melnikoff, D. E., & Bargh, J. A. (2018). The mythical number two. *Trends in Cognitive Sciences*, *22*(4), 280–293.

Neumann, J. v., & Morgenstern, O. (1953). *Theory of games and economic behavior*, (3rd ed.). Princeton: Princeton University Press.

Oaksford, M., & Hall, S. (2016). On the source of human irrationality. *Trends in Cognitive Sciences*, *20*(5), 336–344.

Pachur, T. (2011). The limited value of precise tests of the recognition heuristic. *Judgment and Decision Making*, *6*(5), 413–422.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108.

Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science*, *9*(5), 347–356.

Ratcliff, R., Smith, P. L., Brown, S. D., & Mckoon, G. (2016). Diffusion decision model: Current issues and history. *Trends in Cognitive Sciences*, *20*(4), 260–281.

Shadlen, M. N., & Shohamy, D. (2016). Decision making and sequential sampling from memory. *Neuron*, *90*(5), 927–939.

Spektor, M. S., & Kellen, D. (2018). The relative merit of empirical priors in non-identifiable and sloppy models: Applications to models of learning and decision-making. *Psychonomic Bulletin & Review*, *25*(6), 2047–2068.

Stan-Development-Team (2018). Pystan: The Python interface to Stan, v 2.17.1.0.

Vandekerckhove, J., Matzke, D., & Wagenmakers, E.-J. (2015). Model comparison and the principle of parsimony. In *The Oxford handbook of computational and mathematical psychology*, (pp. 300–319). New York: Oxford University Press.

Watanabe, S. (2013). A widely applicable Bayesian information criterion. *Journal of Machine Learning Research*, *14*, 867–897.

Weber, E. U., & Johnson, E. J. (2006). Constructing Preferences from Memory. In Lichtenstein, S., & Slovic, P. (Eds.) *The construction of preference*, (pp. 397–410). New York: Cambridge University Press.

Weilbächer, R. A., Kraemer, P. M., & Gluth, S. (in press). The reflection effect in memory-based decisions. *Psychological Science*.

Weilbächer, R. A., & Gluth, S. (2017). The interplay of hippocampus and ventromedial prefrontal cortex in memory-based decision making. *Brain Sciences, 7*(1).

Wilson, R. C., & Collins, A. G. E. (2019). Ten simple rules for the computational modeling of behavioral data. *eLife*, 1–33.

A.3 Manuscript 3: Episodic memory retrieval affects the onset and dynamics of evidence accumulation during value-based decisions

EPISODIC MEMORY RETRIEVAL AFFECTS THE ONSET AND DYNAMICS OF EVIDENCE ACCUMULATION DURING VALUE-BASED DECISIONS

A PREPRINT

Peter M. Kraemer
Department of Psychology
University of Basel
Basel, Switzerland
`peter.kraemer@unibas.ch`

Sebastian Gluth
Department of Psychology
University of Hamburg
Hamburg, Germany
`sebastian.gluth@uni-hamburg.de`

May 29, 2022

ABSTRACT

In neuroeconomics, there is much interest in understanding simple value-based choices where agents choose between visually presented goods, comparable to a shopping scenario in a supermarket. However, many everyday decisions are made in the physical absence of the considered goods, requiring agents to recall information about the goods from memory. Here, we asked whether and how this reliance on an internal memory representation affects the temporal dynamics of decision making on a cognitive and neural level. Participants performed a remember-and-decide task, in which they made simple purchasing decisions between money offers and snack items while undergoing EEG. Snack identity was presented either visually (value trials) or had to be recalled from memory (memory trials). Behavioral data indicated comparable choice consistency across both trial types, but considerably longer response times (RT) in memory trials. Drift-diffusion modeling suggested that this RT difference was due to longer non-decision time of decision processes as well as altered evidence accumulation dynamics (lower accumulation rate and higher decision threshold). The non-decision time effect was supported by a delayed onset of the lateralized readiness potential. These results show that both, decision and non-decision processes are prolonged when participants need to resort to internal memory representations during value-based decisions.

1 Introduction

Decision neuroscience often employs simple consumer choices to investigate the cognitive and neural basis of value-based decisions. These choices are usually studied in a supermarket scenario, where participants are exposed to visually presented consumer goods and choose among them (e.g., Webb et al., 2021; Krajbich et al., 2010; Polanía et al., 2015; Frömer et al., 2019; Bakkour et al., 2019). While this scenario offers a well-controlled experimental setting, it has the limitation of only considering choices with the options being visually present. However, many value-based choices are made in the physical absence of choice options so that decision processes need to draw on internal memory representations (Lynch and Srull, 1982; Alba and Hutchinson, 1987; Stewart et al., 2006; Zhao et al., 2021). Here, we examine how this reliance on internal memory representations affects value-based decision processes.

Value-based decision making is often conceptualized with a two-stage model of valuation and action selection (e.g., Platt and Plassmann, 2013; Kable and Glimcher, 2009). In brief, this model distinguishes between valuation processes, where subjective value of choice options is integrated and feeds into an action selection process, where different action plans compete until the winning plan is executed. A large body of research associated valuation with activity in striatal and frontal brain regions, emphasizing the ventromedial prefrontal cortex (vmPFC) (see, Bartra et al., 2013; Clithero and Rangel, 2014; Vaidya and Fellows, 2020; Levy and Glimcher, 2012, for reviews). This region seems to encode subjective value of choice options in various choice tasks, including the supermarket scenario. Importantly, when decisions are based on memory representations, valuation depends on the co-activation of the vmPFC and brain regions that account for memory retrieval, such as the hippocampus and the anterior prefrontal cortex (Zhang et al., 2021; Gluth et al., 2015; Kraemer et al., 2022). While these studies focus on the effect of memory on valuation, the effect on action selection has rarely been studied.

Action selection is frequently described as a competitive activation process within fronto-parietal brain regions where the activity level of neural populations represent different action plans such as, approaching one vs. another choice option (Cisek, 2007; Gold and Shadlen, 2007). Over time, the activity levels change as a function of incoming valuation signals (Hare et al., 2011; Grueschow et al., 2015; Gluth et al., 2012). As soon as the activity level of one action plan outweighs the others by some critical margin, the corresponding action is triggered and executed by the motor system (Thura and Cisek, 2014; Rizzolatti and Kalaska, 2013). The dynamic and competitive nature of action selection can be described by cognitive models of the sequential sampling framework (Shadlen and Kiani, 2013; Smith and Ratcliff, 2004). These models describe decision making as a noisy accumulation of *evidence* (see Fig. 1C). Here, evidence is an abstract unit of preference for either choice option. Over time, relative evidence accumulates until a threshold level is reached which – analogously to the neural process of action selection – triggers a corresponding action. Thereby, the time to make a decision, the response time (RT), depends on the duration of the evidence accumulation process as well as on the non-decision time which is thought to include the duration of pre-decisional processes such as perceptual encoding and memory retrieval, as well as post-decisional processes such as motor execution (Ratcliff and McKoon, 2008; Ratcliff et al., 2016). Applied to economic choices, such as consumer choices, sequential sampling models have received wide acceptance in neuroeconomics and decision neuroscience (Clithero, 2018; Fehr and Rangel, 2011; Busemeyer et al., 2019).

We investigated the neural dynamics of action selection by leveraging the temporal precision of electroencephalography (EEG), focusing on the lateralized readiness potential (LRP, Coles and Gratton, 1988) as a neural signature. Instead of being a pure motor component, the LRP has been suggested to track the onset and progression of evidence accumulation (e.g., Schurger et al., 2012; Van Vugt et al., 2014; Lui et al., 2021; Gluth et al., 2013; Polanía et al., 2014). However, a detailed relation between LRP properties and evidence accumulation parameters is yet to be established. Here, we hypothesized that the onset, the slope and the peak amplitude of the LRP may be related to the onset, rate and threshold level of evidence accumulation, respectively.

We utilized this approach to compare the cognitive and neural dynamics of consumer choices, where goods were either presented visually vs. were recalled from memory. Cognitive modeling revealed major differences in the dynamics between both kinds of choices: Memory-based decisions yielded a lower rate of evidence accumulation, a higher decision threshold level, and a delayed decision onset. Ultimately, the integration of different LRP properties into a neurally-informed sequential sampling model allowed us to identify the computational mechanisms of action selection in memory-based decisions.

2 Materials and Methods

2.1 Participants

In total, 48 participants took part in the study. 9 participants had to be excluded due to dietary incompatibilites of the snacks (n=3), acute headache (n=1), problems in understanding or performing the tasks (n=2) or technical problems with the EEG system (n=3). Our final data set comprised 39 healthy, right-handed human volunteers (28 female, mean age = 22.5, age range: $[19, 29]$). Participants were recruited via online recruitment systems of the University of Basel and were reimbursed either with a money amount of 90 CHF or with course credits. Participants were instructed to fast for at least four hours before the start of the experiment. Additionally, the tasks were incentivized (see 2.2). The study was approved by the ethics committee of the University of Basel, and all participants gave written informed consent to the procedures.

2.2 Experimental design

The study was conducted in two separate sessions (mean time between sessions = 7.5 days, range: $[7, 15]$). Session 1 was a training session, where participants were familiarized with the task structure. This was done to minimize learning effects in session 2, where the relevant data for this study was recorded. In both sessions, participants first rated 55 snack items regarding their willingness to pay. Next, they performed 10 runs of a remember-and-decide task. In a post-experiment survey, participants rated their subjective familiarity with the snacks and were interviewed about potential problems and personal strategies of the task procedures.

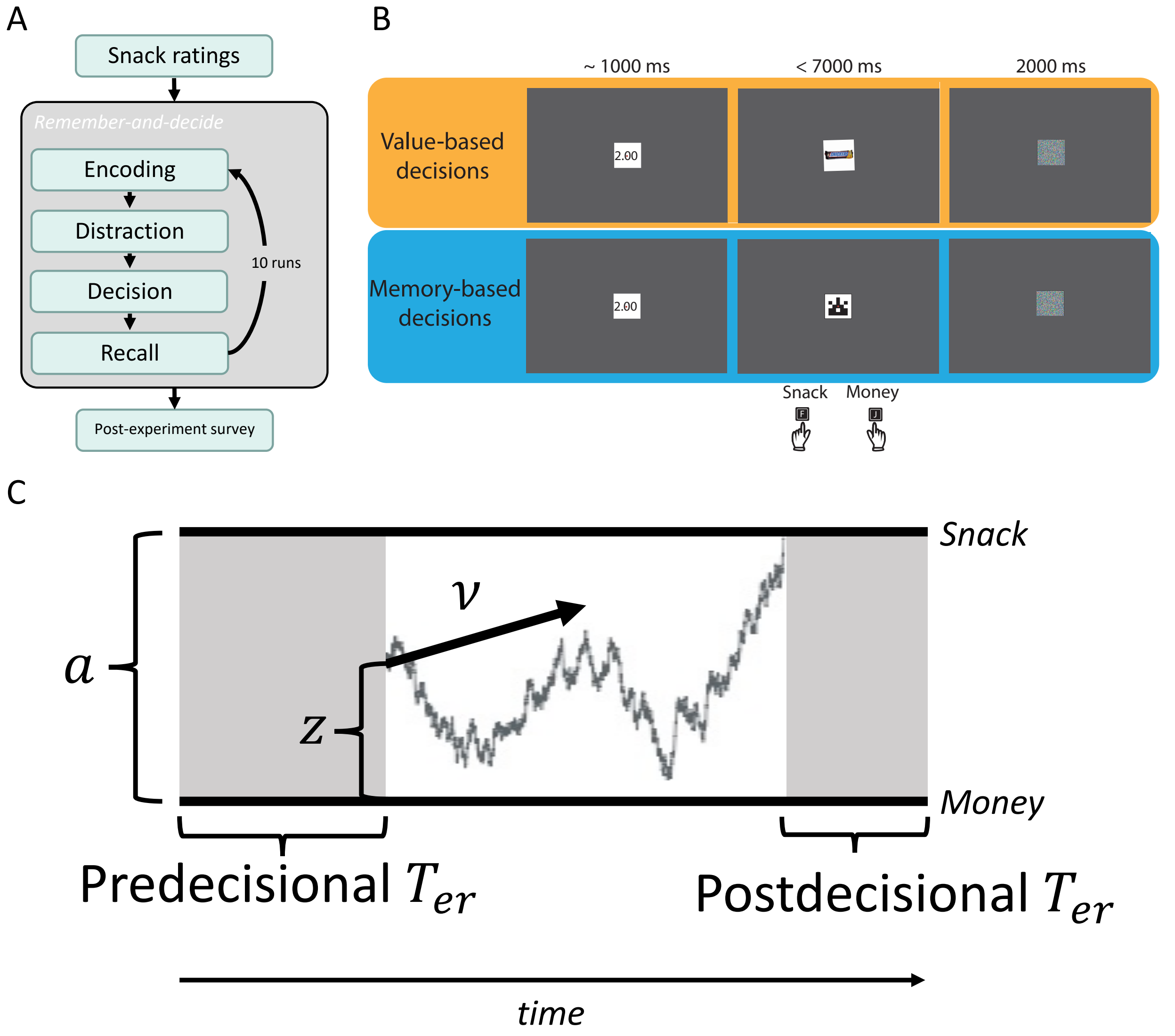


Figure 1: **A** Flow-chart of the experimental periods of the remember-and-decide task. **B** Illustration of the stimulus sequence of a value trial (orange) and a memory trial (blue). In each trial, participants chose between a monetary value and a snack option, which was presented either directly (value trial) or indicated by a unique identicon (memory trial). **C** Illustration of the dynamic choice process. Evidence accumulates over time with a drift-rate ν. The separation of the decision boundaries is defined by the parameter a. Here, the boundaries represent the two choice options of the remember-and-decide task (snack vs. money). The a-priori starting point bias is represented by the parameter z. Pre- and post-decisional non-decision time T_{er} are depicted in grey.

2.2.1 Setup

In session 1, we collected behavioral data. In the laboratory, participants were seated in front of a screen (size = 47.38×29.61 cm $\hat{=}24''$ screen diagonal, resolution = 1680×1050 pixels, refresh rate = 60 Hz). Their heads were fixed with a chin rest at 60 cm distance to the screen. Eye tracking data was collected with an SMI iViewX RED 500 system (SensoMotoric instruments, Berlin, Germany) with 500 Hz sampling rate and SMI BeGaze (version 3.4) as recording software. Note that the purpose of using an eye tracker was to control and restrict eye movements rather than to investigate any potential effects of attention.

In session 2, we collected behavioral and EEG data. The setup was identical to session 1 with the exception that the SMI eye tracker in the EEG laboratory had a sampling rate of 60 Hz. EEG data was recorded with a 64 electrode ActiveTwo system (BioSemi, Amsterdam, The Netherlands) at a sampling rate of 1024 Hz. The recording software was

BioSemi ActiView. Scalp electrodes were placed corresponding to the 10-10 system using elastic caps. To record EOG, we placed two electrodes temporal to the eyes and two electrodes above and below the right eye. EMG activity at both hands were recorded using two electrodes at the opponens pollicis and the flexor digitorum.

All experiments were programmed in Python using the exPyriment library (Krause and Lindemann, 2014, version 0.6.3). The eye-tracker was coupled to the experiment using PyGaze (Dalmaijer et al., 2014, version 0.6.0). Eye-tracking recording software was iView X (version 3.1.0). EEG recording software was ActiView (version 7.04).

2.2.2 Snack ratings

After participants gave written informed consent and were instructed about the experimental procedures, they were familiarized with the snack stimuli. Participants first saw every snack and its name once. They were allowed to take each snack in their hand and read the information about the ingredients provided by the package. Afterwards we assessed their willingness to pay for each snack. Thereto, the snacks were presented on a screen and participants moved a slider continuous scale between 0 and 5 CHF to rate them. The slider was initialized on a middle position and had to be moved at least once to commit a rating. Snack order was randomized. Every snack was rated twice. Following previous studies (e.g., Gluth et al., 2015; Krajbich et al., 2010), we used the average rating of each snack as a proxy for subjective snack value. The task was incentivized as one snack rating was chosen randomly and compared to a random number from a uniform distribution between 0 and 5. The participants would receive the snack if its rating was higher than the random number, or the random number as money if it was higher than the snack rating.

2.2.3 Remember-and-decide task

The remember-and-decide task consisted of ten consecutive runs in which participants completed the four periods encoding, distraction, decision, and recall (in that order).

During encoding, participants learned associations between abstract symbols (identicons) and snacks. In each trial, participants fixated on a red fixation dot within a small central square (size: 84×84 pixels) in the center, flanked by two large lateral squares (size: 320×320 pixels), one in every hemifield. After a minimum fixation time (jittered interval drawn from a uniform distribution between 966 and 1033 ms, controlled via online eye tracking), an identicon appeared in the center square alongside with a snack image in either lateral square. Participants memorized the association of each identicon with its respective snack. They maintained fixation throughout the trial. Fixation control was ensured by simultaneous eye tracking. When the gaze of the participants left the central square, the trial would abort with a message calling out the fixation break, shown for 3 s. Participants were further informed that every fixation break would reduce their chance of winning a snack after the experiment by 2 $\%$. After 2000 ms the squares were superseded by visual masks as inter-trial intervals in which participants were allowed to blink. In every run, participants learned 5 identicon-snack associations. Each identicon-snack association was presented several times. To investigate the effect of presentation times on learning performance, the associations were presented 3 or 5 times (counterbalanced across runs) in session 1 and 4 times in session 2. To avoid random clustering of specific identicon-snack associations at a specific time window in the encoding period (e.g., that the identicon-Snickers association is presented several times at the end of the encoding period), we pseudo-randomized their presentation order so that all associations were presented in mini-blocks (not noticeable to the participants) within which the order was fully randomized.

During distraction, participants performed a 2-back task so that they could not rehearse information obtained in the encoding phase. For 30 s, digits were presented in the center of the screen. Participants were instructed to press the space button on their keyboard when the current digit was identical to the penultimate digit. Digits were presented for 900 ms with an inter-trial interval of 100 ms. The order of digits was pseudo-randomized so that on average one third of the digits were equal to the penultimate digit.

During the decision period, participants made choices between snacks and money amounts. In each decision trial, participants first saw a money offer presented in a white square (size: 84×84 pixels) with a red fixation dot. Participants were required to look at the fixation dot throughout the whole trial. After a minimum fixation time (again, jittered interval as during encoding), the money stimulus was superseded by a snack stimulus. The snack stimulus could either be a snack image (value trials) or an identicon (memory trials), learned during the encoding period. Only in value trials, the snack identity was visually accessible. In memory trials, it had to be retrieved from memory in order to make an informed choice. Participants were free to choose either the money amount or the snack by pressing either f vs. j button with their left vs. right index finger. Button-option assignment was counter-balanced across participants. If a maximum decision time of $>$ 7000 ms was reached, the trial aborted calling out that no decision was made. In every decision period, participants performed 4 blocks of 5 choices each. In each block, participants chose between the five snacks of the current run and a fixed money amount (1, 2, 3, or 4 CHF). Blocks were separated by a short instruction screen, indicating that the next 5 trials would offer the respective money amount. The order of the blocks and snack stimuli was randomized. The task was incentivized as participants were told in advance that a random trial would be selected after the experiment and they would receive their choice in that trial, be it a money amount or the snack. If no choice was made for this trial, they would not receive any option.

During the recall period we tested whether participants could recall the identicon-snack associations correctly. In each recall trial, we presented a red fixation dot in a white central square (jittered minimum fixation time as during encoding), succeeded by an identicon image. Participants pressed either the f or j button on the keyboard to indicate whether they could recall the snack correctly. Button-option assignment was counter-balanced across participants. A screen followed asking "Which snack?". Participants verbally reported which snack they believed to be associated with the identicon. The experimenter noted the answer and initiated the source recall procedure. A screen asking "Which side?" was presented. Participants responded via button press, if they thought the snack was presented on the left (botton f) or on the right (button j) hemifield during the encoding period. Each recall period consisted of 5 trials, one for every identicon-snack association. The order of stimuli was randomized.

Participants were familiarized with (session 1) or remembered of (session 2) the experimental procedures in the beginning of each session. In both sessions, they performed a practice run before data collection started and were encouraged to ask questions before and after the practice run. We collected 7 runs of the memory condition ($\hat{=}$ 140 memory trials) and 3 runs of the value condition ($\hat{=}$ 60 value trials). Runs contained either memory or value trials. The order of runs was pseudo-randomized so that the first runs (session 1: runs 1 through 4, session 2: runs 1 and 2) contained only memory trials. This was done to increase participants' familiarity with the task affordances. For the following runs, the order was randomized. The composition of the 5 snacks in each run was pseudo-randomized so that each run contained a snack of each willingness to pay quintile, obtained from the snack ratings.

2.2.4 Post-experiment survey

After finishing the remember-and-decide task, participants rated their subjective familiarity with each snack. As for the snack ratings, participants moved a slider on a continuous scale to indicate how familiar they were with each snack. Again, the slider had to be moved at least once. Each snack familiarity was rated once. The order of the snacks was randomized.

After the familiarity rating task, participants would receive their incentives and were allowed to eat them during the following interview. In the semi-structured interview, participants indicated if they had specific strategies and/or difficulties while solving the tasks, and, if so, verbalized their respective strategies and/or difficulties. The experimenter took notes, and, when needed, asked clarification questions.

2.3 Statistical analyses

2.3.1 Trial selection

Data analysis in this paper focuses on trials from the decision period of the experimental session 2. We selected trials which fulfilled three criteria before pursuing data analysis. First, we selected trials in which we could assume that choice and RT data depended on a terminated drift-diffusion process. Therefore, we selected only trials where participants made a decision after 200 ms (48 trials) and before the response deadline (21 trials), coherent with our previous work (Kraemer et al., 2021a). Second, we excluded trials with excessive EEG noise (102 trials, see 2.3.4 for details of EEG preprocessing). Third, we wanted to compare value trials with memory trials, in which participants had access to the information of snack identity (in contrast to other work from our group, which investigated trials in which snack identities are only retrieved partially; cf. Kraemer et al., 2022). Thus, we rejected memory trials where participants could not recall the snack identity correctly during the recall period (636 trials). In total, we analyzed 2299 value trials (per participant $M = 58.95, s.d. = 1.93$, range: $[51, 60]$, 98.25% of all value trials) and 4712 memory trials (per participant $M = 120.82, s.d. = 15.97$, range: $[62, 134]$, 86.62% of all memory trials).

2.3.2 Behavioral modeling

Our behavioral analysis served two purposes: First, we wanted to know whether there are behavioral differences between value and memory trials. Second, we examined the suitability of the DDM for this task by testing whether its qualitative predictions are coherent with participants' behavior. The DDM predicts that a) choices should follow a binary choice curve which depends on value difference of the choice options, and b) RT should describe an inverted U shape as a function of value difference (e.g., Clithero, 2018), or put differently: RT should decrease with absolute value difference of choice options.

To address these questions, we formulated two mixed effects regression models, henceforth labeled the choice model and the response time model. Both models were fitted in a hierarchical Bayesian framework (Lee and Wagenmakers, 2013) and had the functional form:

$$y_{p,t} = \beta_{Intercept_p} + \beta_{Slope_p} \times (value_{Snack_{p,t}} - value_{Money_{p,t}}) + \beta_{Memory} \times m_{p,t} + \epsilon, \quad (1)$$

where y_t is the data (binary choice or log-transformed RT) of a trial t. y_t depended on participant-specific intercept and slope parameters $\beta_{Intercept_p}$ and β_{Slope_p}, the difference of z-transformed subjective snack value and money amount, the fixed effect of trial type β_{Memory} which could affect the estimation in memory trials via the boolean variable m_t ($m = 1$, if t is a memory trial), and an unspecific error term ϵ. $\beta_{Intercept_p}$ and β_{Slope_p} were participant-specific random effects which depended on group-level normal distributions $\mathcal{N}(\mu_{Intercept}, \sigma_{Intercept})$ and $\mathcal{N}(\mu_{Slope}, \sigma_{Slope})$. We specified standard-normal prior distributions for $\mu_{Intercept}, \sigma_{Intercept}, \mu_{Slope}, \sigma_{Slope}$ and β_{Memory}. As variability parameters, $\sigma_{Intercept}, \sigma_{Slope}$ and ϵ were constrained to be larger or equal zero. Importantly, the two models differed only with respect to a $logit$ link function in the choice model, which mapped the model parameters to a binary choice outcome.

To estimate the models, we used a Markov-Chain Monte-Carlo (MCMC) approach for hierarchical Bayesian statistics using the probabilistic programming language *Stan* (Stan-Development-Team, 2018, version 2.17.0). Four chains of 4,000 samples each were initialized of which 50% warm-up samples were discarded. The Gelman-Rubin $\hat{R}$ statistic (Gelman and Rubin, 1992) indicated convergence for all relevant parameters ($\hat{R} < 1.01$). After having estimated posterior probability distributions of the model parameters, we performed statistical inference by calculating the 95% - Bayesian highest density intervals (Kruschke, 2015) and Bayes Factors. To calculate Bayes Factors, we applied the Savage-Dickey method to evaluate the inverse ratio of posterior and prior density at a null-effect level of zero (Lee and Wagenmakers, 2013). If this ratio is smaller than 1, evidence points toward the null-hypothesis that there is no effect. If it is larger than 1, evidence points toward the alternative hypothesis. The exact value of the Bayes factor specifies, how much more likely the alternative hypothesis is than the null hypothesis, given the model and the data.

2.3.3 Cognitive modeling

To investigate whether and how decision processes differ when information about value is sampled from memory, we applied the DDM (Ratcliff, 1978; Ratcliff and McKoon, 2008), arguably the most widely used sequential sampling model (Ratcliff et al., 2016). Our drift diffusion model estimated the four parameters non-decision time T_{er}, boundary separation a, starting point bias z and drift-rate ν. Choices and RT were thus assumed to follow a first-passage Wiener distribution.

$$choice_{p,t}, RT_{p,t} \sim Wiener(a_p, z_p, T_{er_{p,t}}, \nu_{p,t}). \quad (2)$$

Whereas the parameters a_p and z_p were estimated for each individual (index p for participant), the parameters $T_{er_{p,t}}$ and $\nu_{p,t}$ additionally varied from trial to trial (index t for trial). In general, the diffusion parameters depended on a combination of random intercepts β which depended on group-level normal distributions $\mathcal{N}(\mu, \sigma)$ (see table 1 for respective prior distributions). Critically, we equipped the model with additional fixed effects parameters (δ parameters) which modeled the difference between value and memory condition. A credibly positive (negative) δ can be interpreted as an increased (decreased) value of the corresponding diffusion parameter in the memory condition. At the same time, evidence for the null hypothesis of no condition difference can be tested by assessing the degree to which δ overlaps with zero. The boundary separation was modeled on the participant level as

$$a_p = SoftPlus(\beta_{a_p} + \delta_a * m_{p,t}), \quad (3)$$

so that it depended on a random intercept β_{a_p} which was drawn from a group-level normal distribution $\mathcal{N}(\mu_a, \sigma_a)$. δ_a was a fixed effect of the memory condition which affected the estimation during memory trials as indicated by the boolean dummy-variable $m_{p,t}$. The sum of these terms was *SoftPlus*-transformed ($f(x) = ln(1 + e^x)$), which, like the *exponential transformation*, constrains values to be positive, but has the advantage of ensuring a rather linear increase for higher parameter values. Starting point bias was estimated as a random effect where $z_p = \Phi(\beta_z)$. The random intercept β_z was Phi-transformed to warrant that z_p is limited to values between zero and one. Non-decision time was estimated on the trial level so that the estimate was drawn from a normal distribution $T_{er_{p,t}} \sim SoftPlus(\mathcal{N}(T_{er_p}, s_{Ter_c}))$. The center of the distribution was the participant-specific non-decision time T_{er_p}, and the scale was the condition-specific non-decision time variability s_{Ter_c} which was estimated for value and memory trials separately. We applied a SoftPlus-transformation to constrain the estimate to be positive. The participant-specific non-decision times was modeled as

$$T_{er_p} = \beta_{T_{er_p}} + \delta_{Ter} * m_{p,t}, \tag{4}$$

where $\beta_{T_{er_p}}$ was a random intercept and δ_{Ter} was a fixed effect which specified the T_{er} difference in memory trials. Finally, the drift-rate was modeled as a scaled value difference of trial-specific snack- and money values (z-transformed) with an additional drift-rate bias term.

$$\nu_{p,t} = Scale_p * (Value_{Snack_{p,t}} - Value_{Money_{p,t}} + Bias_p). \tag{5}$$

The drift-rate bias modeled the general preference of participants for either snack or money options, which was not explained with a starting point bias. We specified the bias as $Bias_p = \beta_{Bias} + \delta_{Bias}$, where β_{Bias} was a random intercept and δ_{Bias} was specified condition-specific difference of bias. The scale parameter $Scale_p$ was modeled as

$$Scale_p = SoftPlus(\beta_{Scale_p} + \delta_{Scale} * m_{p,t}) \tag{6}$$

β_{Scale_p} was a random intercept and δ_{Scale} was a fixed effect, specifying the condition-specific effect. We $SoftPlus$-transformed the sum to obtain strictly positive slope values.

The model was fitted in a hierarchical Bayesian framework in Stan (four chains of 4,000 samples each; 50% warm-up; $\hat{R} \leq 1.01$). For statistical inference, we considered the 95%-HDI and Bayes Factors, which we computed with the Savage-Dickey method for δ parameters.

2.3.4 EEG preprocessing

We preprocessed EEG data with a custom-made script, drawing on the mne-Python library (Gramfort et al., 2013, version 0.17). We referenced the data to the average potential, obtained at the Mastoid electrodes. After applying a band-pass filter (between $1/7$ Hz and 60 Hz) and a Notch-filter (at 50 Hz), we visually inspected trials for excessive noise. We fitted an independent components analysis and carefully selected components to exclude based on topography (spatially confined artifacts), periodicity (components that were only present in some blocks), and power spectrum (untypical drop in power spectrum). Further, components that were related to horizontal and vertical eye movements (as measured via EOG) were removed from the data.

We analyzed EEG data separately for stimulus-locked and response-locked epochs, covering the time windows $[-700, 2000]$ ms relative to the snack/identicon presentation and $[-1000, 100]$ ms relative to the participants' response. We baseline-corrected all epochs to a time window of $[-500, -100]$ ms relative to stimulus onset and down-sampled the data to obtain a temporal resolution of 8 ms. We further applied a current source density transformation to the data to improve topological localization of the signals.

2.3.5 EEG analyses

To measure the temporal dynamics of the decision process, we focused on three properties of the LRP. The stimulus-locked LRP onset, the slope of the response-locked LRP and the response-locked LRP peak amplitude. To estimate these properties, we first calculated the empirical LRP using a double subtraction process, where the average effector-specific activity over the left and right motor cortices (electrodes C3 and C4) are subtracted (Coles, 1989).

$$LRP_p = (\overline{C3}_{choose\_right} - \overline{C3}_{choose\_left}) - (\overline{C4}_{choose\_right} - \overline{C4}_{choose\_left}) \tag{7}$$

For every participant p and condition (memory and value trials), we calculated the LRP relative to the stimulus presentation and to the response. We applied a Gaussian smoothing kernel (s.d. = 24 ms) to the time-resolved LRP to deal with momentary signal noise.

Our analysis was centered around three properties of the LRP. We assumed that the stimulus-locked onset of the LRP marks the time when as much choice-relevant information is available to initate the evidence accumulation / action selection process (Gluth et al., 2013; Gratton et al., 1997; Klein-Flügge and Bestmann, 2012). Further, since the response-locked LRP has been demonstrated to resemble response-locked evidence accumulation (Polanía et al., 2014; Schurger et al., 2012), we assumed that the response-locked slope might be related to the rate of evidence accumulation; and that the LRP peak amplitude might be related to the boundary separation. Note, that these assumptions have not yet been validated (which is done in Section 2.3.6).

We estimated the LRP properties of onset, slope, and peak amplitude with a segmented regression method (Schwarzenau et al., 1998) where the LRP time course follows a function $y(t) = f(t) + \epsilon$. $f(t)$ describes the progression of the LRP as straight lines in a pre-onset and post-onset period.

$$f(t) = \begin{cases} \alpha, & \text{for } t_a < t < t_0, \\ \alpha + \rho(t), & \text{for } t_0 < t < t_e, \end{cases} \tag{8}$$

In the pre-onset period between the trial onset (t_a) and the LRP onset t_0, the signal is modeled as a horizontal line where the intercept α can be interpreted as pre-onset baseline activity. In the post-onset period between t_0 and the LRP peak latency (t_e), the signal is modeled as a straight line, originating at baseline level and progressing towards the peak amplitude with a slope ρ.

We fitted 2 × 2 (condition: memory and value; event-relation: stimulus-locked and response-locked) segmented regression models to the LRP time courses. t_a was 0 ms in stimulus-locked trials and -1,000 ms in response-locked trials. t_e was the peak latency of the respective LRP time course. We estimated the models in a hierarchical Bayesian framework, where α_p, ρ_p and t_{0_p} were random effects on the participant level which depended on group level normal distributions $\mathcal{N}(\mu_\alpha, \sigma_\alpha)$, $\mathcal{N}(\mu_\rho, \sigma_\rho)$ and $\mathcal{N}(\mu_{t_0}, \sigma_{t_0})$. We specified standard-normal prior distributions for all population parameters. The variability parameters σ_α, σ_ρ and σ_{t_0} were constrained to be non-negative. The onset parameter μ_{t_0} was constrained to be equal or larger than t_a. We estimated the model in *Stan*, initializing four chains of 4,000 samples each (50% warm-up). $\hat{R}$ were smaller than 1.05 for all group-level parameters of the models, which indicated acceptable convergence of the chains.

To compare stimulus-locked LRP onsets and response-locked slopes, we computed posterior distributions of difference between memory and value condition. Posterior samples of stimulus-locked μ_{t_0} and response-locked μ_ρ in the value condition were subtracted from the corresponding samples in the memory condition. The ratio of samples larger than 0 can be interpreted as the probability, that the respective parameters were larger in the memory condition than in the value condition, given the model and the data. To compare response-locked peak amplitudes – which were not estimated by the segmented regression models – we performed a paired t-test on the measured minimum amplitudes within $[-250, -50]$ ms relative to participants' responses. We computed the Bayes Factors with the Python-based Pingouin library (Vallat, 2018, version 0.3.4) and specified the default Cauchy-prior with a scale parameter of 0.707.

We further sought to inform a neuro-cognitive model with individual estimates of the LRP properties onset, slope and peak (see 2.3.6). To deal with the relatively poor signal-to-noise ratio of EEG data on the participant level, we used a jackknifing method to obtain individual estimates of the LRP properties (Stahl and Gibbons, 2004). In a leave-one-participant-out procedure, we calculated the average LRP waveform and fitted a non-hierarchical Bayesian segmented-regression model to average LRP waveform (4 chains of 1,000 samples each; 50% warm-up; $\hat{R} \leq 1.02$ indicating good convergence). We did this for every participant, every condition and every event-relation. We used the resulting posterior mean estimates of stimulus-locked t_0 as $LRP_{Onset_{p,c}}$, the response-locked posterior mean ρ estimates as $LRP_{Slope_{p,c}}$ and the response-locked peak amplitudes of the waveforms as $LRP_{Peak_{p,c}}$. These estimates indicated how each individual contributed to the grand average LRP waveforms and thereby yielded estimates of individual variation for the participant. We z-standardized these estimates and embedded them as covariates in the neuro-cognitive model.

2.3.6 Neuro-cognitive modeling

To investigate whether the LRP properties were related to the parameters of the DDM, we extended this model. We followed a *direct input* approach, where neuronal data was allowed to inform the parameters of the cognitive model (Turner et al., 2017). Individual LRP properties (estimated in the jackknifing procedure, see 2.3.5) were treated as covariates on the participant level which could explain variance via fixed effects θ parameters. A credibly negative θ parameter value implies – somewhat counter-intuitively – a positive correlation of individual LRP property and participant level DDM parameter value. The reason for this lies in the jackknifing procedure which omits the respective participant to estimate his/her effect on the grand-average (Stahl and Gibbons, 2004; Gluth and Meiran, 2019). If a θ parameter is indifferent from zero, one can infer that there is no relation of individual LRP properties and participant-level DDM parameter values.

The model was largely equivalent to the purely cognitive model (see 2.3.3). However, the parameters T_{er}, a and ν were estimated with additional fixed effects.

$$T_{er_p} = \beta_{T_{er_p}} + \delta_{Ter} * m_{p,t} + \theta_{Onset} * LRP_{Onset_{p,c}}, \tag{9}$$

$$a_p = SoftPlus(\beta_{a_p} + \delta_a * m_{p,t} + \theta_{Peak} * LRP_{Peak_{p,c}}) \tag{10}$$

$$Scale_p = SoftPlus(\beta_{Scale_p} + \delta_{Scale} * m_{p,t} + \theta_{Slope} * LRP_{Slope_{p,c}}) \tag{11}$$

Thus, θ_{Onset} was a fixed effect which modeled the effect of the LRP onset in the respective condition. a_p depended on θ_{Peak} which covered the effect of LRP peak amplitude on boundary separation. Finally, θ_{Slope} was a fixed effect which modeled the effect of the response-locked LRP slope in the respective condition. All covariates $LRP_{Onset_{p,c}}$,$LRP_{Peak_{p,c}}$ and $LRP_{Slope_{p,c}}$ stemmed from the jackknifing procedure (see 2.3.5) and was calculated for each participant and condition (memory and value).

The model was fitted in a hierarchical Bayesian framework in Stan (four chains of 4,000 samples each; 50% warm-up; $\hat{R} \leq 1.01$). For statistical inference, we considered the 95%-HDI and Bayes Factors, which we computed with the Savage-Dickey method for δ and θ parameters.

2.4 Data and code availability

Data and analysis code are uploaded on the Open Science Framework (`https://osf.io/enwtd/`) and are freely available.

3 Results

To study the differences of value-based and memory-based decisions, we invited hungry participants to take part in a laboratory study. In a remember-and-decide task, participants (N=39) cycled through several experimental periods (see Fig. 1B). During encoding, they associated abstract symbols (identicons) with individual snacks. After a 2-back distraction task, they made incentivized choices between money and snack offers (see Fig. 1C). Some trials (henceforth "value trials") mimicked the supermarket scenario, with snacks being visually accessible. In other trials (henceforth "memory trials"), participants saw identicons and had to retrieve the associated snack identities from memory. Thus, in memory trials, their decisions relied on an internal memory representation of the snacks.

3.1 Behavioral results

Figure 2 depicts the average choice and RT data of the remember-and-decide task. For statistical analysis, we fitted hierarchical Bayesian logistic and linear regression models to the choice data (choice model) and RT data (RT model), respectively. While the choice model provided strong evidence that memory and value trials did not differ with respect to choice behavior (β_{Memory}: 95% HDI = $[-0.134, 0.096]$, $BF_{10} = 0.06$, Fig. 2B), the RT model provided decisive evidence that memory-based choices took longer (on average 395 ms; $sd = 213$ ms) than value-based choices (β_{Memory}: 95% HDI = $[0.265, 0.313]$, $BF_{10} = 1.34 * 10^{123}$, Fig. 2D).

In addition to the effect on RT, we found decisive evidence that choice behavior depended on value difference of the choice options (logistic model, μ_{Slope}: 95% HDI = $[0.559, 0.751]$, $BF_{10} = 1.80 * 10^{37}$, Fig. 2B), and substantial evidence that RT decreased as a function of absolute value difference (linear model, μ_{Slope}: 95% HDI = $[-0.045, -0.013]$, $BF_{10} = 3.66$, Fig. 2D). Both results are in line with core predictions of sequential sampling models (Clithero, 2018).

We found strong evidence that RT did not differ depending on whether the snack or the money was chosen (linear model, $\mu_{Intercept}$: 95% HDI = $[-0.075, 0.106]$, $BF_{10} = 0.05$, Fig. 2D), and anecdotal evidence for unbiased choice behavior (logistic model, $\mu_{Intercept}$: 95% HDI = $[-0.538, 0.064]$, $BF_{10} = 0.47$, Fig. 2B), both suggesting the absence of an a-priori preference for either option (hence, a starting-point bias in DDM terminology; cf. Lopez-Persem et al., 2016).

3.2 Cognitive modeling

The central findings of our behavioral analyses were that participants had similar choice consistency in value and memory trials but took significantly longer to execute memory-based choices. Given that choice consistency and response times are inherently related in the sequential sampling framework, this pattern of results can be explained by two distinct, not mutually exclusive mechanisms: First, increased RT may result from increased non-decision time and a corresponding shift in RT while leaving choice consistency unaffected. A second explanation may be prolonged decision time, caused by altered evidence accumulation dynamics. For instance, increased boundary separation has been linked to increased RT while affecting choice coherence only moderately (Fontanesi et al., 2019).

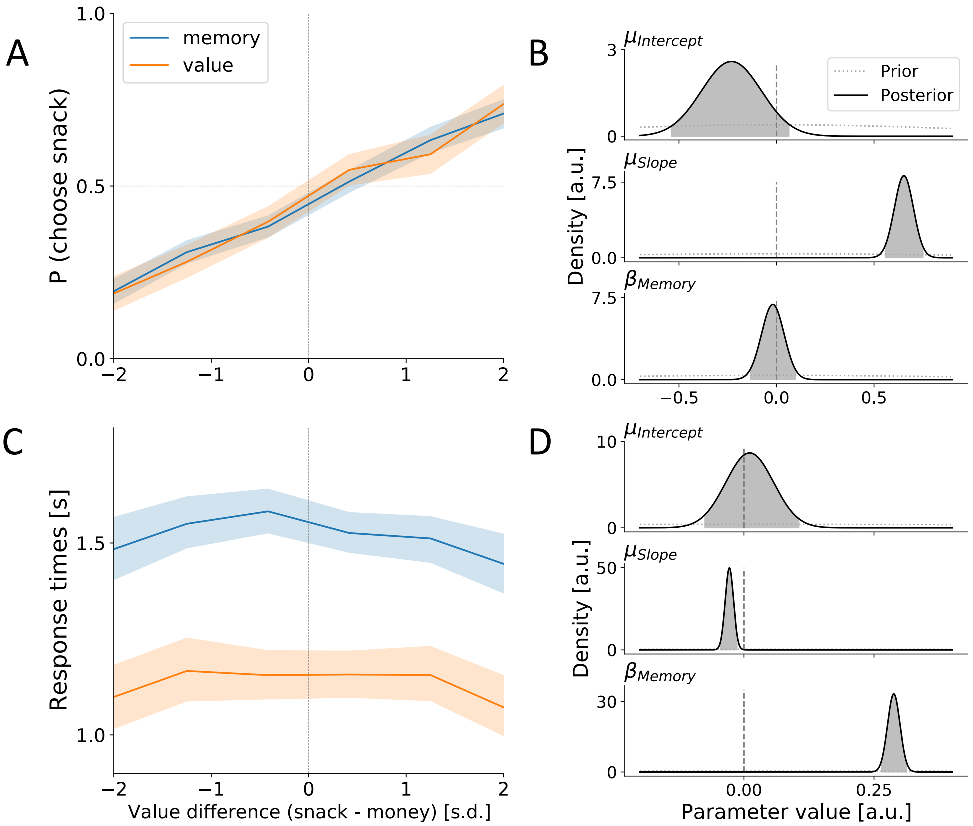


Figure 2: Behavioral results. **A** Mean proportion of snack choices as a function of value difference. Shaded areas indicate the bootstrapped 95% confidence intervals. **B** Logistic regression estimates of choices. Full lines indicate the posterior probability distribution of relevant parameters ($\mu_{Intercept}$ and μ_{Slope} for intercept and slope of the regression line; β_{Memory} models the difference between memory trails and value trials). Shaded areas indicate the 95% highest density interval. Dotted lines indicate the prior probability distribution. Vertical dashed lines indicate the parameter value specifying the null hypothesis. **C** Mean response times as a function of value difference. **D** Linear regression estimates of response times.

We investigated these potential explanations by fitting a drift-diffusion model (DDM) to the behavioral data. The model is depicted in Figure 3 and fully specified in the Methods (section 2.3.3). Importantly, while individual variance of the diffusion parameters is explained by random effects, the difference between value trials and memory trials is modeled with fixed effects δ parameters.

We found decisive evidence that participants exhibited a longer non-decision time during memory trials (δ_{Ter} : 95%-HDI: $[0.22, 0.38]$, $BF_{10} = 7.14 * 10^8$). Concurrently, the dynamics of the diffusion process seemed to be altered. The boundary separation in memory trials was estimated credibly larger than in the value condition (δ_a : 95%-HDI: $[0.31, 0.46]$, $BF_{10} = 2.01 * 10^{18}$). Additionally, the rate of evidence accumulation, as governed by the $Scale$ parameter, may be lower in memory trials, although evidence is relatively weak: While the 95%-HDI ([-0.32,-0.05]) excluded zero, the Bayes factor of 2.07 only provided anecdotal evidence for this lower drift scale.

With respect to potential biases in the diffusion process, we found that neither the starting point bias μ_z, nor a drift-rate bias μ_{Bias} (which models a general preference for snacks or money during the accumulation process Kraemer et al., 2021a; Krajbich, 2021) were credibly different from zero as indicated by the 95%−HDIs of these parameters (see Table 1). Furthermore, we found moderate and very strong evidence against potential biases in memory trials as compared to value trials (δ_z : 95%-HDI: $[-0.05, 0.06]$, $BF_{10} = 0.03$; δ_{Bias} : 95%-HDI: $[-0.35, 0.11]$, $BF_{10} = 0.21$), letting us conclude that diffusion processes had no general preference for money or snack choices.

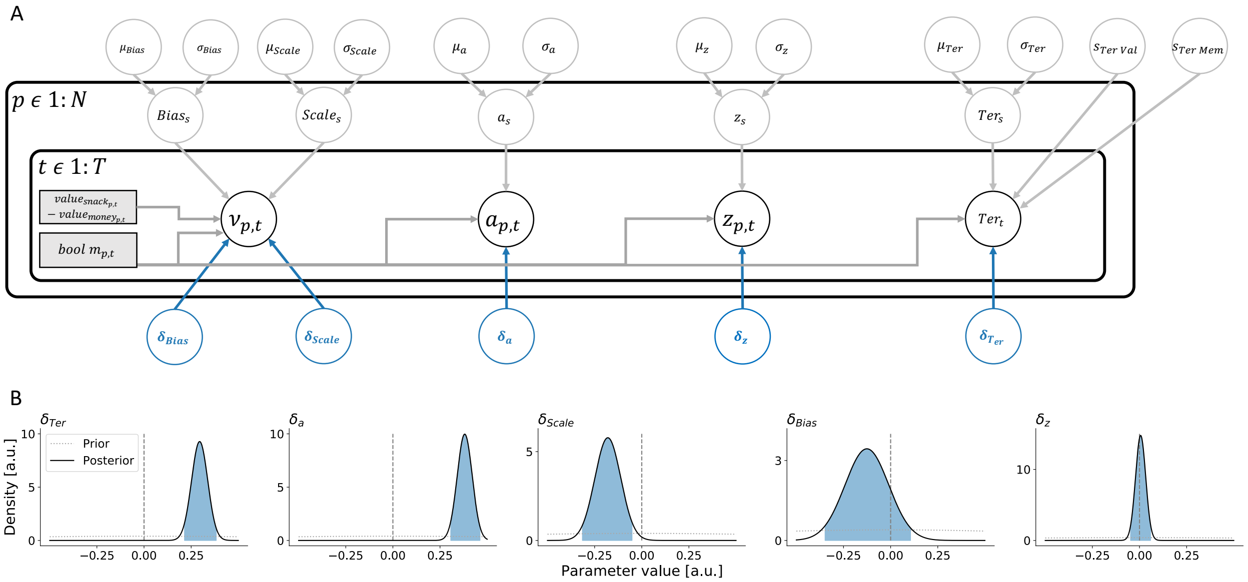


Figure 3: Cognitive modeling. **A** Graphic illustration of the structure of the drift-diffusion model. Parameters are depicted in circles, variables in rectangles. Arrows indicate the inter-relation of parameters and variables. Indices represent the participant level p and the trial level t. **B** Probability distributions for δ parameters (with positive values indicating higher parameter estimates for memory compared to value trials). Full lines indicate the posterior probability distribution of relevant parameters. Shaded areas indicate the 95%- highest density interval. Dotted lines indicate the prior probability distribution. Vertical dashed lines indicate the parameter value which specifies the null hypothesis.

Table 1: Parameter estimates of the cognitive drift-diffusion model.

	Prior	Posterior M	Posterior sd	95%-HDI	BF_{10}
$\mu_{T_{er}}$	$\mathcal{N}(-1,1)$	-0.754	0.120	[-0.99,-0.52]	-
$\sigma_{T_{er}}$	$\mathcal{HN}(0,1)$	0.707	0.091	[0.54,0.89]	-
$\delta_{T_{er}}$	$\mathcal{N}(0,1)$	0.295	0.043	[0.22,0.38]	$7.14 * 10^8$
$s_{T_{er},Value}$	$\mathcal{HN}(0,1)$	0.392	0.028	[0.34,0.44]	-
$s_{T_{er},Memory}$	$\mathcal{HN}(0,1)$	0.446	0.021	[0.4,0.49]	-
μ_a	$\mathcal{N}(2,1)$	1.521	0.081	[1.37,1.68]	-
σ_a	$\mathcal{HN}(0,3)$	0.457	0.058	[0.35,0.57]	-
δ_a	$\mathcal{N}(0,1)$	0.381	0.040	[0.31,0.46]	$2.01 * 10^{18}$
μ_{Scale}	$\mathcal{N}(0,1)$	-0.923	0.089	[-1.1,-0.76]	-
σ_{Scale}	$\mathcal{HN}(0,1)$	0.406	0.068	[0.28,0.54]	-
δ_{Scale}	$\mathcal{N}(0,1)$	-0.180	0.069	[-0.32,-0.05]	2.07
μ_{Bias}	$\mathcal{N}(0,1)$	-0.291	0.211	[-0.69,0.14]	-
σ_{Bias}	$\mathcal{HN}(0,1)$	1.174	0.160	[0.88,1.49]	-
δ_{Bias}	$\mathcal{N}(0,1)$	-0.126	0.116	[-0.35,0.11]	0.21
μ_z	$\mathcal{N}(0,1)$	0.026	0.035	[-0.04,0.09]	-
σ_z	$\mathcal{HN}(0,1)$	0.161	0.026	[0.11,0.21]	-
δ_z	$\mathcal{N}(0,1)$	0.006	0.027	[-0.05,0.06]	0.03

The table lists the respective prior distributions, mean of the posterior distribution, standard deviation of the posterior distribution, the 95%-Highest density interval, and, where applicable, the Bayes factor.

3.3 EEG results

The cognitive modeling analyses suggested altered diffusion dynamics (boundary separation and drift scale) as well as an increased non-decision time in memory trials. We next asked whether these findings are supported by an analysis of the simultaneously recorded LRP. Notably, the LRP onset has been shown to carry relevant information about incoming valuation signals (Gluth et al., 2013). Furthermore, Schurger et al. (2012) and Polanía et al. (2014) showed that the temporal progression of the response-locked LRP resembles the progression response-locked evidence accumulation processes remarkably well. To investigate this relationship with respect to our research question, we assumed that: First, the stimulus-locked LRP onset serves as a marker for the end of predecisional non-decision time; second, the response-locked LRP slope serves as a marker for speed of evidence accumulation; and third, the response-locked peak amplitude serves as a marker for decision threshold. In the following, we first test, whether memory and value trials differ with respect to the LRP properties onset, slope and peak amplitude. In section 3.4 we employ a neuro-cognitive modeling approach, to test, whether the properties relate to DDM parameters.

Figure 4A shows the stimulus-locked LRP waveforms for both conditions. We estimated the LRP onset time for both conditions using a hierarchical Bayesian segmented-regression method. Figure 4C depicts the difference of the LRP onset between memory and value trials as the difference in their posterior probability estimates. Calculating the proportion of posterior samples larger than 0 indicated that there is probability of 98.1% that memory trials had a later LRP onset than value trials, given the model and the data. The unit of parameter values in Figure 4C can also be interpreted as units of seconds. Thereby, the average difference in non-decision time amounts to 83 ms ($sd = 41$ms). This finding suggests that the delayed LRP onset may account for a part of the 395 ms RT difference between the conditions.

Analysis of the response-locked LRP properties did not indicate differences between value and memory trials. The ratio of posterior difference samples for LRP slope only indicated a 44.3% probability for a larger slope in memory trials. A Bayesian t-test of LRP peak amplitudes yielded substantial evidence against a difference between conditions ($t(38) = 0.68; BF_{10} = 0.22$).

In sum, we found credible evidence that memory trials have a later LRP onset, which partially explains the behavioral difference in RT. The properties which we hypothesized to relate to evidence accumulation (i.e. slope and peak amplitude), however, were not different between conditions.

3.4 Neuro-cognitive modeling

In a next step, we sought to relate the cognitive modeling and EEG results by testing whether the different LRP properties can inform the parameters of the cognitive model. To answer this question, we re-estimated our DDM and added fixed effects θ parameters which allowed us to test, whether the individual variability of LRP properties explained variance of the diffusion parameters on the participant level. The structure of the neuro-cognitive DDM is displayed in Figure 5. As indicated in green, the θ parameters were allowed to affect the scale parameter of the drift-rate (θ_{Slope}), the boundary separation (θ_{Peak}) and the non-decision time (θ_{Onset}) on the participant level (see 2.3.6 for details).

Prior and posterior parameter distributions can be inspected in Table 2. Consistent with the purely cognitive DDM, the results of estimating the neuro-cognitive DDM suggest that memory trials were associated with larger non-decision time (δ_{Ter} : 95%-HDI: $[0.23, 0.39], BF_{10} = 2.69 * 10^{11}$), larger boundary separation (δ_a : 95%-HDI: $[0.29, 0.45], BF_{10} = 2.22 * 10^{18}$) and (moderate evidence for) decreased rate of evidence accumulation (δ_{Scale} : 95%-HDI: $[-0.31, -0.04], BF_{10} = 1.43$). Again, diffusion processes were unbiased between snack and money choices (μ_z : 95%-HDI: $[-0.04, 0.1]$; μ_{Bias} : 95%-HDI: $[-0.69, 0.14]$).

Most importantly, we found a positive relationship of LRP onsets and non-decision time which implies that participants who exhibit a later LRP onset also exhibit a larger non-decision time. This was indicated by θ_{Onset} being credibly smaller than zero (95%-HDI: $[-0.17, -0.09]$, $BF_{10} = 1.56{*}10^7$; parameter values are negative for purely mathematical reasons, see 2.3.6 for details). Our analysis showed that, not only does increased non-decision time in memory trials coincide with a delayed LRP onset on the population level, but also that the individual LRP onsets were related to individual estimates of non-decision time.

With respect to LRP peak amplitudes and LRP slope, we found evidence for the null hypotheses that they were unrelated to the boundary separation (θ_{Peak} : 95%-HDI: $[-0.01, 0.07], BF_{10} = 0.05$) and scale parameter ($\theta_{Slope}$: 95%-HDI: $[-0.03, 0.14], BF_{10} = .1$), respectively. Thus, the altered diffusion dynamics (boundary separation and drift scale) could not be linked to individual LRP properties.

4 Discussion

We investigated the differences of action selection processes between value-based and memory-based decisions. Whereas participants exhibited choice behavior equally coherent with subjective value ratings, their RT were considerably longer in memory-based decisions. According to our diffusion model analysis, this difference was not attributed to a single

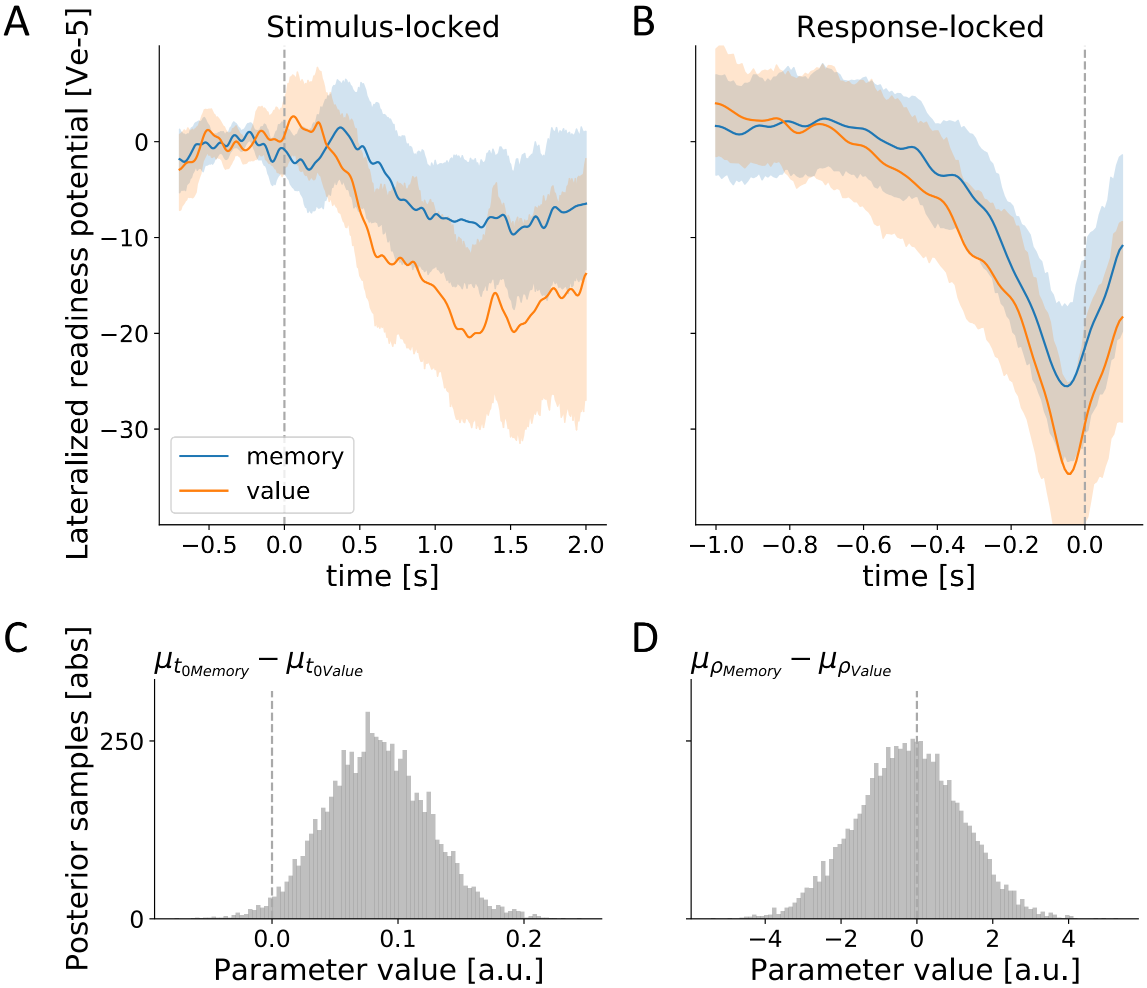


Figure 4: LRP analyses. **A** Mean stimulus-locked LRP waveforms for both conditions. Shaded areas indicate 95% bootstrapped confidence intervals. **B** Mean response-locked LRP waveforms. **C** Posterior difference in LRP onset between memory and value trials. Histogram shows posterior samples from group-level onset estimates of a hierarchical Bayesian segmented-regression model. Vertical dashed line indicate onset equivalence. **D** Posterior difference in response-locked LRP slope between memory and value trials.

but to multiple underlying mechanisms: on the one hand, we found a longer non-decision time, presumably related to memory retrieval processes, and on the other hand there was a longer accumulation-to-bound process as described by both a larger boundary separation and a (potentially) smaller drift-rate. On the neural level, the finding of a longer non-decision time was supported by a delayed LRP onset in general as well as in a positive correlation between non-decision time parameter and LRP onset across participants. Contrary to our hypotheses, the slope and peak amplitude of the LRP were unrelated to evidence accumulation dynamics.

Prominent theories about memory-based decision making state that decisions are made by retrieving and integrating information bits as samples over time (Johnson et al., 2007; Stewart et al., 2006; Zhao et al., 2021). This idea is taken up by sequential models of memory-based decision making (Shadlen and Shohamy, 2016; Kraemer et al., 2022). According to our cognitive modeling efforts, participants applied a higher decision threshold to memory-based decisions, requiring them to sample information for a longer time period. At the same time, the rate of evidence accumulation, as indicated by the drift-scale parameter, was potentially lower, which suggests that memory-based information was less directive for the eventual decision outcome. We argue that these altered evidence accumulation dynamics may be linked to the additional cognitive demands of episodic retrieval in memory trials (Weilbächer et al., 2021). More specifically, when internal memory representations guide momentary evidence, individual samples may be less informative for the

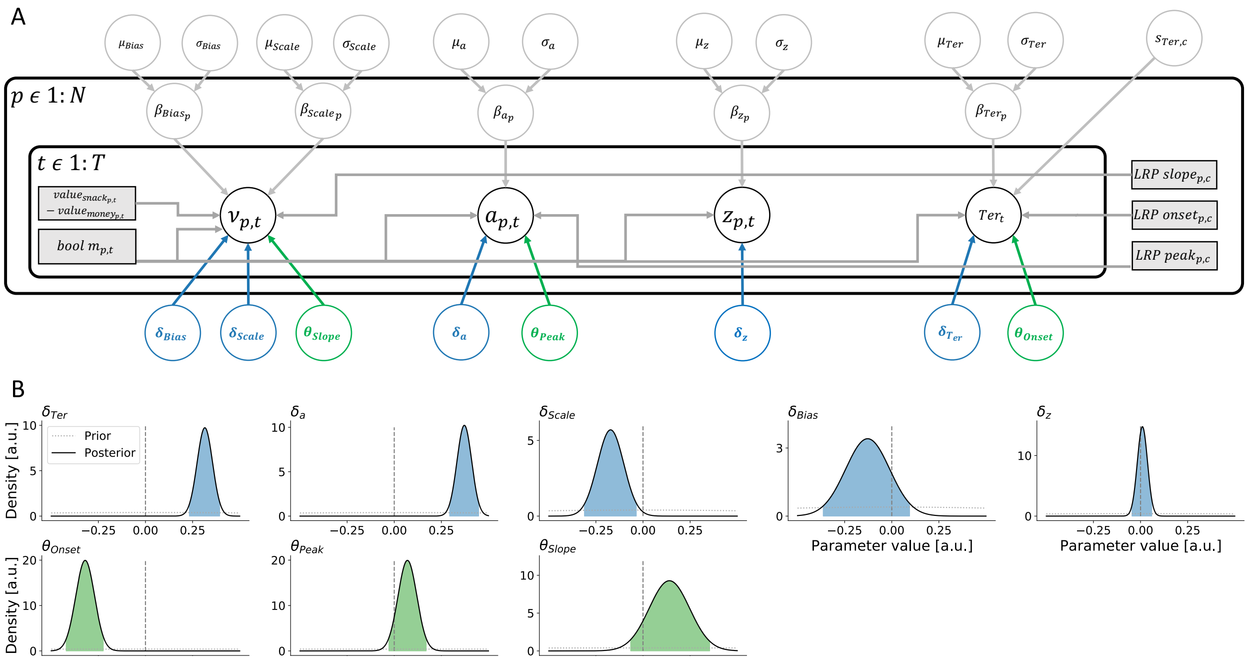


Figure 5: Neuro-cognitive modeling. **A** Graphic illustration of the structure of the drift-diffusion model. Parameters are depicted in circles, variables in rectangles. Arrows indicate how parameters and variables are related. Indices represent the participant level p and the trial level t. **B** Probability distributions for δ and θ parameters. Full lines indicate the posterior probability distribution of relevant parameters. Shaded areas indicate the 95%- highest density interval. Dotted lines indicate the prior probability distribution. Vertical dashed lines indicate the parameter value which specifies the null hypothesis.

valuation and action selection processes. The decision processes adapt to this situation by sampling for a longer time, which can lead to similar choice consistency but longer RT.

In our study, we find clear indications that the LRP can be viewed as a neural marker of the onset of decision processes. While the LRP remains being mainly viewed as a motor component, it has originally been proposed as a "window on the mind and brain" (Coles, 1989). Coles and Gratton (1988) suggested to use the LRP as a neural marker of early communication, such that "when lateralization is observed, following stimulus presentation, the subject presumably has access to a particular aspect of the stimulus information" (p. 87). The LRP onset can therefore be considered as a measure of when external information from visual stimuli vs. internal information from memory begin to affect the action selection process (Gluth et al., 2013). Our findings are in line with this assumption as the delayed LRP onset coincided with a larger non-decision time estimate for memory trials. The onset of the decision process may thus be delayed due to additional time affordances of memory retrieval processes (note, however, that memory retrieval was likely not completed at the time of the LRP onset, see below). Concurrently, individual LRP onsets were informative to estimate non-decision times on the participant level, coherent with earlier findings in perceptual decision making (Van Vugt et al., 2014). These findings support the assumption that the LRP onset may serve as a neural marker for the end of pre-decisional non-decision time, and hence, the beginning of the evidence accumulation process. A more systematic test of this hypothesis is needed, for instance via an experimental manipulation of pre-decisional non-decision time and (Nunez et al., 2019) and the simultaneous measurement of LRP onsets. Nonetheless, the LRP onset bears great potential for estimating the time at which particular stimulus information is accessible to the neural system and can affect evidence accumulation, as has been discussed in recent neuroeconomic literature (Maier et al., 2020; Sullivan et al., 2015).

Whereas the LRP onset was related to non-decision time, the other LRP properties we considered were unrelated to evidence accumulation: Slope and peak amplitude were not different between value and memory trials and were not informative for the estimation of drift scale and boundary separation on the individual level. Thus, we reject our initial hypotheses which stated that these properties may reflect evidence accumulation dynamics in this direct way. Unfortunately, we therefore lacked a neural marker of evidence accumulation to back up the differences in drift scale and boundary separation, as indicated by cognitive modeling. Another attempt, focused at the centro-parietal

Table 2: Parameter estimates of the neuro-cognitive drift-diffusion model.

	Prior	Posterior M	Posterior sd	95%-HDI	BF_{10}
μ_{Ter}	$\mathcal{N}(-1,1)$	-0.780	0.117	[-1.01,-0.55]	-
σ_{Ter}	$\mathcal{HN}(0,1)$	0.670	0.086	[0.51,0.84]	-
δ_{Ter}	$\mathcal{N}(0,1)$	0.315	0.041	[0.23,0.39]	$2.69 * 10^{11}$
θ_{Onset}	$\mathcal{N}(0,1)$	-0.128	0.020	[-0.17,-0.09]	$1.56 * 10^{7}$
$s_{Ter,Value}$	$\mathcal{HN}(0,1)$	0.368	0.026	[0.32,0.42]	-
$s_{Ter,Memory}$	$\mathcal{HN}(0,1)$	0.438	0.020	[0.4,0.48]	-
μ_a	$\mathcal{N}(2,1)$	1.535	0.079	[1.38,1.69]	-
σ_a	$\mathcal{HN}(0,3)$	0.461	0.059	[0.35,0.58]	-
δ_a	$\mathcal{N}(0,1)$	0.372	0.039	[0.29,0.45]	$2.22 * 10^{18}$
θ_{Peak}	$\mathcal{N}(0,1)$	0.028	0.020	[-0.01,0.07]	0.05
μ_{Scale}	$\mathcal{N}(0,1)$	-0.929	0.091	[-1.11,-0.75]	-
σ_{Scale}	$\mathcal{HN}(0,1)$	0.404	0.069	[0.28,0.54]	-
δ_{Scale}	$\mathcal{N}(0,1)$	-0.172	0.070	[-0.31,-0.04]	1.43
θ_{Slope}	$\mathcal{N}(0,1)$	0.056	0.043	[-0.03,0.14]	0.1
μ_{Bias}	$\mathcal{N}(0,1)$	-0.287	0.212	[-0.69,0.14]	-
σ_{Bias}	$\mathcal{HN}(0,1)$	1.188	0.166	[0.9,1.54]	-
δ_{Bias}	$\mathcal{N}(0,1)$	-0.128	0.117	[-0.36,0.1]	0.21
μ_z	$\mathcal{N}(0,1)$	0.024	0.034	[-0.04,0.1]	-
σ_z	$\mathcal{HN}(0,1)$	0.158	0.026	[0.11,0.21]	-
δ_z	$\mathcal{N}(0,1)$	0.010	0.027	[-0.05,0.06]	0.03

The table lists the respective prior distributions, mean of the posterior distribution, standard deviation of the posterior distribution, the 95%-Highest density interval, and, where applicable, the Bayes factor.

positivity – a component which has been linked to evidence accumulation in perceptual (O'Connell et al., 2012; Kelly and O'Connell, 2013), and value-based decision making (Pisauro et al., 2017) – was rejected as we did not observe the expected response-locked ramping activity of a putative CPP in our data (See Appendix 8). Given that also other authors struggled to establish a close relationship between CPP and evidence accumulation (Lui et al., 2021; Frömer et al., 2021), we notice that the field lacks the knowledge of EEG components which reflect evidence accumulation over a wider range of tasks.

The two-stage model of valuation and action selection suggests two processes that contribute to decision making. Importantly, the model remains agnostic about whether valuation must have been terminated before action selection begins (Platt and Plassmann, 2013). Under this assumption of strictly serial processes, participants in our task would have completed episodic memory retrieval before starting the action selection process, because a proper value representation requires a precise memory of the choice option in our task. To investigate this, we aimed to identify neural signatures of memory retrieval and decision making, and to observe these signals as they unfold over time. However, we could not find a marker for (lateralized) memory signals as signs of replay, as other researchers did (Waldhauser et al., 2016, 2012; Ede et al., 2019) (Appendix 8.2). Nonetheless, based on the timing of the LRP onset, we speculate that memory retrieval, valuation and action selection processes are unlikely to occur in a strictly serial manner: In cued recall (as required in our task) memory reinstatement occurs between 500 and 1,500 ms (see, Staresina and Wimber, 2019, for a review), and as the LRP onset was estimated at 235 ms in our task, we reason that action selection likely started before the critical time period for retrieval was reached. Hence, memory retrieval and action selection processes at least seem to run in parallel over some time. This is consistent with models following the parallel distributed processing doctrine (Hunt and Hayden, 2017; Yoo and Hayden, 2018) which argue for non-sequential and instead a largely parallel processing during value-based decision making.

Moreover, the LRP onset results have important implications for sequential sampling models, which often assume that the duration of memory retrieval is related to (pre-decisional) non-decision time (Ratcliff and McKoon, 2008; Ratcliff et al., 2016; Shepherdson et al., 2018). Our findings support the notion that the requirement to retrieve relevant information from memory affects both, decision dynamics and non-decision time. How can future sequential sampling models account for memory-based decisions? First, non-decision time may be equipped with additional parameters which model the effects of memory retrieval, as we did in our study with the δ_{Ter} and s_{Ter} parameters. Second, evidence accumulation dynamics should account for the fact that memory retrieval is not an instantaneous event but rather a process where information gets more vivid over time (presumably in theta rhythm, Kerrén et al., 2018; Staresina and Wimber, 2019). Such retrieval processes could be embedded in sequential sampling models where the state of memory retrieval at a time causes non-linear accumulation dynamics, as have been proposed for conflict tasks (White et al., 2017) and in judgments drawing on semantic memory (van Maanen et al., 2012; Kraemer et al., 2021b). The validation of such models will crucially depend on the identification of temporally precise neural markers of the onset, continuation and termination of memory and decision processes.

Research on episodic memory is often concerned with the question of whether qualitative information about an item is recollected or whether participants just sense a feeling of familiarity (e.g., Rugg and Curran, 2007; Wixted, 2007). Although we cannot rule out that participants might have (at least partially) relied on a sense of familiarity during the decision period, we consider it more likely that they were able to perform recollection of the choice options when making memory-based decisions. One reason for this assumption is that we limited our analysis to memory trials in which participants were able to verbally recall the snack being cued by the corresponding identicon in the subsequent recall period. Furthermore, participants exhibited equivalent choice consistency in memory and value trials, suggesting that they made well-informed decisions when being asked to retrieve the options from memory.

5 Author contributions

P.M.K and S.G. conceptualized the study design and methodology and administrated the project. P.M.K performed the software programming (experiment and analyses), computational and statistical analyses, conducted the experiments, curated the data, visualized the results and drafted the manuscript. S.G. validated the results, provided the resources, reviewed and edited the draft, supervised the work and acquired funding.

6 Competing interests

The authors declare no competing interests.

7 Acknowledgements

We thank Marie Habermann, Gregory Elbel and Noelle Burri for their support in data collection and Maria Wimber for helpful comments on data analysis. This work was supported by the Swiss National Science Foundation (SNSF Grant No. 172761 to Sebastian Gluth) and the Research Fund of the University of Basel (Grant No. 3PE1049 to Peter Kraemer).

8 Appendices

8.1 Appendix 1 - Identification of a memory signal

We conceptualized the remember-and-decide task not only to measure the LRP as a process of action selection, but also to identify a neural signature of episodic memory retrieval, unrelated to the decision process. To do this, we aimed to exploit the bihemispheric organization of the visual memory system (Gratton et al., 1997). When participants encode information in one visual hemifield, the information is represented by neural activity in early visual brain areas of the contralateral hemisphere. If the laterally encoded stimulus is retrieved from episodic memory, a reactivation process can be measured from the same brain areas which originally encoded the stimulus (Waldhauser et al., 2012, 2016). We reasoned that, if this procedure worked in the remember-and-decide task, we would be able to identify a neural signature of memory retrieval and study the temporal inter-relation of memory and decision processes.

During the encoding period, the identicon was presented in the center and the snack was presented either in the left or right visual hemifield. Participants maintained fixation on a red fixation dot in the center of the screen as ensured via online-eye tracking. When the identicon is presented in the decision period, we expected to see a signal of reactivation in those electrodes, which encoded the snack during the encoding period. To test this, we first identified electrode clusters which encoded visual information during the encoding period. In a second step, we tested if, during the decision period, those electrode clusters exhibited a hemisphere-specific reactivation, temporally locked to the presentation of the identicon.

For step one, we focused on the encoding period. We extracted epochs between -700 to 2.200 ms, relative to the stimulus onset. Following the procedures by Waldhauser et al. (2016), we selected electrodes posterior to the central channels (Fig. 6, grey) and applied a current source density transformation. For every participant and electrode, we computed the time frequency representation (TFR) of the signal between 1 and 30 Hz using Morlet wavelets. The

TFR was truncated to a time window $[-.5, 2]$s and baseline-corrected to a time window $[-.5, 0]$s (both relative to stimulus onset). After applying a z- transformation, for every participant, we averaged the TFR of the trials where snacks were presented on the right and left hemifield and subtracted the values to obtain the hemifield-specific power difference $\Delta_{TFR} = TFR_{Snack:Left} - TFR_{Snack:Right}$. A positive value means that the electrode exhibits stronger desynchronisation when the snack was presented in the right hemifield vs. when it was presented in the left hemifield (and vice versa for negative values). Accordingly, electrodes in the left hemisphere represent visual information in the right hemifield with positive Δ_{TFR}, and electrodes in the right hemisphere represent information with negative values. We tested, whether the electrodes encode the visual information by performing permutation cluster tests (1,000 permutations, critical $p = .05$). Those electrodes which contained a significant cluster were treated as encoding visual information. We identified two clusters which encoded visual information (Fig. 6, green).

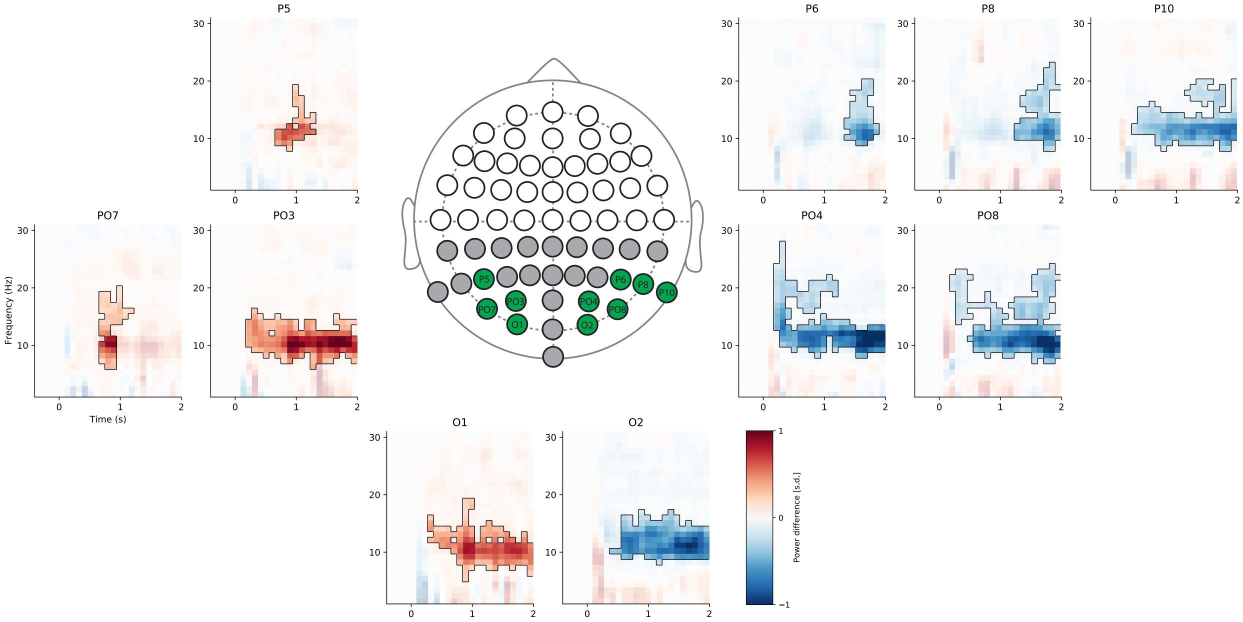


Figure 6: Identification of encoding electrodes. Plots show average power differences in time frequency representation (Δ_{TFR}) between trials where snacks were encoded on the left vs. right hemifield. The drawing in the center pictures the electrodes. Grey electrodes depict the electrodes which were tested for significant Δ_{TFR} clusters. Green electrodes were found significant in permutation cluster tests.

Next, we tested, whether we see hemifield-specific reactivation in the found electrode clusters. We extracted epochs from the decision period ($[-.7, 2.2]$s; baseline corrected $[-.5, -.1]$, both relative to stimulus onset; z-transformed). We averaged the power values for both clusters and computed Δ_{TFR} as above. Permutation cluster tests (1,000 permutations) indicated no hemisphere-specific reactivation during decision trials (best left cluster: $p = .17$; best right cluster: $p = .8$, see Fig. 7).

In sum, whereas we were able to identify electrodes which encoded the location of the snack, these clusters did not exhibit hemifield-specific reactivation as we predicted, based on the literature (Waldhauser et al., 2012, 2016; Ede et al., 2019). An additional decoding exercise (comparable to Kerrén et al., 2018), where we aimed to decode hemifield-specific activity from trials in the decision period, did not indicate periods of reactivation. We assume that this null finding is related to different task demands between the reactivation paradigms in the literature and the remember-and-decide task. Whereas the stimulus location is relevant to solve the task in the studies Waldhauser et al. (2012, 2016); Ede et al. (2019), in the remember-and-decide task, participants only need to extract information about the snack identity, not in which visual hemifield it was presented. Future studies aiming to study the inter-relation of memory retrieval and decision making might adopt experimental designs that facilitate the identification of neural activity related to stimulus identity.

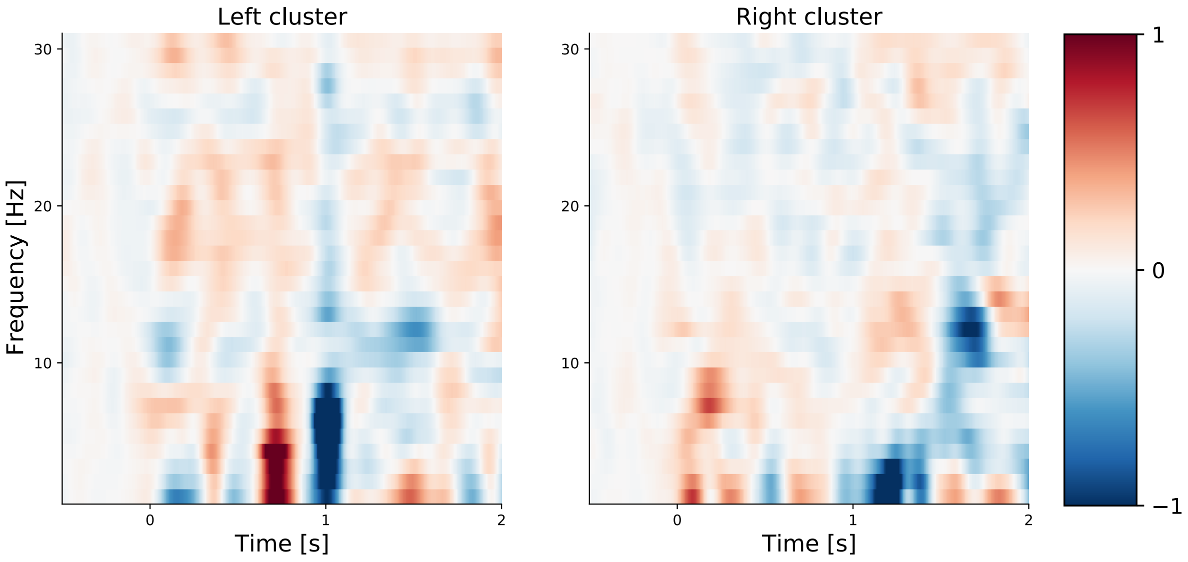


Figure 7: Test for reactivation in both clusters. Plot shows average power differences in time frequency representation (Δ_{TFR}) in the decision period. Both, the left cluster (electrodes O1, PO3, PO7 and P5) and the right cluster (electrodes O2, PO4, PO8, P6, P8 and P10) show no statistically significant differences between trials, where the snack was encoded in the left vs. in the right visual hemifield.

8.2 Appendix 2 - Centro-parietal positivity

In addition to the LRP component, we tested whether another EEG component might yield a relationship to decision-making mechanisms. Specifically, we looked at the centro-parietal positivity (CPP, O'Connell et al., 2012; Kelly and O'Connell, 2013), a component recorded over centro-parietal areas (O'Connell et al., 2012; Kelly and O'Connell, 2013), which has been proposed as a neural marker for built-up rate of decision variables (like the drift-rate in terms of the DDM) in perceptual decisions and is presumably related to the P300 component (Twomey et al., 2015). This idea was extended to consumer choices decisions (Pisauro et al., 2017), according to which there should be an build-up several hundreds of milliseconds relative to the time of response. To check, whether this was the case in our data – and therefore whether the CPP might yield information about evidence accumulation in the remember-and-decide task – we extracted EEG epochs ($[-1, .1]$ relative to the response) of the CPz electrode and averaged them over trials and participants. As can be inspected in Figure 8, the CPP characteristic of an response-locked signal build-up was not present in our data. Also, another approach including the simulation of response-locked evidence accumulation traces and correlation with EEG activity [similar to]Pisauro2017,Polania2014 did not allow the identification of a reliable build-up. Realizing that we had, in comparison to Pisauro et al. (2017), only relatively few trials and comparatively variable RT (in our case, RT could be up to 7 s; Pisauro et al., 2017, had a time limit of 1.25 s), it is possible that we lacked statistical power to draw conclusions from this null-finding. We therefore refrained from further analyses, noting, however, that several recent studies suggest a relatively high task-specificity of the CPP (Lui et al., 2021; Frömer et al., 2021).

References

Alba, J. W. and Hutchinson, J. W. (1987). Dimensions of Consumer Expertise. *Journal of Consumer Research*, 13(4):411.

Bakkour, A., Palombo, D. J., Zylberberg, A., Kang, Y. H., Reid, A., Verfaellie, M., Shadlen, M. N., and Shohamy, D. (2019). The hippocampus supports deliberation during value-based decisions. *eLife*, 8:1–28.

Bartra, O., McGuire, J. T., and Kable, J. W. (2013). The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. *NeuroImage*, 76:412–427.

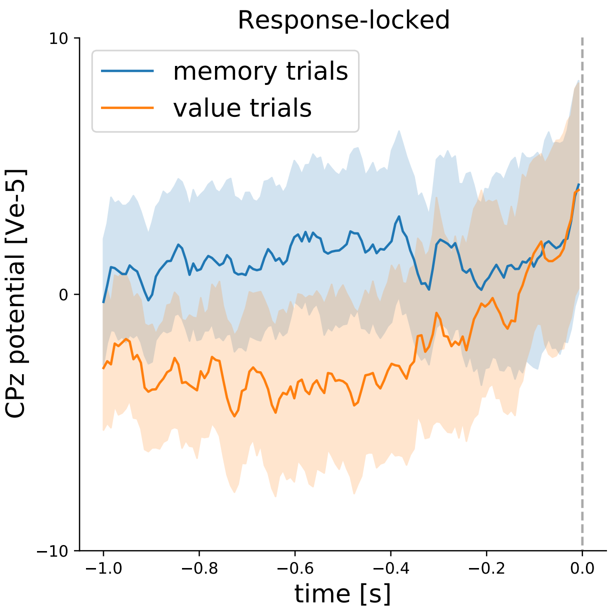


Figure 8: Mean Response-locked CPP signal for both conditions. Shaded areas indicate 95% bootstrapped confidence intervals. The vertical dashed line indicates the event of participant response.

Busemeyer, J. R., Gluth, S., Rieskamp, J., and Turner, B. M. (2019). Cognitive and Neural Bases of Multi-Attribute, Multi-Alternative, Value-based Decisions. *Trends in Cognitive Sciences*, 23(3):251–263.

Cisek, P. (2007). Cortical mechanisms of action selection: The affordance competition hypothesis. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 362(1485):1585–1599.

Clithero, J. A. (2018). Response times in economics : Looking through the lens of sequential sampling models. *Journal of Economic Psychology*, 69:61–86.

Clithero, J. A. and Rangel, A. (2014). Informatic parcellation of the network involved in the computation of subjective value. *Social Cognitive and Affective Neuroscience*, 9(9):1289–1302.

Coles, M. G. (1989). Modern mind-brain reading: Psychophysiology, physiology, and cognition. *Psychophysiology*, 26(3):251–269.

Coles, M. G. H. and Gratton, G. (1988). Detecting early communication: Using measures of movement-related potentials to illuminate human information processing. *Biological Psychology*, 26:69–89.

Dalmaijer, E. S., Mathôt, S., and Van der Stigchel, S. (2014). PyGaze: an open-source, cross-platform toolbox for minimal-effort programming of eyetracking experiments. *Behavior research methods*, 46(4):913–921.

Ede, F. V., Chekroud, S. R., Stokes, M. G., and Nobre, A. C. (2019). visual working memory guided action. *Nature Neuroscience*, 22(March).

Fehr, E. and Rangel, A. (2011). Neuroeconomic foundations of economic choice-recent advances. *Journal of Economic Perspectives*, 25(4):3–30.

Fontanesi, L., Gluth, S., Spektor, M., and Rieskamp, J. (2019). A reinforcement learning diffusion decision model for value-based decisions. *Psychonomic Bulletin and Review*.

Frömer, R., Dean Wolf, C. K., and Shenhav, A. (2019). Goal congruency dominates reward value in accounting for behavioral and neural correlates of value-based decision-making. *Nature Communications*, 10(1):1–11.

Frömer, R., Nassar, M., Ehinger, B., and Shenhav, A. (2021). Two distinct patterns of EEG activity emerge during value-based choice, neither related to evidence accumulation . *Proceedings of the 19th Annual Meeting of the Society for Neuroeconomics*.

Gelman, A. and Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, 7(4):457–511.

Gluth, S. and Meiran, N. (2019). Leave-One-Trial-Out , LOTO , a general approach to link single-trial parameters of cognitive models to neural data. *eLife*, 8:e42607.

Gluth, S., Rieskamp, J., and Buchel, C. (2012). Deciding When to Decide: Time-Variant Sequential Sampling Models Explain the Emergence of Value-Based Decisions in the Human Brain. *Journal of Neuroscience*, 32(31):10686–10698.

Gluth, S., Rieskamp, J., and Büchel, C. (2013). Classic EEG motor potentials track the emergence of value-based decisions. *NeuroImage*, 79:394–403.

Gluth, S., Sommer, T., Rieskamp, J., and Büchel, C. (2015). Effective Connectivity between Hippocampus and Ventromedial Prefrontal Cortex Controls Preferential Choices from Memory Article Effective Connectivity between Hippocampus and Ventromedial Prefrontal Cortex Controls Preferential Choices from Memory. *Neuron*, pages 1078–1090.

Gold, J. I. and Shadlen, M. N. (2007). The Neural Basis of Decision Making. *Annual Review of Neuroscience*, 30(1):535–574.

Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., and Hämäläinen, M. (2013). MEG and EEG data analysis with MNE-Python. *Frontiers in Neuroscience*, 7(7 DEC):1–13.

Gratton, G., Shin, E., and Fabiani, M. (1997). Hemispheric Organization of Visual Memory. *Mechanisms of Sensory Working Memory*, pages 75–88.

Grueschow, M., Polania, R., Hare, T. A., and Ruff, C. C. (2015). Automatic versus Choice-Dependent Value Representations in the Human Brain. *Neuron*, 85(4):874–885.

Hare, T. A., Schultz, W., Camerer, C. F., O'Doherty, J. P., and Rangel, A. (2011). Transformation of stimulus value signals into motor commands during simple choice. *Proceedings of the National Academy of Sciences of the United States of America*, 108(44):18120–18125.

Hunt, L. T. and Hayden, B. Y. (2017). A distributed, hierarchical and recurrent framework for reward-based choice. *Nature Reviews Neuroscience*, 18(3):172–182.

Johnson, E. J., Häubl, G., and Keinan, A. (2007). Aspects of Endowment: A Query Theory of Value Construction. *Journal of Experimental Psychology: Learning Memory and Cognition*, 33(3):461–474.

Kable, J. W. and Glimcher, P. W. (2009). The Neurobiology of Decision: Consensus and Controversy. *Neuron*, 63(6):733–745.

Kelly, S. P. and O'Connell, R. G. (2013). Internal and External Influences on the Rate of Sensory Evidence Accumulation in the Human Brain. *Journal of Neuroscience*, 33(50):19434–19441.

Kerrén, C., Linde-Domingo, J., Hanslmayr, S., and Wimber, M. (2018). An Optimal Oscillatory Phase for Pattern Reactivation during Memory Retrieval. *Current Biology*, 28(21):3383–3392.e6.

Klein-Flügge, M. C. and Bestmann, S. (2012). Time-dependent changes in human corticospinal excitability reveal value-based competition for action during decision processing. *Journal of Neuroscience*, 32(24):8373–8382.

Kraemer, P. M., Fontanesi, L., Spektor, M. S., and Gluth, S. (2021a). Response time models separate single- and dual-process accounts of memory-based decisions. *Psychonomic Bulletin and Review*, 28:304–323.

Kraemer, P. M., Weilbächer, R. A., Mechera-Ostrovsky, T., and Gluth, S. (2022). Cognitive and neural principles of a memory bias on preferential choices. *Current Research in Neurobiology*, 3:100029.

Kraemer, P. M., Wulff, D. U., and Gluth, S. (2021b). A sequential sampling account of semantic relatedness decisions. *Proceedings of the 43th Annual Meeting of the Cognitive Science Society*, pages 1788–1794.

Krajbich, I. (2021). Multi-parameter utility and drift-rate functions conflate attribute weights and choice consistency. *psyArXiv*.

Krajbich, I., Armel, C., and Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, 13(10):1292–1298.

Krause, F. and Lindemann, O. (2014). Expyriment: A Python library for cognitive and neuroscientific experiments. *Behavior Research Methods*, 46(2):416–428.

Kruschke, J. K. (2015). *Doing Bayesian data analysis, a tutorial with R, JAGS, and Stan.* Academic press, London.

Lee, M. D. and Wagenmakers, E. J. (2013). *Bayesian cognitive modeling: A practical course.* Cambridge University Press, Cambridge.

Levy, D. J. and Glimcher, P. W. (2012). The root of all value: A neural common currency for choice. *Current Opinion in Neurobiology*, 22(6):1027–1038.

Lopez-Persem, A., Domenech, P., and Pessiglione, M. (2016). How prior preferences determine decision-making frames and biases in the human brain. *eLife*, 5(NOVEMBER2016):1–20.

Lui, K. K., Nunez, M. D., Cassidy, J. M., Vandekerckhove, J., Cramer, S. C., and Srinivasan, R. (2021). Timing of Readiness Potentials Reflect a Decision-making Process in the Human Brain. *Computational Brain and Behavior*, 4(3):264–283.

Lynch, J. G. and Srull, T. K. (1982). Memory and Attentional Factors in Consumer Choice: Concepts and Research Methods. *Journal of Consumer Research*, 9(1):18.

Maier, S. U., Raja Beharelle, A., Polanía, R., Ruff, C. C., and Hare, T. A. (2020). Dissociable mechanisms govern when and how strongly reward attributes affect decisions. *Nature Human Behaviour*, 4(9):949–963.

Nunez, M. D., Gosai, A., Vandekerckhove, J., and Srinivasan, R. (2019). The latency of a visual evoked potential tracks the onset of decision making. *NeuroImage*, 197(April):93–108.

O'Connell, R. G., Dockree, P. M., and Kelly, S. P. (2012). A supramodal accumulation-to-bound signal that determines perceptual decisions in humans. *Nature Neuroscience*, 15(12):1729–1735.

Pisauro, M. A., Fouragnan, E., Retzler, C., and Philiastides, M. G. (2017). Neural correlates of evidence accumulation during value-based decisions revealed via simultaneous EEG-fMRI. *Nature Communications*, 8:15808.

Platt, M. L. and Plassmann, H. (2013). *Multistage Valuation Signals and Common Neural Currencies*. Elsevier Inc.

Polanía, R., Krajbich, I., Grueschow, M., and Ruff, C. C. (2014). Neural Oscillations and Synchronization Differentially Support Evidence Accumulation in Perceptual and Value-Based Decision Making. *Neuron*, 82(3):709–720.

Polanía, R., Moisa, M., Opitz, A., Grueschow, M., and Ruff, C. C. (2015). The precision of value-based choices depends causally on fronto-parietal phase coupling. *Nature Communications*, 6.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, 85(2):59–108.

Ratcliff, R. and McKoon, G. (2008). Drift Diffusion Decision Model: Theory and data. *Neural Computation*, 20(4):873–922.

Ratcliff, R., Smith, P. L., Brown, S. D., and Mckoon, G. (2016). Diffusion Decision Model : Current Issues and History. *Trends in Cognitive Sciences*, 20(4):260–281.

Rizzolatti, G. and Kalaska, J. F. (2013). Voluntary Movement: The Parietal and Premotor Cortex. In Kandel, E. R., Schwarz, J. H., Jessell, T. M., Siegelbaum, S. A., and Hudspeth, A. J., editors, *Principles of Neural Science*, pages 865–893. McGraw-Hill Education LLC, New York.

Rugg, M. D. and Curran, T. (2007). Event-related potentials and recognition memory. *Trends in Cognitive Sciences*, 11(6):251–257.

Schurger, A., Sitt, J. D., and Dehaene, S. (2012). An accumulator model for spontaneous neural activity prior to self-initiated movement. *Proceedings of the National Academy of Sciences of the United States of America*, 109(42).

Schwarzenau, P., Falkenstein, M., Hoormann, J., and Hohnsbein, J. (1998). A new method for the estimation of the onset of the lateralized readiness potential (LRP). *Behavior Research Methods, Instruments, and Computers*, 30(1):110–117.

Shadlen, M. N. and Kiani, R. (2013). Decision making as a window on cognition. *Neuron*, 80(3):791–806.

Shadlen, M. N. and Shohamy, D. (2016). Decision Making and Sequential Sampling from Memory. *Neuron*, 90(5):927–939.

Shepherdson, P., Oberauer, K., and Souza, A. S. (2018). Working memory load and the retro-cue effect: A diffusion model account. *Journal of Experimental Psychology: Human Perception and Performance*, 44(2):286–310.

Smith, P. L. and Ratcliff, R. (2004). Psychology and neurobiology of simple decisions. *Trends in Neurosciences*, 27(3):161–168.

Stahl, J. and Gibbons, H. (2004). The application of jackknife-based onset detection of lateralized readiness potential in correlative approaches. *Psychophysiology*, 41(6):845–860.

Stan-Development-Team (2018). Pystan: the python interface to stan, v 2.17.1.0.

Staresina, B. P. and Wimber, M. (2019). A Neural Chronometry of Memory Recall. *Trends in Cognitive Sciences*, 23(12):1071–1085.

Stewart, N., Chater, N., and Brown, G. D. (2006). Decision by sampling. *Cognitive Psychology*, 53(1):1–26.

Sullivan, N., Hutcherson, C., Harris, A., and Rangel, A. (2015). Dietary Self-Control Is Related to the Speed With Which Attributes of Healthfulness and Tastiness Are Processed. *Psychological Science*, 26(2):122–134.

Thura, D. and Cisek, P. (2014). Deliberation and commitment in the premotor and primary motor cortex during dynamic decision making. *Neuron*, 81(6):1401–1416.

Turner, B. M., Forstmann, B. U., Love, B. C., Palmeri, T. J., and Van Maanen, L. (2017). Approaches to analysis in model-based cognitive neuroscience. *Journal of Mathematical Psychology*, 76:65–79.

Twomey, D. M., Murphy, P. R., Kelly, S. P., and O'Connell, R. G. (2015). The classic P300 encodes a build-to-threshold decision variable. *European Journal of Neuroscience*, 42(1):1636–1643.

Vaidya, A. R. and Fellows, L. K. (2020). Under construction: Ventral and lateral frontal lobe contributions to value-based decision-making and learning. *F1000Research*, 9:1–8.

Vallat, R. (2018). Pingouin: statistics in python. *The Journal of Open Source Software*, 3(31):1026.

van Maanen, L., van Rijn, H., and Taatgen, N. (2012). RACE/A: An architectural account of the interactions between learning, task control, and retrieval dynamics. *Cognitive Science*, 36(1):62–101.

Van Vugt, M. K., Simen, P., Nystrom, L., Holmes, P., and Cohen, J. D. (2014). Lateralized readiness potentials reveal properties of a neural mechanism for implementing a decision threshold. *PLoS ONE*, 9(3).

Waldhauser, G. T., Braun, V., and Hanslmayr, S. (2016). Episodic Memory Retrieval Functionally Relies on Very Rapid Reactivation of Sensory Information. *Journal of Neuroscience*, 36(1):251–260.

Waldhauser, G. T., Johansson, M., and Hanslmayr, S. (2012). Alpha/Beta Oscillations Indicate Inhibition of Interfering Visual Memories. *Journal of Neuroscience*, 32(6):1953–1961.

Webb, R., Glimcher, P. W., and Louie, K. (2021). The normalization of consumer valuations: Context-dependent preferences from neurobiological constraints. *Management Science*, 67(1):93–125.

Weilbächer, R. A., Krajbich, I., Rieskamp, J., and Gluth, S. (2021). The influence of visual attention on memory-based preferential choice. *Cognition*, 215(August 2020).

White, C. N., Servant, M., and Logan, G. D. (2017). Testing the validity of conflict drift-diffusion models for use in estimating cognitive processes : A parameter-recovery study. *Psychon Bull Rev*.

Wixted, J. T. (2007). Dual-process theory and signal-detection theory of recognition memory. *Psychological Review*, 114(1):152–176.

Yoo, S. B. M. and Hayden, B. Y. (2018). Economic Choice as an Untangling of Options into Actions. *Neuron*, 99(3):434–447.

Zhang, Z., Wang, S., Good, M., Hristova, S., Kayser, A. S., and Hsu, M. (2021). Retrieval-constrained valuation: Toward prediction of open-ended decisions. *Proceedings of the National Academy of Sciences*, 118(20):e2022685118.

Zhao, W. J., Richie, R., and Bhatia, S. (2021). Process and content in decisions from memory. *Psychological Review*.

A.4 Manuscript 4: A sequential sampling account of semantic relatedness decisions

A sequential sampling account of semantic relatedness decisions

Peter M. Kraemer (peter.kraemer@unibas.ch)
University of Basel, Missionsstrasse 62a, Basel 4057, Switzerland

Dirk U. Wulff (dirk.wulff@unibas.ch)
University of Basel, Missionsstrasse 64a, Basel 4057, Switzerland,
MPI for Human Development, Lentzeallee 94, 14195 Berlin, Germany

Sebastian Gluth (sebastian.gluth@uni-hamburg.de)
University of Hamburg, Von-Melle-Park 11, Hamburg 20146, Germany

Abstract

Semantic memory research often draws on decisions about the semantic relatedness of concepts. These decisions depend on cognitive processes of memory retrieval and choice formation. However, most previous research focused on memory retrieval but neglected the decision aspects. Here we propose the sequential sampling framework to account for choices and response times in semantic relatedness decisions. We focus on three popular sequential sampling models, the Race model, the Leaky Competing Accumulator model (LCA) and the Drift Diffusion Model (DDM). Using model simulations, we investigate if and how these models account for two empirical benchmarks: the relatedness effect, denoting faster ”related” than ”unrelated” decisions when judging the relatedness of word pairs; and an inverted-U shaped relationship between response time and the relatedness strength of word pairs. Our simulations show that the LCA and DDM, but not the Race model, can reproduce both effects. Furthermore, the LCA predicts a novel phenomenon: the inverted relatedness effect for weakly related word pairs. Reanalyzing a publicly available data set, we obtained credible evidence of such an inverted relatedness effect. These results provide strong support for sequential sampling models – and in particular the LCA – as a viable computational account of semantic relatedness decisions and suggest an important role for decision-related processes in (semantic) memory tasks.

Keywords: Semantic memory; Memory Retrieval; Decision-Making; Cognitive Modeling; Sequential Sampling Models

Introduction

As part of human declarative memory, semantic memory contains our general knowledge about the world. Most theoretical perspectives view semantic memory as some kind of space or structure, such as a network that carries conceptual representations of objects in the world and the relationships between them (Jones, Willits, & Dennis, 2015). In this article, we investigate the cognitive processes involved in retrieving and acting on the strength of relationship between concepts, commonly referred to as semantic relatedness. Specifically, we evaluate three sequential sampling models as novel theoretical accounts for key empirical benchmarks in a frequently used semantic relatedness task.

Two benchmarks of semantic relatedness decisions

The literature has proposed many tasks to behaviorally measure people's representations of semantic relatedness (Kumar, 2020; Wulff et al., 2019). Here we focus on the semantic relatedness decision task (SRDT), a two-alternative, forced-choice task that requires participants to decide whether two words are semantically related or not. Using this task, previous research has established two key benchmarks that models of the underlying processes should be able to account for.

The first benchmark is the so-called relatedness effect, describing that ”related” responses tend to be given faster than ”unrelated” responses (Balota & Black, 1997). The relatedness effect has been demonstrated repeatedly using the SRDT (Karwoski & Schachter, 1948; Balota & Paul, 1996; Balota & Black, 1997). The second benchmark is an inverted-U shaped relationship between semantic relatedness and response times (RTs), with strongly and weakly related words resulting in shorter RTs than moderately related words. The inverted-U shaped relationship was demonstrated by two recent studies (Kenett, Levi, Anaki, & Faust, 2017; Kumar, Balota, & Steyvers, 2019) using a similar SRDT, but different approaches to semantic relatedness.

Both benchmarks have been linked to theoretical accounts based on spreading activation in a semantic network (Collins & Loftus, 1975). According to this and other accounts of memory retrieval, such as random walks (Abbott, Austerweil, & Griffiths, 2015) or compound cue mechanisms (Ratcliff & McKoon, 1988, 1994), RTs are proportional to the distance between two concepts within the network. In the case spreading activation, distance determines the amount of activation required to spread from one concept to the other. Spreading activation, thus, produces faster responses to strongly-related compared to moderately-related word pairs (see Kenett et al., 2017), explaining half of the inverted U-shaped relationship. It also predicts the relatedness effect, as long as ”related” responses are given to more strongly related word pairs than ”unrelated” responses (Balota & Black, 1997).

It remains unclear, however, how spreading activation would explain faster responses to weakly as compared to moderately related pairs, and whether spreading activation alone is sufficient to explain the relatedness effect, or if other decision-relevant processes such as response caution or response competition play a role.

Present study

We propose that sequential sampling models, a popular modeling framework in the field of judgment and decision making (Busemeyer, Gluth, Rieskamp, & Turner, 2019; Ratcliff & McKoon, 2008), can potentially account for the benchmarks described above and help to illuminate the cognitive processes underlying semantic relatedness decisions. Sequential sampling models assume an accumulation process that, in essence, is similar to the notion of spreading activation and embed it within a decision process. Next, we will describe three prominent representatives of sequential sampling models and explain how they give rise to ”related” and ”unrelated” decisions in the SRDT. Then, we present a simulation study evaluating the model predictions with respect to the inverted-U shaped relationship and the relatedness effect. Finally, we present an analysis of existing data to test a novel prediction derived from our simulation analysis.

Sequential Sampling Models

The family of sequential sampling models comprises numerous different specifications. In order show that sequential sampling models can account for empirical benchmarks of the SRDT, we focus on basic implementations of three frequently used variants, the Race model, the Leaky Competing Accumulator model (LCA) and the Drift-Diffusion Model (DDM), following the implementations by Bogacz, Brown, Moehlis, Holmes, and Cohen (2006). There exist more flexible versions of these variants that might allow them to individually explain a broader set of phenomena (see General Discussion). However, we would like to emphasize that the goal of this study is not to provide decisive evidence between these models but to investigate how the sequential sampling framework in general can be used to identify mechanisms in semantic relatedness decisions.

Race Model

The Race model formulates a decision process where independent accumulators I_1 and I_2 accumulate noisy evidence over time until one of them reaches a decision threshold Z (see Figure 1). In this context, evidence is an abstract unit of preference for either choice option.

To account for behavior in the SRDT, one accumulator $I_{related}$ is set to an externally derived estimate of semantic relatedness of a given word pair. Conceptually, this accumulator can be regarded as analogue to the strength of memory trace activation within a spreading-activation account. The accumulator, $I_{unrelated}$, is estimated from the data and serves as a reference value against which $I_{related}$ is compared. Thus, $I_{unrelated}$ acts as decision criterion comparable to the criterion in signal detection theory (Green & Swets, 1966). Specifically, when $I_{related}$ is larger than $I_{unrelated}$, the agent likely responds ”related” and vice versa. It is assumed that the two accumulators are independent of each other.

Leaky Competing Accumulator Model

The Leaky Competing Accumulator model (LCA, Usher and McClelland, 2001) also models the decision as a competition between two accumulators [1]. In contrast to the Race model, however, the accumulators in the LCA are not independent, but influence each other through a lateral inhibition process (w). Lateral inhibition inhibits the rate of one accumulator as a function of the evidence state of the competing accumulator. Figure 1 illustrates that lateral inhibition can both speed up (solid lines) and slow down (dashed lines) the divergence of the accumulators, depending on how similar the accumulation rates are. Finally, the LCA is equipped with a leakage parameter k that results in a decay of evidence over time.

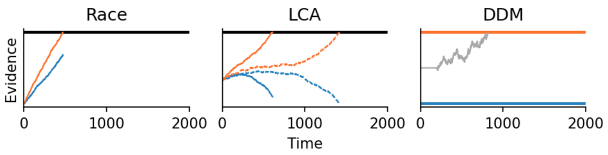


Figure 1: Sequential sampling models. The left panel illustrates two accumulators in the race model representing ”related” (orange) and ”unrelated” (blue) decisions in the SRDT. The middle panel illustrates two decisions under the LCA, subject to different levels of lateral inhibition. The right panel illustrates the relative decision variable (gray) in the DDM between two decision boundaries.

To account for behavior in the SRDT, $I_{related}$ is set equal to the semantic relatedness of two words. The leakage k and the within-trial noise c are fixed. All other parameters, including $I_{unrelated}$, lateral inhibition w, and threshold Z are estimated from the data.

Drift Diffusion Model

In contrast to the other two models, the DDM assumes a process of relative evidence accumulation. Specifically, the accumulation drifts according to a Wiener process in-between two decision boundaries, one for each response option, until one of them is reached. The direction and rate of accumulation is determined by the drift-rate ν. Additional model parameters include a boundary separation a, often interpreted as response caution, a starting point bias z, representing an a-priori preference towards either option, and a non-decision time T_{er}, reflecting sensory and motor preparatory processes.

To account for behavior in the SRDT, the drift-rate ν is equal to the difference between the semantic relatedness and the reference value (i.e., $\nu = I_{related} - I_{unrelated}$). Within-trial noise c is fixed. All other parameters are estimated from the data.

Simulation of semantic relatedness decisions

To investigate how well the three models can account for the inverted-U shaped relationship of RTs and the relatedness effect, we generated data from each of the three models using a range of plausible parameter values and analyzed whether and how consistently they produce the two benchmark effects in question.

---

[1] Note that we consider the implementation by Bogacz et al. (2006), which, in contrast to the original implementation by Usher and McClelland, permits negative accumulator states.

Simulation details

Parameter values for the two parameters, $I_{related}$ and $I_{unrelated}$, were chosen as follows. $I_{related} = (.09, .20, .32, .43, .60)$ was set to five different levels representing low, low-medium, medium, medium-high, and high relatedness. The exact values were derived by calculating the cosine similarity values of a representative word-pair data set (Bruni, Tran, & Baroni, 2014), using the *fastText word2vec* model (Grave, Bojanowski, Gupta, Joulin, & Mikolov, 2018). $I_{unrelated} = (.20, .26, .32, .38, .43)$ was set to five values ranging between ”low-medium” and ”medium-high” relatedness. This range was chosen to allow $I_{related}$ to be either smaller, equal or larger than $I_{unrelated}$.

The threshold parameter $Z = (.05, .10, .15, .20, .25)$ in the Race model and the LCA, and the boundary separation $a = (.05, .10, .15, .20, .25)$ in the DDM were set to five equally spaced levels in a range taken from a recent simulation study on the LCA (Miletić, Turner, Forstmann, & Maanen, 2017). Following the same study, the within-trial noise c was set to .01, and the lateral inhibition parameter $w = (.5, 1, 2, 4)$ was set to four different values. The leakage parameter k was fixed to 1. The non-decision time T_{er} of the DDM was set to a plausible value of .2. We chose three levels of starting point bias z, reflecting an a-priori bias towards ”unrelated” ($z < .5$) and ”related” ($z > .5$), as well as an unbiased DDM ($z = .5$).

For each parameter combination, we simulated a total of 10,000 semantic relatedness decisions and associated RTs. To limit computational load, responses were simulated up to a maximum response time of 7 seconds. Trials that would have taken longer were rejected.

Inverted-U shaped relationship

Figure 2 shows the relationships between relatedness and RTs produced by the three models under the various parameter combinations. The results for the Race model revealed a strictly monotone relationship, with higher levels of relatedness being associated with lower RTs. Hence, the Race model did not produce the inverted-U shaped relationship.

For nearly all parameter combinations, the LCA exhibited an inverted-U shaped relationship between relatedness and RTs. Only for the smallest values of the criterion parameter $I_{unrelated}$, the threshold parameter Z, or the lateral inhibition parameter w, this pattern did not emerge. Conversely, the inverted-U shaped relationship tended to be more pronounced for large criterion, threshold, and inhibition parameters. The pattern produced by the LCA exhibited a consistent right-skew, with moderately-low relatedness exhibiting the slowest RTs and very high relatedness being associated with faster RTs compared to very low ones. This pattern was particularly pronounced for low criterion ($I_{unrelated}$) values and attenuated for high criterion values.

The results for the DDM revealed equally consistent inverted-U shaped relationships. In contrast to the LCA, the DDM tended, on average, to produce symmetric relationships centered around $I_{related} \approx I_{unrelated}$, where the drift was minimal (Ratcliff & Rouder, 1998). The slope of the inverted-U shape scaled with boundary separation. The inverted-U shape was skewed to either side depending on whether the starting point bias favored the ”related” or ”unrelated” decision.

Taken together, the LCA and DDM but not the Race model produced the inverted-U shaped relationship of RTs. These results are consistent with previous research showing that independent accumulator models fail to account for inverted-U shaped RTs associated with choice difficulty (Teodorescu & Usher, 2013). It suggests that the lateral inhibition process in the LCA, which introduces accumulator dependency and distinguishes it from the Race model, and the relative accumulation in the DDM are chiefly responsible for model’s abilities to account for the inverted-U shaped relationship.

Relatedness effect

To assess how well the candidate models can account for the relatedness effect, we calculated for each simulation the standardized difference in RTs between ”related” and ”unrelated” measured as Cohen’s *d*. Figure 3 shows these differences as a function of the difference between $I_{related}$ and $I_{unrelated}$, with positive values of Cohen’s *d* reflecting a positive relatedness effect.

As illustrated in Figure 3, the Race model simulation results demonstrate a consistently linear relationship across parameter combinations, where Cohen’s *d* values grow steadily from a substantial negative relatedness effect for negative differences between $I_{related}$ and $I_{unrelated}$ towards a substantial positive relatedness effect for positive differences. Threshold values moderated this relationship, with large thresholds resulting in a steeper relationship than lower ones. These results imply that the Race model predicts the relatedness effect for $I_{related} > I_{unrelated}$ and an inverted relatedness effect for $I_{related} < I_{unrelated}$. The LCA simulation results exhibit the same positive linear relationships as the Race model, with a similar moderation of the effect size by the threshold and lateral inhibition parameters. Overall the relationships emerged as somewhat more extreme for the LCA, with high threshold and high lateral inhibition values resulting in stronger effects.

In contrast to the Race and LCA models, the DDM simulation results showed only weak differences between RTs for ”related” and ”unrelated” responses[2]. If anything, we found a slightly negative relationship between the difference in $I_{related} > I_{unrelated}$ and effect size. That is, the DDM predicted an inverted relatedness effect for $I_{related} < I_{unrelated}$ and a conventional relatedness effect for $I_{related} > I_{unrelated}$. The boundary separation and starting point bias had no systematic effect on the direction of this relationship. However, changes in starting point resulted in additive shifts that implied either a consistent conventional ($z > .5$) or inverted ($z < .5$) relatedness effect irrespective of the difference between $I_{related}$ and $I_{unrelated}$.

---

[2] This finding is consistent with the property of (unbiased) diffusion processes to yield equal expected RTs for both alternatives (Ratcliff & McKoon, 2008). This constraint is relaxed when assuming between-trial variability in drift-rate (see General Discussion).

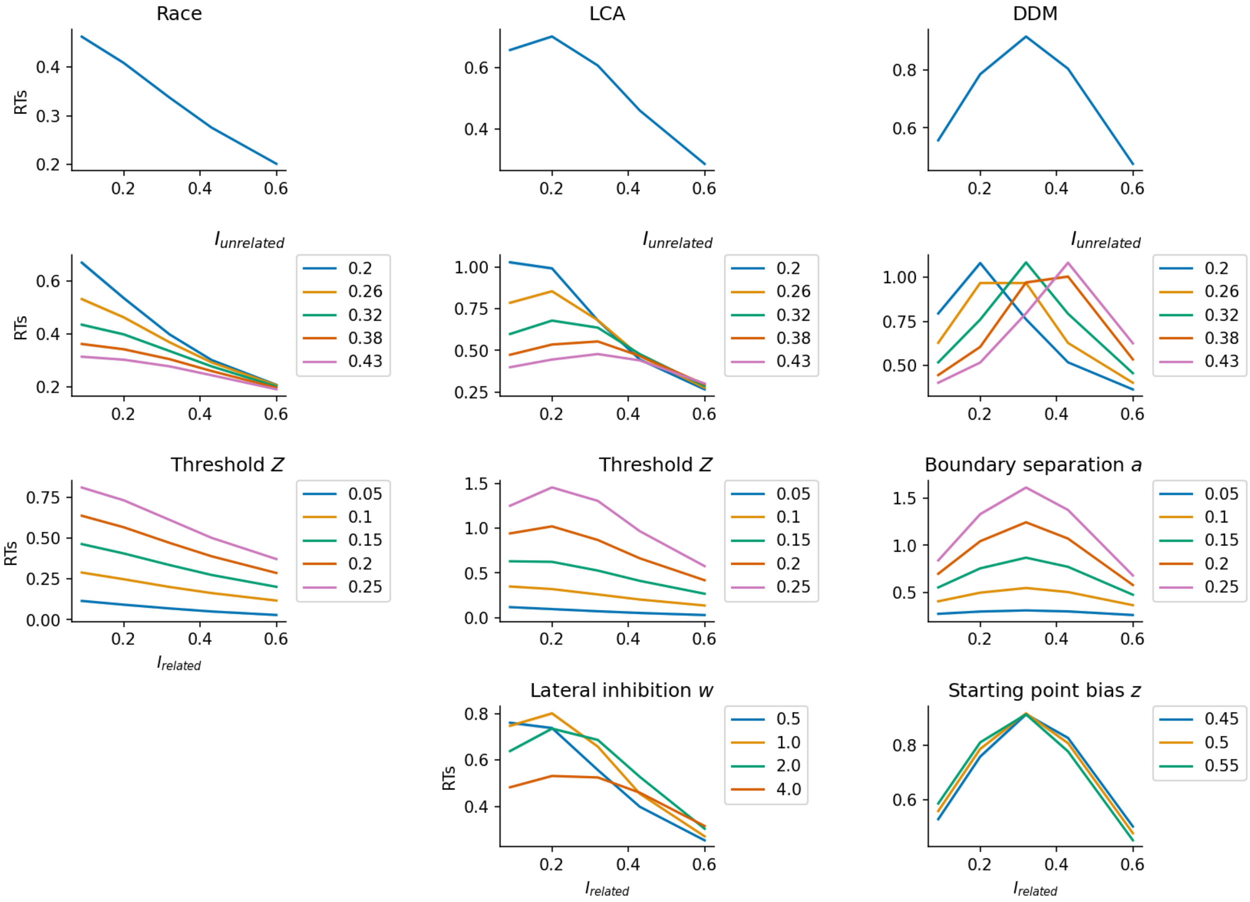


Figure 2: Response times as a function of semantic relatedness ($I_{related}$) for the Race model (left column), the LCA (middle column), and the DDM (right column). The rows show the predictions pooled across all simulations (first), as well as stratified for decision reference values $I_{unrelated}$ (second), decision threshold Z and boundary separation a values (third), and lateral inhibition k and starting point bias z values (fourth).

In sum, all the three models are in principle able to predict the relatedness effect, but they do so to different degrees, under different circumstances, and using different mechanisms. For all parameter combinations, the Race and LCA models predicted a relatedness effect, but only when $I_{related} > I_{unrelated}$. The DDM on the other hand predicted a constant relatedness effect independent of the difference between $I_{related}$ and $I_{unrelated}$, but only in the presence of a starting point bias. These differences in model predictions suggest a novel, critical test for cognitive mechanisms underlying the SRDT: Does the relatedness effect emerge consistently across different levels of relatedness or could there be an inverted relatedness effect for less strongly related word pairs? In the next section, we will use empirical data to investigate this question.

The Inverted Relatedness Effect

To test the prediction of an inverted relatedness effect for weakly-related word pairs, we reanalyzed a publicly available data set by Kumar et al. (2019). In this study, $N = 40$ participants from Amazon Mechanical Turk performed 240 trials in a SRDT as described above. To be able to analyze RTs as a function of relatedness, we determined for each word pair cosine similarity scores using the *fastText word2vec* model (Grave et al., 2018). As done in previous analyses (Kumar et al., 2019; Kenett et al., 2017), we excluded trials with extremely short RTs ($<$ 250 ms) since they are unlikely to have arisen from an evidence-accumulation process. In total, we analysed on average 220.7 ($SD = 26.8$) trials per participant, for which cosine values could be determined.

Figure 4 illustrates the relationship between relatedness (cosine similarity) and response time for both ”related” (orange) and ”unrelated” (blue) decisions. For the upper range of cosine similarity values ($cosine > .4$) the data show the con-

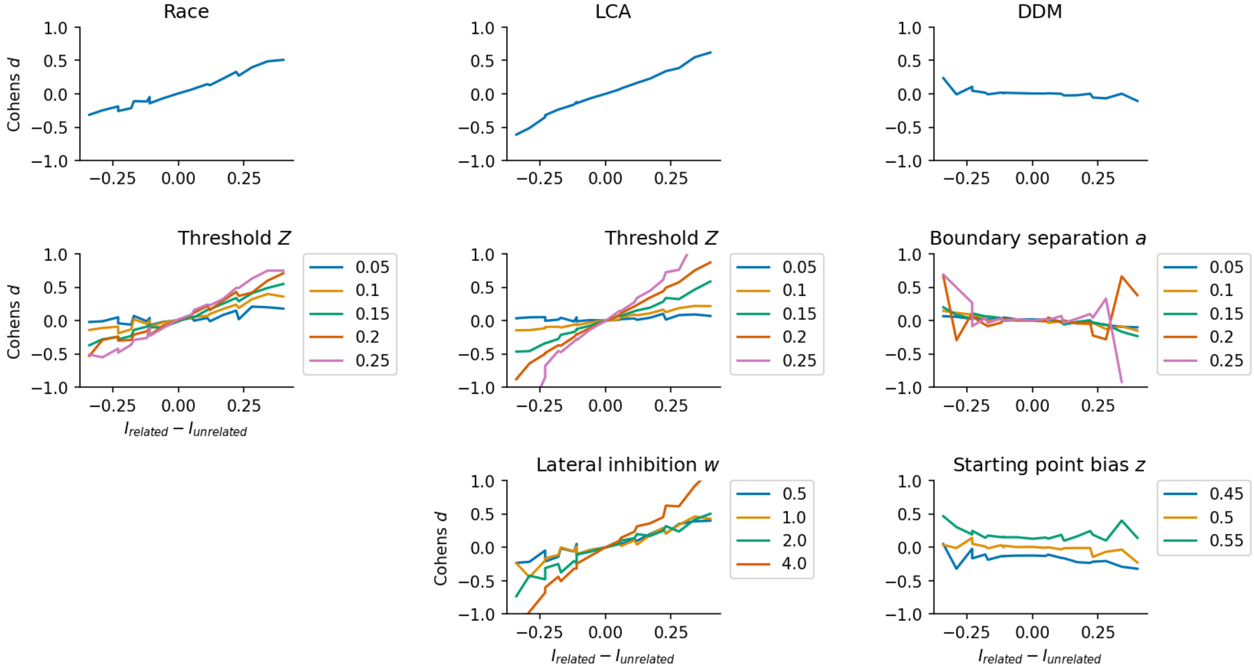


Figure 3: Relatedness effect in Cohen's *d* as a function of accumulation rate difference ($I_{related} - I_{unrelated}$) for the Race model (left column), the LCA (middle column), and the DDM (right column). The rows show the predictions pooled across all simulations (first), as well as stratified for decision threshold Z and boundary separation a values (second), and lateral inhibition k and starting point bias z values (third).

ventional relatedness effect, where "related" responses are on average faster than "unrelated" responses. For the remaining lower range, however, we observe the inverted relatedness effect, where "related" responses are actually slower than "unrelated" responses.

To confirm the above effect, we ran a Bayesian linear random effects model with random effects on the participant level. Consistent with the reversal of relatedness effects, we found a credible interaction effect of cosine similarity × response type on log RTs (95% highest posterior density interval, HDI: $[-.68, -.42]$). Also, there were main effects of cosine similarity (95% HDI: $[.09, .28]$) and response type (95% HDI: $[.14, .25]$), indicating slower RTs for more related pairs and for "related" responses, respectively. The former implies that, unlike previous studies, the current data set did not produce the conventional relatedness effect on aggregate[3].

The reversal of relatedness effects for low relative to high relatedness values is inconsistent with the DDM, which can only account for constant relatedness effects, but is predicted by the Race and LCA models. Another noteworthy observation from Figure 4, lending further support for the LCA, is the noticeable right-skew in distribution of RTs, which is consistent with the shape of LCA's simulation results (Figure 2).

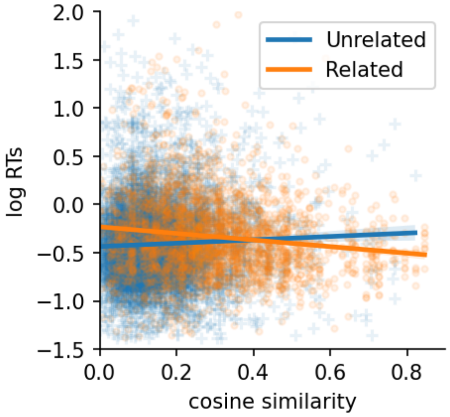


Figure 4: Empirical log RTs as a function of word2vec cosine similarity for "unrelated" (plus, blue) and "related" responses (circle, orange). Regression lines for both response types are depicted with 95% bootstrapped confidence intervals.

General Discussion

Semantic relatedness is a key concept in cognitive science that underlies models of human memory, reasoning, and cre-

---

[3] The regression analysis additionally controlled for two other known influences on RTs, word frequency (95% HDI: $[-.01, .05]$) and word length (95% HDI: $[.01, .03]$), of which the latter effect was credible (longer words led to higher RTs).

ativity. The behavioral output of these models is oftentimes thought to be linked directly to estimates of semantic relatedness as derived, for instance, using vector-space models. This has resulted in a simplified view of semantic relatedness decisions, where the probability of a ”related” decision and associated response times are thought to be proportional to the strength of semantic relatedness. Our results suggest that this view needs correction. We demonstrated that the class of sequential sampling models, which is regularly employed for various kinds of decisions, such as old-new decisions in recognition memory (Ratcliff, 1978) or preferential choices between monetary lotteries (Busemeyer & Townsend, 1993), can fully account for existing and novel benchmarks of semantic relatedness decisions. The LCA achieved this by not only considering the strength of semantic relatedness, but also a reference level against which semantic relatedness is evaluated, as well as competition between the responses. These results highlight the importance of decision-related processes in behavior pertaining to semantic relatedness and suggest interesting avenues for future scientific inquiry.

Table 1: Phenomena explained.

	Race	LCA	DDM
Inverted U Shape		√	√
Relatedness effect	√	√	√
Interaction effect	√	√	

A key implication of our results is that semantic relatedness decisions are likely to be susceptible to typical decision-related phenomena such as sensitivity to differences in base rates or incentives, or to strategic tendencies, such as embodied by speed-accuracy trade-offs. This is fully consistent with resource-rational accounts of memory retrieval (Dougherty, Harbison, & Davelaar, 2014), according to which the continuation of retrieval processes is subject to an assessment of costs and benefits. We believe that formal accounts as presented by sequential sampling models can be instrumental in describing and predicting existing and novel phenomena in this direction, especially due to their ability to jointly account for choice and response times (Kraemer, Fontanesi, Spektor, & Gluth, 2020; Wilson & Collins, 2019).

Among the sequential sampling models considered in the present study, only the LCA was able to account for the established benchmarks and the inverted relatedness effect (see Table 1). The failure of the Race model and the DDM to account for some of the benchmarks might be due to the model specifications in our study. Alternative specifications of the models could account for the benchmarks in question. For instance, an extended form of the DDM (Ratcliff & McKoon, 2008) depends on additional between-trial variability parameters which allow the model to account for a wider range of empirical phenomena (Ratcliff & Smith, 2004). The between-trial variability of drift-rate would allow the extended DDM to predict ”slow errors”, thereby potentially accounting for the inverted relatedness effect for weakly related word pairs. The Race model, on the other hand, could be formulated as an advantage Race model (van Ravenzwaaij, Brown, Marley, & Heathcote, 2020; Miletić et al., 2021), which should help to account for the inverted-U shape. Future work interested in arbitrating between these models should consider a more diverse set of model variants. In the present study, however, our main goal was to establish sequential sampling models as a general framework to explain and predict empirical phenomena that memory retrieval processes alone cannot explain.

Our findings also tie into an ongoing discussion on disentangling representational (*structures*) and the cognitive *processes* that draw on it (Siew, Wulff, Beckage, & Kenett, 2019; Kenett, Beckage, Siew, & Wulff, 2020). It has been argued that computational modeling may be one route to potentially accomplishing this (Kumar, 2020; Wulff et al., 2019). Approaches in this direction typically consider a representational structure, such as a word-vector space or a free-association network, and retrieval processes, such as such as spreading activation or random walks (Siew et al., 2019). Some of these retrieval processed include elements of decision processes, such as Luce choice rule to transform memory activation to response probabilities (Jones, Gruenenfelder, & Recchia, 2018; Wulff, Hills, & Hertwig, 2013). However, with few exceptions (e.g, Jones et al., 2018), these elements are viewed as auxiliary assumptions rather than an integral part of the cognitive processes underlying behavior. Based on our results, we would argue that there is much to gain by taking decision-related processes more seriously. One route to doing this could be to integrate sequential sampling models, such as the LCA, with plausible memory frameworks, with the goal of building joint models of representational structure, retrieval processes, and decision processes.

Acknowledgments

We thank Adam Osth and Sudeep Bhatia for valuable feedback on this study.

References

Abbott, J. T., Austerweil, J. L., & Griffiths, T. L. (2015). Random walks on semantic networks can resemble optimal foraging. *Psychological Review*, *122*(3), 558–569. doi: 10.1037/a0038693

Balota, D. A., & Black, S. (1997). Semantic satiation in healthy young and older adults. *Memory & cognition*, *25*(2), 190–202.

Balota, D. A., & Paul, S. T. (1996). Summation of activation: evidence from multiple primes that converge and diverge within semantic memory. *Journal of experimental psychology. Learning, memory, and cognition*, *22*(4), 827–845.

Bogacz, R., Brown, E., Moehlis, J., Holmes, P., & Cohen, J. D. (2006). The physics of optimal decision making: A formal analysis of models of performance in two-alternative forced-choice tasks. *Psychological Review*, *113*(4), 700–765. doi: 10.1037/0033-295X.113.4.700

Bruni, E., Tran, N. K., & Baroni, M. (2014). Multimodal distributional semantics. *Journal of Artificial Intelligence Research*, *49*, 1–47. doi: 10.1613/jair.4135

Busemeyer, J. R., Gluth, S., Rieskamp, J., & Turner, B. M. (2019). Cognitive and Neural Bases of Multi-Attribute, Multi-Alternative, Value-based Decisions. *Trends in Cognitive Sciences*, *23*(3), 251–263. doi: 10.1016/j.tics.2018.12.003

Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review*, *100*(3), 432–459. doi: 10.1037/0033-295X.100.3.432

Collins, A. M., & Loftus, E. F. (1975). A Spreading Activation Theory of Semantic Processing. *Psychological Review*, *82*(6), 407–428. doi: 10.1037//0033-295X.82.6.407

Dougherty, M. R., Harbison, J. I., & Davelaar, E. J. (2014). Optional stopping and the termination of memory retrieval. *Current Directions in Psychological Science*, *23*(5), 332–337.

Grave, E., Bojanowski, P., Gupta, P., Joulin, A., & Mikolov, T. (2018). Learning word vectors for 157 languages. In *Proceedings of the international conference on language resources and evaluation (lrec 2018).*

Green, D. M., & Swets, J. A. (1966). *Signal Detection Theory and Psychophysics*. New York: Wiley.

Jones, M. N., Gruenenfelder, T. M., & Recchia, G. (2018). In defense of spatial models of semantic representation. *New Ideas in Psychology*, *50*, 54–60.

Jones, M. N., Willits, J., & Dennis, S. (2015). Models of Semantic Memory. In J. R. Busemeyer, Z. Wang, J. T. Townsend, & A. Eidels (Eds.), *The oxford handbook of computational and mathematical psychology* (pp. 232–254). New York, NY, US: Oxford University Press.

Karwoski, T. F., & Schachter, J. (1948). Psychological Studies in Semantics: III. Reaction Times for Similarity and Difference. *Journal of Social Psychology*, *28*(1), 103–120. doi: 10.1080/00224545.1948.9921759

Kenett, Y. N., Beckage, N. M., Siew, C. S., & Wulff, D. U. (2020). *Cognitive network science: A new frontier.* Hindawi.

Kenett, Y. N., Levi, E., Anaki, D., & Faust, M. (2017). The semantic distance task: Quantifying semantic distance with semantic network path length. *Journal of Experimental Psychology: Learning Memory and Cognition*, *43*(9), 1470–1489. doi: 10.1037/xlm0000391

Kraemer, P. M., Fontanesi, L., Spektor, M. S., & Gluth, S. (2020). Response time models separate single- and dual-process accounts of memory-based decisions. *Psychonomic Bulletin & Review*. doi: 10.31234/osf.io/4pqyx

Kumar, A. A. (2020). Semantic memory: A review of methods, models, and current challenges. *Psychonomic Bulletin and Review*. doi: 10.3758/s13423-020-01792-x

Kumar, A. A., Balota, D. A., & Steyvers, M. (2019). Distant Concept Connectivity in Network-Based and Spatial Word Representations. In *Proceedings of the 41th annual meeting of the cognitive science society* (pp. 1348–1354).

Miletić, S., Boag, R. J., Trutti, A. C., Stevenson, N., Forstmann, B. U., & Heathcote, A. (2021). A new model of decision processing in instrumental learning tasks. *eLife*, *10*, 1–55. doi: 10.7554/eLife.63055

Miletić, S., Turner, B. M., Forstmann, B. U., & Maanen, L. V. (2017). Parameter recovery for the Leaky Competing Accumulator model. *Journal of Mathematical Psychology*, *76*, 25–50. doi: 10.1016/j.jmp.2016.12.001

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108.

Ratcliff, R., & McKoon, G. (1988). A Retrieval Theory of Priming in Memory. *Psychological Review*, *95*(3), 385–408. doi: 10.1037/0033-295X.95.3.385

Ratcliff, R., & McKoon, G. (1994). Retrieving Information From Memory: Spreading-Activation Theories Versus Compound-Cue Theories. *Psychological Review*, *101*(1), 177–184. doi: 10.1037/0033-295X.101.1.177

Ratcliff, R., & McKoon, G. (2008). Drift Diffusion Decision Model: Theory and data. *Neural Computation*, *20*(4), 873–922.

Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science*, *9*(5), 347–356.

Ratcliff, R., & Smith, P. L. (2004). A Comparison of Sequential Sampling Models for Two-Choice Reaction Time. *Psychological Review*, *111*(2), 333–367. doi: 10.1037/0033-295X.111.2.333

Siew, C. S., Wulff, D. U., Beckage, N. M., & Kenett, Y. N. (2019). Cognitive network science: A review of research on cognition through the lens of network representations, processes, and dynamics. *Complexity*, *2019*.

Teodorescu, A. R., & Usher, M. (2013). Disentangling decision models: From independence to competition. *Psychological Review*, *120*(1), 1–38. doi: 10.1037/a0030776

Usher, M., & McClelland, J. L. (2001). *The time course of perceptual choice: The leaky, competing accumulator model* (Vol. 108) (No. 3). doi: 10.1037/0033-295X.108.3.550

van Ravenzwaaij, D., Brown, S. D., Marley, A. A., & Heathcote, A. (2020). Accumulating Advantages: A New Conceptualization of Rapid Multiple Choice. *Psychological Review*, *127*(2), 186–215. doi: 10.1037/rev0000166

Wilson, R. C., & Collins, A. G. E. (2019). Ten simple rules for the computational modeling of behavioral data. *eLife*, 1–33.

Wulff, D. U., De Deyne, S., Jones, M. N., Mata, R., Consortium, A. L., et al. (2019). New perspectives on the aging lexicon. *Trends in cognitive sciences*, *23*(8), 686–698.

Wulff, D. U., Hills, T. T., & Hertwig, R. (2013). Worm holes in memory: Is memory one representation or many? In *Proceedings of the annual meeting of the cognitive science society* (Vol. 35).

A.5 Individual contributions

The table below lists my personal contributions to the presented manuscripts. Adopting the *Contributer Roles Taxonomy* (https://credit.niso.org, May 27th 2022), 14 potential roles are defined which describe potential individual contributions to a research article. Here, a ✓marks a significant contribution of myself to the manuscript. It may also indicate contributions which are shared with my coauthors. If there were no personal contribution with respect to the respective role, this is indicated with an ✗. Finally, a "n.a." indicates that the role was not applicable to the respective manuscript.

	Manuscript 1	Manuscript 2	Manuscript 3	Manuscript 4
Conceptualization	✓	✓	✓	✓
Data curation	n.a.	✓	✓	✓
Formal analysis	n.a.	✓	✓	✓
Funding acquisition	✓	✗	✓	✓
Investigation	n.a.	n.a.	✓	✓
Methodology	n.a.	✓	✓	✓
Project administration	✗	✓	✓	✓
Resources	✗	✗	✗	✗
Software	n.a.	✓	✓	✓
Supervision	✗	✗	✗	✗
Validation	n.a.	✓	n.a.	n.a.
Visualization	✓	✓	✓	✓
Writing - original draft	✓	✓	✓	✓
Writing - review & editing	✓	✓	✓	✓

Appendix B

Academic Curriculum Vitae

Peter Maximilian Kraemer (M.Sc.)
Curriculum Vitae

Education

PhD candidate 2017-2022[expected]
Graduate School for Social, Economic, and Decision Psychology, University of Basel
Thesis advisors: Prof. Dr. Sebastian Gluth & Prof. Dr. Jörg Rieskamp
Thesis title: The cognitive and neural dynamics of memory-based decisions

M.Sc. in Neural and Behavioral Sciences 2014-2017
Graduate Training Centre for Neuroscience, International Max Planck Research School (*IMPRS*), University of Tübingen
Thesis advisor: Prof. Dr. Peter Thier
Thesis title: Cortical underpinnings of the integration of geometric and context-dependent information for the allocation of social attention

B.Sc. in Psychology 2010-2014
University of Bamberg
Thesis advisor: Prof. Dr. Claus-Christian Carbon
Thesis title: On the impact of authenticity information on the aesthetic evaluation of artworks

Abitur 2010
Staatliche Fachoberschule für Wirtschaft, Verwaltung und Rechtspflege, Munich

Professional Activities

Research assistant 2017-2021
Department for Decision Neuroscience, University of Basel
EEG and behavioral experiments on memory-based decision making
Computational Modeling (hierarchical Bayes, maximum-likelihood)

Student research assistant 2014-2016
Department of Cognitive Neurology, Hertie Institute for Clinical Brain Research, Tübingen
fMRI and behavioral experiments on social attention

Lab rotation student 2015-2016
Department of Neural Information Processing, University of Tübingen
Computational modeling in Psychophysics

Internship 2013-2014

Department of User Interfaces, BMW Group, Munich
User experience studies on cognitive distraction in vehicles

Internship 2013

Department of Physiological Psychology, University of Bamberg
EMG and EDA experiments on the perception of pain

Student research assistant 2011-2013

Department for General Psychology and Methodology, University of Bamberg
Behavioral studies on empirical aesthetics, face perception, and usability

Service to the Scientific Community

Ad-hoc reviewer for the peer-reviewed journals *eLife*, *PLOS ONE* and *Psychological Bulletin*

Student representative of the PhD candidates at the Graduate School for Social, Economic and Decision Psychology, University of Basel 2021-2022

Member of scientific societies

Cognitive Science Society (2021)
Society for Mathematical Psychology (since 2020)
American Psychological Society (since 2020)
Swiss Psychological Society (2018-2019)
Society for Neuroscience (2019)
Society for Neuroeconomics (since 2018)

Science communication

Affiliate of the think tank research and technology in Switzerland (reatCH). In 2018, I gave a "Nano-Talk" for public audiences with the title "Reading brains – writing brains. Current developments in brain computer interfaces".

Founding-member of the non-profit organization Pro-Test Deutschland e.V., which publicly discusses the ethics and use of research animals in biological and medical science.

Grants

Excellent young researchers grant 2020

The grant covers personal salary for the time period of 12 months. It was awarded by the Grants Office of the University of Basel.
Volume: 43,534.00 CHF

SED-PSY travel grant 2019

The grant covered conference fees, travel and accommodation expenses for the annual meeting of the Society for Neuroscience (SfN 2019) in Chicago, and a subsequent research visit at the Ohio State University. It was awarded

by the Graduate School for Social, Economic, and Decision Psychology (SED-PSY) at the University of Basel.
Volume: 2,200.00 CHF

SED-PSY travel grant 2019
The grant covered workshop fees, travel and accommodation expenses for the Model-based Neuroscience Summer School at the University of Amsterdam. It was awarded by the Graduate School for Social, Economic, and Decision Psychology (SED-PSY) at the University of Basel.
Volume: 2,000.00 CHF

SED-PSY travel grant 2018
The grant covered workshop fees, travel and accommodation expenses for the Computational and Mathematical Modeling of Cognition Summer School in Couches, France. It was awarded by the Graduate School for Social, Economic, and Decision Psychology (SED-PSY) at the University of Basel.
Volume: 1,000.00 CHF

Workshops and Summer Schools

Practice-oriented introduction to the version-control system Git Teacher: Philip Jakob	2021
Registered Reports Teachers: Dr. Hans IJzerman	2021
Interdisciplinary College. Summer School by the German Society for Information Technology.	2021
Simulation-based Bayesian modeling. Workshop at the University of Basel, Basel, Switzerland Teacher: M.Sc. Stefan Radev	2021
Collecting data efficiently through sequential analysis. Workshop at the University of Basel, Basel, Switzerland. Teacher: Prof. Dr. Daniel Lakens	2020
Model-based Neuroscience Summer School by the University of Amsterdam, Amsterdam, the Netherlands.	2019
Python for Psychologists. Workshop at the University of Basel, Basel, Switzerland. Teacher: Prof. Dr. Thomas Knapen.	2018
Mixed models with lme4. Workshop at the University of Basel, Basel, Switzerland. Teacher: Prof. Dr. Douglas Bates.	2018
Fifth European Summer School on Computational and Mathematical Modeling of Cognition, Couches, France.	2018
Statistical power analysis: Theory and Practice. Workshop at the University of Basel, Basel, Switzerland.	2018

Teacher: Prof. Dr. Edgar Erdfelder.

Bayesian data analysis in cognitive science. Workshop at the University of Basel, Basel, Switzerland. 2017
Teacher: Dr. Thorsten Pachur.

Matters of Taste: Summer School of the Forum Scientarium of the University of Tübingen, Heiligenkreuztal, Germany. 2015

Functional Magnetresonancetomography in psychological research: Spring School of the Bender Institute of NeuroImaging (BION), Gießen, Germany. 2013

Skills

Neuroscientific methods
Used in own research: fMRI, EEG, Eye-tracking
Received training: DTI, EMG, EDA, Single-Unit & Patch-Clamp recordings, microscopy

Computer Skills
Advanced: Python, Stan, MATLAB, R, SPSS, MS Office, Latex
Intermediate: JavaScript, JASP, Shell Scripting, Endnote, Citavi, Adobe (Photoshop, Premiere, Illustrator)

Languages
German (native)
English (fluent)
Spanish (intermediate)
Japanese (beginner)
Romanian (beginner)

Teaching

Seminar: Empirical project seminar I & II WS 2019 – SS 2020
Seminar for Bachelor's students of psychology at the University of Basel. Involved supervision of three groups of students over all phases of a research project.

Seminar: Current Topics in Decision Making and Economic Psychology SS 2018 – SS 2020
Seminar for Master's and PhD students at the University of Basel. Involved presentation and critical discussion of methodological and theoretical research in judgment and decision making.

Tutorium: Functional Neuroanatomy WS 2015
Tutoring students of the Master classes Neural & Behavioral Sciences, Neural Information Processing und Cellular and Molecular Neuroscience at the Graduate Training Centre for Neuroscience, University of Tübingen.

Involved sheep brain dissections in coronar cuts, identification of brain structures (grey and white matter, striatum, hippocampus) and answering general questions about the study material.

Peer-reviewed Articles

Kraemer, PM, Weilbächer, RA, Mechera-Ostrovsky, T, & Gluth, S (2022). Cognitive and Neural Principles of a Memory Bias on Preferential Choices. *Current Research in Neurobiology*.

Kraemer, PM, Wulff, DU, & Gluth, S. (2021). A sequential sampling account of semantic relatedness decisions. In *Proceedings of the 42nd annual meeting of the cognitive science society. PsyArXiv*. DOI: 10.31234/osf.io/ksa2g.

Kraemer, PM, Fontanesi, L, Spektor, MS, & Gluth, S. (2021). Response time models separate single- and dual-process accounts of memory-based decisions. *Psychonomic Bulletin & Review*. 28: 304-323. DOI: 10.3758/s13423-020-01794-9.

Weilbächer, RA, Kraemer, PM & Gluth, S (2020). The reflection effect in memory-based decisions. *Psychological Science*. 31: 11. 1439-1451.

Kraemer, PM, Goerner, M, Ramezanpour, H, Dicke, P, & Thier, P (2020). Frontal, parietal and temporal brain areas are differentially activated when disambiguating potential objects of joint attention. *eNeuro*, DOI: 10.1523/ENEURO.0437-19.2020.

Book Chapter

Kraemer, PM, Weilbächer, RA, Fontanesi, L, & Gluth, S (2020). Neural Bases of Financial Decision Making: From Spikes to Large-Scale Brain Connectivity. In Zaleskiewicz & Traczyk, (eds.). Psychological Perspectives on Financial Decision Making. Springer.

Ongoing Projects

Kraemer, PM, & Gluth, S (submitted). Episodic memory retrieval affects the onset and dynamics of evidence accumulation during value-based decisions. *BioArXiv*. DOI: https://doi.org/10.1101/2022.04.26.489332

Scientific Talks and Posters (1st author)

Kraemer, PM & Gluth, S (2021). Episodic memory retrieval affects the build-up of decision variables in value-based choices. Talk at the Annual Meeting of the Society for Neuroeconomics.

Kraemer, PM, Wulff, DU & Gluth, S (2021). A sequential sampling account of semantic relatedness decisions. Poster presentation at the annual meeting of the Cognitive Science Society (CogSci). Vienna, Austria.

Kraemer, PM, Wulff, DU & Gluth, S (2021). A sequential sampling account of semantic relatedness decisions. Talk at the Annual Meeting of the Society for Mathematical Psychology.

Kraemer, PM & Gluth, S (2021). Memory-based decisions depend on slower preference accumulation mechanism than value-based decisions. Poster presentation at the 46th Psychologie & Gehirn. Tübingen, Germany.

Kraemer, PM (2021). A cooperative semantic word game as a model for memory-based decision making. Poster presentation at the Interdisciplinary College by the German Society of Information Technology. Günne, Germany.

Kraemer, PM, Gluth, S, & Wulff, DU (2021). A sequential sampling account of semantic relatedness judgments. Talk at the 63th Conference of Experimental Psychologists (TEAP). Ulm, Germany.

Kraemer, PM, Fontanesi, L, Spektor, MS, & Gluth, S (2020). Response time models separate single- and dual-process accounts of memory-based decisions. Talk at the Annual Meeting of the Society for Mathematical Psychology. Toronto, Canada. https://virtual.mathpsych.org/presentation/30

Kraemer, PM, & Gluth, S (2019). How memory-based decisions evolve over time. Poster presentation at SfN 2019. Chicago, USA.

Kraemer, PM, & Gluth, S (2019). The emergence of value-based decisions from memory. Poster presentation at the Model-based Neuroscience Summer School, Amsterdam, the Netherlands.

Kraemer, PM, Fontanesi, L, Spektor, MS, & Gluth, S (2019). Single and dual process models in memory-based decision making. Talk at the young investigator conference JDMx. Trento, Italy.

Kraemer, PM, Fontanesi, L, Spektor, MS, & Gluth, S (2018). How response time analysis aides model selection in memory-based decisions. Poster presentation at the 16th Annual Meeting of the Society for NeuroEconomics. Philadelphia, USA.

Kraemer, PM, Fontanesi, L, Spektor, MS, & Gluth, S (2018). Comparing single- and dual process DDMs for memory-based decisions. Poster presentation at the 5th European Summer School on Computational and Mathematical Modeling of Cognition, Couches, France.

Kraemer, PM, & Gluth, S (2018). The temporal emergence of value-based decisions from memory. Talk at the young investigator conference JDMx. Konstanz, Germany.

Kraemer, PM, Fontanesi, L, Spektor, MS, & Gluth S (2018). Evidence for a single-process account of memory-based decisions. Talk at the annual Bernoulli-Workshop. Basel, Switzerland.

Kraemer, PM, Goerner, M, Ramezanpour, H, Dicke P, & Thier, P (2018). Cortical underpinnings of geometrical gaze following – an fMRI study. Poster presentation at the 60th Conference of Experimental Psychologists (TEAP). Marburg, Germany.

Kraemer, PM, Goerner, M, Ramezanpour, H, Dicke P, & Thier, P (2017). Towards the neural underpinnings of geometrical gaze following. Poster presentation at the 7th NIPS/CIN joint symposium. Tokyo, Japan.

Kraemer, PM, & Carbon, C.-C. (2012). How expectation changes the appreciation of arts. Poster presentation at the 35th European Conference on Visual Perception (ECVP). Alghero, Italy.