Cognition 263 (2025) 106217

Contents lists available at ScienceDirect

Cognition

journal homepage: www.elsevier.com/locate/cognit

The role of familiarity and recollection in value-based decisions

Tamara Gomilsek [a,b], Wolfgang Gaissmaier [a], Janina A. Hoffmann [a,c,*]

[a] Department of Psychology, University of Konstanz, Germany
[b] Department of Organizational Behavior, Faculty of Business and Economics, University of Lausanne, Switzerland
[c] Department of Psychology, University of Bath, United Kingdom

ARTICLE INFO

Keywords:
Recognition
Familiarity
Recollection
Exemplar model
Value-based decisions

ABSTRACT

Value-based decisions often require retrieving previous experiences from memory. A sense of familiarity, the subjective feeling of having encountered an option before, guides these search and decision processes. The current work explores the scope and boundaries of familiarity-based retrieval in predicting value-based decisions. To reach this goal, we formulate a familiarity-based decision making model (FB-DMM) that relies upon global matching of the current options to previously seen choice options within the current context. FB-DMM predicts that people prefer frequently encountered options to less frequent ones and explains why familiarity elicits preferences for high-value rather than low-value options. In Experiment 1, FB-DMM predicted participants' choices well when participants chose between option pairs with the same frequency of encounters, but different values. Against FB-DMM's prediction, participants rejected frequently repeated options with low values, indicating that individuals may have recollected the options' values instead. Experiment 2 aimed to diminish recollection-based processing by restricting decision times. Imposing time pressure reduced accuracy of participants' choices and slightly reduced decisions against familiar options with low values. A comparison of FB-DMM to a recollection-based model indicated that participants engaged less in recollection-based retrieval under time pressure. Taken together, our results suggest that familiarity-based matching processes capture a wider range of decision phenomena than suggested initially. Still, FB-DMM needs to be complemented by recollection-based processes to explain decisions going beyond the familiarity principle.

1. Introduction

Imagine that you are searching through websites for a restaurant for dinner. One restaurant may elicit a subtle sense of recognition as if you have seen this restaurant before, even though you cannot recall when or why. Still, individuals often prefer this familiar dining option over unfamiliar options. Familiarity, the subjective feeling of having encountered an option before (Atkinson & Juola, 1974; Jacoby & Dallas, 1981; Yonelinas, 1999), has been identified as an essential decision cue in inferential decisions (Pachur & Hertwig, 2006; Pleskac, 2007; Rosburg et al., 2011; Schwikert & Curran, 2014) and preferential choice (Zajonc, 1968). Yet, it is often hard to tell if individuals follow the global familiarity signal or if additional information, such as the value of the option, is recollected to make a decision. Familiarity-based retrieval is fast and automatic; people "know" that they saw the object before but cannot retrieve any further information (Yonelinas, 2002). Recollection-based retrieval, in contrast, is slow and controlled; people "remember" the object and can recall additional details (Yonelinas, 2002). So far, it remains however unclear in which situations familiarity-based retrieval alone can explain value-based decisions without resorting to recollection.

Our paper aims to identify the limits of a familiarity-based decision strategy in predicting value-based decisions. Thereby, our work theoretically advances the formal modeling of familiarity-based matching processes by considering one's *aspiration level,* that is, specific goals driving the decision (Siegel, 1957), as a contextual retrieval cue. Contrasting the predictions of a familiarity-based model against human choices allows us to uncover under which circumstances value-based decisions are predominantly influenced by familiarity and when recollection kicks in.

1.1. Familiarity and recollection processes in episodic memory

Episodic memory is the ability to recall specific events from one's past, including both the content of the event and its context, such as its location or time (Underwood, 1969). Formal models of memory often

* Corresponding author at: University of Bath, Department of Psychology, 10W Claverton Campus, Bath BA2 7AY, United Kingdom.
E-mail address: j.a.hoffmann@bath.ac.uk (J.A. Hoffmann).

https://doi.org/10.1016/j.cognition.2025.106217
Received 2 September 2024; Received in revised form 22 April 2025; Accepted 9 June 2025
Available online 20 June 2025

posit that individuals encode each event in another memory trace (sometimes called exemplars) with distinct features storing content information and contextual details (Cox & Shiffrin, 2017; Hintzman, 1988). At a restaurant, for instance, a guest may encode the restaurant's name, the menu, and its interior design, but also details about the location, the quality of the food, or the friendliness of the staff. When encountering the restaurant again while searching for a dining option, individuals may attempt to recall specific details about the restaurant using the restaurant's name as a retrieval cue. Recollection refers to the cued recall of associated information in a recognition situation (Mayes et al., 2007). Familiarity describes instead the "feeling of a memory" in the absence of recollective detail (Mayes et al., 2007; Yonelinas et al., 2024). A restaurant may appear familiar to a person as if the person has dined there before, but they cannot remember details of the dining experience. Memory research conceptualizes familiarity as a "strength of contextually mediated episodic information" (p.928, Yonelinas et al., 2024) implying that the feeling of familiarity is context-dependent. In line with this idea, memory models propose that this familiarity signal is elicited by comparing the content and the context of the current event to all events stored in memory (Cox & Shiffrin, 2017).

To dissociate familiarity from recollection, research has sought to identify manipulations that selectively interfere with one process but leave the other untouched. Encoding manipulations, such as a longer study duration or the number of repetitions, often increase recollection and familiarity alike (Yonelinas, 2002; Yonelinas et al., 2024). Manipulations that encourage a deeper encoding, such as semantic compared to perceptual processing, affect recollection more than familiarity (Yonelinas, 2002). During retrieval, it has been found that speeded responses reduce recollection, but affect familiarity-based processes less (Koenig et al., 2015; Koenig et al., 2020; Yonelinas, 2002). Vice versa, enhancing the processing fluency of the items during retrieval strengthens familiarity, but does not increase recollection (Yonelinas et al., 2024). To date, research on recognition memory still debates to what extent a dual-process account that distinguishes recollection and familiarity best captures empirical phenomena in recognition memory (Diana et al., 2006; Mandler, 2008; Yonelinas et al., 2024) or if a single familiarity-based process suffices to support item and associative recognition (Cox, 2024). This debate may also carry implications for understanding how individuals quickly decide between options in value-based choice.

1.2. The role of familiarity and recollection in value-based decisions

Familiarity influences the decision process most noticeably in situations when individuals lack any additional information about the options. Without further information, individuals pick familiar options over unfamiliar ones or use detectable differences in familiarity to decide between options (Honda et al., 2011; Schwikert & Curran, 2014; Shirasuna et al., 2020; Xu et al., 2018; Zajonc, 1968). Individuals also prefer familiar options to unfamiliar ones in preferential choice (Alter & Oppenheimer, 2008; Honda et al., 2011; Zajonc, 1968). A key marker of recollection is the availability of further knowledge about the options, for instance, additional information about their value. Matching the idea that recollection supports value-based decisions, individuals often pick the high-value familiar option because they can consciously recollect its value (Bornstein et al., 2017; Carpenter & Schacter, 2018; Duncan & Shohamy, 2016; Murty et al., 2016; Wimmer & Buchel, 2016). Still, individuals also prefer remembered low-value options over unfamiliar ones, even when it would be wise to choose the unfamiliar option (Gluth et al., 2015; Mechera-Ostrovsky & Gluth, 2018). This finding points towards the possibility that familiarity with an option influences value-based choices independent of recollection.

Resorting to a quick sense of familiarity, instead of awaiting a slower recollection-based evaluation, might often be adaptive. The familiarity signal provides a continuous index of memory strength (Rosburg et al., 2011), sensitive to the frequency of previous encounters and the similarity to the current decision context. This familiarity information suffices to reliably discriminate between truly novel and certainly experienced options (Pachur & Hertwig, 2006). Whenever more frequently encountered options are associated with higher values, global familiarity may be exploited as a signal of value certainty (Erdfelder et al., 2011; Marewski et al., 2010). Along these lines, it has been argued that individuals reject badly remembered options because they are uncertain about their value (Kraemer et al., 2022; Weilbacher et al., 2020). Taken together, the familiarity signal may suffice to convey value uncertainty. Here, we separate familiarity- from recollection-based decisions by predicting value-based choices with a memory model.

1.3. A familiarity-based decision-making model (FB-DMM) for value-based choice

Exemplar models are well-established cognitive models for describing retrieval processes in episodic memory (Brown et al., 2007), categorization (Medin & Schaffer, 1978; Nosofsky, 1988), judgment (Hoffmann et al., 2014, 2016), and decision making (Pachur & Olsson, 2012; Trippas & Pachur, 2019). Typically, retrieval of values involves a similarity-based matching of the current probe to all exemplars stored in memory (Izydorczyk & Broder, 2021). The retrieved values then determine the final decision, mimicking recollection processes. The familiarity signal, the global activation of all exemplars, however, has rarely been exploited as a decision cue beyond recognition decisions (Hoffmann et al., 2018; Nosofsky, 1988; Nosofsky et al., 2014). The current project explored to what extent the global familiarity signal can predict value-based decisions. To achieve that goal, our familiarity-based decision making model (FB-DMM) enriches a classical exemplar model with a familiarity-based decision component to predict value-based choices.

FB-DMM assumes that people store each encountered option, characterized by its features x_j and its value v_j, as an exemplar j in memory (Appendix A). When presented with a choice, for instance, the choice between a familiar restaurant and an unfamiliar one, each option ("the probe") elicits a global familiarity signal f_i. Every repetition of each previously encountered exemplar j strengthen this familiarity signal for the probe i (Nosofsky, 1988, 2011),

$$f_i = \sum_j s_{ij} \tag{1}$$

with s_{ij} denoting the similarity between probe i and exemplar j. Familiarity accumulates faster for a probe, if more exemplars similar to the probe have been frequently encountered in the past. This similarity is a decaying function of the distance, $dist_{ij}$, between probe and exemplar, $s_{ij} = e^{-c^* dist_{ij}}$ where c captures memory sensitivity (Nosofsky & Zaki, 1998). An option is thus perceived as more familiar if similar options have been encountered frequently in the past. An exemplar that closely matches the probe is perceived as highly similar, whereas more distant exemplars are perceived as dissimilar. Further, distant exemplars are harder to discriminate from each other in memory. The global familiarity signal does not, however, allow to trace familiarity back to individual exemplars or single features and, hence, does not aid to recall specific details about the options.

How can this familiarity signal guide value-based choice? In value-based choice from memory, individuals approach the decision task with a goal orientation, that is, to choose the option with the higher value, with the specific goal often referred to as the *aspiration level* in decision science (Siegel, 1957). Setting an aspiration level may orient retrieval towards the target information at an early stage and help to limit retrieval of less goal-relevant information (Gray & Gallo, 2015; Jacoby et al., 1999). While this top-down retrieval orientation has been conceptualized as a recollection process (Gray & Gallo, 2015), evidence from ERP studies suggests that a top-down retrieval orientation also influences the familiarity signal (Ecker & Zimmer, 2009). In FB-DMM, we propose that the aspiration level serves as a retrieval cue; notably, the maximum *aspiration value* $\max_j v_j$ one hopes to receive may provide an anchor for familiarity-based matching. Conceptually, this top-down retrieval orientation implies that the familiarity signal encompasses the familiarity elicited by the probe, here the choice option, and the familiarity elicited by the choice context, here the aspiration value, with *choice context* broadly defined as factors with the potential to shift the choice outcome by altering the decision process (Thomadsen et al., 2018). In a familiarity-based matching process, this information is then compared to all encountered exemplars, consisting of the features of previously encountered options and additional information present at encoding (Mensink & Raaijmakers, 1989), here the previously encountered values as part of the choice context. Supporting this idea, people also perceive options as more familiar when the retrieval context matches encoding (Hockley et al., 2012; Kahana et al., 2008). Attention weights w modulate the degree to which an individual pays more attention to the option under evaluation, here the option's features x_{im}, or the choice context, here the aspiration value v_i. Accordingly, the perceived distance $dist_{ij}$ between option i and exemplar j depends upon how much their features match each other $|x_{im} - x_{jm}|$ and how much the exemplar's value matches this aspiration value $|v_i - v_j|$, weighted by the attention w devoted to features relative to value:

$$dist_{ij} = w\sum_{m=1}^{M} |x_{im} - x_{jm}| + (1-w)^* M^* |v_i - v_j| \tag{2}$$

where M denotes the number of features. In principle, a satisfactory familiarity-based choice requires to devote attention to both the aspiration value and the option's characteristics. If individuals only consider the aspiration value but ignore the option's characteristics, or vice versa, they won't perceive a previously encountered high-value option as familiar. Finally, individuals probabilistically choose the more familiar option,

$$P(R_i|f_i) = \frac{e^{f_i{}^*\beta}}{\sum e^{f_i{}^*\beta}} \tag{3}$$

where a high choice sensitivity β implies a more deterministic choice.

As a global memory matching model, FB-DMM should account for any familiarity effects elicited by repeated exposure, the similarity to previously encountered options, or context similarity, here aspiration level. As a side-effect of this goal-oriented familiarity-based activation, FB-DMM should choose higher-valued options because these options better match the aspiration level, making them appear more familiar. We simulated how FB-DMM decides between two types of option pairs (Fig. 1 and Appendix B): In *same-value pairs,* both options possessed the same value, but were encountered with a different number of repetitions. In *same-frequency pairs,* both options possessed different values, but were encountered with the same number of repetitions. Importantly, FB-DMM predicted an interaction between repetitions and value: Mimicking classical mere-exposure effects (Hintzman, 1986; Zajonc, 1968), FB-DMM preferred the more frequently encountered option on same-value pairs, but only if both options possessed a high value. On same-frequency pairs, FB-DMM preferred high-value options over low-value options. Thus, FB-DMM explains classical value-based choice without assuming more than familiarity-based matching.

Yet, there are limits to the predictions any familiarity-based choice model can make – FB-DMM cannot predict systematic decisions against familiar options. For decisions against familiar options, detailed knowledge about the criterion value needs to be retrieved and thus recollection has to step in. In two experiments, we contrasted these predictions of FB-DMM against participants' choices in a predominantly familiarity-based decision task. Further, this perspective suggests that familiarity and recollection make unique contributions to value-based decisions. To dissect the contributions of familiarity- and recollection-based processes to value-based decisions, we imposed time pressure during the decision phase (Experiment 2) – a manipulation that interferes more with recollection than familiarity-based processes (Koenig et al., 2015; Koenig et al., 2020; Yonelinas, 2002). We further examine to what extent recollection of each option's value better accounts for value-based choices than familiarity by considering which values participants remembered in subsequent memory recall. Finally, we rigorously test FB-DMM against a recollection-based model that reconstructs the value of each choice option before making a decision.

2. Experiment 1

2.1. Method

Experiment 1 contrasted FB-DMM's predictions with participants' choices in a value-based decision making task. We used random line

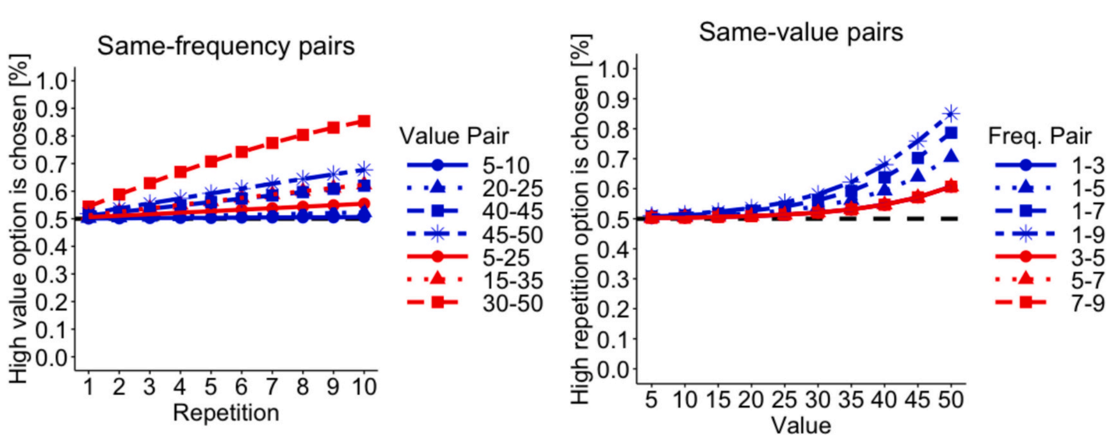

Fig. 1. Simulating value-based choices with FB-DMM. FB-DMM encountered in a learning phase different options (exemplars) associated with values from 5 to 50 and repeated a different number of times from 1 to 10. In a test phase, it decided between pairs of previously encountered options without knowing the value. Same-frequency pairs: The two options were encountered with the same number of repetitions (x-axis) and had small (e.g. 5 compared to 10, blue lines) or high differences (e.g. 5 compared to 25, red lines) in value. FB-DMM more likely picked the high-value option if value differences were high, if options possessed values closer to the aspiration level, and if options were frequently presented. Same-value pairs: The two options possessed the same value but were encountered a different number of times. The first option was encountered either once and the second option was encountered 3, 5, 7, or 9 times (blue lines) or both options were encountered more often (e.g. 3 and 5 times, red lines). FB-DMM more likely picked the high-repetition option if both options possessed a high value, or if the high-repetition option was repeated more often. Depicted simulations were based on median parameter estimates values ($c = 0.75$, $w = 0.75$, $\beta = 0.22$) for the condition without time pressure across both experiments. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

drawings that should be difficult to process semantically. These line drawings may discourage participants from engaging in deeper encoding processes that facilitate recollection (Yonelinas, 2002).

During the learning phase, participants (and FB-DMM) studied line drawings, each associated with a value (Fig. 2). We systematically varied the number of repetitions during the learning phase for each option (the exemplars). In a later decision phase, participants and FB-DMM were asked to choose the option with the higher value in each choice pair, allowing a rigorous comparison between model predictions and participants' choices. If participants engaged in familiarity-based choice, we expected to replicate FB-DMM's choice pattern in our participants (Fig. 1): Individuals should choose the high-value option more often in same-frequency pairs if both options were encountered with a high number of repetitions. Individuals should decide randomly on same-frequency pairs with a low number of repetitions. On same-value pairs, individuals should choose more often the frequently repeated option if both options possessed high values, but individuals should decide randomly between options if both options possessed low values.

2.1.1. Participants

Forty-nine participants (38 females; $M_{Age} = 22$ years, $SD_{Age} = 3.2$) were recruited at the University of Konstanz. Participants were paid based on their performance; they received 0.04 € for each correct answer and earned on average 7.4 € ($SD = 0.86$). Sample size was determined in an a priori power analysis for a repeated measures ANOVA (10 measurements, correlation $\rho = 0.5$ between measures), suggesting a required sample size of $N = 46$ participants to detect an effect size $f = 0.15$ at an α-level $= 0.05$ with a power $P_{Stat} = 0.90$.

2.1.2. Stimuli and design

Participants and FB-DMM encountered 30 unique line drawings (the exemplars) during the learning phase. Each exemplar consisted of 20 lines (the features) that could be present or absent and its value (Fig. 2). The exemplar's value varied on a scale from 5 to 50, incremented by 5. We excluded item sets for which the number of present features was predictive of the value.

Each exemplar belonged to one out of three sets (increasing, decreasing, or a noise set). Each set contained ten exemplars, one for each value (Fig. 3A). Between sets, we systematically varied the number of repetitions during the learning phase in relation to their value. In the noise set, all exemplars were repeated only once. In the increasing set, the most frequently repeated exemplar possessed the highest value; in the decreasing set, the most frequently repeated exemplar possessed the lowest value (Fig. 3A). Thus, the exemplars' values were uncorrelated with the number of repetitions in the learning phase. These repetitions resulted in 120 exemplars presented in the learning phase: 55 exemplars from the increasing set, 55 from the decreasing set, and ten noise exemplars.

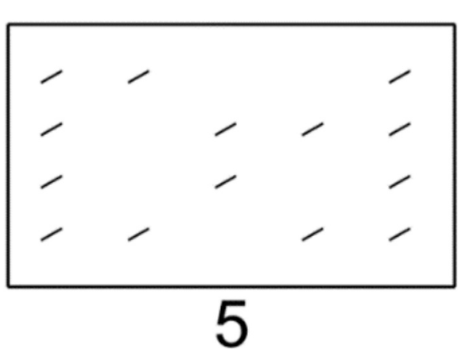

Fig. 2. Presentation of an exemplar during the learning phase. Features were represented as lines. The exemplar's value was displayed below the exemplar.

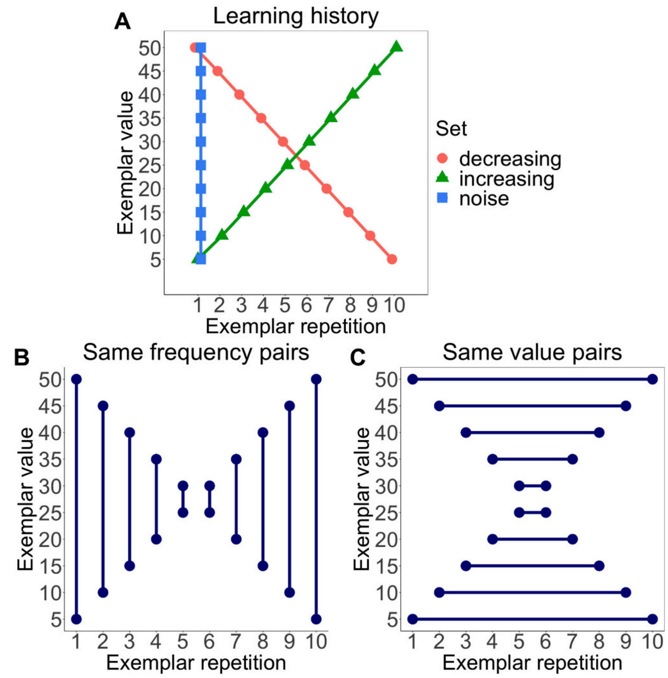

Fig. 3. (A) FB-DMM and participants encountered three sets of exemplars during the experiment: a decreasing set (red circles), an increasing (green triangles), and a noise set (blue squares). (B) Same-frequency pairs were encountered an equal number of times during the learning phase but associated with different values. (C) Same value pairs had the same value but differed in the number of repetitions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.1.3. Procedure

The experiment consisted of learning and a decision phase. In the learning phase, participants were told to memorize the presented exemplars and that subsequent decisions would require this memory, but they did not know the task details. Next, all 120 exemplars were shown in random order. In each trial, participants saw first a blank screen (1000 ms), then a fixation cross (500 ms), and finally the exemplar and its value (2000 ms).

In the subsequent decision phase, the 20 unique options (10 options from the increasing, 10 from the decreasing set) were exhaustively paired with one another, resulting in 190 decisions. For each decision, participants first saw a blank screen (1000 ms), then a fixation cross (500 ms), and finally, two options without their values next to each other. Participants had to select the one with a higher value. Two types of pairings are most informative to contrast the impact of value and repetition on familiarity-based choice. In same-frequency pairs, the two options were repeated the same number of times but possessed a different value (Fig. 3B). Same-frequency pairs thus allow measuring the impact of the value. In same-value pairs, in contrast, the two options possessed the same value but were repeated a different number of times throughout the learning phase (Fig. 3C). Same-value pairs thus allow measuring the impact of repetitions. Same-frequency and same-value pairs were shown five times to reliably estimate choice preferences on these pairs, resulting in 270 decisions in total.[1] All decision pairs were presented in random order.

[1] By mistake, participants made only one decision on the same frequency pairs that were repeated one, two, three, or four times in the learning phase. Instead, they were probed on another five irrelevant item pairs. We corrected this mistake in the Experiment 2.

2.1.4. Simulating familiarity-based decisions with FB-DMM

We simulated participants' decisions a priori with FB-DMM. FB-DMM encountered the same exemplars as participants in the learning phase. In a test phase, FB-DMM repeatedly decided between two options with the same value but encountered with a different number of repetitions (*same-value pairs*) or between two options encountered with the same number of repetitions but with different values (*same-frequency pairs*). We based our predictions for participants' decisions on one set of parameter values ($c = 1$, $w = 0.5$, $\beta = 0.2$) for the following reasons: An attention weight $w = 0.5$ divides attention equally between the presented item and its value. A high memory sensitivity c indicates that participants should more accurately perceive close to the aspiration level. However, a memory sensitivity $c > 1$ also implies that participants should be less sensitive to differences in values for each value pair (Fig. B2). Therefore, we considered a memory sensitivity $c = 1$ in the simulation. We chose a choice sensitivity $\beta = 0.2$, as FB-DMM's predictions provided very deterministic predictions for same-value pairs for high levels of choice sensitivity β. FB-DMM's predictions for same-frequency pairs were less sensitive to variations in choice sensitivity (see Appendix B).

As illustrated in Fig. 4, FB-DMM predicts an interaction between repetitions and value: Individuals should pick the high-value option only if the choice options were repeated frequently, that is, on *high-repetition pairs*, but individuals need to guess the high-value option if the options were only presented once, that is, on *low-repetition pairs* (Fig. 4, left panel). Vice versa, more frequently encountered options are only chosen on *high-value pairs* if both options possess a high value (e.g., fifty, Fig. 4, right panel) and not on *low-value pairs*.

2.1.5. Data analysis

First, we tested FB-DMM's general prediction that the number of repetitions interacts with value in a mixed logistic regression model on all choice pairs. We predicted choice of option 1 with the repetition frequency of each option, their values, and the interaction between repetition and value for each option, with participant as a random intercept. Second, we investigated to what extent participants' choices matched FB-DMM's predictions on same-frequency pairs and same value pairs. Specifically, we predicted choice percentages of the higher value option across all same-frequency pairs in a repeated-measures ANOVA with repetition as within-factor. We conducted a parallel analysis for same-value pairs, predicting choice percentages of the high-repetition option with value. We used contrast coding to test for FB-DMM's prediction that familiarity only influences choices on high-value or high-repetition pairs, but participants choose randomly between low-value or low-repetition options. We specified one contrast stating that individuals should prefer higher valued options more on same-frequency pairs with a low (5 repetitions or less) compared to a high number of repetitions (6 repetitions or more). A second contrast tested for high-repetition pairs (6 repetitions or more) if choice preferences for the high-valued option increased with the number of repetitions. A third contrast tested separately for low- repetition pairs (5 repetitions or less) if choice preferences for the higher valued option also increased – an effect that FB-DMM would not predict. We corrected for multiple comparisons with the Holm-Bonferroni correction (Holm, 1979). We set up equivalent contrasts for same-value pairs, defining here high-value pairs as pairs possessing values of 30 or higher and low-value pairs as pairs possessing values of 25 or lower. Finally, we fitted FB-DMM to choices of each individual participant using maximum likelihood estimation to identify where FB-DMM captures familiarity-based decisions well and where it fails.

The data, the simulations, and the associated code for Experiment 1 are openly available at the Open Science Framework (https://osf.io/d9n8z/).

2.2. Results

On average, participants correctly picked the high-value option on 61.81 % of decision pairs ($SD = 9.7$, same-value pairs excluded) and better than 50 % chance, $t(48) = 8.51$, $p < .001$, $d = 1.22$. In a first step, we investigated in a mixed logistic regression across all choices to what extent participants were more likely to pick an option that was more often repeated and possessed a higher value, testing for FB-DMM's predicted interaction between repetition and value. This mixed logistic regression (D = 17,271, AIC = 17,287, R^2 = 10.0 %) suggested that participants were more likely to choose an option, the higher its encountered value was, $OR = 1.39$ [1.34; 1.44], $z = 17.6$, $p < .001$, and the smaller the encountered value of the alternative option was, $OR = 0.72$ [0.70; 0.75], $z = -17.4$, $p < .001$. However, how often each option in the choice pair was repeated during the learning phase did not influence choice of the option per se, repetition effect of option 1, $OR = 1.03$ [1.00; 1.07], $z = 1.7$, $p = .094$, repetition effect of the alternative option, $OR = 0.97$ [0.93; 1.01], $z = -1.7$, $p = .092$. Participants only

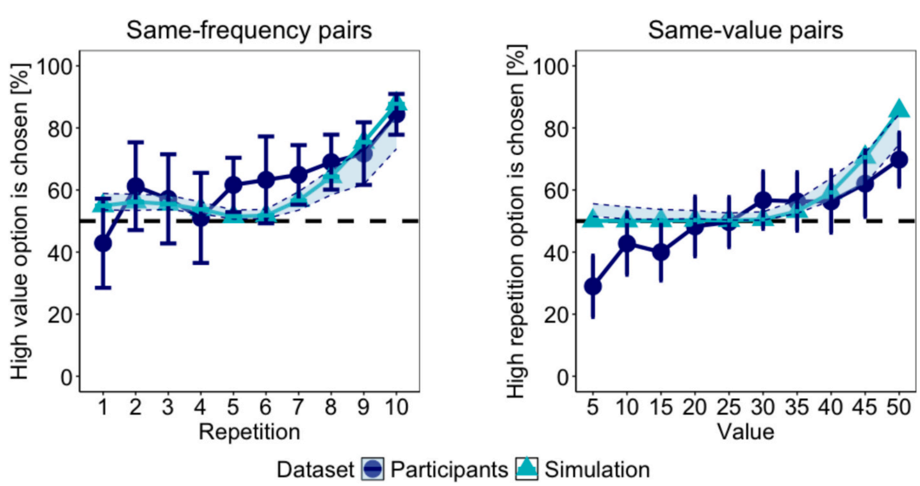

Fig. 4. Predictions of FB-DMM (Simulation, turquoise triangles) and participants' choice percentages (Experiment 1, blue circles) of the high value option on same-frequency pairs (left panel) and the high repetition option on same-value pairs (right panel). Error bars represent 95 %- confidence intervals. Light blue 95 % confidence bands indicate FB-DMM's predictions when fitted to the choices of individual participants. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

chose the option more, if it had been frequently repeated and a high value, $OR = 1.18$ [1.15; 1.22], $z = 11.7$, $p < .001$, and chose the option less, if the alternative had been frequently repeated and a high value, $OR = 0.86$ [0.84; 0.89], $z = -10.5$, $p < .001$. These findings provide initial evidence for FB-DMM's prediction that the number of repetitions per se does not predict how likely participants choose an option, but only in connection to its value.

How well do participants' choices align with FB-DMM's predictions? As predicted for same-frequency pairs, the number of repetitions affected choices of the high-value item, $F(6.3300.4) = 3.87$, $p < .001$, $\eta^2 = 0.065$ (Greenhouse-Geisser corrected, see Fig. 4 for average choice percentages). Participants chose the high-value item more often in high-repetition pairs than in low-repetition pairs, $b = 15.9$, $SE = 3.7$, $t(432) = 4.3$, $p < .001$. Preference for the high-value option increased with number of repetitions in high-repetition pairs, $b = 8.2$, $SE = 3.0$, $t(432) = 2.7$, $p = .015$, but not in low-repetition pairs, $b = 4.6$, $SE = 3.0$, $t(432) = 1.5$, $p = .135$. FB-DMM captured choices on same-frequency pairs better than chance (AIC = 338, $SD = 38$ vs. $AIC_{Base} = 374$), although participants chose the high-value option more often than FB-DMM when options were repeated 5 or 6 times.

For same-value pairs, value affected choices of the high-repetition option, $F(9,432) = 6.2$, $p < .001$, $\eta^2 = 0.104$. Participants chose the frequently repeated option more often on high-value pairs than on low-value pairs, $b = 18.3$, $SE = 3.0$, $t(432) = 6.1$, $p < .001$. Preference for the frequently-repeated option increased with value in high-value pairs, $b = 5.3$, $SE = 2.5$, $t(432) = 2.1$, $p = .034$, but as value decreased participants – unexpectedly – preferred the less frequent option in low-value pairs, $b = 7.8$, $SE = 2.6$, $t(432) = 2.5$, $p = .004$. This contradicts FB-DMM's prediction that participants should choose randomly between low-value pairs and, consequently, FB-DMM failed to capture decisions against the more familiar option when fitted to participant's choices.

2.3. Discussion

Experiment 1 tested the benefits and limits of FB-DMM in predicting value-based decisions. As predicted by FB-DMM, participants chose the high-value option more often if both options had been encountered repeatedly. Notably, the percentage of choices of the high-value option increased with the number of repetitions. If options were only repeated a few times, participants had to guess. Replicating classical findings, individuals preferred more frequently presented options (Zajonc, 1968). As predicted by FB-DMM, individuals more often chose the frequently presented option if it had a high value. Yet, FB-DMM could not predict that participants decided against the more frequently presented low-value option, suggesting that participants recollected additional knowledge (Honda et al., 2011).

3. Experiment 2

Experiment 2 implemented time pressure to further limit the explicit recollection of additional knowledge, here the option's value, beyond familiarity. Time pressure has been found to interfere more with recollection than with familiarity-based processes in recognition decisions (Koenig et al., 2015; Koenig et al., 2020; Yonelinas, 2002). If the familiarity signal is generated faster than the option's value is recollected, restricting decision time should impair recollection and reveal familiarity-based decisions (Pachur & Hertwig, 2006; Yonelinas, 2002). Consequently, decisions against familiar options with low values should be reduced and approach guessing, as predicted by FB-DMM. To further test for the influence of recollection, we asked participants to remember the value of each option in a subsequent memory test and compared FB-DMM's performance against a recollection-based model.

3.1. Method

We manipulated time pressure between participants in Experiment 2 which was otherwise identical to Experiment 1. In addition, we measured recollection with a memory test for the options' values.

3.1.1. Participants

We conducted an a priori power analysis to determine the sample size necessary to detect a 15 % reduction in rejection rates of the low-value, high repetition option under time pressure. This a priori power analysis suggested a required sample size of $N = 114$ to detect an effect size of Cohen's $d = 0.47$, at an α-level $= 0.05$ with power $P_{Stat} = 0.80$ in a one-sided t-test. We collected data from 117 participants from the University of Konstanz (94 females; $M_{Age} = 23$ years, $SD_{age} = 4.4$). On average, they earned 8.2 € ($SD = 1.2$). Participants from Experiment 1 were not allowed to participate in Experiment 2.

3.1.2. Stimuli, design, and procedure

We made the following changes compared to Experiment 1: (i) Participants made the decisions during the decision phase either under the strict time pressure of 2 s or without time pressure (random assignment, between-subjects). Missed answers were not rewarded and omitted from the data analysis. (ii) After the decision phase, a memory recall asked participants to retrieve the value of each presented option. Options were presented sequentially in random order without time restriction and were shown three times to increase reliability. We measured how often participants correctly recollected the option's value. Participants received four cents for each correctly retrieved value in memory recall and two cents if the retrieved value was within ± six units of the correct value.

3.1.3. Data analysis

As in Experiment 1, we first tested the general prediction that the number of repetitions interacts with value in a mixed logistic regression model on all choice pairs. Because Experiment 2 manipulated time pressure between conditions, we added time pressure as an additional predictor as well as its interaction with the repetition frequency of each option, their values, and the interaction between repetition and value for each option.

We conducted the same repeated-measures ANOVAs on same-frequency and same-value pairs as in Experiment 1, but with the additional between-participant factor of time pressure. In addition, we added a contrast that tested specifically for the effect that time pressure reduced participants' choices against the more frequently repeated option for low-value pairs with values of 5, 10, and 15 because participants decided against the more frequently repeated option on these pairs in Experiment 1.

To account for the possibility that recollection processes better explain value-based decisions than familiarity-based processes, we included participants' recalled values for each option as additional predictors in the ANOVA on same-value pairs and in the mixed logistic regression model on all choice pairs. Finally, we contrasted the performance of FB-DMM against two competitor models: a guessing model proposing that participants choose randomly between the two options and a recollection-based model that reconstructs each option's value before making a choice (Pachur & Olsson, 2012; Trippas & Pachur, 2019, see also Appendix A). The retrieval of values involves a similarity-based matching of the current option to all exemplars stored in memory based upon each option's features (Izydorczyk & Broder, 2021):

$$dist_{ij} = \sum_{m=1}^{M} |x_{im} - x_{jm}| \tag{4}$$

As in FB-DMM, the similarity is a decaying function of the distance $dist_{ij}$ (Eq. (A.2)). The recalled value $\widehat{V}_i$ for each option is a function of the values V_j of each unique exemplar, weighted by their similarity to the current option and the frequency t of these exemplars in memory,

Table 1
Mixed logistic regression on choice of option 1 with time pressure (TP), repetitions (Rep), values and their interaction as predictors (M1 without recall) and with the additional predictor of recalled values (Recalled) in the memory tests (M2 with recall).

	M1 without recall			*M2 with recall*		
Predictor	*OR [95 %- CI]*	*z*	*p*	*OR (CI)*	*z*	*p*
Intercept	1.01 [0.00; 1.01]	1.3	0.205	1.01 [0.98; 1.05]	0.8	0.433
Time pressure (TP)	0.96 [0.92; 1.01]	−1.5	0.121	0.98 [0.93; 1.03]	−1.0	0.336
Rep_1	1.03 [1.00; 1.07]	1.8	0.071	1.02 [0.98; 1.06]	1.1	0.281
Rep_2	0.99 [0.96; 1.02]	−0.6	0.580	0.99 [0.96; 1.03]	−0.6	0.576
$Values_1$	1.49 [1.45; 1.55]	23.5	<0.001	1.16 [1.12; 1.21]	7.6	<0.001
$Values_2$	0.71 [0.68; 0.74]	−20.1	<0.001	0.88 [0.85; 0.92]	−6.3	<0.001
TP x Rep_1	1.03 [0.98; 1.08]	1.2	0.212	1.02 [0.97; 1.07]	0.7	0.454
TP x Rep_2	0.96 [0.91; 1.00]	−1.9	0.057	0.99 [0.94; 1.04]	−0.5	0.546
TP x $Values_1$	0.81 [0.77; 0.85]	−8.9	<0.001	0.90 [0.85; 0.95]	−3.9	<0.001
TP x $Values_2$	1.16 [1.11; 1.21]	6.1	<0.001	1.07 [1.02; 1.13]	2.5	0.011
Rep_1 x $Values_1$	1.22 [1.19; 1.25]	14.6	<0.001	1.09 [1.06; 1.13]	5.9	<0.001
Rep_2 x $Values_2$	0.84 [0.81; 0.86]	−13.3	<0.001	0.93 [0.90; 0.96]	−4.7	<0.001
TP x Rep_1 x $Values_1$	0.92 [0.88; 0.95]	−4.6	<0.001	0.95 [0.91; 0.99]	−2.7	0.007
TP x Rep_2 x $Values_2$	1.04 [1.00; 1.08]	1.9	0.055	1.01 [0.97; 1.05]	0.4	0.727
$Recalled_1$				2.10 [2.01; 2.19]	34.5	<0.001
$Recalled_2$				0.50 [0.48; 0.52]	−32.6	<0.001
TP x $Recalled_1$				0.74 [0.70; 0.78]	−10.4	<0.001
TP x $Recalled_2$				1.29 [1.22; 1.37]	8.7	<0.001
R^2	8.8 %			22.6 %		
AIC	41,322			38,138		

Notes: TP = Time pressure; Rep = Repetitions; Recalled = Recalled Values; M1 = Model 1; M2 = Model 2; OR = Odd's Ratio; CI = Confidence Interval; R^2 = Explained amount of variance; AIC = Akaike's Information Criterion.
Subscripts for the predictors indicate the option (option 1 or 2).

$$\widehat{V}_i = \frac{\sum_{j=1}^{J} s_{ij} \bullet t_j \bullet V_j}{\sum_{j=1}^{J} s_{ij} \bullet t_j} \quad (5)$$

We quantified model fit with the Akaike's Information Criterion (AIC) that penalizes models for the number of parameters. We based model comparisons on relative AIC weights (AIC_w, Wagenmakers & Farrell, 2004).

The data, the simulations, and the associated code for Experiment 2 are openly available at the Open Science Framework (https://osf.io/d9n8z/).

3.2. Results

3.2.1. Performance

Without time pressure, participants answered correctly on average in 62.7 % of all pairs (SD = 10.7, excluding same-value pairs) and performed better than 50 %-chance, $t(59) = 9.15$, $p < .001$, $d = 1.18$. Under time pressure, participants missed on average 4 out of 270 choices in the decision phase ($SD = 5.11$, M = 0.01 %, SD = 0.02 %) and only answered 56.4 % ($SD = 7.3$) of the pairs correctly. Although they performed worse than participants without time pressure, $t(104.2) = 3.6$, $p < .001$, $d = -0.67$, they still performed better than 50 %-chance, $t(56) = 6.8$, $p < .001$, $d = 0.89$.

In a mixed logistic regression across all choices, we first explored the prediction of FB-DMM that number of repetitions and value interact, that is, participants choose more likely an option if it was frequently repeated and possessed a higher value. Table 1 reports the overall model fit and the parameter estimates for each predictor, converted to odd's ratios. Replicating experiment 1, participants more likely chose an option, if it had a higher value initially or if the alternative option possessed a lower value. How often each option was repeated did not predict choice per se. However, participants chose the option more, if it was frequently repeated and possessed a high value (or if the alternative option was rarely repeated and possessed a low value). Under time pressure, these effects were generally less pronounced: While time pressure did not change how likely people were to choose option 1, participants with time pressure were less likely than participants without time pressure to choose the option if it had a higher value or if the alternative option possessed a low value. Finally, time pressure also attenuated the interaction effect of value and repetition, such that participants with time pressure (compared to participants without time pressure) were less likely to choose an option, if it was frequently repeated and possessed a high value (or if the alternative option was rarely repeated and possessed a low value). This attenuation might indicate that participants based value-based decisions on a different retrieval process under time pressure.

3.2.2. Time pressure on same-value and same-frequency pairs

Do choices under time pressure conflict less with familiarity-based predictions? We expected that if time pressure reduced recollection, participants would decide less often against the more frequently repeated low-value option in same-value pairs and choose more randomly. Participants without time pressure identified more often the high-value option than participants under time pressure in same-frequency pairs (Fig. 5A). A mixed-ANOVA tested how time pressure (between-participant) and repetition (within-participant) affected choice percentage for high-value options. On average, participants without time pressure chose more often the high-value option than participants under time pressure, $F(1, 115) = 7.6$, $p = .007$, $\eta^2 = 0.011$. The more frequently the options were repeated, the more often participants chose the high-value option, $F(9, 1035) = 11.33$, $p < .001$, $\eta^2 = 0.076$. However, the interaction between time pressure and repetition did not influence how often participants chose the high-value option, $F(9, 1035) = 0.45$, $p = .907$, $\eta_p^2 = 0.003$. Contrasts implied that participants chose the high-value option more often in high-repetition pairs than in low-repetition pairs, $b = 11.9$, $SE = 1.7$, $t(1035) = 6.8$, $p < .001$. In high-repetition pairs, the preference for the high-value option increased with number of repetitions, $b = 10.4$, $SE = 1.5$, $t(1035) = 7.2$, $p < .001$, but not in low-repetition pairs, $b = -1.1$, $SE = 1.5$, $t(1035) = -0.8$, $p = .452$.

For same value-pairs, we expected time pressure to reduce choices of the frequently repeated option for low-value pairs where recollection conflicted with familiarity (low-value pairs with values of 5, 10, and 15, Fig. 5B). On average, participants without time pressure did not choose the high-repetition option less often than participants under time pressure, $F(1, 115) = 0.51$, $p = .478$, $\eta^2 < 0.01$. Replicating experiment 1,

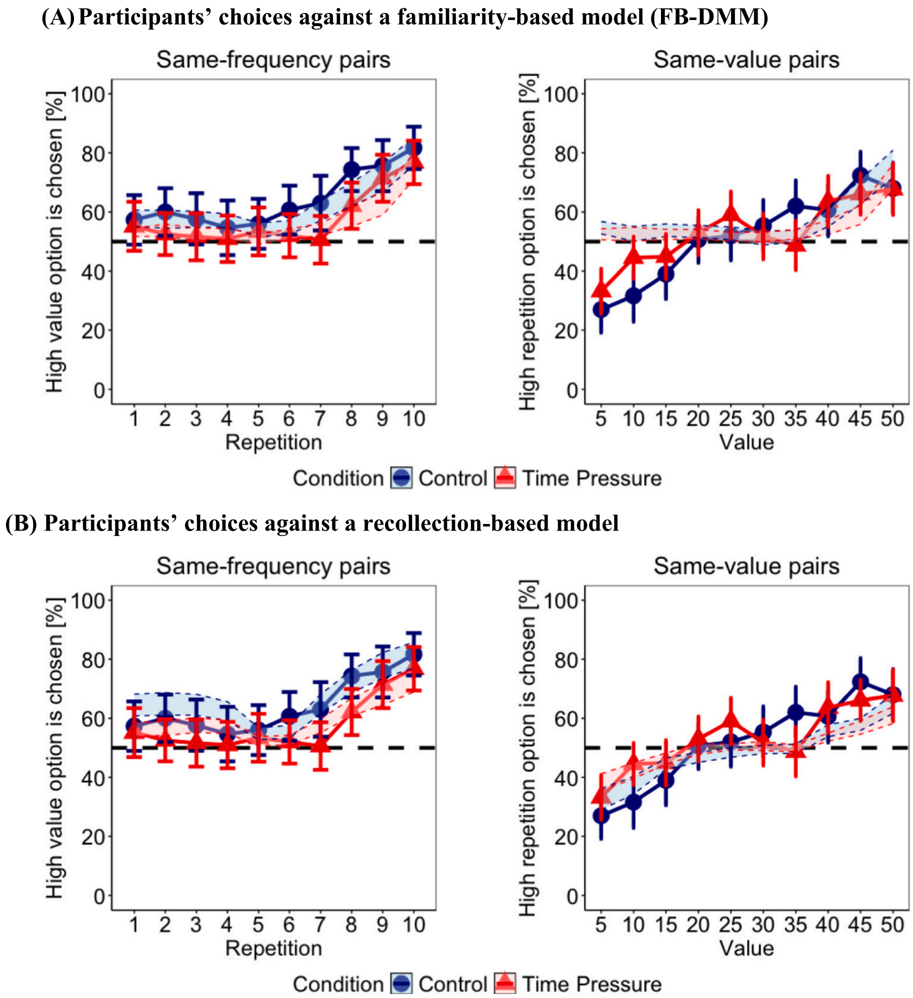

Fig. 5. (A) Predictions of a familiarity-based model (FB-DMM) against participants' choices without time pressure (blue circles) and under time pressure (red triangles) in Experiment 2 for same-frequency (left panel) and same-value pairs (right panel). Error bars represent 95 %- confidence intervals. Light blue and light red 95 % confidence bands indicate FB-DMM's predictions when fitted to the choices of individual participants. (B) Predictions of a recollection-based model against participants' choices. Light blue and light red 95 % confidence bands indicate predictions of a recollection-based model when fitted to the choices of individual participants. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

value affected choices of the high-repetition option, $F(9,1035) = 20.0$, $p < .001$, $\eta^2 = 0.132$. Participants chose the frequently-repeated option more often on high-value pairs than on low-value pairs, $b = 18.1$, $SE = 1.8$, $t(1035) = 10.1$, $p < .001$. Participants preferred the frequently-repeated option more when the values increased on high-value pairs, $b = 7.1$, $SE = 1.5$, $t(1035) = 4.8$, $p = .001$, but also rejected the frequently-repeated option more for low values in low-value pairs, $b = 10.7$, $SE = 1.5$, $t(1035) = 7.2$, $p < .001$.

To what extent time pressure hindered participants to recollect the value for frequently-repeated options was less clear-cut. Descriptively, participants under time pressure ($M = 40.1$ %, $SE = 2.2$ %) more often accepted the frequently-repeated option in low-value pairs than control participants ($M = 32.6$ %, $SE = 2.6$ %), but the effect was small, Cohen's $d = 0.24$, Power $P_{\text{Stat}} = 0.61$. The mixed-ANOVA did not show that time pressure interacted with value, $F(9, 1035) = 1.8$, $p = .071$, $\eta^2 = 0.013$. Still, a planned contrast indicated that time pressure reduced decisions against familiar, low-value options, $b = 8.3$, $SE = 3.4$, $t(676) = 2.4$, $p = .029$. Qualitatively, participants' decisions aligned better with FB-DMM's predictions under time pressure (Fig. 5), but quantitative model fit indicated that individual decisions under time pressure were predicted worse by FB-DMM (AIC = 353, $SD = 23$) compared to the control condition, AIC = 339, $SD = 43$, ΔAIC = 14, boots-trapped 95 %-CI = [2; 27]. However, participants did not resort more often to random guessing. The guessing model did not describe participants better than FB-DMM in the time pressure condition (AIC = 368, $SD = 7$, $\text{AIC}_{\text{w}} = 0.30$, $SD = 0.39$) or the control condition (AIC = 373, SD = 6, $\text{AIC}_{\text{w}} = 0.24$, $SD = 0.38$). Further, the same number of participants was classified as following a guessing model under time pressure (16 out of 57 participants, 28.1 %) and without time pressure (16 out of 60 participants, 26.7 %). Finally, across both conditions, frequently repeated low-value options (e.g., 5) were as often recalled correctly as high-value options (e.g., 50), indicating that individuals did not merely base choices on familiarity (Fig. 6).

Does recollection of the option's value explain why individuals reject the frequently-repeated option on low-value pairs? To directly test for this explanation, we conducted a post-hoc mixed model analysis on the choice percentages for the frequently-repeated option. This mixed model analysis comprised as before the effect of value, time pressure, and their interaction, but also included the difference in recollected values as a predictor on the item-level as well as its interaction with time pressure. For this purpose, we averaged the recalled values for each option across the three repetitions during the memory recall phase for each participant and computed the difference between the average recollected value for the frequently-repeated option and the average recollected value for the rarely-repeated option for each decision. This mixed model analysis replicated the results for value and its interaction

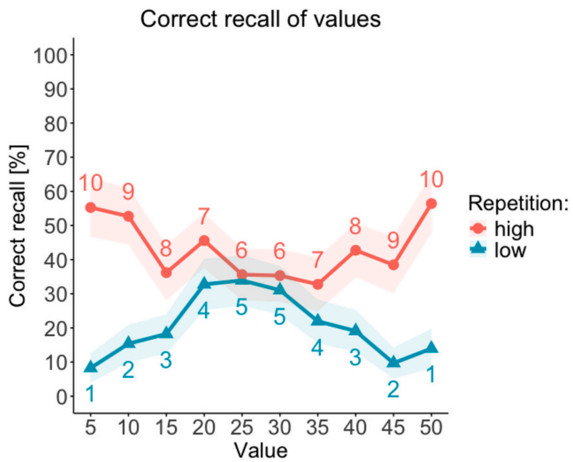

Fig. 6. Average percentage of correctly recalled values for each option in the memory recall test in Experiment 2. Frequently repeated options (red circles) are more often correctly recalled compared to rarely repeated options (blue triangles), especially if the number of repetitions strongly differs. Numbers indicate the number of repetitions of each option in the learning phase; shaded areas represent 95 % confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

with time pressure from the previous analysis, but suggested that the differences in recalled values exerted an even stronger effect on choice. If participants retrieved a higher value for the frequently-repeated option than for the rarely-repeated option in subsequent memory recall, they were more likely to choose the frequently-repeated option, $b = 1.27$, $SE = 0.09$, $F(1, 1142.8) = 316.6$, $p < .001$. This recollection effect was less pronounced when participants were under time pressure than when they had unlimited time, $b = -0.33$, $SE = 0.12$, $F(1, 1142.8) = 7.2$, $p = .007$. This result indicates that participants chose against the frequently repeated option on low-value pairs because they remembered a lower value for this option.

Yet, the preceding analysis does not allow to conclude to what extent the recalled values better explain value-based choices compared to previously encountered values because it considered only options with the same value. To further explore if direct recall better explains value-based choice than repetitions, the previously encountered value, and their interaction, we included the average recalled value for each option (and its interaction with time pressure) as additional predictors in the previously reported mixed logistic regression on choice (see section 3.2.1 Performance). Table 1 reports detailed statistics on model fits and parameter estimates for this mixed logistic regression (referred to as M2 with recall). This mixed logistic regression indicated that a model including the recalled values (M2 with recall) explained a higher amount of variance than the initial mixed logistic regression model (M1 without recall). Further, M2 mostly replicates the initial findings, but effect sizes, as measured in odd's ratio (OR), are slightly smaller, when the recalled values are added as predictors. Finally, M2 suggests a strong effect of recalled value, that is participants were twice more likely to choose an option if they remembered the option to possess a high value. Time pressure attenuates this effect, making participants less likely to choose in accordance with the recalled value for each option. In short, this analysis points towards two conclusions. First, the finding that participants under time pressure were less likely to choose the frequently repeated option on low-value pairs can partially be attributed to a worse recollection of the options' values. Second, recollection and familiarity each explain a unique amount of variance, indicating that both processes contribute independently to value-based decisions.

3.2.3. *Familiarity and recollection in value-based decisions*

The previous results suggest that individuals attempted to retrieve the values for each option, even if they only had a limited time to decide between the two options. In a last step, we evaluated to what extent a recollection-based model better accounted for participants' choices than FB-DMM and a guessing model (see section 3.1.3 Data Analysis and Appendix 1 for a detailed model description). Across both conditions, this recollection-based model (AIC = 343, $SD = 41$, $AIC_w = 0.46$, $SD = 0.43$) fared better than the guessing model (AIC = 371, $SD = 7$, $AIC_w = 0.16$, $SD = 0.28$) in predicting participants choices, but did not systematically outperform FB-DMM (AIC = 346, $SD = 35$, $AIC_w = 0.38$).

Fig. 5 depicts the predictions of this recollection-based model against participants' choices for the selected set of same-value and same-frequency pairs. Indeed, the recollection model successfully predicts that participants reject the frequently repeated option on low-value pairs. Further, it captures the finding that participants identify the high value option more often if both options have been frequently repeated. Yet, the recollection-based model underestimates how often participants pick the high-repetition option on high-value pairs and overestimates how often participants pick the high-value option on low-frequency pairs. Finally, we tested our expectation that participants under time pressure should rely less on recollection-based processes than participants without time pressure. In line with this prediction, the relative AIC_w for the recollection-based model was slightly lower for participants under time pressure ($AIC_w = 0.39$, $SD = 0.40$) compared to participants in the control condition ($AIC_w = 0.53$, $SD = 0.45$). Vice versa, the relative AIC_w for FB-DMM slightly increased under time pressure ($AIC_w = 0.42$, $SD = 0.27$) compared to the control condition ($AIC_w = 0.33$, $SD = 0.43$), as did the relative AIC_w for the guessing model (Time pressure: $AIC_w = 0.19$, $SD = 0.29$; Control: $AIC_w = 0.14$, $SD = 0.28$). In sum, while we find some evidence that participants abandonned recollection-based retrieval under time pressure, this shift towards familiarity-based retrieval was smaller than initially expected. Further, considered in isolation, the recollection-based model neither captured sufficiently why individuals rejected frequently repeated low-value options, but at the same time accepted frequently repeated high-value options to a higher degree.

4. General discussion

The current work predicted value-based decisions solely from the global familiarity of the current option with previously seen options. Simulations showed that individuals should prefer more frequently to less frequently encountered options and high-value to low-value options. Importantly, FB-DMM proposed that individuals should prefer the frequently presented option for high-value options, but not for low-value options. In two experiments, we found that frequency of encounters per se does not predict how likely participants choose an option, but only in connection to its value. For high-value options, individuals indeed opted more often for the frequently encountered option. Yet, FB-DMM cannot explain the finding that individuals opted against the frequent option on low-value pairs, suggesting a complementary recollection-based retrieval of the option's value. In line with this idea, a time pressure manipulation in Experiment 2 slightly reduced choices against the low-value option. Controlling for participants' recalled values in a memory test suggested further that participants may have rejected the frequent low-value option because they remembered its value. A formal model comparison supported this explanation showing that participants relied less on recollection-based retrieval under time pressure compared to the control condition.

As presented, FB-DMM succeeds in explaining central phenomena in value-based decision making based on a global familiarity signal. FB-DMM predicts that individuals can successfully choose higher-valued options without actively reconstructing the value of each option. Key to its success is FB-DMM's capacity to match the to-be-considered option within its choice context to previously encountered options and their values stored in memory. The aspiration value one hopes to gain as a reward forms an integral part of the current choice context and acts as another retrieval cue for familiarity-based matching. Thereby, FB-DMM models value-based decisions within the class of exemplar models – a process-based modeling account with a longstanding tradition in predicting recognition decisions from past exposures (Hintzman, 1988; Hoffmann et al., 2018; Nosofsky, 1988). This extends previous familiarity-based choice models characterizing memory strength with threshold models (Castela & Erdfelder, 2017a, 2017b; Erdfelder et al., 2011), signal detection models (Pleskac, 2007), or as an additional cue in the choice process (Shirasuna et al., 2020). As a process model, FB-DMM further allows to deduce novel predictions for value-based choice from memory. For instance, FB-DMM discriminates better between options close to its aspiration level (e.g. it prefers 50 to 45 more than 10 to 5, Fig. 1). This feature enables FB-DMM to model the revelation effect from memory – the finding that individuals prefer the memorized option for gains, but less so for losses (Kraemer et al., 2022; Weilbacher et al., 2020). Future research may exploit this property to better understand how familiarity with the options and the context interacts with value-based uncertainty to fuel risk preferences (Ludvig et al., 2015; Madan et al., 2021).

However, decisions in both experiments also systematically deviated from FB-DMM's predictions and individuals rarely submitted fully to a familiarity-based decision process. To discourage participants from engaging in deeper encoding processes that ultimately increase reliance on recollection (Yonelinas, 2002), we used random line drawings that should be difficult to process semantically. In the absence of time pressure, the overall accuracy rate across both experiments showed a small but significant advantage in detecting the higher-value option, beyond what would be expected from random guessing, which may be taken as a sign for familiarity-based processing. Experiment 2 manipulated time pressure to increase reliance on familiarity. Time pressure led to a decline in accuracy rates, suggesting that familiarity-based processing was encouraged relative to recollection-based processing. Still, even under time pressure, individuals rejected the frequently encountered option if both options possessed low values. This refines previous work on value-based food choices (Gluth et al., 2015; Mechera-Ostrovsky & Gluth, 2018), indicating that individuals may prefer accepting an unfamiliar option when risks are low. FB-DMM is unable to capture this rejection process. Instead, it is possible that individuals consciously retrieve the value for the often repeated, low-value option, but reconstruct (or guess) an average value for the unfamiliar, low-value option, as proposed by an exemplar-based recollection process (Hoffmann et al., 2018; Izydorczyk & Broder, 2021). Time pressure in Experiment 2 slightly reduced the tendency to reject more frequently encountered options with low values, but the effect was small. A formal model comparison further pointed towards the possibility that recollection supported decisions against the frequently encountered options on low-value pairs. While this model comparison indicated that participants relied less on a recollection-based processes under time pressure, the shift towards familiarity-based processes was less pronounced than expected. Further, in isolation, neither FB-DMM, nor a recollection-based model were able to account for the full choice pattern. These results support the perspective that both familiarity and recollection processes contribute to value-based decisions, matching research suggesting independent contributions of familiarity and recollection to recognition memory (Mandler, 2008; Yonelinas et al., 2024). Jointly considered these results highlight the importance of modeling the interplay between familiarity-based and recollection-based retrieval in value-based decisions.

It is possible that other mechanisms beyond recollection may account for the finding that individuals reject frequently encountered low-value options. For one, aversive stimuli, such as losses or low values, may signal a danger or threat at encoding (Wohl et al., 2014). If individuals seek to minimize losses when making value-based decisions, this aversive feeling may evoke a high certainty to reject the low value choice and can potentially be modelled within a familiarity-based avoidance approach. It is unlike, however, that this mechanism provides a good explanation for choices against familiarity in our paradigm because participants were unaware of the meaning of the values at the encoding stage. Alternatively, individuals may attempt to find a relationship between the line patterns and the values, searching for patterns in random sequences (Falk & Konold, 1997; Gaissmaier et al., 2016). As the patterns were randomly assigned to the values, participants should not be able to reject low value items with a high accuracy.

In the episodic memory literature, research has argued that familiarity supports the formation of associative memories only in exceptional situations (for a recent review see Gardette et al., 2025), conflicting with our idea that the global familiarity signal encompasses item and contextual information. In line with established exemplar models of judgment and decision making (Hoffmann et al., 2014; Izydorczyk & Broder, 2021; Pachur & Olsson, 2012), our formalization was based on the simplifying assumptions that information about each previous option and its corresponding value are stored as one exemplar, that is, in the same memory trace. This approach matches memory models that represent associative information by concatenating information of several items within the same trace (Cox, 2024; Hintzman, 1988). Recent dynamic models of recognition memory aim to formalize the relations between items to advance our understanding of how people form associative memories (Cox, 2024). Future work in value-based decisions may draw upon these insights to enhance our knowledge about how individuals link choice options with their perceived subjective value.

5. Conclusion

Our work demonstrates the surprising capacity but also limits of a purely familiarity-based model. The difficulty to experimentally separate familiarity-based processes from recollection-based decisions illustrates the strength of computational process models to disambiguate cognitive choice processes. Future work may complement familiarity-based processing within FB-DMM with recollection-based retrieval to advance the understanding of value-based decisions.

CRediT authorship contribution statement

Tamara Gomilsek: Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Wolfgang Gaissmaier:** Writing – original draft, Supervision, Conceptualization. **Janina A. Hoffmann:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation, Conceptualization.

Ethics approval

This study was approved by the Ethics Committee of the University of Konstanz (IRB statement 09/16). Informed consent was obtained from all individual participants included in the study.

Funding sources

This study was funded by the Graduate School of Decision Sciences, University of Konstanz, Germany.

Appendix A. Modeling value-based decisions with familiarity and recollection

A.1. Familiarity-based decision-making model (FB-DMM)

In global memory matching models, the familiarity of the value-based option (the "probe") depends on a global similarity-based matching of this probe to all other exemplars in the learning history (Nosofsky, 1988, 2011). These exemplars j (and the probe i) are each characterized by distinct features x, such as the present lines in the line drawing in our experiment, as well as a value v, such as the explicitly learned value v_j associated with each line drawing. In more naturalistic value-based decision tasks, this value v_j may correspond to the intrinsically represented subjective utility of a given option. Here, we propose that the question, identifying the higher-valued option, sets an aspiration level that serves as a contextual cue in addition to the features of the probe. The similarity in these features determines how similar the probe is to each exemplar. FB-DMM then determines the familiarity f_i of the probe i as the sum of all similarities s_{ij} between the probe i and each exemplar j stored in the learning history:

$$f_i = \sum_j s_{ij} \tag{A.1}$$

Multiple repetitions of the same item are stored as separate exemplars, leading to a higher familiarity judgment. A probe is thus more familiar, if it elicits a high similarity and is repeated more often. The similarity of the probe to an exemplar depends on their distance $dist_{ij}$, that is as how distant they are perceived to one another (Nosofsky & Zaki, 1998),

$$s_{ij} = e^{-c^* dist_{ij}} \tag{A.2}$$

where the memory sensitivity parameter c determines how sensitive people are at noticing the differences between the exemplar and the probe. High values of c indicate that people notice already small differences between exemplars. In global familiarity matching models, the distance betweeen the probe and the exemplars depends not only upon the features shared between the probe and stored exemplars but also on the similarity in context (Mensink & Raaijmakers, 1989). Here, we assume that the question, identifying the higher-valued option, sets an aspiration level where the specific aspiration level v_i acts as another contextual retrieval cue. As a result, the distance is a function of the absolute difference between the features of the probe x_{im} and the exemplar's features x_{jm} and the absolute difference between the value v_j of each exemplar and a high hypothetical aspiration value v_i for the probe i, weighted by the attention w devoted to the features relative to the value:

$$dist_{ij} = w \sum_{m=1}^{M} |x_{im} - x_{jm}| + (1 - w)^* M^* |v_i - v_j| \tag{A.3}$$

where M denotes the total number of features. The attention parameter tells how much attention the individuals put on the value of a probe in comparison to other probe features. Ideally, attention is devoted equally to the value and the features: If individuals only attend to the value and ignore the features, then it is later impossible to tell to which probe the value belongs. The features were coded as zero or one and the presented values V normalized to the same range:

$$v_i = \frac{V(i) - (\min(V))}{\max(V) - min(V)} \tag{A.4}$$

Finally, the FB-DMM more likely chooses the probe within a pair that possesses a higher familiarity following Luce' choice rule (Luce, 1977):

$$P(R_i|f_i) = \frac{e^{f_i{}^*\beta}}{\sum e^{f_i{}^*\beta}} \tag{A.5}$$

Higher values of choice sensitivity β imply that people choose more deterministically the probe with a higher familiarity judgment.

A.2. Recollection-based model

Recollection-based decision models propose that individuals actively reconstruct the value of each choice option before making a decision (Pachur & Olsson, 2012; Trippas & Pachur, 2019). The retrieval of values involves a similarity-based matching of the current probe to all exemplars stored in memory based upon each option's features (Izydorczyk & Broder, 2021):

$$dist_{ij} = \sum_{m=1}^{M} |x_{im} - x_{jm}| \tag{A.6}$$

As in FB-DMM, the similarity is a decaying function of the distance $dist_{ij}$ (Eq. (A.2)). The recalled value $\widehat{V}_i$ for the probe is then reconstructed by weighting the similarity of each unique exemplar relative to all exemplars with the corresponding value V_j and the number of exemplar repetitions t,

$$\widehat{V}_i = \frac{\sum_{j=1}^{J} s_{ij} \bullet t_j \bullet V_j}{\sum_{j=1}^{J} s_{ij} \bullet t_j} \tag{A.7}$$

Finally, the recollection-based model more likely chooses the probe within a pair that possesses a higher retrieved recalled value $\widehat{V}_i$ following Luce' choice rule (Luce, 1977):

$$P(R_i|\widehat{V}_i) = \frac{e^{\widehat{V}_i{}^*\beta}}{\sum e^{\widehat{V}_i{}^*\beta}} \tag{A.8}$$

Appendix B. Simulating value-based decisions with the FB-DMM

The simulation investigated two verbal predictions of FB-DMM: a) the prediction that repeated exposures increase familiarity and, thus, more frequently encountered options should be preferred to less frequent ones (Hintzman, 1986; Nosofsky, 1988). b) the prediction that options with values close to the aspiration value are perceived as more familiar and, thus, should be preferred to objects with values further away from the aspired value. If the aspiration value is set to a high value, thus options with higher values should be preferred. Accordingly, we varied in the simulation systematically how often different options were presented, and the value associated with these options.

B.1. Method

FB-DMM learned 100 unique options, each associated with a different value (varied from 5 to 50 in increments of 5) and presented to FB-DMM at a different repetition rate (varied from 1 to 10 in increments of 1). Each option was characterized by 20 dimensions or features, each feature randomly coded as zero or one (present-absent coding). The number of present features was not predictive of the criterion value.

In a decision phase, FB-DMM then decided between pairs of options based upon their familiarity (see Appendix A). For each simulated decision, FB-DMM first calculated the familiarity level for each option within the pair and then decided probabilistically for one option according to Luce choice rule (Luce, 1977). Two types of pairings are most informative to contrast the impact of value and repetition on familiarity-based choice. On same-frequency pairs, the two options were repeated the same number of times but possessed a different value. Same-frequency pairs thus allow to measure the impact of the value. On same-value pairs, the two options possessed the same value but were repeated more or less frequently throughout the learning history. Same-value pairs thus allow to measure the impact of repetitions.

Between simulations, we systematically varied as well FB-DMM's parameter values: The attention weight w was varied from 0 to 1 (with a step size of 0.1), while keeping $\beta = 1$, $c = 1$. Memory sensitivity c (or choice sensitivity β, respectively) was varied from 0 to 2 (with a step size of 0.1), while keeping $w = 0.5$ and $\beta = 1$ ($c = 1$, respectively). We repeated each simulation 10′000 times. We repeated the simulation 10′000 times for each combination of model parameters.

B.2. Results

Fig. B1 illustrates how preferences for the higher valued option change with the number of repetitions as well as distance to the aspiration value and the difference in value between the options (left panel). First, the higher value option is picked more often if both options were more often encountered suggesting an interaction between value and repetition. Second, FB-DMM perceives options as more familiar, the closer they are to its aspiration value (here 50). Thus, if the options' values are further apart (e.g. 5 to 25 compared to 5 vs. 10), the higher valued option is more strongly preferred. Third, as similarity is a decaying function of distance, FB-DMM considers an option as much more familiar, the closer its value is to the aspiration value. Therefore, FB-DMM picks more likely the high-value option when choosing between 45 and 50 compared to 5 and 10. Finally, on same-value pairs (right panel), FB-DMM more likely selects the more frequently presented option, especially for options with high values. However, preference strength only depends upon how many times more the frequently presented option was encountered, not on the base rate of repetitions.

Fig. B2 illustrates how varying FB-DMM's parameters alters how likely FB-DMM's picks the higher value option on same-frequency pairs (all graphs are available in the data repository). When FB-DMM attends predominantly to the value (attention weight $w = 0.8$), it identifies easily high value options as familiar if they are approaching the aspiration value. However, FB-DMM needs to devote more attention to the features to develop more fine-grained preferences for value pairs in which both options have relatively lower values. Increased memory sensitivity similarly eases identifying mostly the high value options. Predictions for same-frequency pairs are relatively little affected by changes in choice sensitivity, likely because the number of repetitions is constant and does not affect familiarity.

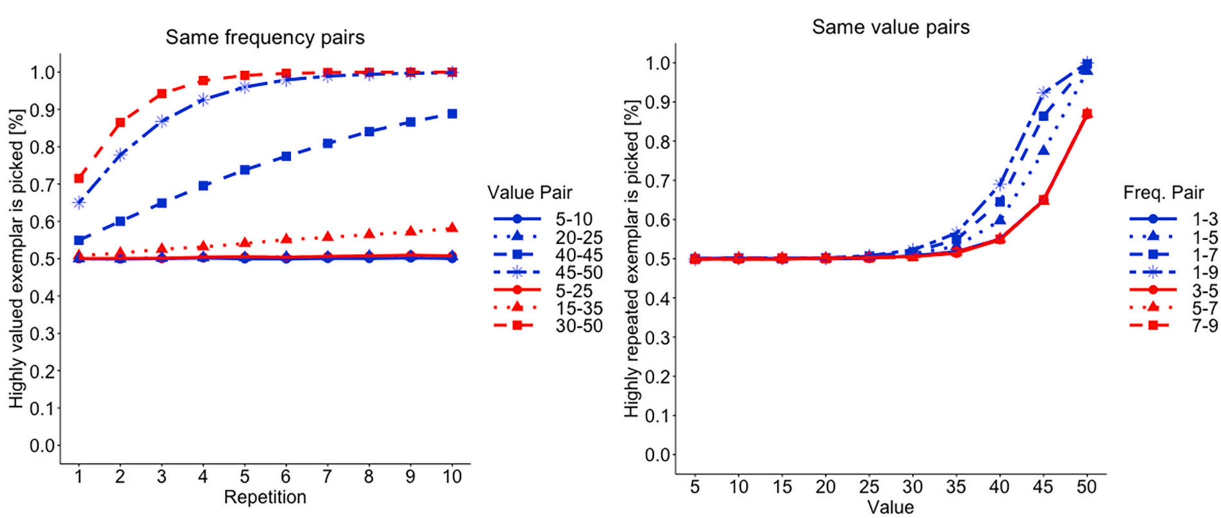

Fig. B1. Simulating value-based choices with FB-DMM. Same-frequency pairs: FB-DMM chooses between two options encountered with the same number of repetitions (x-axis) with small (e.g. 5 compared to 10, blue lines) or high difference (e.g. 5 compared to 25, red lines) in value. Same-value pairs: FB-DMM chooses between two options with the same value (x-axis). The first option is encountered either once and the second option is encountered 3, 5, 7, or 9 times (blue lines) or both options are encountered more often (e.g. 3 and 5 times, red lines). Depicted simulations are based on one set of parameter values ($w = 0.5$, $c = 1$, $\beta = 1$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

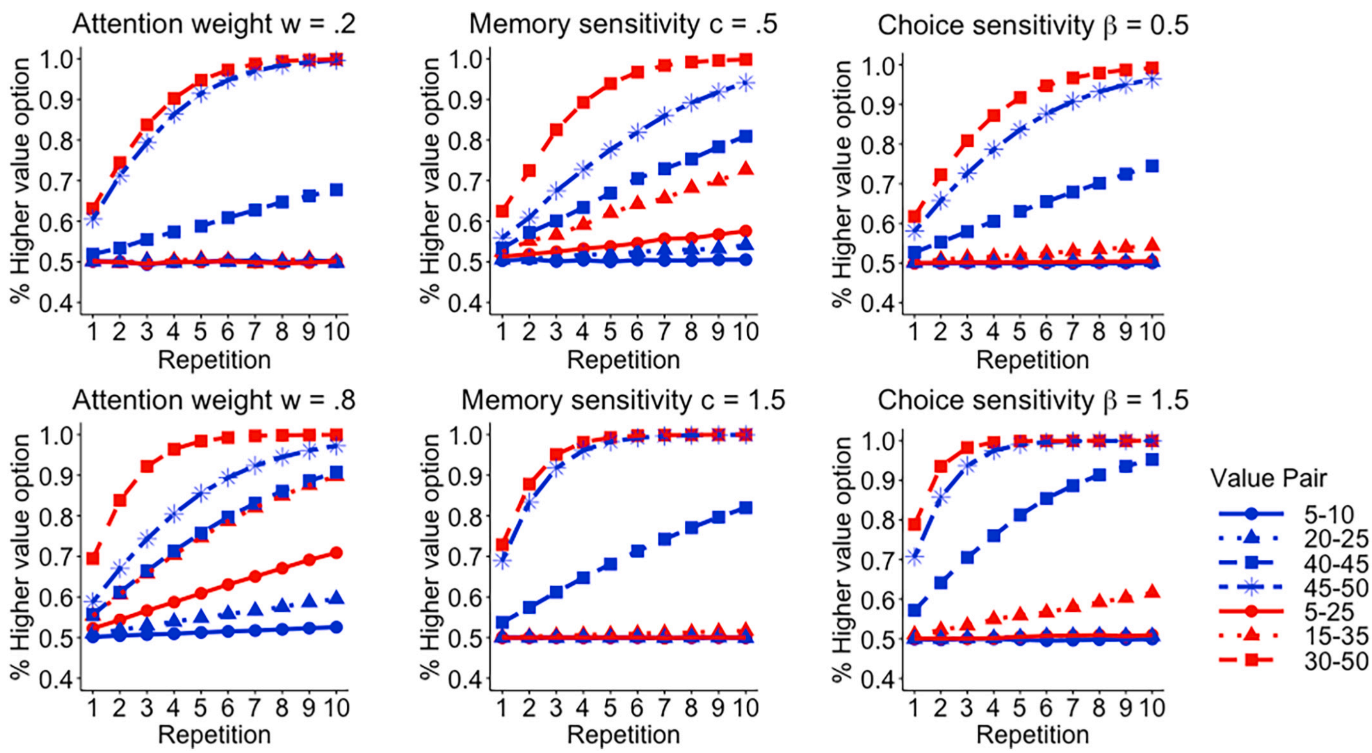

Fig. B2. Effect of varying FB-DMM's parameter values on same-frequency pairs. FB-DMM chooses between two options encountered with the same number of repetitions (x-axis) with small (e.g. 5 compared to 10, blue lines) or high difference (e.g. 5 compared to 25, red lines) in value. The left column displays the simulation in B1 with varied attention weight, the middle column varies memory sensitivity, and the right column varies choice sensitivity. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Data availability

The datasets generated during and/or analyzed during the current study are available in the OSF repository (https://osf.io/d9n8z/). The repository also contains code for the simulations, the material for all experiments, and the code for data analysis.

References

Alter, A. L., & Oppenheimer, D. M. (2008). Easy on the mind, easy on the wallet: The roles of familiarity and processing fluency in valuation judgments. *Psychonomic Bulletin & Review, 15*(5), 985–990. https://doi.org/10.3758/PBR.15.5.985

Atkinson, R. C., & Juola, J. F. (1974). Search and decision processes in recognition memory. In D. H. Krantz, R. C. Akinson, & P. Suppes (Eds.), *Contemporary developments in mathematical psychology* (pp. 243–290). Freeman.

Bornstein, A. M., Khaw, M. W., Shohamy, D., & Daw, N. D. (2017). Reminders of past choices bias decisions for reward in humans. *Nature Communications, 8*, 15958. https://doi.org/10.1038/ncomms15958

Brown, G. D., Neath, I., & Chater, N. (2007). A temporal ratio model of memory. *Psychological Review, 114*(3), 539–576. https://doi.org/10.1037/0033-295X.114.3.539

Carpenter, A. C., & Schacter, D. L. (2018). False memories, false preferences: Flexible retrieval mechanisms supporting successful inference bias novel decisions. *Journal of Experimental Psychology. General, 147*(7), 988–1004. https://doi.org/10.1037/xge0000391

Castela, M., & Erdfelder, E. (2017a). Further evidence for the memory state heuristic: Recognition latency predictions for binary inferences. *Judgment and Decision making, 12*(6), 537–552. https://doi.org/161115b/jdm161115b.pdf.

Castela, M., & Erdfelder, E. (2017b). The memory state heuristic: A formal model based on repeated recognition judgments. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 43*(2), 205–225. https://doi.org/10.1037/xlm0000299

Cox, G. E. (2024). Dynamic retrieval of events and associations from memory: An integrated account of item and associative recognition. *Psychological Review, 131*(6), 1297–1336. https://doi.org/10.1037/rev0000486

Cox, G. E., & Shiffrin, R. M. (2017). A dynamic approach to recognition memory. *Psychological Review, 124*(6), 795–860. https://doi.org/10.1037/rev0000076

Diana, R. A., Reder, L. M., Arndt, J., & Park, H. (2006). Models of recognition: A review of arguments in favor of a dual-process account. *Psychonomic Bulletin & Review, 13*(1), 1–21. https://doi.org/10.3758/bf03193807

Duncan, K. D., & Shohamy, D. (2016). Memory states influence value-based decisions. *Journal of Experimental Psychology. General, 145*(11), 1420–1426. https://doi.org/10.1037/xge0000231

Ecker, U. K., & Zimmer, H. D. (2009). ERP evidence for flexible adjustment of retrieval orientation and its influence on familiarity. *Journal of Cognitive Neuroscience, 21*(10), 1907–1919. https://doi.org/10.1162/jocn.2009.21135

Erdfelder, E., Küpper-Tetzel, C. E., & Mattern, S. D. (2011). Threshold models of recognition and the recognition heuristic. *Judgment and Decision making, 6*, 7–22. https://journal.sjdm.org/11/rh13/rh13.html.

Falk, R., & Konold, C. (1997). Making sense of randomness: Implicit encoding as a basis for judgment. *Psychological Review, 104*, 301–318. https://doi.org/10.1037/0033-295X.104.2.301

Gaissmaier, W., Wilke, A., Scheibehenne, B., McCanney, P., & Barrett, H. C. (2016). Betting on illusory patterns: Probability matching in habitual gamblers. *Journal of Gambling Studies, 32*(1), 143–156. https://doi.org/10.1007/s10899-015-9539-9

Gardette, J., Delhaye, E., & Bastin, C. (2025). The multiple dimensions of familiarity: From representations to phenomenology. *Wiley Interdisciplinary Reviews: Cognitive Science, 16*(1), Article e1698. https://doi.org/10.1002/wcs.1698

Gluth, S., Sommer, T., Rieskamp, J., & Büchel, C. (2015). Effective connectivity between hippocampus and ventromedial prefrontal cortex controls preferential choices from memory. *Neuron, 86*, 1078–1090. https://doi.org/10.1016/j.neuron.2015.04.023

Gray, S. J., & Gallo, D. A. (2015). Disregarding familiarity during recollection attempts: Content-specific recapitulation as a retrieval orientation strategy. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 41*(1), 134–147. https://doi.org/10.1037/a0038363

Hintzman, D. L. (1986). "Schema abstraction" in a multiple-trace memory model. *Psychological Review, 93*(4), 411–428. https://doi.org/10.1037/0033-295X.93.4.411

Hintzman, D. L. (1988). Judgments of frequency and recognition memory in a multiple-trace memory model. *Psychological Review, 95*(4), 528–551. https://doi.org/10.1037/0033-295X.95.4.528

Hockley, W. E., Bancroft, T. D., & Bryant, E. (2012). Associative and familiarity-based effects of environmental context on memory. *Canadian Journal of Experimental Psychology, 66*(2), 81–89. https://doi.org/10.1037/a0027136

Hoffmann, J. A., von Helversen, B., & Rieskamp, J. (2014). Pillars of judgment: How memory abilities affect performance in rule-based and exemplar-based judgments. *Journal of Experimental Psychology. General, 143*(6), 2242–2261. https://doi.org/10.1037/a0037989

Hoffmann, J. A., von Helversen, B., & Rieskamp, J. (2016). Similar task features shape judgment and categorization processes. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 42*(8), 1193–1217. https://doi.org/10.1037/xlm0000241

Hoffmann, J. A., von Helversen, B., Weilbacher, R. A., & Rieskamp, J. (2018). Tracing the path of forgetting in rule abstraction and exemplar retrieval. *Q J Exp Psychol (Hove), 71*(11), 2261–2281. https://doi.org/10.1177/1747021817739861

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics, 7*, 65–70.

Honda, H., Abe, K., Matsuka, T., & Yamagishi, K. (2011). The role of familiarity in binary choice inferences. *Memory & Cognition, 39*(5), 851–863. https://doi.org/10.3758/s13421-010-0057-9

Izydorczyk, D., & Broder, A. (2021). Exemplar-based judgment or direct recall: On a problematic procedure for estimating parameters in exemplar models of quantitative judgment. *Psychonomic Bulletin & Review, 28*(5), 1495–1513. https://doi.org/10.3758/s13423-020-01861-1

Jacoby, L. L., & Dallas, M. (1981). On the relationship between autobiographical memory and perceptual learning. *Journal of Experimental Psychology: General, 110*. https://doi.org/10.1037/0096-3445.110.3.306

Jacoby, L. L., Kelley, C. M., & McElree, B. D. (1999). The role of cognitive control: Early selection versus late correction. In S. Chaiken, & Y. Trope (Eds.), *Dual-process theories in social psychology* (pp. 383–400). Guilford Press.

Kahana, M. J., Howard, M. W., & Polyn, S. M. (2008). Associative retrieval processes in episodic memory. In *Learning and memory: A comprehensive reference* (pp. 1–24). https://doi.org/10.1016/b978-012370509-9.00185-6

Koenig, L., Wimmer, M. C., & Hollins, T. J. (2015). Process dissociation of familiarity and recollection in children: Response deadline affects recollection but not familiarity. *Journal of Experimental Child Psychology, 131*, 120–134. https://doi.org/10.1016/j.jecp.2014.11.003

Koenig, L., Wimmer, M. C., & Trippas, D. (2020). Item repetition and response deadline affect familiarity and recollection differently across childhood. *Memory, 28*(7), 900–907. https://doi.org/10.1080/09658211.2020.1790612

Kraemer, P. M., Weilbacher, R. A., Mechera-Ostrovsky, T., & Gluth, S. (2022). Cognitive and neural principles of a memory bias on preferential choices. *Current Research in Neurobiology, 3*, Article 100029. https://doi.org/10.1016/j.crneur.2022.100029

Luce, R. D. (1977). The choice axiom after twenty years. *Journal of Mathematical Psychology, 15*, 215–233. https://doi.org/10.1016/0022-2496(77)90032-3

Ludvig, E. A., Madan, C. R., & Spetch, M. L. (2015). Priming memories of past wins induces risk seeking. *Journal of Experimental Psychology. General, 144*(1), 24–29. https://doi.org/10.1037/xge0000046

Madan, C. R., Spetch, M. L., Machado, F., Mason, A., & Ludvig, E. A. (2021). Encoding context determines risky choice. *Psychological Science, 32*(5), 743–754. https://doi.org/10.1177/0956797620977516

Mandler, G. (2008). Familiarity breeds attempts: A critical review of dual-process theories of recognition. *Perspectives on Psychological Science, 3*(5), 390–399. https://doi.org/10.1111/j.1745-6924.2008.00087.x

Marewski, J. N., Gaissmaier, W., Schooler, L. J., Goldstein, D. G., & Gigerenzer, G. (2010). From recognition to decisions: Extending and testing recognition-based models for multialternative inference. *Psychonomic Bulletin & Review, 17*(3), 287–309. https://doi.org/10.3758/PBR.17.3.287

Mayes, A., Montaldi, D., & Migo, E. (2007). Associative memory and the medial temporal lobes. *Trends in Cognitive Sciences, 11*(3), 126–135. https://doi.org/10.1016/j.tics.2006.12.003

Mechera-Ostrovsky, T., & Gluth, S. (2018). Memory beliefs drive the memory bias on value-based decisions. *Scientific Reports, 8*(1), 10592. https://doi.org/10.1038/s41598-018-28728-9

Medin, D. L., & Schaffer, M. M. (1978). Context theory of classification learning. *Psychological Review, 85*, 207–238. https://doi.org/10.1037/0033-295X.85.3.207

Mensink, G.-J. M., & Raaijmakers, J. G. (1989). A model for contextual fluctuation. *Journal of Mathematical Psychology, 33*, 172–186. https://doi.org/10.1016/0022-2496(89)90029-1

Murty, V. P., FeldmanHall, O., Hunter, L. E., Phelps, E. A., & Davachi, L. (2016). Episodic memories predict adaptive value-based decision-making. *Journal of Experimental Psychology. General, 145*(5), 548–558. https://doi.org/10.1037/xge0000158

Nosofsky, R. M. (1988). Exemplar-based accounts of relations between classification, recognition, and typicality. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14*, 700–708. https://doi.org/10.1037/0278-7393.14.4.700

Nosofsky, R. M. (2011). The generalized context model: An exemplar model of classification. In E. M. Pothos, & A. J. Wills (Eds.), *Formal approaches in categorization* (pp. 18–39). Cambridge University Press. https://doi.org/10.1017/CBO9780511921322.002.

Nosofsky, R. M., Cao, R., Cox, G. E., & Shiffrin, R. M. (2014). Familiarity and categorization processes in memory search. *Cognitive Psychology, 75*, 97–129. https://doi.org/10.1016/j.cogpsych.2014.08.003

Nosofsky, R. M., & Zaki, S. R. (1998). Dissociations between categorization and recognition in amnesic and normal individuals: An exemplar-based interpretation. *Psychological Science, 9*, 247–255. https://doi.org/10.1111/1467-9280.00051

Pachur, T., & Hertwig, R. (2006). On the psychology of the recognition heuristic: Retrieval primacy as a key determinant of its use. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 32*, 983–1002. https://doi.org/10.1037/0278-7393.32.5.983

Pachur, T., & Olsson, H. (2012). Type of learning task impacts performance and strategy selection in decision making. *Cognitive Psychology, 65*(2), 207–240. https://doi.org/10.1016/j.cogpsych.2012.03.003

Pleskac, T. J. (2007). A signal detection analysis of the recognition heuristic. *Psychonomic Bulletin & Review, 14*(3), 379–391. https://doi.org/10.3758/bf03194081

Rosburg, T., Mecklinger, A., & Frings, C. (2011). When the brain decides: A familiarity-based approach to the recognition heuristic as evidenced by event-related brain potentials. *Psychological Science, 22*, 1527–1534. https://doi.org/10.1177/0956797611417454

Schwikert, S. R., & Curran, T. (2014). Familiarity and recollection in heuristic decision making. *Journal of Experimental Psychology. General, 143*(6), 2341–2365. https://doi.org/10.1037/xge0000024

Shirasuna, M., Honda, H., Matsuka, T., & Ueda, K. (2020). Familiarity-matching: An ecologically rational heuristic for the relationships-comparison task. *Cognitive Science, 44*(2), Article e12806. https://doi.org/10.1111/cogs.12806

Siegel, S. (1957). Level of aspiration and decision making. *Psychological Review, 64*(4), 253–262. https://doi.org/10.1037/h0049247

Thomadsen, R., Rooderkerk, R. P., Amir, O., Arora, N., Bollinger, B., Hansen, K., … Wood, W. (2018). How context affects choice. *Customer Needs and Solutions, 5*, 3–14. https://doi.org/10.1007/s40547-017-0084-9

Trippas, D., & Pachur, T. (2019). Nothing compares: Unraveling learning task effects in judgment and categorization. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 45*(12), 2239–2266. https://doi.org/10.1037/xlm0000696

Underwood, B. J. (1969). Attributes of memory. *Psychological Review, 76*, 559–573.

Wagenmakers, E. J., & Farrell, S. (2004). AIC model selection using Akaike weights. *Psychonomic Bulletin & Review, 11*(1), 192–196. https://doi.org/10.3758/bf03206482

Weilbacher, 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

Wimmer, G. E., & Buchel, C. (2016). Reactivation of reward-related patterns from single past episodes supports memory-based decision making. *The Journal of Neuroscience, 36*(10), 2868–2880. https://doi.org/10.1523/JNEUROSCI.3433-15.2016

Wohl, M. J. A., Branscombe, N. R., & Lister, J. J. (2014). When the going gets tough: Economic threat increases financial risk taking in games of chance. *Social Psychological and Personality Science, 5*, 211–217. https://doi.org/10.1177/1948550613490964

Xu, P., Gonzalez-Vallejo, C., Weinhardt, J., Chimeli, J., & Karadogan, F. (2018). Use of the familiarity difference cue in inferential judgments. *Memory & Cognition, 46*(2), 298–314. https://doi.org/10.3758/s13421-017-0765-5

Yonelinas, A. P. (1999). The contribution of recollection and familiarity to recognition and source-memory judgments: A formal dual-process model and an analysis of receiver operating characteristics. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 25*(6), 1415–1434. https://doi.org/10.1037//0278-7393.25.6.1415

Yonelinas, A. P. (2002). The nature of recollection and familiarity: A review of 30 years of research. *Journal of Memory and Language, 46*, 441–517. https://doi.org/10.1006/jmla.2002.2864

Yonelinas, A. P., Ramey, M. M., & Riddell, C. (2024). Recognition memory: The role of recollection and familiarity. In M. J. Kahana, & A. D. Wagner (Eds.), *Ther Oxford handbook of human memory, two volume pack: Foundations and applications*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190917982.001.0001.

Zajonc, R. B. (1968). Attitudinal effects of mere exposure. *Journal of Personality and Social Psychology, 9*, 1–27. https://doi.org/10.1037/h0025848