Retrieval-constrained valuation: Toward prediction of open-ended decisions

Zhihao Zhang (张之昊)[a,b,1], Shichun Wang (王诗淳)[a], Maxwell Good[a,c,d], Siyana Hristova (Сияна Христова)[a], Andrew S. Kayser[c,d,e,1,2], and Ming Hsu (许明)[a,b,e,1,2]

[a]Haas School of Business, University of California, Berkeley, CA 94720; [b]Social Science Matrix, University of California, Berkeley, CA 94720; [c]Department of Neurology, University of California, San Francisco, CA 94158; [d]Department of Veterans Affairs Northern California Health Care System, Martinez, CA 94553; and [e]Helen Wills Neuroscience Institute, University of California, Berkeley, CA 94720

Edited by Fiery Cushman, Harvard University, Cambridge, MA, and accepted by Editorial Board Member Michael S. Gazzaniga April 5, 2021 (received for review October 30, 2020)

Real-world decisions are often open ended, with goals, choice options, or evaluation criteria conceived by decision-makers themselves. Critically, the quality of decisions may heavily rely on the generation of options, as failure to generate promising options limits, or even eliminates, the opportunity for choosing them. This core aspect of problem structuring, however, is largely absent from classical models of decision-making, thereby restricting their predictive scope. Here, we take a step toward addressing this issue by developing a neurally inspired cognitive model of a class of ill-structured decisions in which choice options must be self-generated. Specifically, using a model in which semantic memory retrieval is assumed to constrain the set of options available during valuation, we generate highly accurate out-of-sample predictions of choices across multiple categories of goods. Our model significantly and substantially outperforms models that only account for valuation or retrieval in isolation or those that make alternative mechanistic assumptions regarding their interaction. Furthermore, using neuroimaging, we confirm our core assumption regarding the engagement of, and interaction between, semantic memory retrieval and valuation processes. Together, these results provide a neurally grounded and mechanistic account of decisions with self-generated options, representing a step toward unraveling cognitive mechanisms underlying adaptive decision-making in the real world.

open-ended decisions | option generation | memory retrieval | valuation

Some decisions, such as choosing an entree at a restaurant, come with a menu of well-defined options and associated information that aid in their evaluation and selection. For many other decisions, such as how to spend one's evening or which career path to choose, the space of potential options is less well-defined and may need to be generated by the decision-maker themself. More generally, option generation is part of a larger set of processes critical for a class of decisions, often referred to as "open-ended" or "ill-structured" problems (1–6), that are characterized by a lack of well-specified goals, alternatives, or evaluation criteria, among others.

Despite their ubiquity, however, such decisions pose considerable difficulties for standard models of decision-making, as processes generating these features are typically considered outside the scope of traditional decision analysis (3–11). To address this ambiguity, researchers have turned to one of two broad strategies. The first, and arguably the most frequent one employed, involves imposing strong auxiliary assumptions about the option set (12). For example, if one is choosing a breakfast cereal, the option set comprises everything on the market. This strategy has the benefit of simplicity and is consistent with the invocation of "full rationality" in neoclassical economic theory.

In contrast, the second strategy attempts to relax these assumptions by emphasizing the "constructed" nature of decisions (13). This approach encompasses processes that can occur prior to valuation of choice options, such as the generation (14–16) and consideration (17–19) of said options, as well as those that can occur in parallel, including heuristics (20, 21) that make use of "fast and frugal" rules that do not require explicit weighing of the relative costs and benefits of each option. However, despite important advances in our understanding of mechanisms underlying factors that influence option generation, much less attention has been paid to connecting these accounts with formal models capable of specifying the contents of the "internal menu" (10–12, 22–25). As a result, it remains challenging to make quantitative predictions about the effects of option generation on choice.

Here, we develop a neurally grounded model capable of making highly accurate predictions of people's decisions for a class of ill-structured environments in which options must be retrieved from memory. Specifically, drawing on Marr's three levels of analysis (26, 27), we replace the strong auxiliary assumptions about contents of the option set in standard choice models with a quantitative model capturing "predecision processes," thereby linking formal models of option generation and choice processes. Across a set of experiments that evaluate decisions incorporating real-world goods, we show that, at Marr's computational/conceptual level, these decisions rely critically upon the interaction of processes involved in valuation and the retrieval of semantic knowledge, the aspect of human declarative memory that deals with general,

ECONOMIC SCIENCES

PSYCHOLOGICAL AND COGNITIVE SCIENCES

Significance

Life is not a multiple-choice test: Many real-world decisions leave goals, choice options, or evaluation criteria to be determined by decision-makers themselves. However, a mechanistic understanding of how such problem structuring processes influence choice has largely eluded standard models of decision-making. By developing a neurally grounded cognitive model that integrates semantic knowledge retrieval and valuation processes, we offer a computational framework providing strikingly accurate out-of-sample predictions of choices with self-generated options. This framework generates psychological insights into the nature and force of memory retrieval's substantial influence on choice behavior. Together, these findings represent a step toward predicting complex, ill-structured decisions in the real world, opening up new approaches that may broaden the scope of formal models of decision-making.

Author contributions: Z.Z., A.S.K., and M.H. designed research; Z.Z., M.G., and S.H. performed research; Z.Z. and S.W. contributed new reagents/analytic tools; Z.Z., S.W., M.G., and S.H. analyzed data; and Z.Z., A.S.K., and M.H. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission. F.C. is a guest editor invited by the Editorial Board.

Published under the PNAS license.

[1]To whom correspondence may be addressed. Email: zhihao.zhang@haas.berkeley.edu, andrew.kayser@ucsf.edu, or mhsu@haas.berkeley.edu.

[2]A.S.K. and M.H. contributed equally to this work.

This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2022685118/-/DCSupplemental.

Published May 14, 2021.

Downloaded at Palestinian Territory, occupied on November 29, 2021

المنارة للاستشارات

www.manaraa.com

culturally shared knowledge of meanings, facts, ideas, and concepts accumulated over the lifetime (28, 29). In particular, we draw upon the rich literature on memory factors in consumer decision-making (24, 25, 30), where such choices are conceptualized as the products of a multistage process (14, 16). At the algorithmic level, we build upon two well-established principles from the cognitive science and neuroscientific literatures on memory retrieval and valuation. First, retrieval of semantic knowledge is a probabilistic process governed by the associative principle (28, 31, 32). Second, given a set of options, choice is governed by subjective preferences over the options, commonly referred to as utility or value (7). At the implementation level, we demonstrate that these memory and valuation processes are indeed subserved by separable neurocognitive systems, which can be probed and characterized independently (29, 33).

By connecting these literatures, which have developed largely independently, the resulting framework makes a number of testable predictions. First, output resulting from the interaction of retrieval and valuation processes can be predicted using outputs from each component process. To test this idea, we use behavioral responses from two distinct tasks capturing valuation and semantic retrieval processes, respectively, to predict behavior in a third task that is hypothesized to require both processes. Furthermore, the framework predicts two reasons that an option was not chosen: 1) the option was not preferred and 2) it was not successfully retrieved. Across a diverse array of real-world goods, we show that our computational model makes highly precise and accurate predictions of the likelihood that each option was chosen by incorporating the extent to which each option benefits from a failure to retrieve some other option or is passed over due to successful retrieval of another option. Finally, we present functional neuroimaging evidence that confirms our model's fundamental predictions about the separable but interactive nature of the valuation and retrieval systems that underlie these decisions.

Results

Choice Behavior without an Explicit Menu. To investigate how agents solve the computational problem of maximizing rewards when options are not explicitly provided, we begin by comparing choices from an "external menu condition" (EMC), where an external menu is present, with those in an "internal menu condition" (IMC), where it is not (Fig. 1*A*). Whereas the former enjoys widespread usage, the latter has received comparatively little attention (10–12, 24). Specifically, we used a between-subjects design in which participants ($N = 2{,}811$) were asked to make either EMC or IMC choices within six categories of real-world goods—fruits, fast food chains, running shoe brands, vegetables, fish for dinner, and salad dressings. Choices involving fast food chains and running shoes were incentivized, whereas the other categories were unincentivized (*Materials and Methods*).

Under standard economic models without memory constraints, all options available in EMC are also available in IMC. Therefore, systematic changes in choice behavior between EMC and IMC must be driven by participants whose favorite items are not included in the EMC menu, requiring them to "satisfice" by choosing other in-menu items. Consequently, options available in the EMC condition should have either equal or greater choice share than in IMC. In contrast to this constrained menu account, a constrained retrieval account predicts that highly (less) accessible items should benefit (suffer) under IMC due to the inability to retrieve less accessible options, irrespective of preference. This hypothesis implies that choice frequency for some items, specifically more accessible ones, may be less, rather than greater, in EMC relative to IMC. Our results strongly support the influence of constrained retrieval on IMC choice, above and beyond value. Comparing choices between EMC and IMC, options chosen less in EMC were in general highly accessible, including McDonald's, apple, salmon, and others. (Fig. 1*B* and *SI Appendix*, Fig. S1).

To better assess this impression, we independently measured mnemonic accessibility in a third group of subjects ($N = 256$) using the Semantic Fluency task (29, 31), a widely used task of memory search in which participants retrieve as many items belonging to a particular category as they can during a limited time period (Fig. 1 *C* and *D* and *SI Appendix*, Figs. S2 and S3). Indeed, across all six categories, items with choice shares that declined in the EMC condition exhibited higher accessibility, as measured by Semantic Fluency, compared to those with increased choice shares (Fig. 1*E* and *SI Appendix*, Fig. S4; mixed effects $p < 10^{-6}$).

Predicting Choices with Self-Generated Options. Although the above results are consistent with a role for semantic retrieval processes in option generation and choice, they provide limited mechanistic insights and predictive power. To provide an algorithmic account capable of capturing the hypothesized interaction between memory retrieval and valuation processes, we developed a retrieval-constrained valuation (RCV) model in which valuation operates on an "internal menu" generated probabilistically via semantic retrieval. This model draws information about memory retrieval and valuation from the Semantic Fluency and the EMC samples, respectively, and its out-of-sample predictive power can be tested against the independent IMC sample (Fig. 2*A*).

More formally, we assume choice probability in IMC is governed by

$$P_{IMC}(i) \propto \sum_{m} P_{Retrieval}\,(m) \times P_{Choice}\,(i|m),$$

where $P_{Retrieval}\,(m)$ is the probability of generating a specific choice set m and $P_{Choice}\,(i|m)$ is the probability of selecting option i from choice set m (Fig. 2*B*).

To capture the output of these component processes, we followed well-established models of semantic retrieval and valuation processes using associative network and multinomial logit models, respectively. First, because no a priori method exists to calibrate the associative network, we drew on popular instantiations to estimate the network empirically, where fluency data are assumed to be generated by a censored random walk, specifically a first-order Markov process (Fig. 3*A*) (31, 34). A split-half cross validation showed the trained associated network was able to provide highly accurate predictions of the hold-out fluency responses with respect to both order of retrieval and overall retrieval probability for all goods across all categories (R^2 between 0.90 and 0.96) (Fig. 3*B* and *SI Appendix*, Fig. S5). Next, using a similar approach, we trained a multinomial logit choice model on half of the EMC choices (35), followed by testing on the remaining half (Fig. 3*C*). As with semantic retrieval, the valuation model calibrated on EMC data provides highly accurate out-of-sample predictions of all goods across all categories (R^2 between 0.89 and 0.98; Fig. 3*D* and *SI Appendix*, Fig. S6). In addition, while some degree of correlation exists between the memory accessibility and value associated with real world goods, the magnitude of this correlation (ranging from 0.42 to 0.84) demonstrates substantial variability across categories, thereby making it possible to characterize their separable effects and interaction (*SI Appendix*, Fig. S7).

Individually, these two components can also be seen as nested models within our RCV model, with the valuation-only model corresponding to valuation under perfect retrieval, and the retrieval-only model corresponding to constrained retrieval but uniform value for all options (Fig. 2*A*). Using either of them to predict IMC, however, showed only limited success, as did a "take-the-first" (TTF) model assuming participants chose the first item retrieved (Fig. 4 *A* and *B* and *SI Appendix*, Fig. S8*A*). In contrast, the RCV model combining memory retrieval and valuation showed a striking improvement in out-of-sample performance over the two nested models. First, it was able to accurately predict the entire response

Downloaded at Palestinian Territory, occupied on November 29, 2021

www.manaraa.com

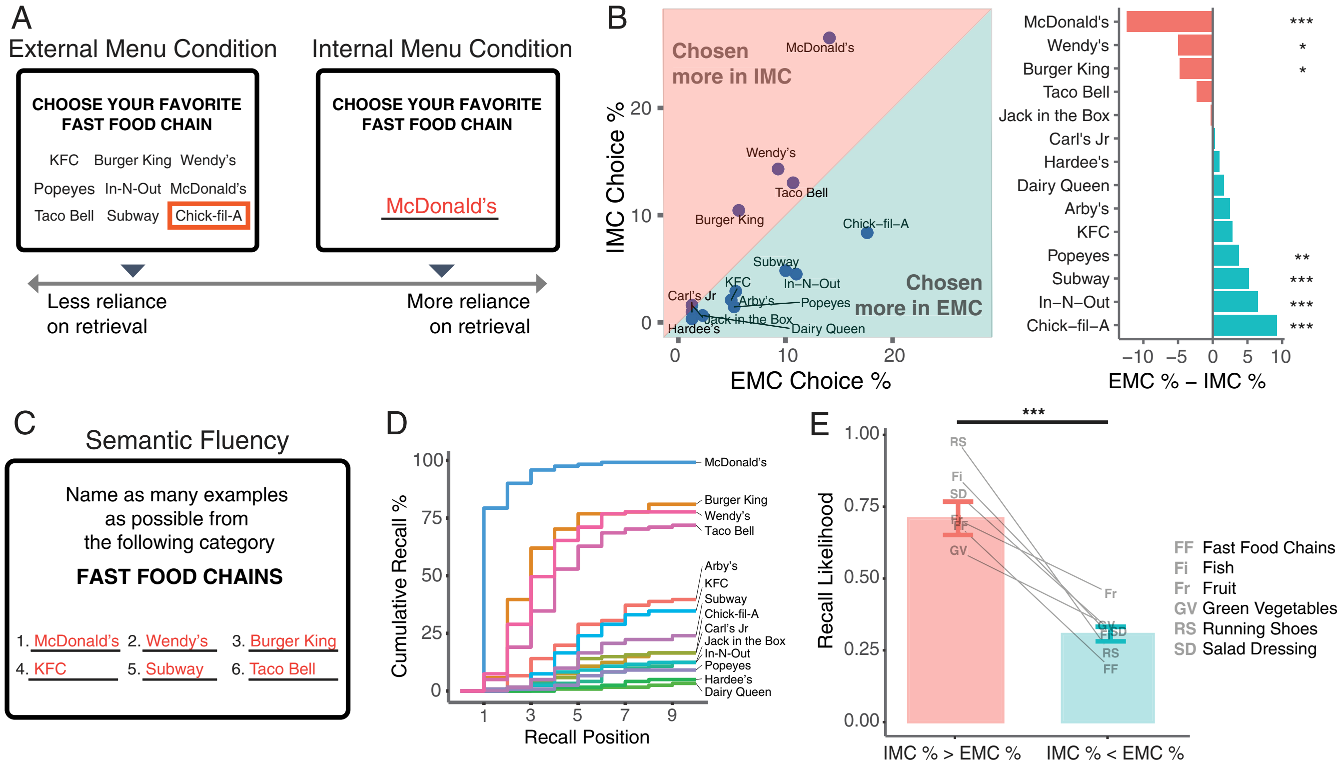

Fig. 1. Task Paradigms. (*A*) Two decision conditions, EMC and IMC, are distinguished by the presence or absence, respectively, of an explicit menu of choice options. (*B*) Consistent with the role of constrained memory retrieval on choices in IMC, (*Left*) deviations between decisions in EMC and IMC are common, as reflected in the off-diagonal items. (*Right*) Items chosen more often in IMC than in EMC (negative EMC – IMC values) are represented by orange bars, with positive EMC – IMC differences in blue. Statistical significance of item-wise choice share differences was determined by permutation tests (Bonferroni corrected). $*P < 0.05$; $**P < 0.01$; $***P < 0.001$. (*C*) To quantify the mnemonic accessibility of different items independently of choice, a third group of participants completed a semantic fluency task in which they listed as many items from memory as possible. (*D*) Cumulative recall probability (*y* axis) of different items as a function of recall position (x-axis). (*E*) Items chosen more often in IMC than EMC are significantly more likely to be recalled in the fluency task than under the reverse case ($P < 0.001$ across categories, mixed-effects model). Error bars indicate the SEM for each group, collapsing across categories.

profile across all categories (mean R^2 of 0.94, range 0.87 to 0.97) despite variations in memory and preference structures between categories (Fig. 4 *C* and *D*, Table 1, and *SI Appendix*, Figs. S8–S10). Second, the regression lines all fell near the identity line, such that coefficients were statistically indistinguishable from 1 despite tight confidence intervals, suggesting that the RCV model is able to predict absolute, in addition to relative, choice shares (Fig. 4*C* and *SI Appendix*, Fig. S9 and Table S4). Moreover, this improvement remained robust to excluding the most accessible item in a category and to measuring the prediction accuracy using (nonparametric) Spearman correlation coefficients (*SI Appendix*, Table S5).

To further investigate the validity of some of the key modeling assumptions, we tested two variants of the RCV model (*SI Appendix*, *SI Methods*). First, we estimated a truncated RCV model that included a parameter that sets an upper limit on the size of the internal menu, thereby permitting us to evaluate the effects

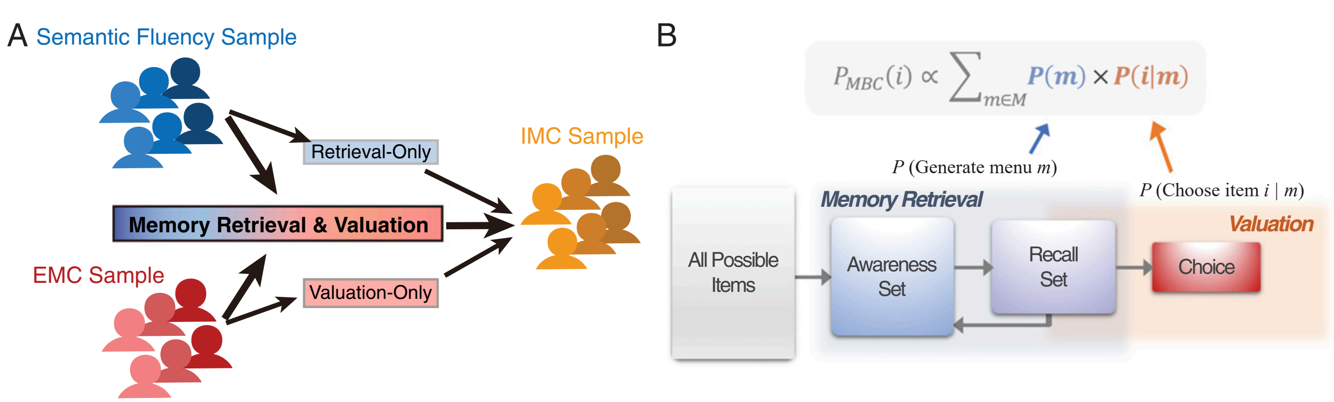

Fig. 2. The RCV Model. (*A*) IMC, EMC, and fluency responses derived from different subject samples were used to construct decision models that incorporate preference only, memory only, or both preference and memory information. (*B*) An algorithmic framework for interaction between memory retrieval and valuation, where the probability of choosing item *i* in the IMC condition, $P_{IMC}(i)$, is proportional to the product of the probability of retrieving some recall set *m*, $P(m)$, and the probability of choosing item *i* from *m*, $P(i|m)$.

Downloaded at Palestinian Territory, occupied on November 29, 2021

www.manaraa.com

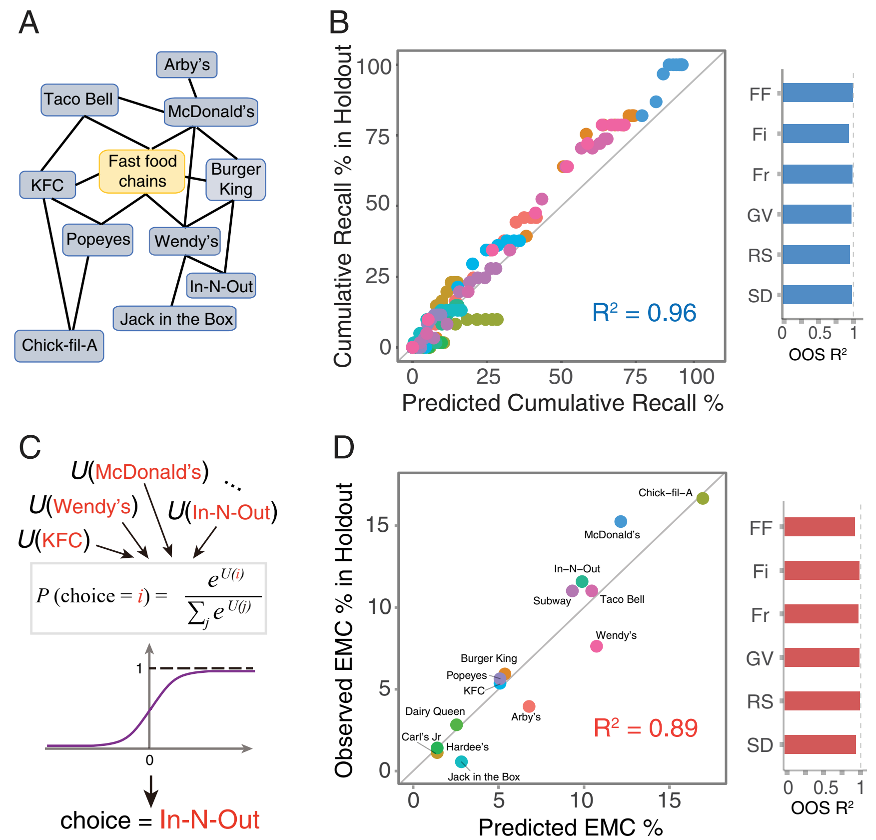

Fig. 3. Modeling Semantic Retrieval and Valuation. (*A*) Schematic depicting retrieval as traversals on an associative semantic network from a category node (e.g., Fast Food Chains) to associated nodes consisting of eligible items. (*B*) Recall probability and recall order in a holdout semantic fluency sample were well-captured by the semantic network model (*Left*), with out-of-sample (OOS) R^2 ranging from 0.90 to 0.96 across tested categories (*Right*). Coloring of the data points follows the same assignment as in panel D below, and the multiple data points for the same item represent the cumulative recall probabilities at different recall positions. (*C*) Valuation processes in the EMC condition were modeled according to a multinomial logit choice rule. (*D*) Participant choices in the holdout sample were well-captured by the logit model (*Left*), with OOS R^2 ranging from 0.89 to 0.98 (*Right*).

of progressively shorter internally generated menus on IMC choices. Second, we estimated an order-weighted RCV model relaxing the assumption that the choice component of the model is insensitive to the order of retrieval. In this latter model, an added parameter allowed an option to be either more or less likely to be chosen if it was retrieved earlier after controlling for accessibility and value. (For both of these models, when the new parameters were set to specific values, they recapitulated the original RCV model.) By examining the prediction performance of these two variants of the RCV model as a function of their additional respective parameters, we found minimal systematic effects captured by these parameters, despite some hints in certain categories for a limited menu or for a slight choice bias favoring options retrieved earlier (*SI Appendix*, Figs. S11 and S12). Unlike the consistent performance of the original RCV model in all categories, however, the limited generalizability of these variants leaves their related mechanistic insights regarding option generation and subsequent choices unclear.

We next evaluated the importance of our assumption regarding the interactive nature of memory and valuation processes by considering a type of mixture model that additively combined the two (*Materials and Methods*). Importantly, although still containing both processes, an additive mixture is conceptually distinct from the RCV model as, rather than generating options, retrieval can be seen to operate as an independent driver of choice behavior. In this potential explanation for the differences between EMC and IMC choices, the retrieval and the valuation processes (the latter assuming that all options are available) compete for behavioral control during IMC choices. Therefore, options with high accessibility, either in a "top-of-mind" or overall sense, may gain choice share in IMC choices through this alternative competitive, rather than interactive, mechanism between the two processes. Compared to the mixture models, the RCV model again exhibited significantly higher out-of-sample IMC prediction accuracy (Table 1 and *SI Appendix*, Fig. S13), highlighting the advantage afforded by a model based on well-validated cognitive processes and plausible assumptions about the way they interact.

Separable Engagement of Neural Systems Underlying Retrieval and Valuation. Finally, we sought to confirm the key predictions of this neurally inspired model at the implementation level—namely, the differential engagement of brain regions thought to underlie cognitive processes, including semantic retrieval and valuation, corresponding to the two components of the RCV model. This hypothesis predicts the critical involvement of medial brain regions, including the ventromedial prefrontal cortex (vmPFC), ventral striatum, and posterior cingulate cortex (PCC), in valuation processing (33) but also the role of a separate set of regions, centered on the lateral prefrontal cortex and the cingulo-opercular network, in semantic retrieval (*SI Appendix*, Fig. S14*A*) (29). Moreover, our model predicts that connectivity with regions important for valuation should strongly reflect the differential demands that specific decision types place on semantic retrieval.

To address these hypotheses, we conducted functional MRI scans of a separate group of subjects (N = 28) while they performed the IMC, EMC, and semantic fluency tasks (*Materials and*

Downloaded at Palestinian Territory, occupied on November 29, 2021

www.manaraa.com

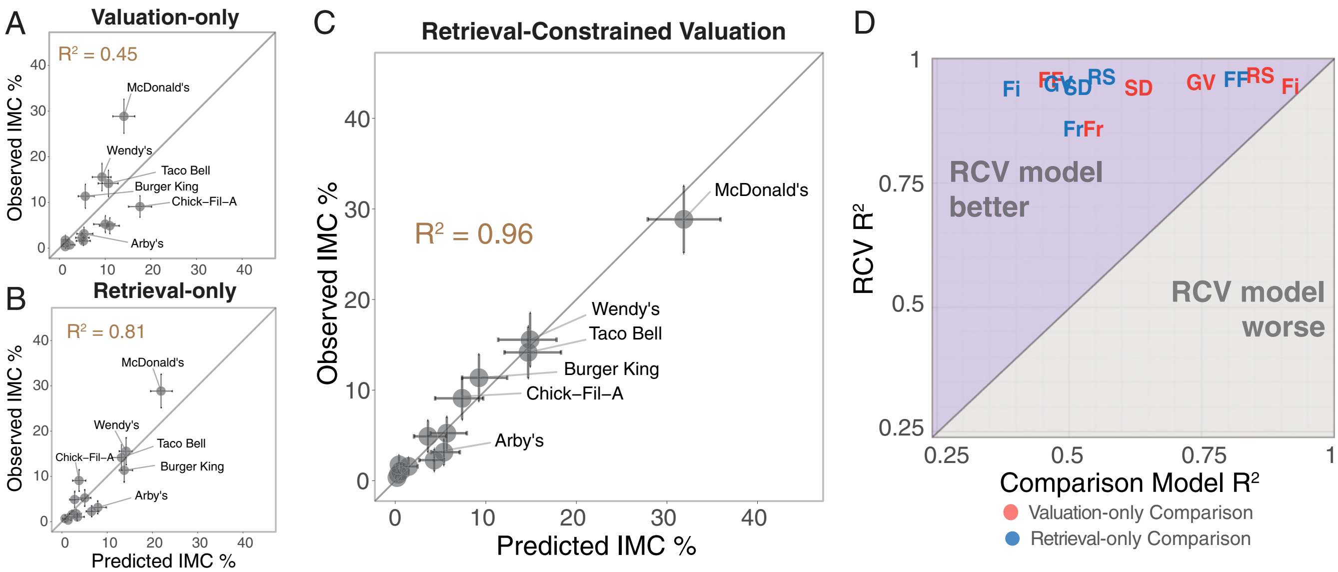

Fig. 4. Predicting IMC. (*A*) Prediction of IMC shares in the Fast Food Chains category using the valuation model calibrated using EMC behavior (out-of-sample [OOS] $R^2 = 0.45$) and (*B*) the memory retrieval model calibrated using semantic fluency responses (OOS $R^2 = 0.81$). (*C*) Fast Food Chains IMC shares were better predicted by the RCV model capturing interaction of memory and valuation (OOS $R^2 = 0.96$). Vertical error bars in *A* through *C* indicate 95% confidence intervals of the observed IMC shares. Horizontal error bars indicate 95% confidence intervals of the predicted IMC shares obtained through a bootstrap procedure. (*D*) Across all categories tested, the retrieval-constrained model demonstrated consistently high accuracy in OOS predictions of IMC behavior and significantly outperformed both memory-only and valuation-only models. Abbreviations for categories are identical to Fig. 1*E*.

Methods and *SI Appendix*, Fig. S14*B*). Consistent with our predictions of separable but interacting systems, IMC showed greater engagement of valuation systems as compared to fluency (vmPFC and PCC $P < 0.05$, cluster-level family-wise error [FWE] corrected; *SI Appendix*, Table S7), and greater engagement of semantic retrieval systems when compared to EMC (inferior frontal gyrus $P < 0.05$ corrected; *SI Appendix*, Table S8 and Fig. 5*A*; see *SI Appendix*, Table S9 for results from the reverse contrast). Moreover, vmPFC showed increased functional connectivity with left anterolateral prefrontal cortex under IMC (*IMC* > *EMC*; $P < 0.05$, small-volume corrected [SVC]), consistent with the hypothesis of an increased need for communication between valuation and retrieval systems during IMC (Fig. 5*B* and *SI Appendix*, Table S11). In contrast, vmPFC showed increased connectivity with the bilateral fusiform gyrus under EMC (*EMC* > *IMC*; $P < 0.05$, SVC; Fig. 5*B* and *SI Appendix*, Table S11), consistent with increased visual processing demands during EMC. Together these findings ground our neurally inspired behavioral model in separable but interacting valuation and retrieval processes in the brain.

Discussion

Some of the most challenging problems that humans face are open-ended, characterized by multiple solutions and solution paths (1–6). Perhaps not surprisingly, this importance has been particularly recognized in applied disciplines ranging from education to artificial intelligence (AI) (3, 36). At the same time, approaches developed in these disciplines have been criticized for being too ad hoc for formal analysis (1–6). Newell, for example, noted that Polya's famous work on problem solving and AI was at once "revered" and "ignored" (1).

Here, we take a modest step toward addressing these long-standing questions by studying cognitive mechanisms underlying a basic but common type of open-ended decision (14, 24). At the computational level, we demonstrate that semantic knowledge structures valuation problems when options are not provided. In particular, incorporation of prior knowledge about the manner in which specific memory systems organize information produces strikingly accurate predictions, substantially expanding the explanatory and predictive scope of standard models of decision-making (7, 8, 24, 25). This framework also explains behavioral observations that are difficult to reconcile with alternative accounts invoking consideration sets or the availability heuristic (18, 22). Participants, for example, retrieved Adidas nearly as often as Nike, but only the latter saw a large gain in choice share moving from EMC to IMC. This example shows how valuation processes can mask effects of accessibility on choice and that an additive relationship between accessibility and valuation is not sufficient to account for IMC choices. Specifically, Adidas did

Table 1. Out-of-sample (OOS) accuracy of IMC choice predictions

	Model	OOS R^2 (mean ± SD)	OOS LL (mean ± SD)	Comparison with RCV model
Proposed model	Retrieval-constrained Valuation (RCV)	0.94 ± 0.04	−1,088 ± 223	—
Single-process models	Valuation-only*	0.69 ± 0.18	−1,150 ± 246	$P < 0.001$
	Retrieval-only†	0.53 ± 0.15	−1,225 ± 169	$P < 0.001$
	Take-the-first (TTF)	0.22 ± 1.33	−1,285 ± 342	$P < 0.001$
Mixture models	Valuation + Accessibility	0.67 ± 0.12	−1,158 ± 227	$P < 0.001$
	Valuation + TTF	0.77 ± 0.17	−1,125 ± 225	$P < 0.001$

Mean and SD across categories are presented for both OOS R^2 and Log Likelihood (LL). Higher R^2 and less negative LL indicate better prediction performance. Comparison with the RCV model is based on OOS R^2 and LL, respectively, across categories via permutation test.
*Perfect retrieval of all available options.
†Constrained retrieval, uniform value.

Downloaded at Palestinian Territory, occupied on November 29, 2021

www.manaraa.com

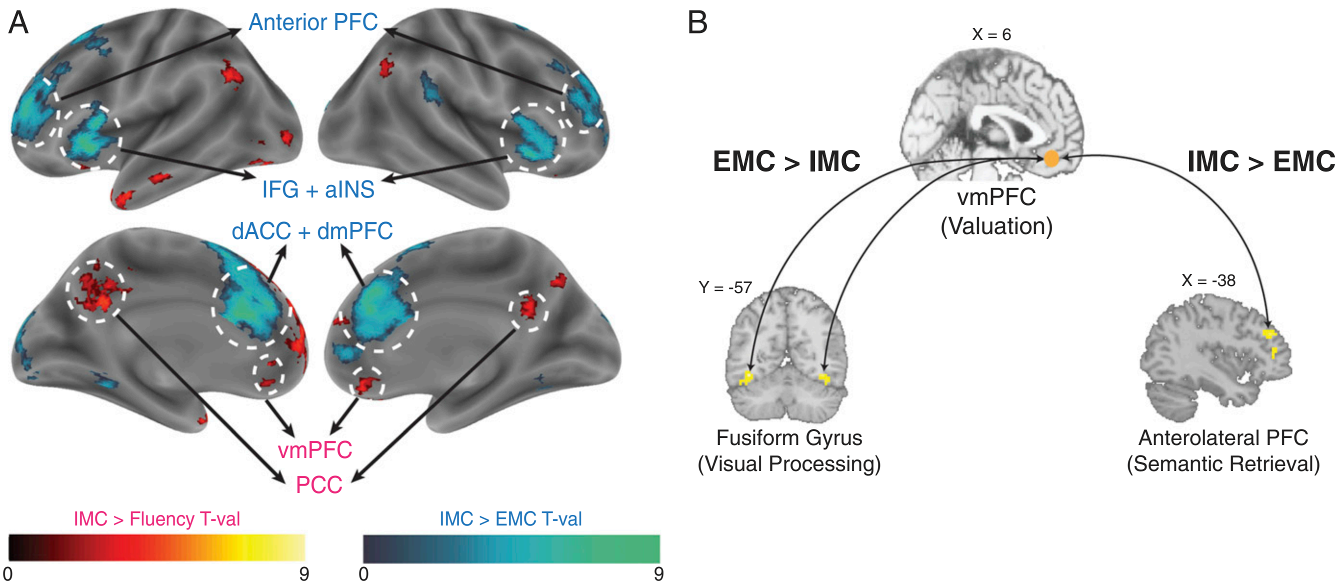

Fig. 5. Neural Substrates of IMC. (*A*) Compared to semantic fluency, IMC elicited greater activity in a priori valuation regions (vmPFC: ventromedial prefrontal cortex, PCC: posterior cingulate). Compared to EMC, IMC elicited greater activity in a priori semantic retrieval regions (aPFC: anterior prefrontal cortex; IFG, inferior frontal gyrus; aINS, anterior insula; dACC, dorsal anterior cingulate cortex; dmPFC, dorsomedial prefrontal cortex). (*B*) Functional connectivity between valuation (vmPFC) and retrieval (aPFC) regions was significantly stronger in IMC, while in EMC, vmPFC was more strongly connected with fusiform gyrus (visual processing).

not see the same degree of gain because 1) it consistently loses to Nike when both are present in the menu, and 2) Nike is rarely missing from the internal menu in IMC and never in EMC.

At the algorithmic level, option generation in IMC, instantiated via associative networks for semantic retrieval, both enables and constrains choice. This modeling approach draws upon and builds on a number of largely separate streams of research, including consumer decision-making (14, 16, 37–39), psychological models of option generation (15, 32, 40), and decision heuristics in complex real-world scenarios (20, 21, 41). Despite differences in many aspects, these works share a common conceptual framework consisting of option generation and their evaluation. At the same time, this understanding has not been incorporated into a formal and generative model with the precision necessary to generate quantitative prediction of choices. To address this gap, we formalize and enrich this framework by modeling option generation using computational models of memory search on associative networks (31, 34, 42). Moreover, when combined with a classic value-based choice model (35), we demonstrate that such models can predict the entire distribution of responses, beyond the most commonly chosen or most accessible items (20).

Apart from its accuracy in choice prediction, another major advantage of a formal, mechanistic model is that it offers a parsimonious framework to explain and unify existing findings as well as to generate testable hypotheses. It can account for the effects of priming and category structures on open-ended decisions (14, 38) through changes in the associative network and their downstream effects on both the composition of the internal menus and on subsequent choices. The model also formalizes how advertising may affect choices separately through consideration and preference (37), and their differential effects in decisions with predefined versus self-generated options (39).

By formalizing previous conjectures about the contribution of memory processes—specifically, semantic knowledge—to option generation (6, 20, 22), we extend insights from previous work showing the myriad ways in which different memory processes contribute to decision-making. Past studies have demonstrated that memory can bias decisions with prior experiences (43, 44); that it can "fill in" missing attribute information when it is not immediately available (45); and that spatial cues associated with specific items can be used to retrieve those items from visuospatial memory for subsequent value-based decisions (46). Here, for example, we demonstrate that the model is flexible enough to accommodate new parameters and/or components, such as the effects of internal menu size and recall order, that test hypotheses regarding associative memory mechanisms.

Our approach to option generation therefore contributes to the past literature emphasizing the "boundedly rational" nature of human decision-making in general and expands upon those models that conceptualize decision-making as a multistage process in particular (16–19). Models of consideration set formation, for example, often posit that the likelihood that an item is "considered" depends on the tradeoff between the expected benefit and cost of including an additional option (i.e., whether the utility of an option merits its consideration) (17, 18, 47). However, because these models typically maintain the assumption that all feasible options are valued, they have difficulty accounting for the frequent and systematic failures to retrieve highly valued options that we observe in our data. Option generation from memory retrieval therefore may be seen as complementary to consideration set formation based on value, as it is possible that the recall set captured by our model is subject to further pruning, resulting in a smaller consideration set.

The RCV model can also be seen as a generalization of models applying decision heuristics to open-ended decisions. In the classic availability heuristic model (22) as well as its more recent extensions (48), information that can be recalled more readily is posited to be more important than information that cannot. More specifically, the "take-the-first" heuristic has been shown to be effective in a variety of situations, especially those involving an ambiguous option space (20, 21, 41). Extending this notion, recent work has proposed an adaptive sampling account in which option generation is biased toward higher value options (49) or in which preferences themselves may be influenced by the order in which supporting evidence is retrieved (50). Our study contributes to this line of inquiry by accommodating different levels of correlation between the value of an option and the probability or order that it will be generated. This flexibility allows the RCV

Downloaded at Palestinian Territory, occupied on November 29, 2021

www.manaraa.com

model to account for choices in categories for which the TTF heuristic is not a good predictor of choice. Importantly, the exact decision strategy used in an open-ended decision likely depends on the context. In some situations in the real world, the TTF model may better explain and predict behavior, such as those involving time pressure or context-specific constraints that could shape retrieval to eliminate unqualified or bad options. The TTF heuristic and the RCV model may represent complementary reflexive and deliberative strategies, respectively, for open-ended decisions. Although there is no clear indication in our data (*SI Appendix*, Table S6), both strategies may be employed by different individuals or jointly govern open-ended decisions in different settings akin to a dual-process model.

The focus on out-of-sample predictions and the inclusion of multiple categories in our study offers a valuable way to examine the generalizability of the proposed RCV model. Importantly, no free parameter is being fit on the IMC choice data when the two components are combined to generate the predictions for IMC choice probabilities. Despite this exceptionally stringent criterion, the RCV model predicts IMC choices with consistently high accuracy across all categories tested, suggesting that the model represents core cognitive mechanisms that generalize regardless of idiosyncrasies in memory and preference structures. By contrast, additional parameters in variants of the RCV model that aim to capture the maximal size of the internal menu or the effect of recall order do not generalize well from one category to another and should be seen as a descriptive component of these extended models. Future studies are necessary to investigate the determinants of these variables of interest—for example, how the size and the composition of the internal menu may be affected by internal (e.g., working memory capacity, category knowledge, and preference structure) and contextual (e.g., environmental memory cues) factors (51–54), as well as their effects on subsequent choices.

At the implementation level, our neural data, as well as those from previous findings on option generation, emphasize the contribution of regions important for controlled semantic retrieval to decision-making (10, 11, 29). Although semantic retrieval can seem automatic and effortless, this link to neural mechanisms has potential implications for clinical assessments of decision-making impairments. For example, given that brain regions identified here as contributing to option generation are known to be pathologically disrupted in Alzheimer's and other dementias (55), evaluations that resemble our EMC condition (i.e., in which available options are provided) may not fully capture day-to-day decision-making deficits in such patients (56).

Finally, we emphasize that our model encompasses only a particular set of open-ended decisions. We do not, for example, address how people identify goals or problems that motivate the need for option generation and decision-making in the first place, how semantic memory mechanisms might be influenced or "nudged" to favor retrieval of specific subsets of options (57), or how people update options in repeated decisions. We also do not consider the potential tradeoff between the mental efforts of memory retrieval and the potential benefit of generating additional options (58). Even what constitutes an "option" remains debated in the option generation and categorization literatures (10). In our study, motivated by the semantic fluency literature, we restricted our attention to so-called natural categories (59). However, more abstract notions of categories and options (32) (e.g., "something red," or "make dinner") may pose difficulties for our model, which assumes that individuals share a common cultural background (28, 29). In a similar vein, many open-ended decisions in everyday life involve options that are not simple concepts or goods but ideas consisting of creative, complex combinations of concepts tailored to the specific context (60). This type of decision may recruit additional cognitive processes and different neural substrates that support them, as is shown by a recent study demonstrating impaired option generation in such decisions in patients with vmPFC lesions (61). Similarly, our study raises questions about the additional influence of encoding processes and their neural substrates, including the medial temporal lobe (43, 46), on subsequent option retrieval. Progress on these and related questions (2–5) is likely to have both theoretical significance and practical implications.

Materials and Methods

Full methodological details are provided in *SI Appendix, SI Methods*.

Participants. A total of 3,067 individuals participated across behavioral studies and 32 in the fMRI study (details are provided in *SI Appendix*, Table S1). This research was approved by the Committee for Protection of Human Subjects at the University of California, Berkeley. Participants provided informed consent before participation.

Behavioral Tasks.

EMC. In the EMC task, participants were asked to imagine a hypothetical shopping scenario in which they needed to choose an item to buy in a given category from a menu of 12 to 14 items (*SI Appendix*, Table S2). The selection of items for the menus ensured reasonable coverage of the most commonly seen and popular items in the categories. There was no time limit on this task. For participants performing this task for the fast food chains and running shoe brands, choices were incentivized by entry into a drawing for a $20 electronic gift card for the brand of their choice. Participants performing this task for the other categories did not receive any additional incentives.

IMC. In the IMC task, participants were similarly asked to imagine a hypothetical shopping scenario in which they needed to choose an item to buy in a given category. However, no menu was provided, and participants needed to type in their response in a text box. There was no time limit for this task. Similar to the EMC task, participants performing the task for the fast food chains and running shoes brands made choices incentivized by the chance to receive a $20 electronic gift card for the brand of their choice, as long as it was a valid brand in the given category. Participants performing this task for the other categories did not receive any additional incentives.

Semantic fluency. Participants were asked to name as many examples as possible for the given category within a time limit (45 s for fast food chains and brands of running shoes, 60 s for the remaining categories). These responses were collected as open-ended text responses. Participants were instructed to input their responses in the order they recalled them, and they were free to finish responding whenever they felt that they could no longer recall any more items. No additional incentives based on the number of the items or their identities were provided. Participants performed this task for multiple categories in randomized orders (*SI Appendix*, Table S1).

Computational Modeling.

Associative network model of semantic knowledge retrieval. Following existing computational modeling studies of semantic fluency, responses in this task were modeled by a censored probabilistic trajectory on a semantic network, or field, determined by the semantic relatedness between the items. We adopted a data-driven approach that defines the transition probabilities from the pooled empirical transitions in the fluency task (see detailed descriptions in *SI Appendix, SI Methods*). We validated this model of semantic knowledge retrieval via split-half cross-validation on the semantic fluency data sets. In light of our goal of predicting the content of retrieval output, we focused on how well the model was able to capture both the identity and the order of responses in the semantic fluency task. Therefore, we adopted cumulative recall probability (CRP, or "Cumulative Recall %" as shown in Fig. 1*D*) for each individual item as the metric for model validation.

Model of valuation in EMC. We used EMC choice data to construct a model of $U(i)$ that captures the value of item i. Following classic choice models, we assumed that, given a predefined choice set (i.e., an external menu of options), the value of item i is transformed to the choice probability of i via a multinomial logit choice rule. Similar to our modeling of semantic knowledge retrieval, we adopted a split-half approach to first infer $U(i)$ from a random half of our EMC sample, then test its predictive performance on the holdout sample.

RCV model. The RCV model is a generative computational model that produces quantitative predictions of IMC choice probabilities for a comprehensive list of items in a given category. It combines the models of semantic knowledge retrieval and of valuation described above and seeks to capture the cognitive mechanism of internal menu generation through memory retrieval and value-based choice over recalled items. Following the law of total probability, the predicted probability of choosing an item i in IMC is

ECONOMIC SCIENCES

PSYCHOLOGICAL AND COGNITIVE SCIENCES

https://doi.org/10.1073/pnas.2022685118
Downloaded at Palestinian Territory, occupied on November 29, 2021
www.manaraa.com

$$P_{IMC}(i) \propto \sum_{M_j \in M} P_{Retrieval}(M_j) * P_{choice}(i|M_j),$$

where $P_{Retrieval}(M_j)$ is the probability of retrieving a particular internal menu M_j, M is the set of all possible internal menus consisting of one or more items from a given category, and $P_{choice}(i|M_j)$ is the choice probability for item i given the internal menu M_j. We obtain $P_{Retrieval}(M_j)$ and $P_{choice}(i|M_j)$ from the models of semantic knowledge retrieval and of valuation described above. Given the lack of an analytical solution for deriving IMC menu probabilities, we used a Monte Carlo approach with 10,000 simulations to approximate $P_{IMC}(i)$. It is worth pointing out that, once the semantic retrieval and the valuation components are trained using the semantic fluency and the EMC choice data, there is no free parameter in the RCV model. Therefore, unlike mixture models below, the RCV model does not need to be fit with IMC choice data.

Single process models. To characterize the respective contributions of semantic knowledge retrieval and valuation in IMC choices, we further examined the prediction performances of single process models, in which only one of these two components is incorporated.

Valuation-only model: This model follows the assumption of standard models of decision-making that all options are available—namely, there is no constraint from semantic knowledge on decision-making even in the IMC choices. In this case, IMC choice probabilities would be governed only by valuation, which can be inferred from the EMC choice data.

Accessibility-only and TTF models: In contrast with the valuation-only model, a memory-only model takes into account semantic knowledge retrieval but not valuation. It shares the same component as IMC for constructing an internal choice set via memory retrieval, but during the second stage, in which an item is chosen from the internal menu, no valuation information is incorporated. Instead, the decision-maker chooses randomly from the options on the internal menu. We also considered a different, more extreme instantiation of the accessibility model, called TTF, in which the decision-maker always chooses the first item that comes to mind.

For the valuation-only and TTF models, the $P_{IMC}(i)$ predictions are analytically defined. For the memory-only model, we employed the same Monte Carlo approach with N = 10,000 independent sample random walks on the network, followed by a random drawing from each menu. Frequencies of choices for different items were then used as an approximation of predicted $P_{IMC}(i)$ from this model.

Mixture models. We also considered an alternative mechanism: that the semantic knowledge structure and the mnemonic properties of an item may compete with value-driven choices during IMC choices and thus explain the differences between IMC and EMC choices. Under this alternative framework, value and mnemonic accessibility are combined in an additive form, which then drives IMC choices:

$$P_{IMC}(i) = (1-\beta) * \frac{e^{U(i)}}{\sum_j e^{U(j)}} + \beta * \frac{A(i)}{\sum_j A(j)},$$

where $A(i)$ denotes the mnemonic accessibility (in the *Valuation + Accessibility mixture* model) or the likelihood that item *i* is the first item recalled (i.e., the "top-of-mind" item; in the *Valuation + TTF mixture* model). Additional procedures necessary to obtain the mixture parameter β and compare their performance with the RCV model are described in *SI Appendix*, *SI Methods*.

fMRI Task. Each participant completed three tasks in a blocked design: an EMC choice task, an IMC choice task, and a semantic fluency task (*SI Appendix*, Fig. S9*B*), consistent with the behavioral study. The fMRI task consisted of 180 categories randomly assigned to one of the three conditions (EMC, IMC, and semantic fluency), and no category was repeated across conditions. Trials of the same condition were grouped into 12 miniblocks in a blocked design. Participants were required to generate explicit verbal responses in the last trial of each miniblock (20% of all trials), unpredictable to the participants beforehand (see full details in *SI Appendix*, *SI Methods*).

fMRI Data Analysis.

Whole-brain univariate analysis. To identify the neural signature of IMC choices and how it relates to the separable semantic retrieval and valuation systems in the human brain, we constructed a general linear model (GLM) in SPM12 for each participant with a regressor for the initial information screen indicating the task condition (5 s boxcar), a regressor for the verbal response phases of all miniblocks (6 s boxcar), a regressor for the semantic fluency questions, a regressor for the EMC choice questions, and a regressor for the IMC choice questions (all boxcars time-locked to the entire durations of the questions). Pairwise contrasts between the three task conditions were specified and entered into group-level analysis (*t* tests with random effects). Clusters defined by a voxel-level threshold of $P < 0.001$ (uncorrected) underwent whole-brain correction for FWE at a significance level of $P < 0.05$, corrected. Additional details regarding the GLM analysis are reported in *SI Appendix*, *SI Methods*.

Functional connectivity analysis. In order to assess changes in functional connectivity of the vmPFC, a key valuation region identified by numerous previous studies as well as the whole-brain univariate analysis for our own data (IMC > fluency, Fig. 5*A*), we first constructed a spherical region-of-interest (ROI) with a 6 mm radius centered on the peak voxel of the vmPFC cluster from our univariate analysis (Montreal Neurological Institute coordinates [6, 38, −18]). This spherical ROI was then used as the seed for a generalized psychophysiological interaction (gPPI) analysis with the following regressors: 1) the physiological regressor of the seed region, namely, the mean blood-oxygen-level-dependent (BOLD) time courses extracted from the vmPFC ROI; 2) the psychological regressors from our univariate GLM analysis (i.e., the same regressors for the information screens, the verbal response phases, the semantic fluency questions, the EMC choice questions, and the IMC choice questions); and 3) PPI terms to represent the interaction between the (deconvolved) physiological regressor and the psychological regressors. We applied FWE cluster-level correction (with a $P < 0.05$ threshold) to activations defined by the initial threshold of $P < 0.005$ within volumes for which we had an a priori hypothesis based on the univariate analysis above (i.e., small-volume correction [SVC]; see full details in *SI Appendix*, *SI Methods*).

Data Availability. Anonymized behavioral data and scripts have been deposited in Open Science Framework (https://osf.io/s5evn/?view_only=6a2c1836aa004f9cbc732e87d300bc67) (62). The fMRI contrast maps have been deposited in NeuroVault (https://neurovault.org/collections/EQPVCIVC) (63).

ACKNOWLEDGMENTS. We thank A. Bakkour and B. Buchsbaum for helpful comments on an earlier draft of the manuscript; E. Evers, A. Westphal, and D. Marciano for insightful conversations; and V. Kulikov, S. Zhang, M. Andrews, and J. Giffin for assistance with data collection. Funding was provided by National Science Foundation Division of Social and Economic Sciences Grant ES1851902 (M.H.), National Institute of Mental Health Grant R01MH112775 (M.H. and A.S.K.), National Eye Institute Grant R01EY024554 (A.S.K.), National Institute on Alcohol Abuse and Alcoholism Grant R01AA026587 (A.S.K.), and National Institute on Aging Grants P30AG012839 (M.H. subaward) and R24AG054355 (Z.Z. subaward).

1. A. Newell, The heuristic of George Polya and its relation to artificial intelligence in *Methods Heuristics*, R. Groner, M. Groner, W. F. Bischoof, Eds. (Lawrence Erlbaum, Hillsdale, NJ, 1983), pp. 195–243.
2. W. R. Reitman, *Cognition and Thought: An Information Processing Approach* (John Wiley & Sons, Inc., 1965).
3. A. Newell, H. A. Simon, *Human Problem Solving* (Prentice-Hall Englewood Cliffs, NJ, 1972).
4. H. A. Simon, The structure of ill structured problems. *Artif. Intell.* **4**, 181–201 (1973).
5. V. Goel, "Comparison of well-structured & ill-structured task environments and problem spaces" in *Proceedings of the Fourteenth Annual Conference of the Cognitive Science Society Hillsdale* (Lawrence Erlbaum, Hillsdale, NJ, 1992), pp. 844–849.
6. L. R. Keller, J. L. Ho, Decision problem structuring: Generating options. *IEEE Trans. Syst. Man Cybern.* **18**, 715–728 (1988).
7. P. A. Samuelson, *Foundations of Economic Analysis* (Harvard University Press, 1947).
8. D. Kahneman, A perspective on judgment and choice: Mapping bounded rationality. *Am. Psychol.* **58**, 697–720 (2003).
9. S. Mullainathan, A memory-based model of bounded rationality. *Q. J. Econ.* **117**, 735–774 (2002).
10. F. Del Missier, M. Visentini, T. Mäntylä, Option generation in decision making: Ideation beyond memory retrieval. *Front. Psychol.* **5**, 1584 (2015).
11. S. Kaiser *et al.*, The cognitive and neural basis of option generation and subsequent choice. *Cogn. Affect. Behav. Neurosci.* **13**, 814–829 (2013).
12. E. U. Weber, W. M. Goldstein, S. Barlas, And let us not forget memory: The role of memory processes and techniques in the study of judgment and choice. *Psychol. Learn. Motiv.* **32**, 33–81 (1995).
13. J. R. Bettman, M. F. Luce, J. W. Payne, Constructive consumer choice processes. *J. Consum. Res.* **25**, 187–217 (1998).

Downloaded at Palestinian Territory, occupied on November 29, 2021

www.manaraa.com

14. P. Nedungadi, Recall and consumer consideration sets: Influencing choice without altering brand evaluations. *J. Consum. Res.* **17**, 263 (1990).
15. A. Kalis, S. Kaiser, A. Mojzisch, Why we should talk about option generation in decision-making research. *Front. Psychol.* **4**, 555 (2013).
16. A. D. Shocker, M. Ben-Akiva, B. Boccara, P. Nedungadi, Consideration set influences on consumer decision-making and choice: Issues, models, and suggestions. *Mark. Lett.* **2**, 181–197 (1991).
17. J. R. Hauser, B. Wernerfelt, An evaluation cost model of consideration sets. *J. Consum. Res.* **16**, 393–408 (1990).
18. J. H. Roberts, J. M. Lattin, Development and testing of a model of consideration set composition. *J. Mark. Res.* **28**, 429–440 (1991).
19. J. H. Roberts, J. M. Lattin, Consideration: Review of research and prospects for future insights. *J. Mark. Res.* **34**, 406–410 (1997).
20. J. G. Johnson, M. Raab, Take the first: Option-generation and resulting choices. *Organ. Behav. Hum. Decis. Process.* **91**, 215–229 (2003).
21. G. Klein, S. Wolf, L. Militello, C. Zsambok, Characteristics of skilled option generation in chess. *Organ. Behav. Hum. Decis. Process.* **62**, 63–69 (1995).
22. A. Tversky, D. Kahneman, Availability: A heuristic for judging frequency and probability. *Cognit. Psychol.* **5**, 207–232 (1973).
23. R. P. Thomas, M. R. Dougherty, A. M. Sprenger, J. I. Harbison, Diagnostic hypothesis generation and human judgment. *Psychol. Rev.* **115**, 155–185 (2008).
24. J. W. Alba, J. W. Hutchinson, J. Lynch, "Memory and decision making" in *Handbook of Consumer Behaviour*, T. S. Robertson, H. H. Kassarjian, Eds. (Prentice Hall, Englewood Cliffs, NJ, 1991), pp. 1–51.
25. J. G. Lynch Jr, T. K. Srull, Memory and attentional factors in consumer choice: Concepts and research methods. *J. Consum. Res.* **9**, 18 (1982).
26. D. Marr, *Vision: A Computational Investigation into the Human Representation and Processing Of Visual Information* (Henry Holt and Co Inc, 1982).
27. Y. Niv, A. Langdon, Reinforcement learning with Marr. *Curr. Opin. Behav. Sci.* **11**, 67–73 (2016).
28. E. Tulving, "Episodic and sematic memory" in *Organisation Of Memory*, E. Tulving, W. Donaldson, Eds. (Academic Press, 1972), pp. 381–403.
29. M. A. L. Ralph, E. Jefferies, K. Patterson, T. T. Rogers, The neural and computational bases of semantic cognition. *Nat. Rev. Neurosci.* **18**, 42–55 (2017).
30. J. R. Bettman, Memory factors in consumer choice: A review. *J. Mark.* **43**, 37 (1979).
31. J. Austerweil, J. Abbott, T. Griffiths, Human memory search as a random walk in a semantic network. *Adv. Neural Inf. Process. Syst.* **25**, 3050–3058 (2012).
32. S. Bhatia, Semantic processes in preferential decision making. *J. Exp. Psychol. Learn. Mem. Cogn.* **45**, 627–640 (2019).
33. O. Bartra, J. T. McGuire, J. W. Kable, The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. *Neuroimage* **76**, 412–427 (2013).
34. J. C. Zemla, J. L. Austerweil, Estimating semantic networks of groups and individuals from fluency data. *Comput. Brain Behav.* **1**, 36–58 (2018).
35. D. L. McFadden, "Conditional logit analysis of qualitative choice behavior" in *Frontiers in Econometrics*, P. Zarembka, Ed. (Academic Press, 1974), pp. 105–142.
36. D. H. Jonassen, Instructional design models for well-structured and III-structured problem-solving learning outcomes. *Educ. Technol. Res. Dev.* **45**, 65–94 (1997).
37. N. Terui, M. Ban, G. M. Allenby, The effect of media advertising on brand consideration and choice. *Mark. Sci.* **30**, 74–91 (2011).
38. P. Nedungadi, A. Chattopadhyay, A. V. Muthukrishnan, Category structure, brand recall, and choice. *Int. J. Res. Mark.* **18**, 191–202 (2001).
39. A. Mitra, J. G. Lynch Jr, Toward a reconciliation of market power and information theories of advertising effects on price elasticity. *J. Consum. Res.* **21**, 644 (1995).
40. A. Morris, J. Phillips, K. Huang, F. Cushman, Generating options and choosing between them rely on distinct forms of value representation. https://psyarxiv.com/2ayw3/. Accessed 5 March 2021.
41. P. Ward, J. Suss, D. W. Eccles, A. M. Williams, K. R. Harris, Skill-based differences in option generation in a complex task: A verbal protocol analysis. *Cogn. Process.* **12**, 289–300 (2011).
42. J. W. Hutchinson, K. Raman, M. K. Mantrala, Finding choice alternatives in memory: Probability models of brand name recall. *J. Mark. Res.* **31**, 441 (1994).
43. G. E. Wimmer, D. Shohamy, Preference by association: how memory mechanisms in the hippocampus bias decisions. *Science* **338**, 270–273 (2012).
44. P. Bordalo, N. Gennaioli, A. Shleifer, Memory, attention, and choice. *Q. J. Econ.* **135**, 1399–1442 (2020).
45. A. Dick, D. Chakravarti, G. Biehal, Memory-based inferences during consumer choice. *J. Consum. Res.* **17**, 82–93 (1990).
46. S. Gluth, T. Sommer, J. Rieskamp, C. Büchel, Effective connectivity between Hippocampus and ventromedial prefrontal cortex controls preferential choices from memory. *Neuron* **86**, 1078–1090 (2015).
47. E. Honka, A. Hortaçsu, M. A. Vitorino, Advertising, consumer awareness, and choice: Evidence from the U.S. Banking industry. *RAND J. Econ.* **48**, 611–646 (2017).
48. F. Lieder, T. L. Griffiths, M. Hsu, Overrepresentation of extreme events in decision making reflects rational use of cognitive resources. *Psychol. Rev.* **125**, 1–32 (2018).
49. J. Phillips, A. Morris, F. Cushman, How we know what not to think. *Trends Cogn. Sci.* **23**, 1026–1040 (2019).
50. E. J. Johnson, G. Häubl, A. Keinan, Aspects of endowment: A query theory of value construction. *J. Exp. Psychol. Learn. Mem. Cogn.* **33**, 461–474 (2007).
51. N. Unsworth, G. A. Brewer, G. J. Spillers, Working memory capacity and retrieval from long-term memory: The role of controlled search. *Mem. Cogn.* **41**, 242–254 (2013).
52. K. L. Keller, Conceptualizing, measuring, and managing customer-based brand equity. *J. Mark.* **57**, 1–22 (1993).
53. J. W. Alba, A. Chattopadhyay, Effects of context and part-category cues on recall of competing brands. *J. Mark. Res.* **22**, 340 (1985).
54. A. Aka, S. Bhatia, What I like is what I remember: Memory modulation and preferential choice. https://psyarxiv.com/3uyfz/ (2020).
55. A. Bejanin *et al.*, Tau pathology and neurodegeneration contribute to cognitive impairment in Alzheimer's disease. *Brain* **140**, 3286–3300 (2017).
56. R. D. Nebes, Semantic memory in Alzheimer's disease. *Psychol. Bull.* **106**, 377–394 (1989).
57. R. H. Thaler, C. R. Sunstein, *Nudge: Improving Decisions About Health Wealth, and Happiness* (Penguin, 2009).
58. A. Shenhav *et al.*, Toward a rational and mechanistic account of mental effort. *Annu. Rev. Neurosci.* **40**, 99–124 (2017).
59. E. Rosch, C. B. Mervis, W. D. Gray, D. M. Johnson, P. Boyes-Braem, Basic objects in natural categories. *Cognit. Psychol.* **8**, 382–439 (1976).
60. O. Toubia, O. Netzer, Idea generation, creativity, and prototypicality. *Mark. Sci.* **36**, 1–20 (2017).
61. S. L. Peters, L. K. Fellows, S. Sheldon, The ventromedial frontal lobe contributes to forming effective solutions to real-world problems. *J. Cogn. Neurosci.* **29**, 991–1001 (2017).
62. Z. Zhang *et al.*, RCV_study. Open Science Framework. https://osf.io/s5evn/?view_only=6a2c1836aa004f9cbc732e87d300bc67. Deposited 14 September 2020.
63. Z. Zhang *et al.*, fMRI contrast maps for "Retrieval-constrained Valuation: Toward prediction of open-ended decisions" by Zhang et al. NeuroVault. https://neurovault.org/collections/EQPVCIVC/. Deposited 14 September 2020.

Downloaded at Palestinian Territory, occupied on November 29, 2021

www.manaraa.com