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BRIEF REPORT

Mental representations distinguish value-based decisions from perceptual decisions

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Abstract

In our daily lives, we make a wide variety of decisions. One major distinction that has been made is between perceptual decisions and value-based (economic) decisions. We argue that this distinction is ill-defined, because these decisions vary on multiple dimensions. We present an alternative way to categorize decisions, based on two dimensions: subjective versus objective criteria, and evaluation of a stimulus versus a representation. We experimentally study the decision-making process (with eye-tracking) in each of the four resulting categories, using the same stimulus set of food images. Using a combination of individual-level and group-level modeling, we find surprisingly consistent patterns of behavior across the categories. However, we find stronger similarities between the subjective and objective categories, and stronger differences between the stimulus and representation categories.

In our everyday lives, we are continually asked to make comparisons. These sorts of comparisons can differ drastically from one example to the next. Which lunch option do you want? Which outfit looks better? Which route home is shortest? Which racehorse is fastest? One goal in decision science is to characterize the processes used to make such comparisons. To do so, we must first create a classification system, identifying clusters of comparisons that seem to be resolved in the same way. Then, we can study each cluster and further refine the boundaries between comparisons, as well as characterize the underlying processes and mechanisms.

We contend that establishing boundaries between clusters of comparisons is central to understanding generalizability. When we discover a new phenomenon in one setting, will it generalize to others? For example, does a phenomenon in decisions about which food to eat extend to judgments about the attractiveness of the package or the size of the food? To answer that question, we need to understand the features that are shared (and not shared) between domains.

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One distinction that researchers have drawn is between value-based (i.e., preference-based) and perceptual decisions (Hanks & Summerfield, 2017; Padoa-Schioppa & Schoenbaum 2015; Shadlen & Shohamy 2016). For example, value-based decisions include choosing which food you want to eat or which gamble you want to take, while perceptual decisions include determining which direction a group of flickering dots is moving (Roitman & Shadlen, 2002) or which line segment is closest to horizontal (as in Tavares et al., 2017). In the past, these two types of decisions have been studied almost entirely separately. However, recent work has investigated the overlap (and distinction) between these decisions (Bakkour et al. 2019; Pisauro et al., 2017; Polanía et al., 2014).

In terms of overlap, decisions in both domains have demonstrated robust relations between difficulty, accuracy, and response time (RT). Choosing the more horizontal line segment is more difficult, less accurate, and slower for line segments with more similar tilts (Tavares et al., 2017). Similarly, choosing which food to eat is more difficult, less accurate (i.e., less internally consistent), and slower for more similar foods (Folke et al., 2016; Gluth et al., 2020; Krajbich et al., 2010; Mormann et al., 2010; Polanía et al., 2014). Additionally, decisions in both domains reveal gaze–choice correlations; alternatives that receive more attention are more likely to be chosen. This gaze–choice relationship is consistent across value-based and perceptual decisions (value-based: Fiedler et al., 2013; Folke et al., 2016; Ghaffari & Fiedler, 2018; Gwinn et al., 2019; Konovalov & Krajbich, 2016; Kovach et al., 2014; Lim et al., 2011; Mormann et al., 2012; Pärnamets et al., 2015; Stewart et al., 2015; Towal et al., 2013; Vaidya & Fellows, 2015; perceptual: Newell & Le Pelley, 2018; Tavares et al., 2017). Sequential sampling models (SSMs) such as the attentional drift diffusion model (aDDM) can simultaneously account for these choice, RT, accuracy, and attention patterns (Amasino et al., 2019; Busemeyer & Townsend, 1993; Cavanagh et al., 2014; Fisher, 2017; Krajbich et al., 2010; Krajbich et al., 2012; Smith & Krajbich, 2019; Stewart et al., 2006).

In parallel, research in neuroscience has illustrated some differences between value-based and perceptual decisions. In one paper, subjects viewed pairs of food images and were asked to indicate which food they preferred, or which food took up more pixels on the screen (Polanía et al., 2014). Electroencephalography (EEG) data revealed overlapping parietal cortex activity between the two conditions, but distinct frontal-cortex activity for the value-based decisions. These results are consistent with perception being typically associated with parietal cortex (Bogacz et al., 2009; Gold & Shadlen, 2007; Hanks & Summerfield, 2017; Mulder et al., 2012; O'Connell et al., 2018; but see Heekeren et al., 2004), and value being typically associated with frontal cortex (Gluth et al., 2015; Lim et al., 2011; Pisauro et al., 2017; Plassmann et al., 2007; Rodriguez et al., 2014; Vaidya & Fellows, 2015).

Much prior literature focuses on the differences between perceptual and value-based domains in terms of assessments of accuracy. Perceptual decisions are characterized as being allocentric (having an objectively correct answer), while value-based decisions are characterized as being egocentric (having a subjectively correct answer). However, there is another important divide typical of these tasks: the source of information required to make the decision. Perceptual decisions generally rely on evaluations of stimuli, while value-based decisions rely on memory-based representations. This second division follows from research that has established distinct neural mechanisms for memory versus perception (Eichenbaum & Cohen, 2014; Squire & Zola-Morgan, 1991; Suzuki & Baxter, 2009).

Prior literature has largely conflated these divisions, resulting in inconsistent distinctions between these two categories. For instance, in their influential article, Shadlen and Shohamy (2016) describe the value-based choice process as follows: "samples are derived by querying memory for past experiences and by leveraging memory for the past to engage in prospective reasoning processes to provide evidence to inform the decision" (p. 927). On the next page, the authors describe the distinction differently: "Unlike perceptual decisions, value-based decisions often do not pose a choice between an objectively correct versus incorrect option. . . . Instead, the decision rests on subjective preferences and predictions about the subjective value of each option" (p. 928). In essence, subjective preference is equated with decisions from memory.[1] While these often do go together, there are certainly exceptions. For example, determining whether it was hotter last July or August is a memory-based decision with an objective answer, while choosing which painting to purchase from an art gallery is a stimulus-based decision with a subjective criterion.

The goal of the present paper is to highlight that when talking about the distinctions between perceptual and value-based decisions, one must be more specific about whether those distinctions are due to the preference (subjective) versus objective dimension, or the stimulus versus memory/representation dimension. To do so, we present an experimental study where we independently manipulate decisions along these two dimensions, using the same stimulus set of food images (see Fig. 1). We then study the decision-making process in each of the four resulting categories, to clarify the distinctions along/between the dimensions. In addition to clarifying the distinction(s) between perceptual and value-based choice, we also identify two decision types that would not have been clearly classified under the existing system.

Method

Participants

Forty-two university students participated in this study. The sample size was determined both by past research (Krajbich et al., 2010; Smith & Krajbich, 2018) and via power analysis. Using data from Smith and Krajbich (2018), we determined that to have 80% power to detect significant cross-category correlations in the influence of attention on choice with 100 trials per category, we would need at least 40 participants. We scheduled several extra sessions in case participants did not show up or failed to complete the experiment. Once we collected 40 participants, we stopped scheduling new sessions, but collected data from the remaining scheduled participants.

Materials

On-screen stimuli (100 food images generated in part by the Rangel lab at Caltech and in part by the Krajbich lab at The Ohio State University, available on OSF) were presented using the MATLAB (Version 8.3; The MathWorks, Natick, MA) Psychophysics toolbox (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997). Eye-tracking data were collected using an EyeLink 1000 Plus at 1000 Hz. Participants gave ratings using a standard mouse and made decisions using a standard

[1] These decisions from memory are similar to what prior consumer behavior research has referred to as memory-based choices (Lynch et al., 1988; Lynch & Srull, 1982). However, we refer to them as representation-based choices in this paper to distinguish our choices from those that are purely recall/memory-based (Gluth et al., 2015).

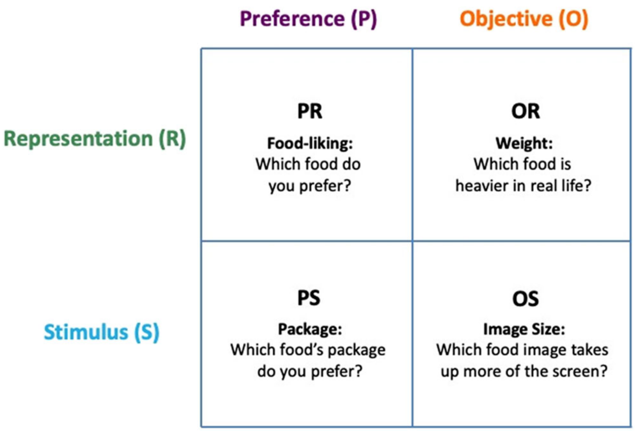

Fig. 1 Experimental setup. Past research has made a distinction between value-based decisions and perceptual decisions. However, these two types of decisions typically vary along multiple dimensions: whether the decision is based on a mental representation of a stimulus or on the stimulus itself, and whether the decision is based on subjective preference or objective criteria

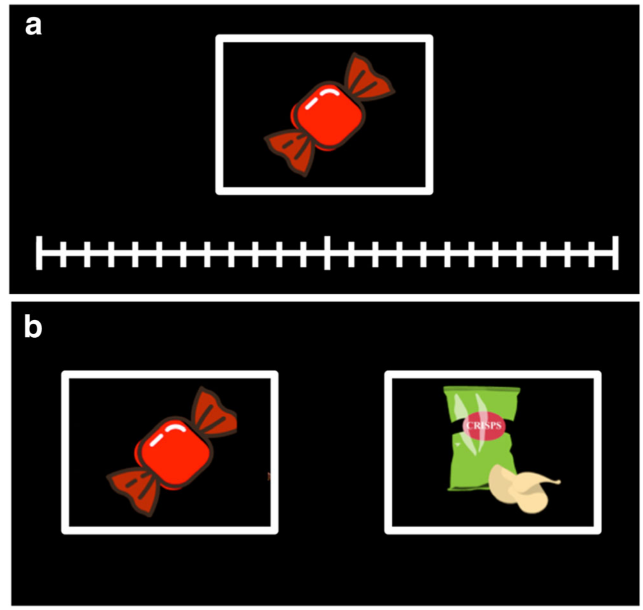

Fig. 2 Experimental setup. **a** Subjects first rated each of 100 food items on each of four dimensions (PR, OS, OR, and PS), blocked by category and presented in a random order. **b** Then, subjects made 100 binary choices in each category (again, blocked by category). The category was cued at the beginning of each block

keyboard. Specifically, they used the *F* key to choose the option on the left side of the screen and the *J* key to choose the option on the right side of the screen.

Task

In the first part of the experiment, participants gave four incentivized ratings per item, for each of 100 food images. The rating stage was blocked by category, with order randomly determined at the participant level. Participants rated each food image on food-liking (how much they wanted to eat the food; preference-representation, PR), image size (how much space the food took up in the picture; objective-stimulus, OS), weight (how much the food weighed, relative to the other snack foods in the stimulus set; objective-representation, OR), and package (how much they liked the image; preference-stimulus, PS). Participants used the mouse to click on a rating scale (1,740 pixels long; see Fig. 2a). They were given instructions on what the ends of the scale meant (e.g., in the food-liking category, they were told to use the left side of the scale for items that they would not like to eat and the right side of the scale for items that they would like to eat). In the PR and PS categories, ratings above/below the midpoint indicated positive/negative subjective values (i.e., liking/disliking the food or image). In the OS and OR categories, ratings above/below the midpoint indicated more/less than half of the box filled or higher/lower than average weight, respectively.

After supplying subjective ratings for all four dimensions, participants were calibrated to the eye tracker (using 9-point calibration). Their eye movements were then tracked for the remainder of the experiment.

In the second part of the experiment, participants made 100 binary choices in each of the four category conditions (see Fig. 2b). As with the rating task, the choice task was also blocked by category, with the order randomly determined at the participant level and independently from the rating task order. Every participant made choices about which of two foods they preferred to eat (PR), which of two food images they preferred (PS), which of two foods took up a greater proportion of the screen (OS), and which of two foods weighed more (OR).

Item pairs were generated randomly, subject to a few constraints. Before generating the trials, we removed options with negative subjective values in either preference category. In generating the trials, we limited the number of times that a food item could be seen in a condition to seven. Additionally, we limited the difference in ratings between the options to ensure that the choices were nontrivial. However, we used different rating-difference limits for each of the conditions, based on pilot testing (n = 6). Specifically, we identified rating-difference cutoffs to achieve 50%–75% rating-choice consistency and the resulting limits on rating difference were 250, 750, 400, and 400 pixels (corresponding to 14%, 43%, 23%, and 23% of the 1,740-pixel rating spectrum) in the PR, OS, PS, and OR categories, respectively.[2]

All ratings and choices were incentivized, as participants received one outcome from each category at the end of the study. For each of the four categories, their payment came from either their ratings or their choices. Specifically, for each category we selected one choice trial. With 50% probability,

[2] We acknowledge that this is an imperfect method for equating difficulty; however, the incentive-compatibility and consistency of choice behavior across categories assuages concerns that one task was inherently more difficult and/or more motivating.

participants were compensated based on which option they had chosen in that trial; in the other half of the cases, we instead used their ratings to determine their choice, compensating them based on the higher rated item. For the PR category, participants received the preferred food item. For the OS and OR categories, participants received payment as a linear function of the size of the image or weight of the food, respectively. For the PS category, participants were required to look at the preferred image for 30 seconds. This setup differs from most previous work in that it incentivizes both ratings and choices; because their payment could be determined by their choice or by their ratings, participants were incentivized to treat every trial (whether it was a rating or a choice) as if it were the only one that mattered.

Data preprocessing

We use a variety of measured variables in this study. In the behavioral/attention results, we use choices, ratings, RTs, direction of the final dwell (at the trial level), and total dwell time on each option (at the trial level).

Two regions of interest (ROIs) were determined a priori: each option was contained in a box (which was visible to participants) and we used this box as the outline for each of the ROIs. Whenever a participant's gaze entered an ROI, this constituted the start of a dwell. This dwell ended when the participant's gaze left the ROI (provided that they entered another ROI before returning to the original ROI). If a participant's gaze left an ROI temporarily (e.g., due to a blink, resulting in a missing gaze-location sample), we continued the dwell until they left the ROI for the final time (i.e., looked at another ROI next). We did not exclude any participants/data due to poor calibration.

Results

Behavioral and eye-tracking results

As expected, participants generally chose in line with their ratings (see Fig. 3a) and, in the objective categories, with objective values (Fig. 3b). Participants were, on average, more accurate in easier decisions. The relationship between absolute value difference and choice accuracy was significantly positive in all categories (mixed-effects logistic regression standardized coefficients on [1] rating difference: PR: β = 0.37, SE = 0.05; OS: β = 0.79, SE = 0.08; PS: β = 0.35, SE = 0.04; OR: β = 0.49, SE = 0.06, all ps < .0001; [2] objective size/weight difference; OS: β = 1.39, SE = 0.17, p < .0001; OR: β = 0.17, SE = 0.06, p = .003).

As in previous research (e.g., Konovalov & Krajbich, 2019), participants generally took longer on more difficult decisions (see Fig. 3c). Mixed-effects regressions indicate an inverse relationship between absolute rating difference and log-transformed RT (standardized coefficients: PR: β = −0.009, SE = 0.01, p = .24; OS: β = −0.07, SE = 0.01, p < .0001; PS: β = –0.010, SE = 0.01, p = .18; OR: β = −0.044, SE = 0.01, p = .0004).[3]

In addition to the relationship between absolute rating difference and RT, there is also evidence of an inverse relationship between summed rating (i.e., left rating + right rating) and RT in the subjective but not objective decisions (see Fig. 3d; mixed-effects standardized regression coefficients, controlling for absolute rating difference: PR: β = −0.037, SE = 0.01, p < .001; OS: β = 0.004, SE = 0.01, p = .72; PS: β = –0.030, SE = 0.009, p = .004; OR: β = −0.010, SE = 0.009, p =.29; see Fig. 3d). This finding is in line with past research as well (Cavanagh et al., 2014; Frömer et al., 2019; Hunt et al., 2012; Pirrone et al., 2018; Smith & Krajbich, 2019).

Participants also tended to choose the option that they looked at more (see Fig. 3e). This gaze–choice relationship holds, even after accounting for the effects of rating/size/weight difference (mixed-effects logistic regression coefficients: PR: β = 0.36, SE = 0.08, p < .0001; OS, subjective: β = 0.43, SE = 0.10, p < .0001; OS, objective: β = 0.40, SE = 0.10, p < .0001; PS: β = 0.85, SE = 0.20, p < .0001; OR, subjective: β = 0.26, SE = 0.08, p = .0005; OR, objective: β = 0.25, SE = 0.08, p = .0008).

Moreover, participants also tended to choose the option that they looked at last (see Fig. 3f). When there was no difference in rating/size/weight between the two options, participants chose the last option they looked at on 60%–70% of the trials. More formally, we regressed choice (of the left option) on the rating/size/weight difference, absolute rating/size/weight difference, final dwell location, and the interaction between absolute rating/size/weight difference and final dwell location. The simple effect of final dwell location represents the difference in choice proportions for the left option between final dwell locations (in trials with zero rating/size/weight difference), and this coefficient is significantly positive in all categories (PR: β = 1.32, SE = 0.16; OS, subjective: β = 1.34, SE = 0.15; OS, objective: β = 1.13, SE = 0.20; PS: β = 1.79, SE = 0.18; OR, subjective: β = 1.21, SE = 0.15; OR, objective: β = 1.27, SE = 0.15; all ps < .0001). For complete regression results, see the supplements.

Overall, these behavioral and eye-tracking results do not systematically support one hypothesis over another. If anything, they support the notion that all four categories were generally quite similar with respect to the measures we collected. Participants' choices (and to some extent, RTs) were similarly affected by rating/

[3] The surprising nonsignificance in the PR and PS categories seems to be driven primarily by one subject who had a strong positive relationship between absolute rating difference and log(RT). When we remove this subject from this analysis, we observe the following standardized coefficients: PR: β = −0.013, SE = 0.01, p = .06; PS: β = −0.013, SE = 0.01, p = .09.

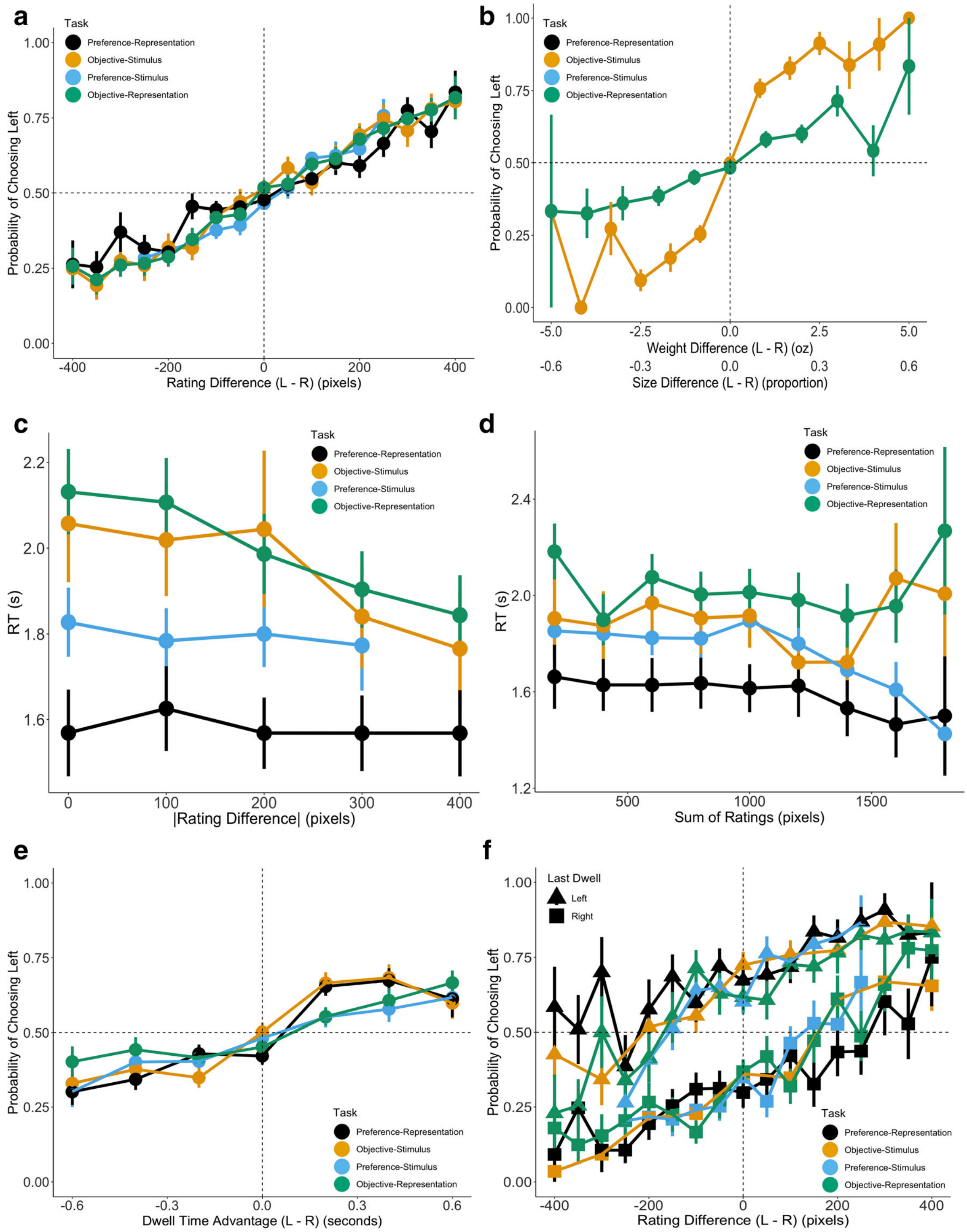

Fig. 3 Behavioral and eye tracking results. **a** Choice proportion for the left option as a function of the relative rating advantage for the left option. **b** Choice proportion for the left option as a function of the relative objective (image size/weight) advantage for the left item. **c** Relationship between absolute rating difference and response time. The PR and PS categories exclude one subject who had a strong positive correlation between RT and absolute rating difference. **d** Relationship between RT and summed ratings. **e** Choice proportion for the left option as a function of relative dwell-time advantage for the left option (i.e., dwell time left minus dwell time right) in seconds. **f** Choice proportion for the left option as a function of the relative rating advantage for the left option and the position of the final dwell (i.e., left vs. right). Bars represent *SEM* across participants

size/weight and attention across the four conditions. The only exception was the difference in the effect of summed rating between the subjective and objective categories.

Consistencies across categories

Clearly, there are many consistencies across the categories, particularly in terms of how attention influences the decision process. We know that people who are highly influenced by their attention in one value-based domain tend to be highly influenced by their attention in another (Smith & Krajbich, 2018). To investigate the consistency of the attention–choice link in these categories, we estimated the following logistic regression for each subject in each category:

$$P(ChooseLeft) = \beta_0 + \beta_1 RatingDifference + \beta_2 TimeAdvantageLeft. \quad (1)$$

The β_2 coefficient represents the extent to which an extra second of gaze to one option influences a participant's choice for that option. We ran pairwise category correlations for these β_2 coefficients between conditions. The strongest correlation was between the PS and OS categories. There was also a correlation between the PS and PR categories (see Table 1).

For robustness, we repeated this analysis with an approximation of the attentional discounting parameter (θ) in the attentional drift diffusion model (aDDM; Krajbich et al., 2010). With this model, we can accurately estimate the degree to which subjects discount (i.e., ignore) the nonlooked at option during the choice process (Smith et al., 2019).

Here, we find the strongest correlations along the stimulus/representation dimension. That is, the strongest (positive) correlations are between the PR and OR categories and the PS and OS categories. We also find negative correlations between the two objective categories (OR and OS) and between the OR and PS categories (which differ along both dimensions; see Table 2).

Together, these analyses provide evidence for stronger distinctions along the stimulus/representation dimension. That is, in terms of the link between attention and choice, the two stimulus-based categories (PS/OS) seem to be the most similar and the two representation-based categories (PR/OR) also seem to be quite similar.

Table 1 Dwell-time advantage coefficient correlations

	OS	PR	OR
PR	0.23		
OR	<u>–0.04</u>	**0.21**	
PS	**0.45****	<u>0.33*</u>	0.15

Note. Bolded numbers indicate comparisons within stimulus or representation categories, while underlined numbers indicate comparisons within objective or subjective categories, and plain text numbers indicate diagonal comparisons. *$p < .05$; **$p < .01$

Table 2 Attentional discounting parameter correlations

	OS	PR	OR
PR	0.13		
OR	<u>–0.28’</u>	**0.29’**	
PS	**0.28’**	<u>0.11</u>	–0.26’

Note. Bolded numbers indicate comparisons within stimulus or representation categories, while underlined numbers indicate comparisons within objective or subjective categories, and plain text numbers indicate diagonal comparisons. ’$p < .10$

Dimension-level regressions

To investigate which dimension (preference/objective; stimulus/representation) is more predictive of differences in the data, we reran each of the primary mixed-effects regressions (described in Behavioral and eye-tracking analyses, above) twice, with two key differences. First, we ran the regressions on pooled data from all four categories. Second, for each pair of models, we included a dummy-coded variable for the dimension of interest (preference/objective or stimulus/representation). This dimension indicator variable was included as a simple effect and as an interaction term with all of the coefficients. We then compared the two models' goodness-of-fit metrics. If one dimension is better able to distinguish between categories (for a given behavioral/eye-tracking result), then the model that includes that dummy-coded variable should fit better.

For four out of five regressions, we find that the model that includes the stimulus/representation dummy variable fits significantly better (see Table 3), while the preference/objective model fits better for only one regression. This suggests that for most choice and eye-tracking measures, the stimulus/representation distinction is stronger than the preference/objective distinction.

Discussion

In past literature, a distinction has been made between value-based decisions and perceptual decisions. In this paper, we have identified two dimensions along which these decisions

Table 3 Behavioral and eye-tracking models with dimension dummy variables

Model	Dummy Variable Included	AIC	BIC	LogLik	Deviance
Correct ~ |Rating Difference|	Pref/Obj	20670	20755	-10324	20648
	Stim/Rep	**20664**	**20748**	**-10321**	**20642**
RT ~ |Rating Difference|	Pref/Obj	19692	19784	-9833.9	19668
	Stim/Rep	**19320**	**19412**	**-9648.1**	**19296**
RT ~ Summed Value	Pref/Obj	19923	20100	-9938.4	19877
	Stim/Rep	**19679**	**19856**	**-9816.6**	**19633**
Choice ~ Dwell Time	Pref/Obj	11195	11352	-5575.7	11151
	Stim/Rep	**11183**	**11339**	**-5569.3**	**11139**
Choice ~ Final Dwell	**Pref/Obj**	**9675.1**	**10140**	**-4771.6**	**9543.1**
	Stim/Rep	9680.1	10144	-4774.1	9548.1

Note. Bolded numbers indicate the model with better fit.

differ: whether the choices are based on a mental representation generated by a stimulus or based on the stimulus itself, and whether the decision criteria are objective or subjective. We independently manipulated these two dimensions and compared the choice process across the four resulting categories.

First and foremost, we find remarkable levels of similarity across the different categories with respect to our measures. The connection between rating difference and choice consistency (i.e., accuracy) is very consistent. The relationship between gaze and choice is also remarkably stable (on average) across the different categories. In the supplement, we consider an alternative analysis using linear classifiers that demonstrates generally similar classification accuracies across categories. These results provide additional evidence for the consistency of the decision process across different domains (Smith & Krajbich, 2018).

However, there are also some differences between these categories. Researchers have been investigating the processes that underlie value-based and perceptual decisions; many have approached this topic through the lens of sequential sampling models (Bogacz et al., 2009; Gluth et al., 2015; Gold & Shadlen, 2007; Hanks & Summerfield, 2017; Heekeren et al., 2004; Lim et al., 2011; Mulder et al., 2012; O'Connell et al., 2018; Pisauro et al., 2017; Plassmann et al., 2007; Ratcliff, Philiastides, & Sajda, 2009; Rodriguez et al., 2014; Vaidya & Fellows, 2015). A commonly debated topic is the distinction between value-based decisions and perceptual decisions: are the choice processes the same? Here, we have argued that this question is ill-posed, since value-based and perceptual choices differ on more than one dimension. Instead, we should be investigating whether the choice process differs between subjective (preference-based) and objective decisions and/or whether the choice process differs between stimulus-based and representation-based decisions. Our present results (including our alternate linear classification analysis in the supplements) suggest that the latter distinction is likely to yield more differences in behavior. However, further research would be helpful to fully map out the classification of decisions.

Addressing the similarity of the decision process among seemingly unrelated choices is important because it has implications for researchers across the range of decision-making research. Many researchers doubt that subjective (preference-based) and objective decisions have similar underlying processes, but the evidence here suggests otherwise. We find strong consistencies in behavior and attentional influence across the objective/subjective division. Moreover, behavior in both types of decisions can be effectively captured and predicted by sequential sampling models (see Ratcliff, 2002, and Philiastides & Ratcliff, 2013, for a straightforward example). There is little conclusive evidence for differences between them, since comparisons of subjective and objective decision processes (e.g., Pisauro et al., 2017; Polanía et al., 2014) have been confounded with the representation/stimulus divide. We do observe one potential difference between these two processes—namely, the effect of overall (summed) value. The subjective decisions are faster for higher overall rating, consistent with prior work (Frömer et al., 2019; Hunt et al., 2012; Pirrone et al., 2018; Smith & Krajbich, 2019), while the objective decisions display no such relation.

It is important to understand where to draw the lines between categories as we search for common principles underlying decision-making. When we discover a new phenomenon in one setting, we often want to know which other settings it will generalize to. Categorizing decisions should help with this. For example, our study suggests that a phenomenon observed in eating decisions is most likely to generalize to weight decisions and less likely to generalize to decisions about image size or package attractiveness.

These distinctions also need to be considered when importing ideas from perception into value-based decision-making (or vice versa). For example, there is a debate about whether divisive normalization, a basic principle in perceptual judgments, extends to value-based decisions (Gluth et al., 2020; Louie et al., 2013; Webb et al., 2020). As we learn more about the types of decisions that do (and do not) share certain mechanisms, we should gain insight into these issues. Additionally, as we increase our knowledge about the neural mechanisms associated with one (or more) type of decisions, we should be able to use that knowledge to predict new phenomena that would occur in one domain but not another (e.g., if parietal neurons exhibit divisive normalization but frontal neurons do not, then we might not expect to observe normalization in domains relying on frontal cortex).

Further research might seek to address some of the open questions. For instance, does the stimulus set matter? Would these results extend beyond food images? Another open question is whether individual differences might add an additional layer to these findings. Are the processes that underlie these decision categories more similar/different for some people than they are for others? Additionally, might there be psychophysical underpinnings to these individual differences? For instance, perhaps people with congenital aphantasia (i.e., people unable to picture things in their "mind's eye") would have a less pronounced separation of representation versus stimulus categories (Zeman et al., 2015).

Ultimately, this research provides a new framework with which researchers can approach intercategory decision comparisons. Rather than asking questions about the differences between value-based and perceptual choices, we hope that future research will take into account the multidimensional aspects of decision making. In this paper, we have set the stage for future research in judgment and decision making with the intent to further our understanding of all types of decision processes: value-based (subjective and representation-based), perceptual (objective and stimulus-based), and everything in between.

Open practices statement The data set collected/analyzed during the current study is available in the Open Science Framework repository (https://osf.io/59kha/?view_only=9849ca67ae7949fa90408ec1ae5acf76). This study was not formally preregistered.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.3758/s13423-021-01911-2.

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S. M. Smith and I. Krajbich designed the experiment and analyses and co-wrote the article. S. M. Smith programmed and conducted the experiment and performed the data analysis. I. Krajbich supervised the project.

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