Cognitive Psychology 147 (2023) 101614

Contents lists available at ScienceDirect

Cognitive Psychology

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

Risky decisions are influenced by individual attributes as a function of risk preference

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A R T I C L E I N F O

Keywords:
Decision-making
Multi-attribute choice
Risky choice
Risk aversion
Drift-diffusion model

A B S T R A C T

It has long been assumed in economic theory that multi-attribute decisions involving several attributes or dimensions – such as probabilities and amounts of money to be earned during risky choices – are resolved by first combining the attributes of each option to form an overall expected value and then comparing the expected values of the alternative options, using a unique evidence accumulation process. A plausible alternative would be performing independent comparisons between the individual attributes and then integrating the results of the comparisons afterwards. Here, we devise a novel method to disambiguate between these types of models, by orthogonally manipulating the expected value of choice options and the relative salience of their attributes. Our results, based on behavioral measures and drift-diffusion models, provide evidence in favor of the framework where information about individual attributes independently impacts deliberation. This suggests that risky decisions are resolved by running in parallel multiple comparisons between the separate attributes – possibly alongside an additional comparison of expected value. This result stands in contrast with the assumption of standard economic theory that choices require a unique comparison of expected values and suggests that at the cognitive level, decision processes might be more distributed than commonly assumed. Beyond our planned analyses, we also discovered that attribute salience affects people of different risk preference type in different ways: risk-averse participants seem to focus more on probability, except when monetary amount is particularly high; risk-neutral/seeking participants, in contrast, seem to focus more on monetary amount, except when probability is particularly low.

1. Introduction

Most of our everyday decisions are between options defined by multiple attributes or dimensions, such as: foods that provide different levels of pleasure and nutrition; houses that vary in terms of size and location; or lotteries that offer different amounts of money available to win and probabilities of winning. The classical economic perspective is that such multi-attribute choices should be

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https://doi.org/10.1016/j.cogpsych.2023.101614
Received 7 December 2022; Received in revised form 13 September 2023; Accepted 5 October 2023
Available online 12 October 2023
0010-0285/

solved by first computing a unique overall *expected value* (EV) for each option and then comparing the EVs of the different options. Classical economic theories that model choice as a comparison of EV do not make any explicit statement regarding the process that integrates the various attributes, so which attributes are integrated, and how, is left un-modeled. This comparison could perhaps be achieved through a process of evidence accumulation to a threshold, as in the *drift-diffusion model* (DDM; (Ratcliff & McKoon, 2008)) or similar mathematical accounts of economic choices (Busemeyer & Townsend, 1993; Rustichini & Padoa-Schioppa, 2015; Usher & McClelland, 2001). Crucially, the process that takes the decision-maker from the observation of the options (and thus of the attributes) to the computation or estimation of the EV must be completed before the comparison and thus before the choice is made. This logically follows from the implicit fundamental assumption that choice is a comparison of EV.

Despite its normative character and its centrality in neuroeconomic thinking, the idea that choices require the decision-maker to form estimates of EV in a step that is completed before the choice may not be compelling as a positive theory of choice. This is because, from a computational perspective, a system that makes decisions by comparing EVs requires delaying the choice until all relevant attributes are integrated, which could be especially challenging when they are numerous. Indeed, previous studies have shown (using large-scale datasets) that using EV alone does not make for the best model of choice (He et al., 2022; Peterson et al., 2021). Rather than deciding via a unique comparison of EV (*integrate-then-compare* model), a more feasible alternative might be running in parallel multiple comparisons – each between the values along one specific attribute dimension – and then integrating the partial results of the competitions afterwards (*compare-then-integrate* model; see (Hunt et al., 2014; Nakahashi & Cisek, 2023; Roe et al., 2001; Turner et al., 2018; Usher & McClelland, 2004)). Furthermore, the two models described so far (*integrate-then-compare* and *compare-then-integrate*) are not mutually exclusive – they could operate simultaneously. Therefore, it is possible to envisage a third model that combines the two models (*combined-comparison*; see (Lee & Hare, 2022; Stewart, 2011)), which would perform multiple comparisons – between the values of individual attributes *and* between their integrated EVs – and then combine the outcomes of all the comparisons to determine the final choice.

The two latter models (*compare-then-integrate* and *combined-comparison*, in which attributes can compete separately) have at least two advantages: they can initiate decisions faster than the *integrate-then-compare* model, and they can operate (at least partially) in parallel. The parallelism is important to the extent that one is also interested in the brain circuits that support multi-attribute choices. Here, again, there is a dispute between classical neuroeconomic models in which decision computations are centralized in prefrontal brain regions (Padoa-Schioppa, 2011) and distributed choice models that recognize that decision computations arise as a distributed consensus that emerges across multiple brain circuits considering separate attributes and subsequently integrating them (Cisek, 2012; Pezzulo & Cisek, 2016). At the same time, the *compare-then-integrate* and *combined-comparison* models that do not only integrate attribute values into an EV would show some deviations from the purported "optimality" criteria of the classical economic model (*integrate-then-compare*) – some of which have been observed experimentally. For example, decisions in which attributes can compete separately would be particularly influenced by the attributes that are considered first or whose comparison is faster – a mechanism that is often exploited in marketing (Amasino et al., 2019; Lim et al., 2018; Maier et al., 2020; Sullivan et al., 2015). Furthermore, decision processes might be affected by options that have low EV but a single appealing attribute (Tversky & Simonson, 1993). Finally, the values of different attributes could interact during the decision, rather than acting independently as assumed by classical models (Park et al., 2011).

When empirically testing whether, during multi-attribute decisions, attributes are considered individually (*compare-then-integrate model*) or integrated to form overall expected values before entering into competition (*integrate-then-compare* model), a recurrent problem is that it is difficult to disentangle the above models experimentally, as they tend to generate very similar predictions across a range of experimental conditions (Stewart, 2011). In other words, most standard paradigms used in economics and neuroeconomics are not sensitive enough to distinguish between the above models. However, certain studies have attempted to do just that, with some success. For example, Noguchi and Stewart (Noguchi & Stewart, 2014) used eye-tracking to show that participants made a series of comparisons within each choice trial, with each comparison taking place within a specific attribute dimension. The authors concluded that psychological models of choice should thus be based on within-attribute comparisons (Noguchi & Stewart, 2014). Other eye-tracking and computational modeling studies investigating risky choice have found that participants seem to perform within-alternative integrations rather than within-attribute comparisons (Fiedler & Glöckner, 2012; Glickman et al., 2019). The topic has also been explored in the domain of intertemporal choice, using mouse-tracking to show that some participants seem to integrate within alternatives whereas others seem to compare individual attributes across alternatives (Reeck et al., 2017). The question about within-alternative versus within-attribute comparisons has been asked with respect to not only human decision-makers, but also rhesus macaques (Farashahi et al., 2019). A few studies have used drift-diffusion modeling to provide evidence that participants compare individual attributes during deliberation about intertemporal choices (Dai & Busemeyer, 2014) or that they seem to both compare attributes across options and integrate values within options during value-based decisions (Lee & Hare, 2022; Yang & Krajbich, 2022). In the current study, we test whether similar results will be found in risky decisions. In this type of decision, where options are typically combinations of monetary amounts to win and probabilities that the stated amounts will be realized, the attributes (amount and probability) may trade off against each other (e.g., higher payoffs are often associated with lower probabilities) and thus may not be fully independent. Furthermore, the integration of amount and probability into EV is generally assumed to be multiplicative, not additive. It is thus unclear if the previous findings related to multi-attribute choice in general will also apply to the somewhat special case of risky choice.

To help resolve the inconsistencies of the studies mentioned above and to further adjudicate amongst *integrate-then-compare*, *compare-then-integrate*, and *combined-comparison* models of decision-making, we designed a risky choice task that parametrically varied not only the EVs of different options (as in previous studies), but also the relative *salience* of the attributes. Our concept of salience aligns with that set forth under Salience Theory (Bordalo et al., 2012), where an option is deemed more salient when it contains a measure of an attribute that is much higher than the attributes of the other option. We reasoned that rendering one attribute more salient than the other on each trial could be particularly diagnostic, as it might make the (putative) within-attribute competition faster, influencing the overall pattern of choice behavior. A similar effect has been demonstrated in a risky choice task featuring numerical streams of potential payoff amounts, where the authors deemed that larger numerical values were more salient to the participants (Tsetsos et al., 2012). The assumption that higher numerical values will be more salient is also supported by previous experimental and computational work based on value-based attentional capture, which assumes that more attention will be focused on options with higher expected values, and that the additional attention will impact choice behavior (Gluth et al., 2018, 2020). Assessing the relative importance of EV versus individual attributes together with the salience of attributes during choices could permit adjudicating between models that postulate *integrate-then-compare*, *compare-then-integrate*, or *combined-comparison* processes.

In our task, participants used a computer mouse to make a series of risky choices between two options (lotteries) characterized by two dimensions: the amount of money to be won and the probability of winning it. An example choice is between “90 % probability of winning €20” and “30 % probability of winning €60”. From this point onward, consistent with the neuroeconomics literature, we label the option having the highest probability (e.g., “90 % of probability of winning €20”) as *safer* and the option having the lowest probability (“e.g., 30 % probability of winning €60”) as *riskier*.

Importantly, in our experiment, the choice option pairs varied across two dimensions: *expected value difference* (dV) and *salience* (SAL). SAL is a categorical variable reflecting the fact that for each trial, either the probability or the amount of money is particularly salient, as it has a high value that is at least 1.5 times greater than the second-highest value on display. (Note that this notion of salience is not related to bottom-up characteristics of the stimuli, such as size, color, or clarity.) Specifically, we assume that SAL is for the safer option if the salient number corresponds to its probability and that SAL is for the riskier option if the salient number corresponds to its amount of money. For example, the choice between “90 % probability of winning €20” and “30 % probability of winning €60” would have dV = 0 (as both options have the same EV) and SAL = safer (as the most salient number is 90, which corresponds to the probability attribute of the safer option). We reasoned that if the attributes are processed independently, the most salient attribute might be processed differently (e.g., faster) than the less salient attribute. In contrast, if the attributes are not processed independently, the salience of individual attributes should have no impact on choice dynamics.

By manipulating the SAL of attributes independent of the EV of options, this experimental design generates a diverse range of trials, for which the *integrate-then-compare*, *compare-then-integrate*, and *combined-comparison* models would make different predictions. Broadly speaking, under the *integrate-then-compare* model, response probabilities, response times, and mouse trajectories should not be sensitive to the SAL of individual attributes, because the attributes would not be processed independently (they would simply be integrated into EV). Conversely, under the *compare-then-integrate* and *combined-comparison* models, both dV and SAL should exert an influence on the decision process and the associated choice variables. However, the predictions made by the above models could be more subtle than what we described. For that reason, we include in our analysis a quantitative model comparison of a set of computational (drift-diffusion) models that formalize the alternative *integrate-then-compare*, *compare-then-integrate*, and *combined-comparison* approaches.

Finally, our experimental design allows us to examine potential differences in participant behavior according to their risk preference type (i.e., how well they tolerate risk when choosing between options with different outcome probabilities). It has long been known that there are individual differences in risk preference (Tversky & Kahneman, 1992), with some people avoiding it (*risk-averse*), some indifferent to it (*risk-neutral*), and some drawn to it (*risk-seeking*). Risk preferences can be deduced by examining how people's choice probabilities deviate from classical economic theory. For instance, in the above example (“90 % probability of winning €20” versus “30 % probability of winning €60”), classical economic theory would predict indifference, because the expected values of the options are identical (€18). A risk-averse person would prefer the first option, because it has the higher probability (i.e., lesser risk). A risk-neutral person would be indifferent and thus adhere to classical economic theory. A so-called risk-seeking person would prefer the second option, because it has the higher monetary amount (and thus the lower probability or greater risk). One might hypothesize, therefore, that different attributes are inherently more or less important than others for different types of people (probability > monetary amount for risk-averse people, probability = monetary amount for risk-neutral people, probability < monetary amount for risk-seeking people). In terms of our salience manipulation, we might then expect a different effect to emerge for the different groups. Specifically, on trials that we classify as SAL = riskier (where the monetary amount of the riskier option is the greatest number on the screen), risk-averse people might actually be repulsed by the riskier option (because it will also have a very low probability, which is more important to them than the large monetary amount). Something analogous might occur for risk-seeking people on trials where SAL = safer. We thus tested for group differences in the behavioral data, and we also tested whether the winning computational model differed across groups. Given that risk preference is a topic that has long been studied, it could be of interest if our modeling analysis illuminates differences in parameters or even models across risk preference groups.

To preview our results, we found that both expected value difference and salience affect the final choices as well as the choice dynamics, as indexed by response time and curvature of the mouse response trajectory. Furthermore, the computational model that best accounts for the data (when considering all participants together) is the one that incorporates the *combined-comparison* framework, along with differential evidence accumulation rates according to salience condition. Grouping participants by risk preference reveals that all groups consider individual attributes in one way or another when making their choices, even if they rely on different overall strategies.

2. Methods

2.1. Ethics approval

The experimental procedure was approved by the Ethics Board of the Institute of Cognitive Sciences and Technologies, National Research Council of Italy.

2.2. Participants

A sample of 43 healthy adults, all males, aged 20–49 years old (mean age 26.7, standard deviation 8.3), took part in the study. All participants were right-handed, with normal or corrected-to-normal vision. Due to technical issues, the data for three participants were not saved. All analyses reported below are thus for $n = 40$ participants.

2.3. Stimuli and procedure

The stimuli used in this study were numerical displays of two options (one towards the left and one towards the right of the computer screen). Each option represented a "risky" choice, in the sense that the chosen monetary amount of would be obtained with probability less than 100 %. Each trial included a safer option (with the higher probability) and a riskier option (with the lower probability). Trials included different levels of expected value difference (dV), specifically: on each trial, the expected value (EV) of the safer option was 50 % greater than, 25 % greater than, equal to, 25 % less than, or 50 % less than the EV of the riskier option. Trials also included different categories of SAL, specifically: on each trial, either the probability or the amount of money had a value that was at least 1.5 times greater than the second-highest value on display for that trial. Each participant made 240 choices in total, as each stimulus pair in the set of 60 pairs was presented four times. The stimuli were presented in a random order, with the position of the stimuli / response buttons counterbalanced across trials.

Participants reported their choices by clicking with a computer mouse one of two response buttons, located at the top-right or top-left of their screens (Barca & Pezzulo, 2012, 2015; Calluso et al., 2015; Freeman & Ambady, 2010; Lepora & Pezzulo, 2015). To begin each trial, participants clicked on the START button located at the bottom-center of the screen (Fig. 1). Then, the two response buttons appeared (one at the upper-left and one at the upper-right of the screen) and remained on the screen until a response was entered.

2.4. Behavioral and kinematic measures

Choice and response time (RT, from when participants pressed START until they reached and pressed one of the response buttons) were recorded for each trial, as were the x and y coordinates of the mouse trajectories (with a sampling rate of approximately 70 Hz). For all analyses reported below, we converted RT to seconds and ignored outlier trials (defined as having log(RT) greater than the median $\pm 3\times$ the median average deviation, within participant). With respect to mouse movement, we focused on the ***maximum deviation*** (MD) of the trajectories, which indexes choice uncertainty and the competition between response alternatives (Hehman et al., 2015; Spivey et al., 2005). The MD is the maximum shortest distance between each point on the observed mouse trajectory and an ideal straight line connecting the start button to the response button. The closer the mouse trajectory is to this ideal line, the smaller the MD will be, indicating a higher confidence in the choice. For each of the regression analyses that we report below, we used mixed effects

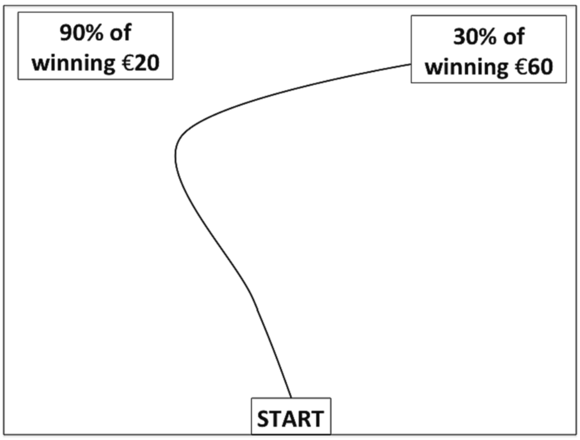

Fig. 1. Experimental setup. Each trial started when participants clicked the START button located at the bottom-center of the screen. At that point, two stimuli (a "safer" option and a "riskier" option) appeared at the top-right and top-left of the screen. Each stimulus pair appeared four times across the experiment, with the position of the safer and riskier options counterbalanced. Participants reported their choices by clicking one of the two response buttons. The figure shows a (fictive) mouse trajectory.

models with random slopes and intercepts for each participant in addition to the regressors of interest.

2.5. Drift-diffusion model-based analysis

To further examine the issue of whether the decision process that guides risky choices is driven by calculations of expected value (i.e., the monetary amount on offer multiplied by the probability of receiving the payoff, if that option is chosen) or independently by the magnitudes of the individual attributes (monetary amount and probability), and to adjudicate between *integrate-then-compare*, *compare-then-integrate*, and *combined-comparison* models, we consider several variants of the drift-diffusion model (DDM) that formalize the alternative hypotheses (Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998; Ratcliff, 1978). The DDM is an evidence accumulation-to-bound model, with evidence referring to a moment-by-moment estimate of the relative value of one option compared to the other. These momentary estimates are noisy (e.g., derived from stochastic neural firing patterns), so the estimates are repeated across time and accumulated to cancel out the noise. The process terminates when a sufficient amount of evidence has been accrued, at which point a choice is made.

We followed the approach used by Lee and Hare (Lee & Hare, 2022) and considered three main model formulations. Model 1 (*expected value DDM* or *evDDM*) is based on comparisons of expected value (EV); Model 7 (*expected utility DDM* or *euDDM*) is based on comparisons of expected utility (EU). We included an EU variant of this model (in addition to the EV variant) because economic decision theory is generally based on subjective utility rather than objective expected value. The main difference between the two is that under expected utility theory, there is not necessarily a linear relationship between objective monetary amounts and their perceived subjective values (e.g., a decreasing marginal utility of money has often been observed). We thus included a version of Model 1 based on EU in order to most appropriately align with economic theory. This would enable Model 1 to account for potential risk biases in the data and remove the disadvantage that it would have had when competing against the other models (which all include inherent abilities to account for risk bias). Model 2 (*multi-attribute DDM* or *maDDM*) is based on independent comparisons of the monetary amount (X) and probability (P) attributes. Model 3 (*multi-attribute DDM plus expected value* or *ev+maDDM*) is based on comparisons of both individual attributes X and P *and* EV. The mathematical details of each model are provided below.

Model 1: expected value DDM (evDDM)

The first model is a basic DDM in which only the *expected values* of the two options influence the evidence accumulation on each trial. Specifically, at each time step, the incremental evidence equals the EV of the riskier option (EV_R) minus the EV of safer option (EV_S), scaled by an efficiency parameter (the drift rate, d^V), plus Gaussian noise (ε) with mean 0 and variance σ^2. The cumulative evidence (e) evolves across deliberation time as follows:

$$DV = EV_R - EV_S \tag{1}$$

$$\mathrm{EV} = \mathrm{X}^*\mathrm{P} \tag{2}$$

$$drift = d^V DV \tag{3}$$

$$e_t = e_{t-1} + drift + \varepsilon \tag{4}$$

$$\varepsilon \sim \ N\left(0, \sigma^2\right) \tag{5}$$

$$e_0 = 0 \tag{6}$$

where EV_R and EV_S are independent variables, t is a time index with arbitrary units, and d^V and σ^2 are free parameters to be estimated to capture the individual-specific rate of evidence accumulation (drift) and level of noise in the accumulation process (diffusion), respectively. Each of these parameters is constrained to be positive. Evidence accumulation terminates when e reaches a response boundary $\in\{\theta, -\theta\}$, with the sign of the final value of e determining the chosen option (arbitrarily defined as positive for the riskier option, negative for the safer option) and the final value of t determining the response time (RT).

Choice probability (p, choice of the riskier option) and mean RT can be analytically derived (Alós-Ferrer, 2018) as a function of *drift* and σ^2, with θ being fixed (here, to $\theta = 1$ for simplicity):

$$p \stackrel{\text{def}}{=} p(ch = riskier) = \frac{1}{1 + e^{\frac{-2^*\theta^* drift}{\sigma^2}}} \tag{7}$$

$$E[RT] = \frac{\theta^*(2p-1)}{drift} + NDT \tag{8}$$

As is common practice in drift-diffusion modeling, we included an addition free parameter *NDT* to estimate the so-called non-decision time (or alternatively, time for stimulus encoding and response implementation). These analytical formulas for choice probability and mean RT will be identical across all models, except that the drift component will be calculated differently.

Model 2: multi-attribute DDM (maDDM)

The second model is similar to Model 1, except that now evidence accumulation is independently driven by the individual attributes of the options (X and P). The process is otherwise identical, and evidence accumulates as follows:

$$DX = X_R - X_S \tag{9}$$

$$DP = P_R - P_S \tag{10}$$

$$drift = d^X DX + d^P DP \tag{11}$$

where X_R, X_S, P_R, and P_S are independent variables, d^X and d^P are free parameters to capture the individual-specific rates of evidence accumulation for DX and DP, respectively.

Model 3: expected value plus multi-attribute DDM (ev+maDDM)

The third model is essentially a hybrid of the first two models, in which evidence accumulation is independently driven by individual attributes in addition to expected value. The idea here is that choices could be made according to expected value in a general sense, but that individual-specific adjustments to the relative importance of each attribute could fine-tune the decision process. The computational structure is otherwise identical to that of Models 1 and 2, and evidence accumulates as follows:

$$drift = d^V DV + d^X DX + d^P DP \tag{12}$$

In this study we are only concerned with comparing different models in terms of their ability to best fit the experimental data. Note that if the goal were to make inferences about the relative impact of EV, X, and P in determining the drift rate, it might have been necessary to employ orthogonalization or dimensionality reduction techniques to control for the correlations between EV and both X and P.

In addition to the above-defined models, we also included variants in which the rates of evidence accumulation can differ as a function of salience condition (Model 4: *expected value DDM plus salience* or *evDDM+sal*, Model 5: *multi-attribute DDM plus salience* or *maDDM+sal*, Model 6: *expected value plus multi-attribute DDM plus salience* or *ev+maDDM+sal*). These latter models reflect a key assumption of our design – that the salience of attributes influences evidence accumulation. The mathematical details of each additional model are provided below.

Model 4: expected value DDM plus salience (evDDM+sal)

The fourth model is similar to Model 1, except that now evidence accumulation rates can differ according to which option is affiliated with the most salient attribute on each trial. The idea here is that whichever option has an attribute that is salient on a given trial will capture more attention and thus adjust the rate at which information is processed about that option relative to the other option. The computational structure is otherwise identical to that of the other models, and evidence accumulates as follows:

$$drift = \left(d^V + d_r^V * risk\right) * EV_R - \left(d^V + d_s^V * safe\right) * EV_S \tag{13}$$

where d_r^V and d_s^V are free parameters to capture the individual-specific rates of incremental evidence accumulation for the riskier option when SAL = riskier and for the safer option when SAL = safer, respectively, $risk = 1$ if salience favors the riskier option (and 0 otherwise), and $safe = 1$ if salience favors the safer option (and 0 otherwise).

Model 5: multi-attribute DDM plus salience (maDDM+sal)

The fifth model is similar to Model 2, except that now evidence accumulation rates can differ according to which attribute is salient on each trial. The idea here is that whichever attribute is salient on a given trial will capture more attention and thus adjust the rate at which information is processed about that attribute relative to when it is not salient. The computational structure is otherwise identical to that of the other models, and evidence accumulates as follows:

$$drift = \left(d_r^X DX + d_r^P DP\right) * risk + \left(d_s^X DX + d_s^P DP\right) * safe \tag{14}$$

where d_r^X and d_r^P are free parameters to capture the individual-specific rates of evidence accumulation for DX and DP, respectively, when SAL = riskier, d_s^X and d_s^P are free parameters to capture the individual-specific rates of evidence accumulation for DX and DP, respectively, when SAL = safer, $risk = 1$ if salience favors the riskier option (and 0 otherwise), and $safe = 1$ if salience favors the safer option (and 0 otherwise).

Model 6: expected value plus multi-attribute DDM plus salience (ev+maDDM+sal)

The sixth model is essentially a hybrid of Modes 4 and 5. The computational structure is identical to that of the other models, and evidence accumulates as follows:

$$drift = \left(d^V + d_r^V * risk\right) * EV_R - \left(d^V + d_s^V * safe\right) * EV_S + \left(d_r^X DX + d_r^P DP\right) * risk + \left(d_s^X DX + d_s^P DP\right) * safe \tag{15}$$

Model 7: expected utility DDM (euDDM)

In this alternative version of Model 1, only the *expected utilities* of the two options influence the evidence accumulation on each trial. Specifically, at each time step, the incremental evidence equals the EU of the riskier option (EU_R) minus the EU of safer option (EU_S), scaled by an efficiency parameter (the drift rate, d^U), plus Gaussian noise (ε) with mean 0 and variance σ^2. The cumulative evidence (e) evolves across deliberation time as follows:

$$DU = EU_R - EU_S \tag{9}$$

$$\mathrm{EU} = \mathrm{X}^{\alpha} * \mathrm{P} \tag{10}$$

$$drift = d^U DU \tag{11}$$

where α is a free parameter to capture the individual-specific utility function. This parameter is constrained to be positive.

We note that our model formulations do not contain a free parameter to represent a *starting point bias* in the evidence accumulation process. This parameter is popular in drift-diffusion modeling studies, as it allows for the possibility that one of the responses may be a sort of default option for a participant before the specific options are even presented. Previous studies on risky choice have found a starting point bias related to loss aversion (Clay et al., 2017; Sheng et al., 2020; Zhao et al., 2020). Although we do not explore loss aversion in this work, we thought it might be possible that the starting point bias parameter could serve to capture the risk-aversion tendencies that we found in our data. We therefore performed quantitative comparisons of our set of models with this additional parameter versus without, using formulations provided in previous studies (Grasman et al., 2009; Lopez-Persem et al., 2016). The models performed better without the starting-point bias parameter. We therefore decided to simplify our analysis by excluding this parameter (or equivalently, fixing it to zero). We also did this (for the same reason) for an optional parameter that allows for a fixed component of the drift rate (i.e., a drift component independent of the trial-specific option values).

Using the VBA toolbox in MATLAB (see below) to fit and compare models allows us to simultaneously fit other choice variables in addition to those included in the DDM (choice probability and RT). VBA simultaneously optimizes parameters over a set of analytical equations, such as those listed above for choice probability and mean RT. Importantly, we can just as easily perform our model comparison while fitting additional equations. To that end, we fit generalized predictions about the relationship between the evidence accumulation (drift) rate and maximum mouse trajectory deviation (MD) in addition to choice probability and mean RT. We estimated MD as a linear function of either expected value/utility difference (ev/u), individual attribute differences (ma), both (ev+ma), or expected value differences, individual attribute differences, or both, dependent on salience condition (ev+sal, ma+sal, ev+ma+sal, respectively). The formula that we used to estimate MD under each model was:

$$MD = \beta_0 + \beta_1 * drift \tag{19}$$

2.6. Model fitting procedure

We fit each of the candidate models to the experimental data, then performed Bayesian model comparison to determine which of the models (if any) performed significantly better than the others across the population of participants. For this model fitting and comparison exercise, we relied on the Variational Bayesian Analysis toolbox (VBA, available freely at https://mbb-team.github.io/VBA-toolbox/; (Daunizeau et al., 2014)) with MATLAB R2022b. Within participant and across trials, we entered the experimental variables {monetary amount, probability, and expected value for each option; observed RT; salience condition} as input and {choice = 1 for the riskier option, 0 for the safer option; RT; MD} as output. All monetary amounts were rescaled to the range (0,1] in accord with the probability measures. We also entered the model-specific mappings from input to output as outlined in the analytical formulas above. As we fixed the threshold parameter θ to 1, the parameters to be fitted were the drift scalar (d), diffusion noise (σ^2), and non-decision time (NDT) terms described above in the model formulations, plus the slope and intercept parameters for MD. VBA requires prior estimates for the free parameters, for which we set the mean and variance equal to: 1.6 and 37 for the positively constrained parameters (noise and all drift scalars); 0.5 and 3.7 for NDT (constrained between 0 and 1); and 0 and 16 for the unconstrained MD parameters. The theoretical drift rate, noise, and NDT parameters are always positive; we thus constrained the search space of our model fitting algorithm to the positive domain by replacing these parameters with the following calculation: log(1 + exp(parameter)) * 2.3. VBA then recovers an approximation to both the posterior density on unknown variables and the model evidence (which is used for model comparison). We used the VBA_NLStateSpaceModel function to fit the data for each participant individually, followed by the VBA_groupBMC function to compare the results of the model fitting across models for the full group of participants.

VBA estimates parameters during model fitting using Variational Bayes: an efficient iterative algorithm that provides a free-energy approximation for the model evidence, which trades off model accuracy (goodness of fit, or log likelihood) and complexity (degrees of freedom, or KL divergence between priors and fitted parameter estimates; see (Friston et al., 2007; Penny, 2012)). This is a critical step for comparing our models, as they differ in number of parameters. The VBA algorithm starts with our relatively flat Gaussian priors for each model's free parameters and eventually provides a posterior density estimate. The log model evidence scores calculated for each participant are then fed into the group-level random-effect Bayesian model selection (BMS) procedure. A key output of the BMS is the exceedance probability, which informs about how likely it is that a given model is more frequently implemented across the population of participants (relative to all other models under consideration; (Rigoux et al., 2014; Stephan et al., 2009)). Previous studies have successfully used this approach to fitting and comparing variants of DDM (Feltgen & Daunizeau, 2021; Lee & Hare, 2022; Lee & Usher, 2023; Lopez-Persem et al., 2016).

The VBA toolbox also allows models to be formally tested across what is known as "families" based on fundamental similarities across all models within each family. We established two types of family in our set of models. The first model family category represented our primary research question: is evidence integrated then compared, compared then integrated, or some combination of both. These families were thus: ev = {Model 1, Model 4, Model 7}; ma = {Model 2, Model 5}; ev+ma = {Model 3, Model 6}. The second model family category represented our secondary research question: does the salience of individual attributes impact evidence accumulation. These families were thus: DDM = {Models 1–3, Model 7}; DDM+sal {Models 4–6}. We compared the aggregated model performance across families using the *options.families* input to the VBA_groupBMC function.

2.7. Model recoverability

To verify that our model-fitting procedure is suitable for this specific analysis, we performed a test of model recoverability. Specifically, we took as the model input the same monetary amounts and probabilities from the choice trials that the participants were faced with. We then simulated the set of choice probabilities, mean RTs, and MDs for each participant, separately according to each of our models, using the actual participant-specific fitted parameters for each model. Finally, we fit all simulated data (per participant) to each of our models and performed the same formal model comparison as with our real experimental data. The results of this procedure can be seen in Fig. 2. This matrix shows, for each true generative model, the percentage of participants (simulated under that model) that were attributed to each of the best fitting models by our model-fitting procedure. As shown in the matrix, model confusion was low and the procedure attributed the true generating model as the best-fitting model for the vast majority of participants (recovery accuracy: 82 % for *evDDM*, 76 % for *maDDM*, 78 % for *ev+maDDM*, 99 % for *evDDM+sal*, 90 % for *maDDM+sal*, 86 % for *ev+maDDM+sal*, and 85 % for *euDDM*). There was a small amount of confusion between the *ev+maDDM* and the *evDDM* and *maDDM*, which is to be expected since the *ev+maDDM* is essentially a combination of those other models.

3. Results

3.1. Behavioral measures

We first examined the three decision variables of interest (choice, response time or RT, and maximum deviation or MD) in a model-free manner by observing their relationships with the relative attractiveness of the risker option compared to the safer option. Specifically, we considered the difference in the expected value (EV = monetary amount * probability) of the riskier option minus that of the safer option. The closer this difference is to zero, the more difficult the choice is presumed to be (for risk-neutral decision-makers). Pooling together all trials across all participants, we separated the data into bins of equal widths covering the full range of EV difference. Within each bin, we calculated the percentage of trials where the riskier option was chosen, the mean RT, and the mean MD. Standard psychometric findings would show that choices are close to chance level (50%), RTs are longest, and MDs are largest when

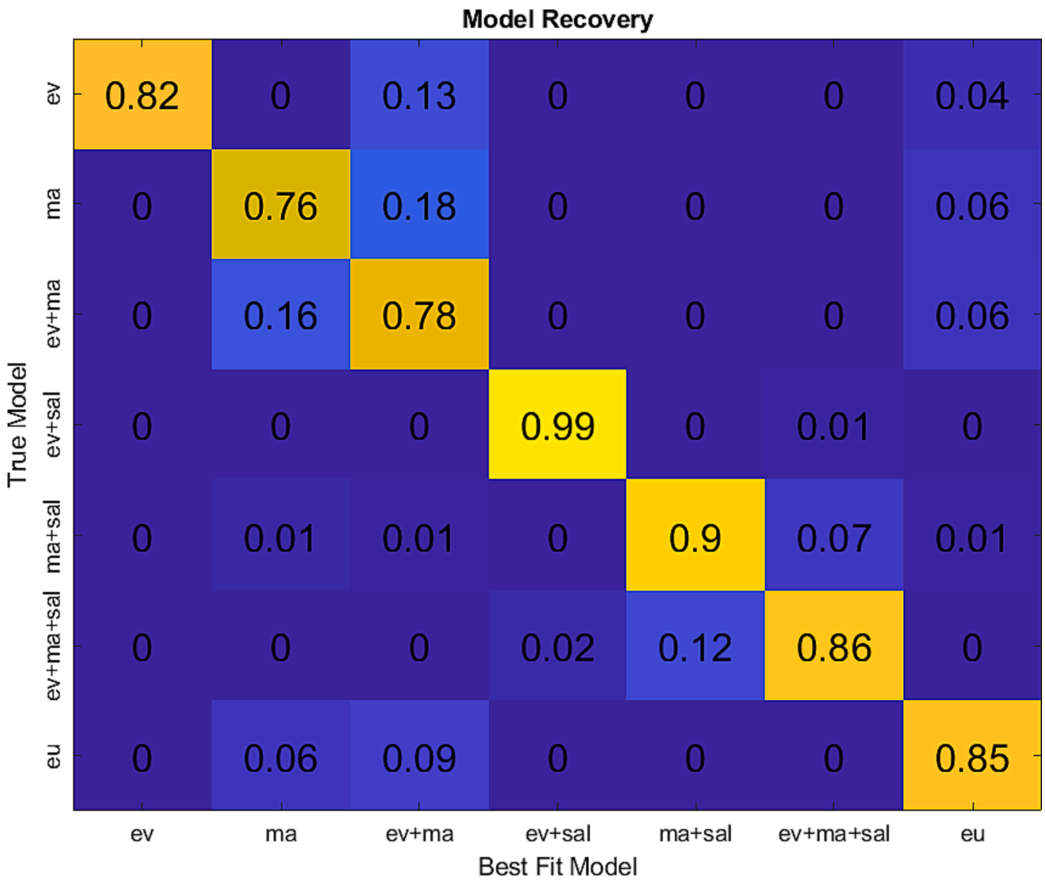

Fig. 2. Model recovery analysis. The cells in each "confusion matrix" summarize the percentage of participants (simulated under each true model) for which our model-fitting procedure attributed each of the (best fit) models.

the decision variable (here, EV difference) is closest to zero. However, we found a clear skew in our data, where this inflection point was shifted away from zero toward the right of the EV difference scale (Fig. 3A–C). This indicates that our participants (on average) were averse to risk, as has often been reported in studies of risky choice (O'Donoghue & Somerville, 2018).

It is well known that people vary in terms of their risk preferences. Given that our data clearly indicated that our participants (as a whole) were averse to risk, we checked if we could reasonably split our participants into groups: risk-averse, risk-neutral, and risk-seeking. To do this, we first estimated a parameter α that is commonly used to capture risk aversion by transforming EV to EU (cf, Prospect Theory (Tversky & Kahneman, 1992)), separately for each participant: $X \leftarrow X^{\alpha}$ (X = monetary amount). We used VBA to fit a basic logistic model of choice probability for each participant and we examined the best-fit α values for each participant. A value of α close to 1 indicates no influence of risk, whereas a value of α lesser/greater than 1 indicates risk aversion/seeking. We thus created groups of participants whose estimated α parameter was in the range 0.8–1.2, below this range, or above this range (we offer an additional validation of the group partition alongside the model-based results; see Fig. 10). We labeled these groups "risk-neutral" ($n = 13$), "risk-averse" ($n = 23$), and "risk-seeking" ($n = 4$), respectively. Note that due to the small sample size within each group, especially the risk-seeking group, results should be interpreted with care. We then repeated the above qualitative analysis, separately by group. Clearly this separation into groups was meaningful, as three distinct patterns in the data emerged. Risk-averse participants rarely chose the riskier option unless the EV of the riskier option was much greater than the EV of the safer option (Fig. 3D in red). They also took longer to decide and deviated more from a straight trajectory as the EV of the riskier option increased (within the available range; Fig. 3E-F in red). Risk-neutral participants showed the patterns expected for people who choose based on simple economic calculations unaffected by risk aversion. Their probability of choosing the riskier option also increased as a function of EV difference (riskier - safer), but their point of neutrality ($p(ch) = 0.5$) was when EV difference equaled zero (Fig. 3D in blue). Furthermore, their RTs were longest and MDs were largest on trials where EV difference was closest to zero (Fig. 3E-F in blue). Risk-seeking participants showed patterns opposite to those of the risk-averse group: a greater tendency to choose the riskier option even when it did not have the higher EV, longest RT and largest MD when the EV of the safer option was much greater than the EV of the riskier option (Fig. 3D-F in green).

To confirm the apparent group differences, we regressed choice (of the riskier option) on EV difference (dV), log(RT) on abs(dV), and MD on abs(dV), separately for each dependent variable and risk preference group. The relative magnitudes of the regression coefficients across groups suggest that EV had a much greater influence on the choice probability, RT, and MD of the risk-neutral and risk-seeking participants relative to the risk-averse participants (coefficients for dV: **choice**: risk-averse = 1.31, 95 % CI = [0.99 1.62]; risk-neutral = 4.01, 95 % CI = [3.79 4.24]; risk-seeking = 3.08, 95 % CI = [1.52 4.65]; **RT**: risk-averse = −0.47, 95 % CI = [−0.71 −0.24]; risk-neutral = −1.99, 95 % CI = [−2.51 −1.47]; risk-seeking = 1.02, 95 % CI = [0.30 1.74]; **MD**: risk-averse = 0.04, 95 % CI = [−0.23 0.32]; risk-neutral = −1.23, 95 % CI = [−1.73 −0.74]; risk-seeking = 1.93, 95 % CI = [0.54 3.32]). Given the clear differences in group behavior, we decided to also test for group differences in the model comparison analysis reported below.

Beyond the effects of EV difference, we hypothesized that choice behavior would differ according to attribute salience. Specifically,

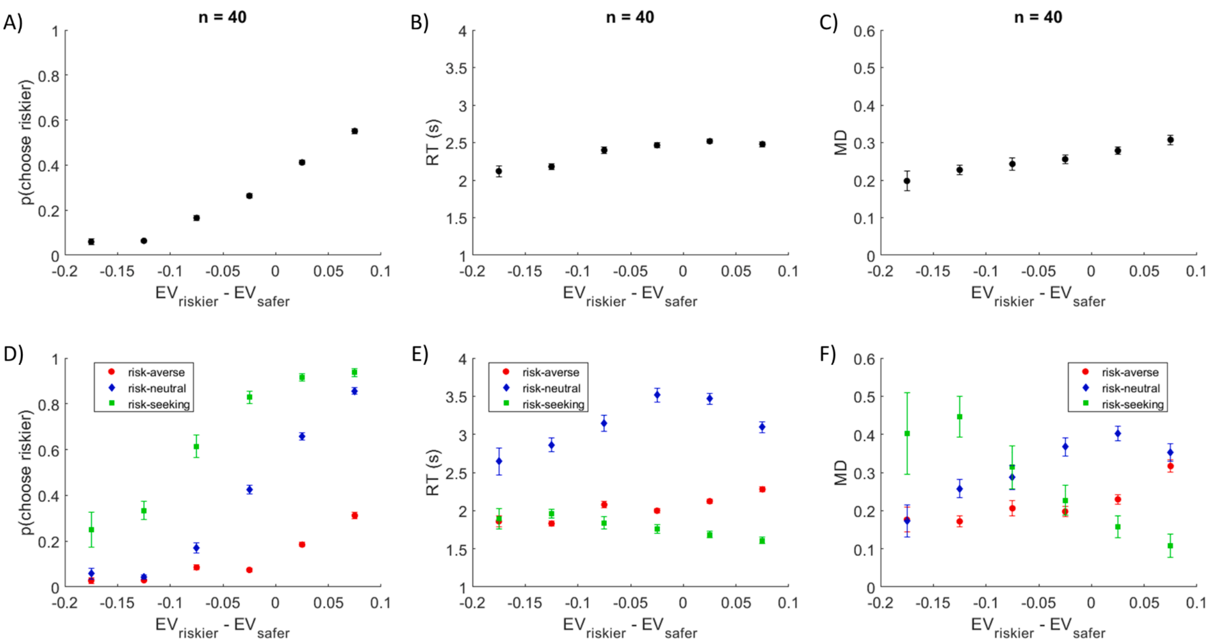

Fig. 3. Behavioral results. Choice probability (of choosing the riskier option), response time (RT), and maximum mouse trajectory deviation (MD) plotted against EV difference (riskier minus safer), pooled across all participants (plots A–C). Choice probability, RT, and MD plotted against EV difference, pooled across participants after grouping by risk preference type (plots D–F). Each dot represents an average across all trials within EV difference bins of equal range. Error bars represent the standard error of the mean of the data points within each bin.

we predicted that information processing about the salient attribute on each trial would be facilitated relative to the less salient attribute. This should lead to more extreme choice probability, faster RT, and smaller MD on trials where salience aligned with EV difference (i.e., when the EV of the riskier option is higher and the salient attribute is monetary amount, or when the EV of the safer option is higher and the salient attribute is probability). We label such trials as *no conflict* trials. In the opposite situation, where salience conflicts with EV difference (*conflict* trials), choice probability should be closer to 50 % (i.e., chance level), RT should be slower, and mouse trajectories should deviate more. To test for this, we split trials by conflict type (no or yes) and repeated the analysis reported above. Overall, we found no difference in choice probability (Fig. 4A), but a shift in the peak of the RT and MD distributions (Fig. 4B–C). Expecting to find group differences (risk-averse vs. risk-neutral vs. risk-seeking), we repeated this conflict analysis while

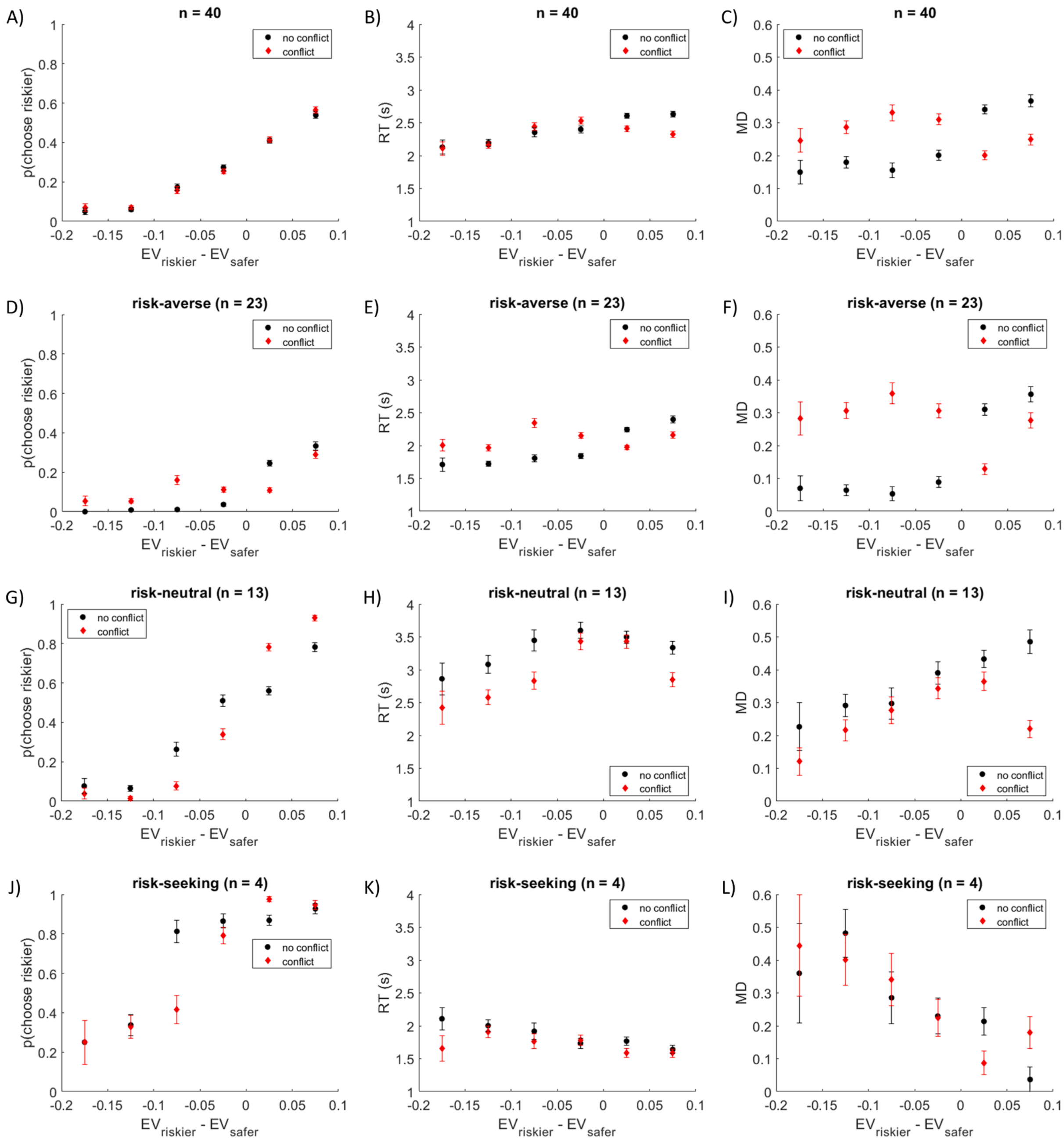

Fig. 4. Impact of conflict on choice behavior. Choice probability (of choosing the riskier option), response time (RT), and maximum mouse trajectory deviation (MD) plotted against EV difference (riskier minus safer), pooled across all participants (plots A–C), risk-averse participants (plots D–F), risk-neutral participants (plots G–I), and risk-seeking participants (plots J–L). Each plot shows the data separated by trial type (conflict versus no conflict). Each dot represents an average across all trials within EV difference bins of equal range. Error bars represent the standard error of the mean of the data points within each bin.

splitting the data by group. With the risk-averse participants, we found the anticipated patterns: for trials where the safer EV was higher, conflict increased the probability of choosing the riskier option (towards chance level) and increased both RT and MD; for trials where the riskier EV was higher, conflict decreased the probability of choosing the riskier option (away from chance level) and decreased both RT and MD (Fig. 4D–F). However, with the risk-neutral and risk-seeking participants, we found different patterns. For both groups, for trials where the safer EV was higher, conflict decreased the probability of choosing the riskier option (away from chance level; see Fig. 4G, J); for trials where the riskier EV was higher, conflict increased the probability of choosing the riskier option (away from chance level; see Fig. 4G, J). For the risk-neutral group, conflict decreased both RT and MD across all trials (Fig. 4H–I). For the risk-seeking group, conflict decreased RT and had no significant impact on MD across all trials (Fig. 4K–L). The behavioral data are internally consistent, in the sense that RT and MD both decreased whenever choice probability moved away from chance level and RT and MD both increased whenever choice probability moved towards chance level. But salience seemed to affect the risk-neutral and risk-seeking participants in a way opposite to what we predicted. It is likely that our salience labels (safer or riskier) were indeed accurate even for those groups, based on the behavioral effects. However, it seems that the attributes that were salient for those groups were the low magnitude attributes rather the high ones (on average, when our options had an especially high level of one attribute, they had an especially low level of the other). In other words, risk-averse participants might focus more on probability, except when monetary amount is particularly high. Risk-neutral and risk-seeking participants, in contrast, might focus equally on both attributes or more on monetary amount, respectively, except when probability is particularly low. Thus, it seems that high monetary amounts are salient for risk-averse people, and low probabilities are salient for risk-neutral and risk-seeking people.

To confirm the group differences, we regressed choice on dV + dV * conflict, log(RT) on abs(dV) + abs(dV) * conflict, and MD on abs(dV) + abs(dV) * conflict, separately for each dependent variable and risk preference group (where conflict is an indicator variable equal to 1 on conflict trials and equal to 0 on no-conflict trials). The regression coefficients for dV were qualitatively similar across groups with respect to choice (risk-averse = 1.65, 95 % CI = [1.11 2.19]; risk-neutral = 3.41, 95 % CI = [2.97 3.85]; risk-seeking = 2.83, 95 % CI = [1.24 4.42]; Fig. 5), but qualitatively opposite for the risk-seeking group compared to the others (**RT**: risk-averse = −0.76, 95 % CI = [−1.07 −0.45]; risk-neutral = −1.19, 95 % CI = [−1.76 −0.62]; risk-seeking = 1.41, 95 % CI = [0.59 2.22]; **MD**: risk-averse = −0.53, 95 % CI = [−0.87 −0.19]; risk-neutral = −0.69, 95 % CI = [−1.21 −0.18]; risk-seeking = 2.00, 95 % CI = [0.20 3.79]; Fig. 5). In contrast, the regression coefficients for dV * conflict were generally qualitatively opposite for the risk-averse group compared to the others (**choice**: risk-averse = −0.72, 95 % CI = [−1.61 0.17]; risk-neutral = 1.27, 95 % CI = [0.48 2.06]; risk-seeking = 0.54, 95 % CI = [−0.67 1.74]; **RT**: risk-averse = 0.65, 95 % CI = [0.28 1.01]; risk-neutral = −1.80, 95 % CI = [−2.68 −0.93]; risk-seeking = −0.88, 95 % CI = [−1.52 −0.24]; **MD**: risk-averse = 1.29, 95 % CI = [0.67 1.92]; risk-neutral = −1.23, 95 % CI = [−2.26 −0.19]; risk-seeking = −0.14, 95 % CI = [−1.78 1.49]; Fig. 5).

3.2. Qualitative model predictions

The DDM variants that we compare make distinguishable predictions regarding the impact of EV difference and conflict on choice behavior, when separately considering the different risk preference groups. We show in Fig. 6 the qualitative predictions that each model (*evDDM*, *maDDM*, *ev+maDDM*, *evDDM+sal*, *maDDM+sal*, *ev+maDDM+sal, and euDDM*, each simulated under its participant-specific best-fitting parameters) makes with respect to the effects of EV difference (dV; riskier minus safer) and dV in *conflict* trials (relative to *no conflict* trials) on choice probability (for the riskier option), RT, and MD, and how this compares to the empirical data. To generate the synthetic data, we used the same choice trials that participants faced, along with each participant's best-fitting parameters for each of the models. Next, we performed mixed effects regressions of choice (binomial) on dV and dV * conflict, and of log(RT) and MD (linear) on |dV| and |dV| * conflict, pooling together data from all simulated participants and including participants as random effects. Here, *conflict* is an indicator variable, meaning that dV * conflict shows the incremental effects dV on *conflict* trials relative to *no conflict* trials. For the risk-averse group, interestingly, all models except Model 1 can account for the relative magnitudes and directionality of the associations between dV (with and without conflict) and choice probability, RT, and MD (Fig. 6A). For the risk-neutral

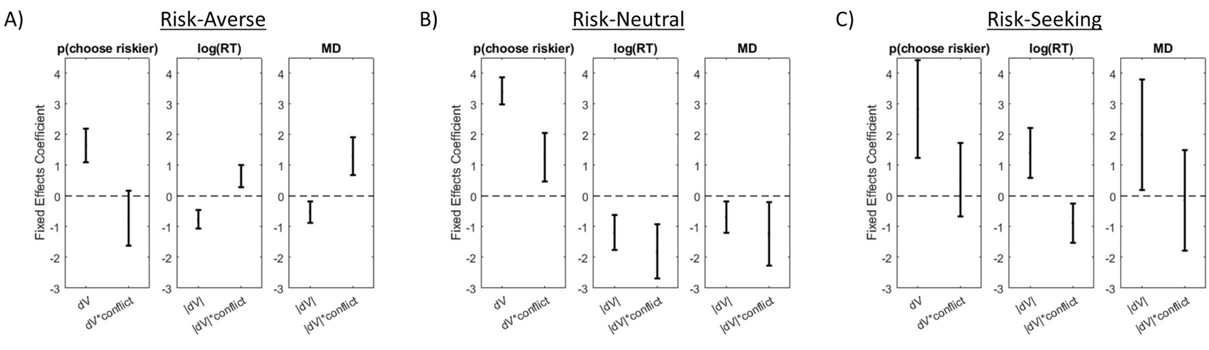

Fig. 5. Impact of expected value difference and conflict across risk preference groups. The effects of expected value difference (dV = EV of riskier option − EV of safer option) and dV on conflict trials (dV * conflict) on choice probability (for the riskier option), log(RT), and maximum deviation (MD) for risk-averse (plot A), risk-neutral (plot B), and risk-seeking (plot C) participants; dV is unsigned for RT and MD; diamonds represent fixed effects regression coefficients; error bars represent 95 % confidence intervals.

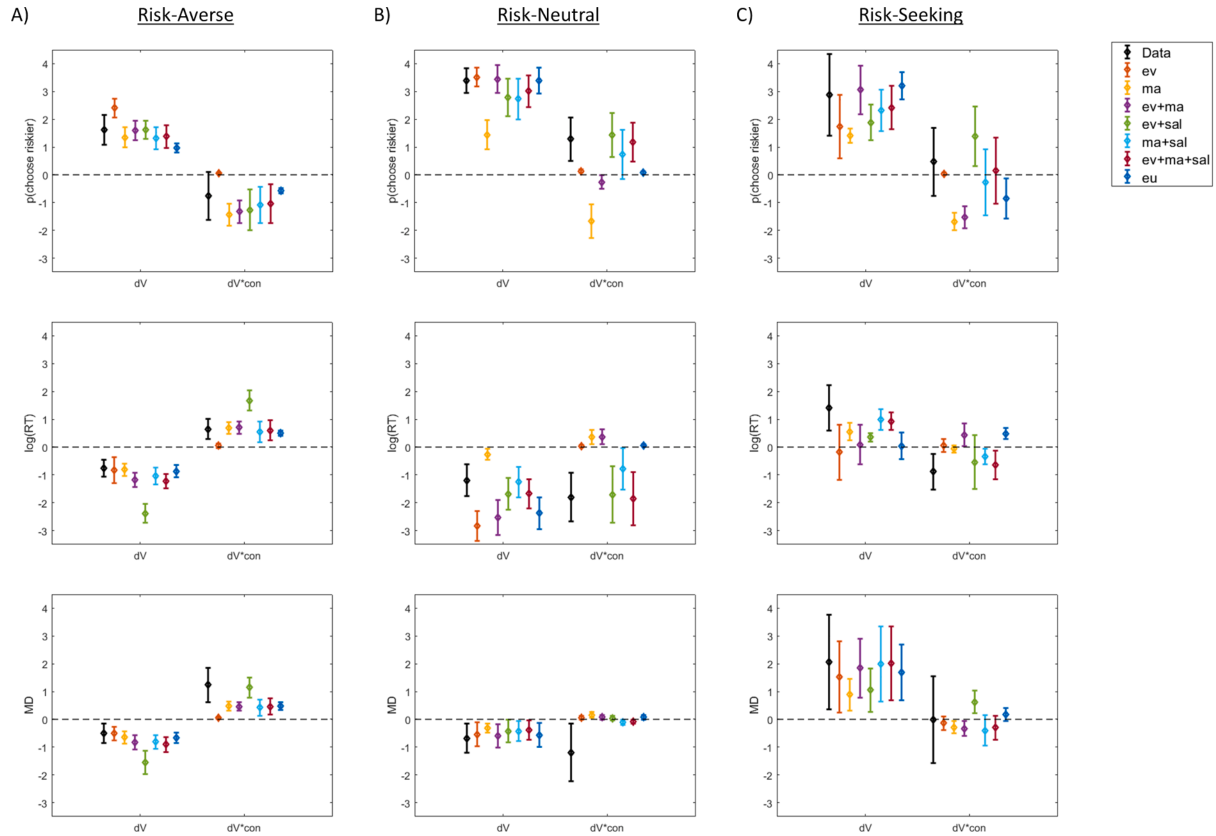

Fig. 6. Model predictions. Qualitative predictions of the effect of expected value difference (dV = EV of riskier option − EV of safer option) and the incremental effect of dV on conflict trials (dV * conflict) on choice probability (for the riskier option), log(RT), and maximum deviation (MD) in the empirical (in black) and simulated data (see legend for the color code for Models 1–7; shown for responses simulated using the best-fitting parameters for each model); dV is unsigned for RT and MD; diamonds represent fixed effects regression coefficients; error bars represent 95 % confidence intervals. Column A shows the risk-averse group, column B shows the risk-neutral group, column C shows the risk-seeking group.

group, only the models that include a salience parameter (Models 4–6) account for the qualitative patterns of the associations between the variables (Fig. 6B). For the risk-seeking group, Models 4 and 6 best account for the patterns in the data (Fig. 6C). Note that what is important here is the qualitative patterns of the coefficients for dV and dV * conflict *within* each data source, not the absolute magnitudes or comparisons across data sources.

3.3. Model comparison

To directly test whether our participants relied on information about expected value/utility (EV/U), individual attributes, or both expected value (EV) and individual attributes, independent of any potential salience effect, we performed a model comparison of only Models 1–3 & Model 7 (*evDDM*, *maDDM*, *ev+maDDM*, and *euDDM*). We found that Model 3 marginally dominated across all participants, with an estimated model frequency of 0.52 and an exceedance probability of 0.74 (Fig. 7A). Thus, it appears that most participants rely on comparisons of EV as well as additional comparisons of individual attributes when deciding. This aligns with previous findings (Lee & Hare, 2022). Repeating the model comparison for the risk-averse group only, Model 7 marginally won the competition (estimated model frequency = 0.55, exceedance probability = 0.75; Fig. 7B). Repeating this comparison for the risk-neutral group only, Model 3 decidedly dominated (estimated model frequency = 0.78, exceedance probability = 0.99; Fig. 7C). Repeating this comparison for the risk-seeking group only, Models 3 and 7 performed equally well (estimated model frequencies = 0.45 each, exceedance probabilities = 0.48 and 0.49, respectively; Fig. 7D). These results suggest heterogeneity in what information different types of people consider when deliberating about risky choices.

Our primary interest when conducting a model comparison of the DDM variants was in knowing whether risky decisions were made purely based on comparisons of EV/U of the available options, on direct comparisons of each of the individual attributes (monetary amount X and probability P), or on comparisons of EV as well as individual attributes. Our secondary interest was in knowing whether risky decisions were made based on EV and/or individual attributes plus an additional influence of the most salient attribute on each trial. We thus considered two core research questions: 1) if people integrate evidence before comparing it, compare evidence before integrating it, or both; 2) if the salience of individual attributes influences evidence accumulation. We tested each of these questions

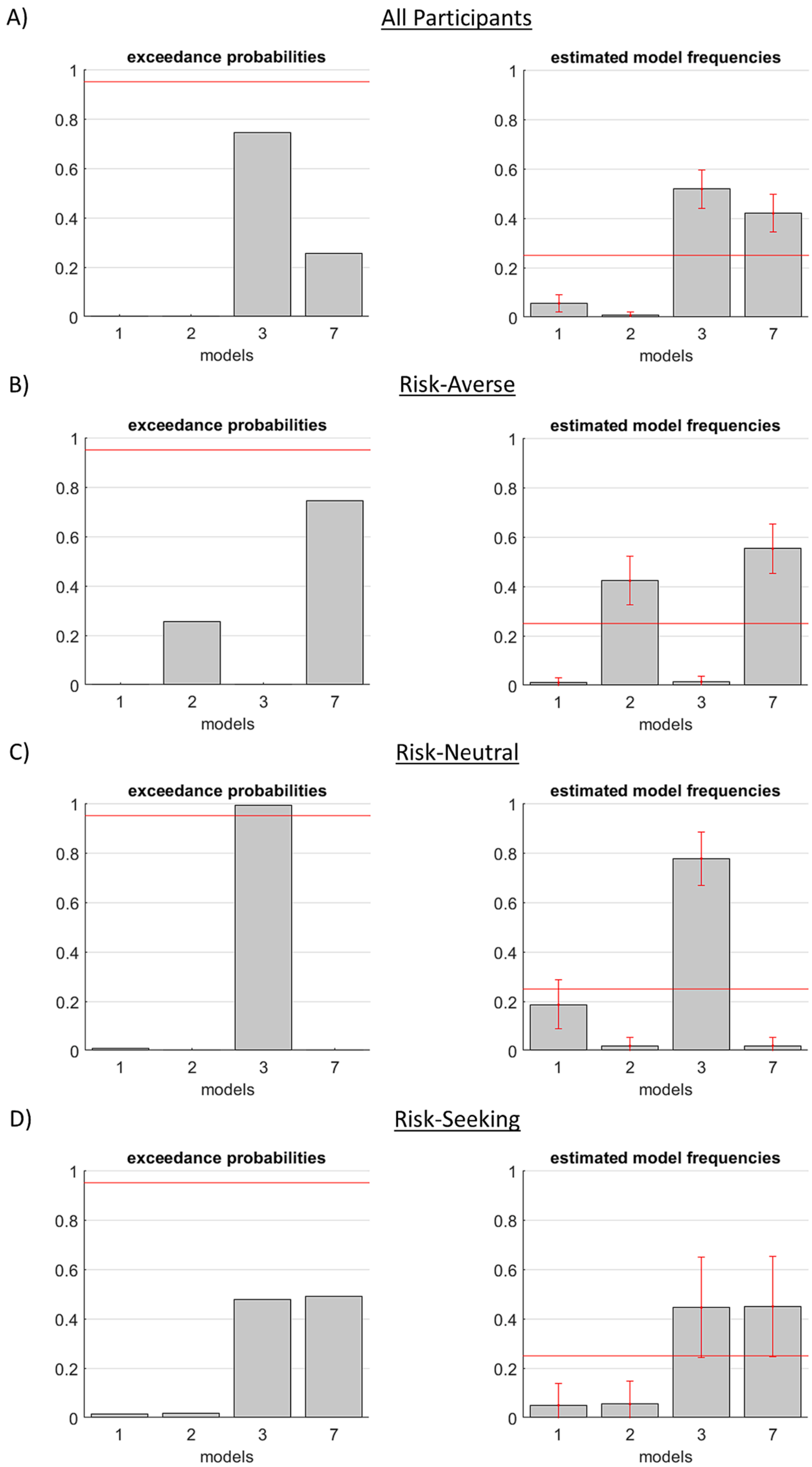

Fig. 7. Comparison of Models 1–3. Exceedance probabilities (left column) and estimated model frequencies across participants (right column) for each model. Row A shows all participants, row B shows risk-averse participants only, row C shows risk-neutral participants only, and row D shows risk-seeking participants only. Red lines indicate 95 % threshold for exceedance probabilities (left plots) or chance level of model frequency if models were equally probable a priori (right plots). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

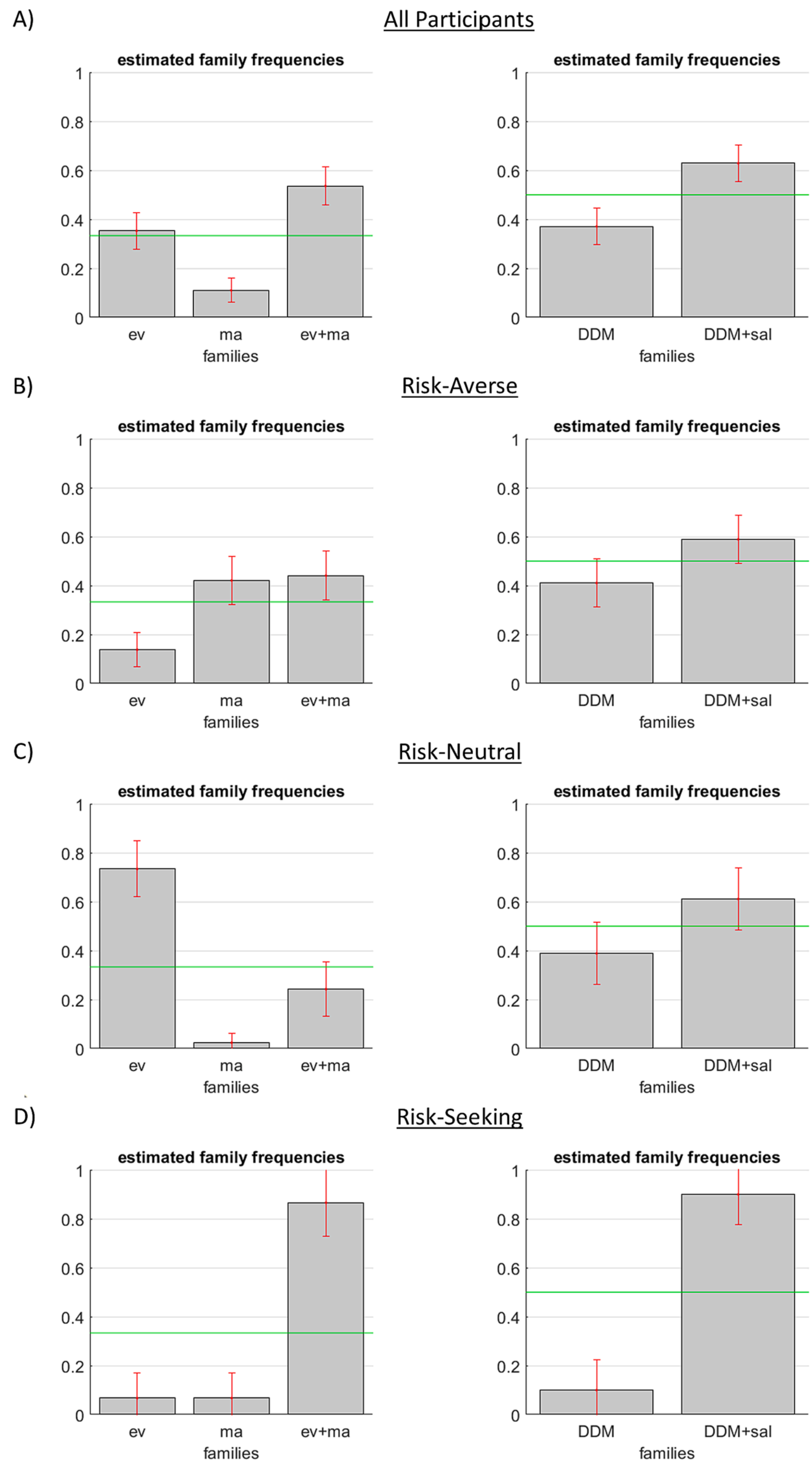

Fig. 8. Model family comparison. Estimated frequencies for model families based on evidence accumulation strategies (EV, individual attributes, or both; left column) or influence of attribute salience (not present or present; right column). Row A shows all participants, row B shows risk-averse participants only, row C shows risk-neutral participants only, and row D shows risk-seeking participants only. Green lines indicate chance level of family frequency if families were equally probable a priori. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

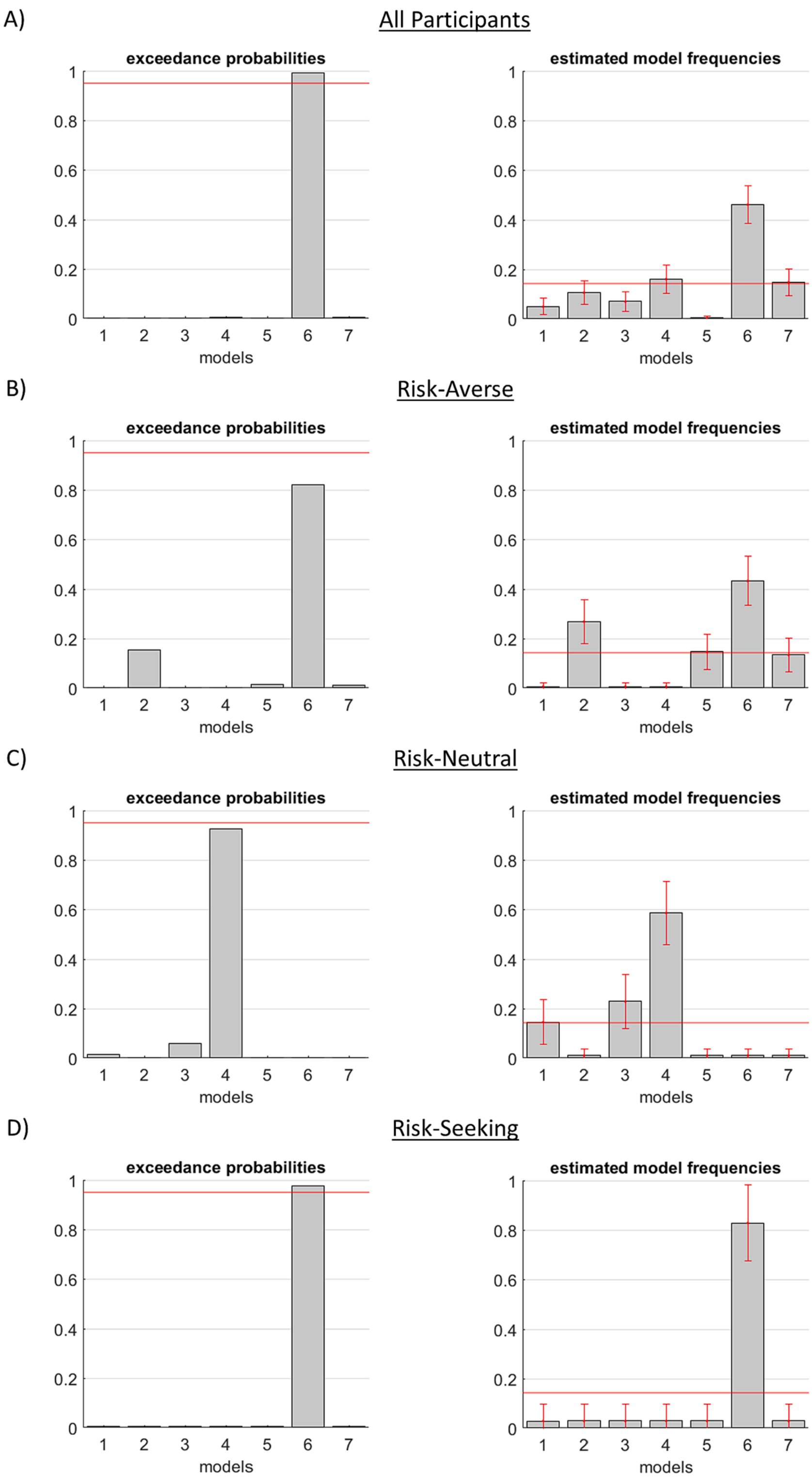

Fig. 9. Comparison of Models 1–6. Exceedance probabilities (left column) and estimated model frequencies across participants (right column) for each model. Row A shows all participants, row B shows risk-averse participants only, row C shows risk-neutral participants only, and row D shows risk-seeking participants only. Red lines indicate 95 % threshold for exceedance probabilities (left plots) or chance level of model frequency if models were equally probable a priori (right plots). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

separately by performing model family comparisons based on the core model features reflective of each question. In brief, the model family approach consists in pooling together model evidence for models that share core components, to test those specific components against competitors (while setting aside other differences between models within each family). This approach is more robust than comparing individual models when they can be considered variants of similar models or subclasses of a model class. As we have two main research questions, and each individual model contains features relevant to either question, we classified our models into family sets in two different ways. The first model family classification separates the models by evidence accumulation mechanism: Models 1, 4, and 7 all rely on comparisons of EV/U; Models 2 and 5 both rely on comparisons of individual attributes; and Models 3 and 6 both rely on comparisons of both EV and individual attributes. We examined this family classification with respect to research question 1 above. The second model family classification separates the models by the impact of attribute salience: Models 1–3 & 7 are not impacted by salience and Models 4–6 are. We examined this family classification with respect to research question 2 above.

For question 1, we found that the ev+ma model family, which uses comparisons of both individual attributes and EV, dominated (estimated family frequency = 0.54; Fig. 8A). Family frequency is defined as the portion of participants with more evidence in favor of a particular model family. Testing the risk-averse group separately, we found that both families that incorporated comparisons of individual attributes dominated the family that only incorporated comparisons of EV/U (estimated family frequencies: ma = 0.42, ev+ma = 0.44; Fig. 8B). Testing the risk-neutral group separately, we found that the family that incorporated only comparisons of EV/U dominated (estimated family frequency = 0.73; Fig. 8C). Testing the risk-seeking group separately, we found that family that incorporated comparisons both of EV and of individual attributes dominated (estimated family frequency = 0.87; Fig. 8D). Thus, we can conclude that risk-neutral participants mostly rely on an integrate-then-compare strategy (in line with classical economic theory) and that both risk-averse and risk-seeking participants mostly rely on a compare-then-integrate strategy, but also that a sizeable portion of participants in each group seem to use a mixed strategy by considering both EV and individual attributes.

For question 2, we found that the DDM+sal model family dominated (estimated family frequency = 0.63; Fig. 8A). This pattern held across all individual risk preference groups (estimated family frequencies: risk-averse = 0.59, risk-neutral = 0.61, risk-seeking = 0.90; Fig. 8B–D). We can thus conclude that most participants are affected by the salience of individual attributes. Interestingly, even participants who mostly compare EV/U across options (the risk-neutral group) seem to be influenced by differences in attribute salience. This provides clear evidence that even those who seem to choose based on classical economic theory (i.e., to maximize EV/U) nevertheless pay attention to the values of the individual attributes as a function of their salience.

To summarize, both our analyses indicate that participants consider individual attributes when making their choices, possibly in combination with EV comparisons.

We next performed a standard quantitative model comparison that included all our individual models (Models 1–7). Across all participants, Model 6 (*ev+maDDM+sal*) dominated (estimated model frequency = 0.46, exceedance probability = 0.99; Fig. 9A). Model frequency is defined as the portion of participants with more evidence in favor of a particular model, and exceedance probability quantifies the likelihood that a particular model accounts for the data better than the other models (Stephan et al., 2009). Given the results of the model family comparisons reported above, it is not surprising that Model 6 won the individual model comparison, as it is the only model that is a member of both winning families. Repeating the individual model comparison for the risk-averse group only, we found that Model 6 (*ev+maDDM+sal*) outperformed the others (estimated model frequency = 0.43, exceedance probability = 0.82; Fig. 9B). Note that the best-performing model relies on comparisons of individual attributes. Repeating the model comparison for the risk-neutral group only, we found that Model 4 (*evDDM+sal*) outperformed the others (estimated model frequency = 0.59, exceedance probability = 0.93; Fig. 9C). Note that the best-performing model relies on the influence of individual attributes according to their salience. Repeating the individual model comparison for the risk-seeking group only, we found that Model 6 (*ev+maDDM+sal*) outperformed the others (estimated model frequency = 0.83, exceedance probability = 0.98; Fig. 9D). Although different models performed best for the different groups, all best-performing models required information about individual attributes in one way or another.

Finally, although Model 3 did not win any of the competitions, we thought that examining the best fitting parameters across

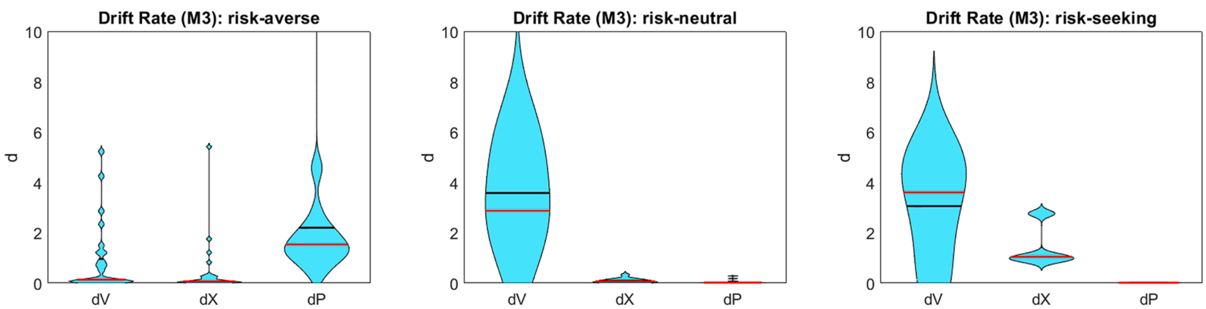

Fig. 10. Drift rate parameters across risk preference groups. Best fit drift rate parameters from the model (Model 3) based on EV as well as individual attributes (X = monetary amount, P = probability). Risk-neutral participants (middle plot) seemed to choose based solely on EV, whereas risk-averse participants (left plot) were influenced by P in addition to EV and risk-seeking participants (right plot) were influenced by X in addition to EV. Black lines indicate means, red lines indicate medians. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

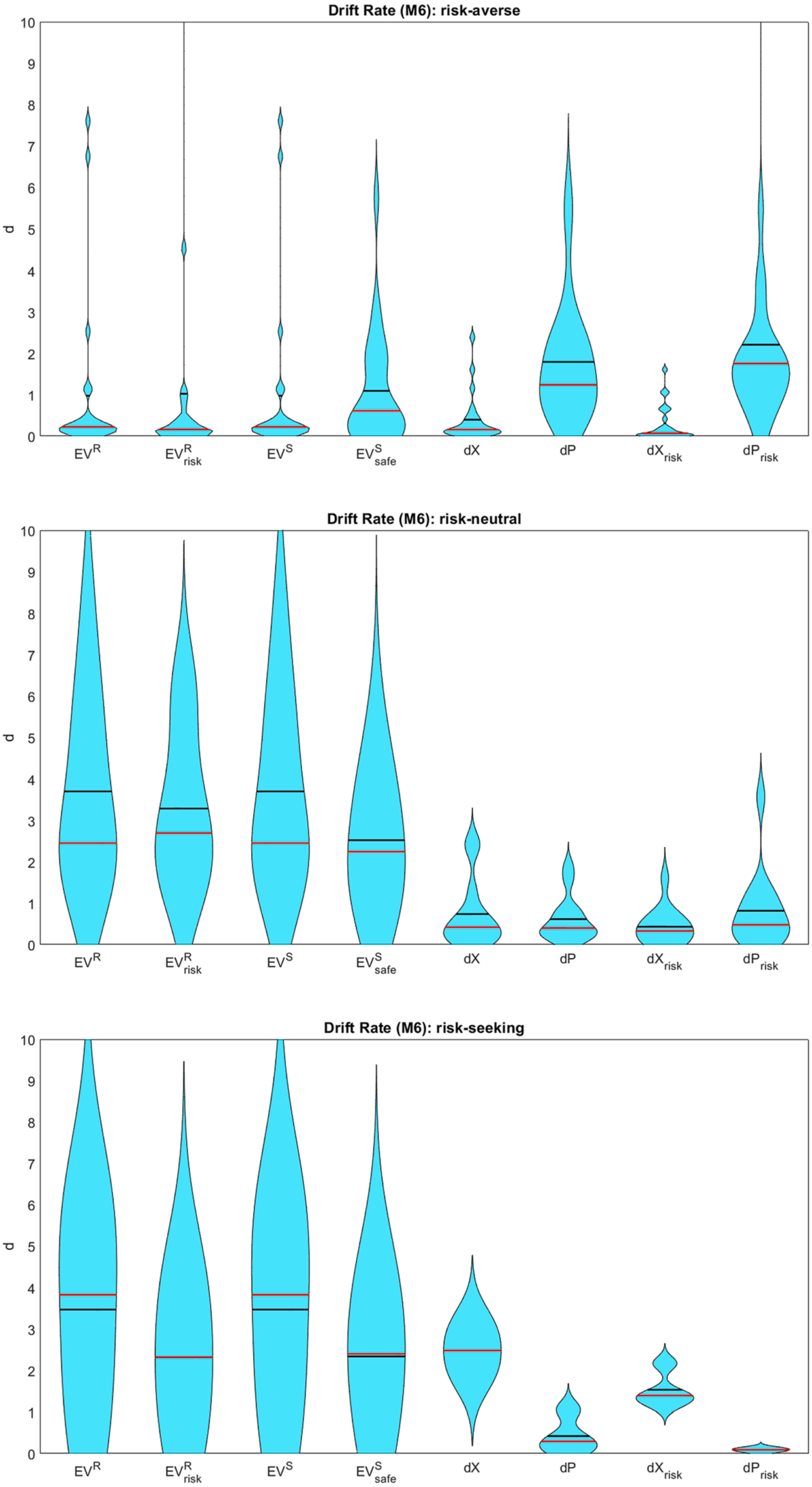

Fig. 11. Drift rate parameters across risk preference groups. Best fit drift rate parameters from the overall winning model (Model 6) based on EV as well as individual attributes (X = monetary amount, P = probability), with differential drift rates depending on salience condition. Black lines indicate means, red lines indicate medians. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

participants could be informative with respect to the way we grouped participants according to risk preference (see Fig. 10). Risk-averse participants had high drifts rate for probability (mean = 2.2), moderate drift rates for EV (mean = 1.0), and very low drift rates for monetary amount (mean = 0.1). This shows that these participants made their decisions based partially on EV comparisons, but also heavily influenced by differences in probability. Risk-neutral participants had very high drift rates for EV (mean = 3.6), very low drift rates for monetary amount (mean = 0.1), and negligible drift rates for probability (mean = 0.0). This shows that these participants made their decisions primarily based on EV comparisons. Risk-seeking participants had high drift rates for EV (mean = 3.1), moderate drift rates for monetary amount (mean = 1.0), and negligible drift rates for probability (mean = 0.0). This shows that these participants made their decisions based partially on EV comparisons, but also influenced by differences in monetary amount. In sum, these parameters validate our risk preference groupings.

Given that examining the parameter estimates for Model 3 was quite informative, we thought it might also be useful to examine the best-fitting parameters for Model 6, which was the overall winner when comparing models across all participants pooled together. This could help us better understand how preferences were modulated by salience and how this differs between risk preference groups, which could provide a more in-depth explanation of the group-dependent effects of salience on behavior. First, as expected, we found that the drift rates for risk-neutral participants did not change according to salience condition. For risk-averse participants, we found that on risk-salient trials, the drift rate for probability increased ($p = .002$). For risk-seeking participants, we found that on risk-salient trials, the drift rates for both monetary amount and probability decreased ($p = .019$ and $p = .047$, respectively). All other cross-condition differences were statistically non-significant. (See Fig. 11.)

We include a summary of posterior predictive checks for each model in the Supplementary Material, including choice probability, RT, and MD. We also include a demonstration that the winning model (M6) successfully accounts for a key pattern in the experimental data, namely that risk-neutral participants took significantly longer to respond, on average, compared to risk-averse or risk-seeking participants (see Supplementary Material).

4. Discussion

In this paper, we asked whether choices between options defined by multiple attributes or dimensions, specifically risky choices defined by the dimensions of “amount of money” and “probability of winning”, are resolved by considering the expected value (EV) of each option that results from the preliminary integration of the different attributes (*integrate-then-compare*), the values of the individual attributes separately (*compare-then-integrate*), or both the EV and the individual attributes (*combined-comparison*). To address this question, we designed a risky choice task in which participants made decisions between pairs of options (one safer and one riskier) that varied systematically in terms of both EV and salience, here defined as one attribute having a value substantially greater than all other attribute values within a given pair of options, plausibly influencing a *compare-then-integrate* decision mechanism.

Our analyses of behavioral and kinematic indexes of response probabilities, response times (RTs), and curvatures of mouse trajectories during decisions indicate that participants performed the task properly (e.g., their response probabilities are significantly modulated by the EV of the options within each choice pair). Moreover, our analyses revealed three main findings. First, participants seem to rely on a *combined-comparison* approach to information processing during deliberation. The quantitative model comparison showed that the model family based on parallel comparisons of EV and of individual attributes outperformed the others, and that the dominant individual model was also based on the *combined-comparison* approach. Second, participants could be categorized into distinct groups based on risk preference type: risk-averse, risk-neutral, or risk-seeking. Third, attribute salience significantly affected response probability as well as decision dynamics (as evident in both RT and response trajectory curvature), but differently for the different risk preference groups. When salience conflicted with the higher EV option, risk-averse participants were more likely to choose the salient option, whereas risk-neutral and risk-seeking participants were less likely to choose the salient option. Furthermore, all groups were faster to respond when conflict (or lack of conflict) caused their choice probabilities to move away from chance level. On these trials, participants also moved the mouse with a more direct trajectory – which is an index of increased choice confidence and decreased attraction from the non-selected alternative (Hehman et al., 2015; Spivey et al., 2005). Note that the RT and trajectory curvature results are consistent with the different choice preferences of the different groups.

This pattern of results can perhaps be explained by the fact that risk-averse participants prefer options with higher probabilities (by definition), whereas risk-seeking participants prefer options with lower probabilities (by definition; due to the relationship between lower probability and higher monetary payoff, holding EV constant) and risk-neutral participants mostly consider EV (by definition). In our experimental design, on trials where salience was for the riskier option, such options included both an exceptionally large monetary amount and an exceptionally small probability. It seems that risk-averse participants, who usually pay more attention to probability, paid particular attention to the large monetary amount when it was salient, thus making the riskier option more attractive (hence the higher choice probability when EV favored the safer option but salience favored the riskier option) and the choice more difficult (hence the slower RT and more deviant response trajectory). The opposite applies for trials where the large probability was salient: the riskier option became less attractive (hence the lower choice probability when EV favored the riskier option but salience favored the safer option) and the choice became easier (hence the faster RT and more direct response trajectory). Conversely, risk-neutral and risk-seeking participants seem to have paid particular attention to the small probability when SAL = riskier and the small monetary amount when SAL = safer, thus making the corresponding options (with the apparently salient small-valued attributes) less attractive. Thus, for these participants, conflict between EV difference and salience (as we defined it, according to the largest attribute value) actually made the choices easier (hence the steeper psychometric choice curve, faster RT, and more direct response trajectory on conflict trials). Although this divergence of the attribute salience effect across risk preference types was not something we predicted, we believe that the overall pattern of results clearly shows that salience exerted an influence on choice behavior and decision dynamics. [Note that for the purposes of this study, it is sufficient to infer the effect of salience by examining the behavioral data and by using computational models. This is because it is not a study of salience *per se*, but rather a study that takes advantage of behavior effects related to salience during multi-attribute decision-making. Even so, future work could include eye-tracking to provide even more evidence to support claims about which attributes or options are more salient to decision-makers.]

Taken together, these results show that people are sensitive to both the EV of the different options and the individual attributes of the options, and that the salience of the different attributes during choices also impacts behavior. The above results lend some support to conceptual models that highlight separate, within-attribute comparisons, but cannot fully distinguish whether these attribute comparisons are alternative to EV comparisons or concurrent to them (as envisaged by the *combined-comparison* models).

To address this last question more directly, we designed and systematically compared seven versions of drift-diffusion model (DDM) that incorporate different hypotheses about how multi-attribute decisions are made: two versions of an *integrate-then-compare model* (Model 1: *evDDM* and Model 7: *euDDM*) that only allow EV/EU comparisons; a *compare-then-integrate model* (Model 2: *maDDM*) that only allows separate comparisons of individual attributes; a *combined-comparison model* (Model 3: *ev+maDDM*) that allows both EV and attribute comparisons; a variant of the *integrate-then-compare model* that allows evidence to accumulate at different rates depending on which option contains the salient attribute on a given trial (Model 4: *evDDM+sal*); a variant of the *compare-then-integrate model* that allows evidence to accumulate at different rates depending on which attribute is salient on a given trial (Model 5: *maDDM+sal*); and a variant of the *combined-comparison model* that allows evidence to accumulate at different rates depending on which option contains the salient attribute on a given trial and on which attribute is salient on a given trial (Model 6: ev+*maDDM+sal*).

Our results show that the model family in which evidence accumulates according to comparisons of both EV and individual attributes outperforms the families in which either only EV or only attributes is considered. Our results also show that the model family in which evidence accumulation is affected by attribute salience dominates the family in which it is not. At the level of individual models, the model that best accounts for the data is Model 6, which contains comparisons of both EV and individual attributes, plus additional flexibility by allowing evidence accumulation to be influenced by attribute salience. Note that the extra flexibility provided by Model 6 gives it an advantage in the model comparison that holds despite the fact that our model comparison method balances accuracy and complexity (hence disfavoring model flexibility when it is not accompanied by a significant increase in accuracy). Model 6 has the most free parameters of any of our models, yet still dominates in the quantitative comparison. These results suggest that all types of people (risk-averse, risk-neutral, and risk-seeking) accumulate evidence about both EV and individual attributes while deliberating, and that information processing during risky decisions is influenced by the salience of the individual option attributes.

Salience is understood to impact the cognitive processes involved in decision-making through its ability to attract and capture attention. Attention-related arousal has been shown to accompany the presentation of offers with exceptionally high monetary amounts (Leuker et al., 2019). When a decision set contains a relatively high numerical magnitude for one of the options or attributes, the attention that it captures is thought to cause the decision-relevant information about that option or attribute to be weighted more heavily (Bordalo et al., 2012; Tsetsos et al., 2012). The idea that attention leads to differential weighting has been computationally demonstrated in previous work based on the *attentional drift-diffusion model* (aDDM; (Krajbich et al., 2010; Smith & Krajbich, 2019)). Under the aDDM, the evidence accumulation rate for the option that holds the attention of the decision-maker at any point in time (assumed to be the option that is visually fixated) is enhanced. This work has recently been extended to include attention towards a particular attribute in addition to attention towards a particular option (Yang & Krajbich, 2022). Our *evDDM+sal* and *maDDM+sal* models align well with the aDDM framework, in that attention (whether assumed by monitoring visual fixations or the highest numerical magnitudes) changes evidence accumulation rates. For our risk-averse group, it seems that the highest numerical magnitudes were the most salient. For our risk-neutral and risk-seeking groups, it seems that it was the *lowest* numerical magnitudes that were the most salient, rather than the highest. This would be consistent with increased evidence accumulation for the "worse" attribute (for the risk-neutral group) if these participants were choosing which option to reject rather than which to accept, which has been demonstrated in previous aDDM work (Sepulveda et al., 2020).

Our results are in line with recent work demonstrating that the evidence accumulation process assumed by sequential sampling models, and thus the ensuing choice behavior, differs as a function of attribute salience (He & Bhatia, 2023). In that study, the authors present a complex model in which evidence accumulates in a linear, additive way (as in our DDM variants), but attention is partially controlled by the salience of the attributes (whereas our models do not incorporate any attentional control mechanisms). Specifically, in their model, high values in a particular attribute will increase the probability that the next shift in attention will be towards the other attribute within the same choice option. This produces an effect similar to that of our Models 4 and 6, in which evidence accumulation for a particular option increases when that option contains the attribute with the greatest magnitude. Given that these are precisely the two models that won the model comparisons (within each risk preference group), our results might provide additional support for the theory proposed in that study.

Although the results of the full model comparison and the model family comparison show that most of our participants seemed to rely on a *combined-comparison* strategy that considers both EV and individual attributes, a sizeable minority of participants also seemed not to separately compare individual attributes. This was corroborated by the results of the direct comparison of only the three core models. There, therefore, seems to be a fair degree of heterogeneity in how different types of people might process information during risky choice deliberation. It is worth noting, however, that the support we observed for the model based only on EU (Model 7) was almost entirely due to the inclusion of the α parameter that distorts the weight of monetary amount. When repeating our model-based analyses using a version based on standard EV (without the distortion parameter; Model 1), it gained almost no support. It is interesting to note that including a parameter to distort the weight of monetary amount is somehow similar to including separate weighting parameters for monetary amount and for probability. One might thus interpret the benefit that the α parameter brings as additional evidence that people consider different attributes separately when faced with risky choices.

Although our model comparison results did show a clear winner, it is worth mentioning that this is not something that was obvious *a priori*. Comparing many models that are very similar to each other could possibly degrade the output of the model-fitting procedure, as different models could make very similar predictions. In such a situation, models could get confused with each other during a model recovery analysis. It is also likely that models would steal support from each other during a model comparison analysis. In that case, no model would be likely to gain enough support to be declared the overall winner. In this study, our models had multiple core similarities. For one thing, EV (X * P) and attribute sums (X + P, ignoring the weights) are usually highly correlated (when the variables are normalized). This would also be true for EV combined with attribute sums (X * P + X + P). So, our Models 1–3 might not have been easy to tell apart. Another thing is that the salience parameters in our Models 4–6 might have produced very similar effects, because they were all based on the same fundamental idea that evidence accumulation rates vary according to which attribute is salient and/or which option contains the salient attribute. In the end, however, our models were well recoverable, and the formal model comparison was indeed able to differentiate between them and establish a winner.

A more exhaustive model comparison might have included twelve models instead of only the seven which we focused on: Models 1–6 plus a version of each of those models based on EU instead of EV. However, this surely would have led to some of the problems outlined above. Furthermore, some of the models that we considered did not need the help of the EU distortion parameter for monetary amount (*alpha*) and thus would have been penalized for the additional parameter without receiving much benefit in terms of increased predictive performance. This could have caused those models to appear as losers in a model comparison, even though they won when the alpha parameter was not forced upon them. Regardless, it is outside the scope of this study to debate whether EU or EV is the better variable to include in drift-diffusion models of choice. Some studies use computational modeling to compare theories about potential cognitive mechanisms, using experimental data to validate the models. Others use it to account for effects observed in experimental data, comparing models only to expose the effects under scrutiny. This study belongs to the latter category.

When we reported group differences in our results, we conjectured that risk-averse participants might focus more on probability, risk-neutral participants might focus equally on both attributes, and risk-seeking participants might focus more on monetary amount. One possible interpretation of this idea would be that people have some personality trait that determines their risk preference, and that this trait causes them to process information in a biased manner during deliberation (e.g., by thinking more about one of the attributes than the other). However, the opposite direction of causality is equally plausible: people have some cognitive or neural variation that causes them to process information in a biased manner, which leads to the development of (or at least the appearance of) a particular risk preference. Here, we do not intend to support either of these interpretations over the other. Indeed, we believe that risk preferences (as defined in risky choice paradigms) and information processing strategies might be indistinguishable: something in the mind of a decision-maker might cause one attribute to be "overweighted" during deliberation, creating an apparent bias towards or away from riskier options. From this perspective, the processing strategy and the risk preference arise simultaneously from the same source. Future work might seek to differentiate the two, in which case an interesting research question would be whether there is a clear direction of causality between the two.

In sum, our results, based on both behavioral measures and drift-diffusion models, suggest that risky decisions are resolved differently for different types of people. For risk-averse and risk-seeking people, such decisions seem to be resolved by running in parallel multiple competitions between the individual attributes – in combination with an additional competition between expected values – and then integrating the partial results of the separate competitions afterwards (Hunt et al., 2014; Roe et al., 2001; Turner et al., 2018; Usher & McClelland, 2004). For risk-neutral people, risky decisions seem to be resolved by a competition between expected values but influenced by the salience of individual attributes. These results stand in contrast with the assumption of standard economic theory that choices require a unique comparison of expected values, and suggest that at the cognitive level, decision processes might be more distributed than commonly assumed. Furthermore, our results show that choice behavior can be altered when one attribute for one option is particularly salient. It would be interesting for future work to explore the possibility that the information processing strategy itself could be altered as a function of context or environment. Finally, and intriguingly, individual differences in risk preference correspond to distinct patterns in the effects of attribute salience, and these differences manifest differential evidence accumulation rates for either individual attributes or options according to trial type and risk preference trait.

Funding

This research received funding from the European Union's Horizon 2020 Framework Programme for Research and Innovation under the Specific Grant Agreement No. 945539 (Human Brain Project SGA3) to GP, the European Research Council under the Grant Agreement No. 820213 (ThinkAhead) to GP, the PNRR MUR projects PE0000013-FAIR and IR0000011–EBRAINS-Italy to GP. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Declaration of Competing Interest

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

Appendix A. Supplementary material

Posterior predictive checks and additional behavioral predictions. Supplementary material for this article can be found online at https://doi.org/10.1016/j.cogpsych.2023.101614.

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