

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

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

2

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Abstract

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, using behavioral measures and drift-diffusion models, provide evidence in favor of the framework where information about individual attributes independently impact 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 the opposite manner: risk-averse participants seem to focus more on probability, except when monetary amount is particularly high; risk-neutral participants, in contrast, seem to focus more on monetary amount, except when probability is particularly low.

40 **Introduction**

41 Most of our everyday decisions are between options defined by multiple attributes or
42 dimensions, such as: foods that provide different levels of pleasure and nutrition; houses that vary
43 in terms of size and location; or lotteries that offer different amounts of money available to win
44 and probabilities of winning. The classical economic perspective is that such multi-attribute
45 choices should be solved by first computing a unique overall *expected value* (EV) for each option,
46 which integrates all value-relevant attributes, and then comparing the EVs of the different options.
47 This comparison could perhaps be achieved through a process of evidence accumulation to a
48 threshold, as in the *drift-diffusion model* (DDM; (Ratcliff & McKoon, 2008)) or similar
49 mathematical accounts of economic choices (Rustichini & Padoa-Schioppa, 2015; Usher &
50 McClelland, 2001).

51 Despite its normative character and its centrality in neuroeconomic thinking, the idea that
52 choices require a mandatory integration of attribute values to form estimates of EV might be less
53 compelling than it appears. This is because, from a computational perspective, a system that makes
54 decisions by comparing EVs requires delaying the choice until all relevant attributes are integrated,
55 which could be especially challenging when they are numerous. Indeed, previous studies have
56 shown (using large-scale datasets) that EV alone is not the best model for choice (He et al., 2022;
57 Peterson et al., 2021). Rather than deciding via a unique comparison of EVs (*integrate-then-*
58 *compare* model), a more feasible alternative might be running in parallel multiple comparisons –
59 each between the values along one specific attribute dimension – and then integrating the partial
60 results of the competitions afterwards (*compare-then-integrate* model; see (Hunt et al., 2014; Roe
61 et al., 2001; Turner et al., 2018; Usher & McClelland, 2004)). Furthermore, the two models
62 described so far (*integrate-then-compare* and *compare-then-integrate*) are not mutually exclusive

63 – they could operate simultaneously. Therefore, it is possible to envisage a third model that
64 combines the two models (*combined-comparison*; see (Stewart, 2011)), which would perform
65 multiple comparisons – between the values of individual attributes *and* between their integrated
66 EVs – and then combine the outcomes of all of the comparisons to determine the final choice.

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

86 When empirically testing whether, during multi-attribute decisions, attributes are
87 considered individually (*compare-then-integrate model*) or integrated to form overall expected
88 values before entering the competition (*integrate-then-compare model*), a recurrent problem is that
89 it is difficult to disentangle the above models experimentally, as they tend to generate very similar
90 predictions across a range of experimental conditions (Stewart, 2011). In other words, most
91 standard paradigms used in economics and neuroeconomics are not sensitive enough to distinguish
92 between the above models. However, some studies have attempted to do just that, with some
93 success. For example, Noguchi and Stewart (Noguchi & Stewart, 2014) used eye-tracking to show
94 that participants made a series of comparisons within each choice trial, with each comparison
95 taking place within a specific attribute dimension. The authors concluded that psychological
96 models of choice should thus be based on within-attribute comparisons (Noguchi & Stewart,
97 2014). Other eye-tracking and computational modeling studies investigating risky choice have
98 found that participants seem to perform within-alternative integrations rather than within-attribute
99 comparisons (Fiedler & Glöckner, 2012; Glickman et al., 2019). The topic has also been explored
100 in the domain of intertemporal choice, using mouse-tracking to show that some participants seem
101 to integrate within alternatives whereas others seem to compare individual attributes across
102 alternatives (Reeck et al., 2017). The question about within-alternative versus within-attribute
103 comparisons has been asked not only with respect to human decision-makers, but also rhesus
104 macaques (Farashahi et al., 2019). A few studies have already used drift-diffusion modeling to
105 provide evidence that participants compare individual attributes during deliberation about
106 intertemporal choices (Dai & Bussemeyer, 2014) or that they seem to both compare attributes across
107 options and integrate values within options during value-based decisions (Lee & Hare, 2022; Yang
108 & Krajbich, 2022).

109 To help resolve the inconsistencies of the above studies and to further adjudicate amongst
110 *integrate-then-compare*, *compare-then-integrate*, and *combined-comparison* models of decision-
111 making, we designed a “risky” choice task that parametrically varied not only the expected values
112 of different options (as in previous studies), but also the relative *saliency* of the attributes that enter
113 the competition. Our concept of saliency aligns with that set forth in Saliency Theory (Bordalo et
114 al., 2012), where an option is deemed more salient when it contains a measure of an attribute that
115 is much higher than the attributes of the other option. We reasoned that rendering one attribute
116 more salient than the other on each trial could be particularly diagnostic, as it might make the
117 (putative) within-attribute competition faster, influencing the overall pattern of choice behavior.
118 A similar effect has been demonstrated in a risky choice task featuring numerical streams of
119 potential payoff amounts, where the authors deemed that larger numerical values were more salient
120 to the participants (Tsetsos et al., 2012). The assumption that higher numerical values will be more
121 salient is also supported by previous experimental and computational work based on value-based
122 attentional capture, which assumes that more attention will be focused on options with higher
123 expected values, and that the additional attention will impact choice behavior (Gluth et al., 2018,
124 2020). Assessing the relative importance of EV versus individual attributes together with the
125 saliency of attributes during choices could permit adjudicating between models that postulate
126 *integrate-then-compare*, *compare-then-integrate*, or *combined* processes.

127 In our task, participants used a computer mouse to make a series of risky choices between
128 two options (lotteries) characterized by two dimensions: the amount of money to be won and the
129 probability of winning it. An example choice is between “90% probability of winning €20” and
130 “30% probability of winning €60”. From this point onward, consistent with the neuroeconomics
131 literature, we label the option having the highest probability (e.g., “90% of probability of winning

132 €20”) as *safer* and the option having the lowest probability (“e.g., 30% probability of winning
133 €60”) as *riskier*.

134 Importantly, in our experiment, the choice option pairs varied across two dimensions:
135 *expected value difference* (dV) and *saliency* (SAL). The two categories of SAL reflect the fact that
136 for each trial, either the probability or the amount of money is particularly salient, as it has a high
137 value that is at least 1.5 times greater than the second-highest value on display. (Note that this
138 notion of saliency is not related to bottom-up characteristics of the stimuli, such as size, color, or
139 clarity.) We reasoned that if the attributes are processed independently, the most salient attribute
140 might be processed differently (e.g., faster) than the less salient attribute. In contrast, if the
141 attributes are not processed independently, the saliency of individual attributes should have no
142 impact on choice dynamics. Specifically, we assume that SAL is for the safer option if the salient
143 number corresponds to its probability and that SAL is for the riskier option if the salient number
144 corresponds to its amount of money. For example, the choice between “90% probability of winning
145 €20” and “30% probability of winning €60” would have dV = equal (as both options have the same
146 EV) and SAL = safer (as the most salient number is 90, which corresponds to the probability
147 attribute of the safer option).

148 By manipulating the SAL of attributes independent of the EV of options, this experimental
149 design generates a diverse range of trials, for which the *integrate-then-compare*, *compare-then-*
150 *integrate*, and *combined-comparison* models would make different predictions. Broadly speaking,
151 under the *integrate-then-compare* model, response probabilities, response times, and mouse
152 trajectories should not be sensitive to the SAL of individual attributes, because the attributes would
153 not be processed independently (before being integrated into EV). Conversely, under the *compare-*
154 *then-integrate* and *combined-comparison* models, both dV and SAL should exert an influence on

155 the decision process and the associated choice variables. However, the predictions made by the
156 above models could be more subtle than what we described. For that reason, we base our analysis
157 on a quantitative model comparison of a set of computational (drift-diffusion) models that
158 formalize the alternative *integrate-then-compare*, *compare-then-integrate*, and *combined-*
159 *comparison approaches*.

160 Finally, our experimental design allows us to examine potential differences in participant
161 behavior according to their risk preference type (i.e., how well they tolerate risk when choosing
162 between options with different outcome probabilities). It has long been shown that there are
163 individual differences in risk preference (Tversky & Kahneman, 1992), with some people avoiding
164 it (risk-averse), some indifferent to it (risk-neutral), and some drawn to it (risk-seeking). Risk
165 preferences can be deduced by examining how people's choice probabilities deviate from classical
166 economic theory. For instance, in the above example ("90% probability of winning €20" versus
167 "30% probability of winning €60"), classical economic theory would predict indifference, because
168 the expected values of the options are identical (€18). A risk-neutral person would be indifferent
169 and thus adhere to classical economic theory. A risk-averse person would prefer the first option,
170 because it has the higher probability (i.e., lesser risk). A risk-seeking person would prefer the
171 second option, because it has the higher monetary amount (and thus the lower probability or greater
172 risk). One might hypothesize, therefore, that different attributes are inherently more or less
173 important than others for different types of people (probability > monetary amount for risk-averse
174 people, probability < monetary amount for risk-seeking people). In terms of our salience
175 manipulation, we might then expect a different effect to emerge for the different groups.
176 Specifically, on trials that we classify as SAL = riskier (where the monetary amount of the riskier
177 option is the greatest number on the screen), risk-averse people might actually be repulsed by the

178 riskier option (because it will also have a very low probability, which is more important to them
179 than the large monetary amount). Something analogous might occur for risk-seeking people on
180 trials where SAL = safer. We thus tested for group differences in the behavioral data, and we also
181 tested whether the winning computational model might differ across groups. Given that risk
182 preference is a topic that has long been studied, it could be of interest if our modeling analysis
183 illuminated differences in parameters or even models across risk preference groups.

184 To preview our results, we found that both expected value difference and salience affect
185 the final choices as well as the choice dynamics, as indexed by response time and the curvature of
186 the response trajectory. Furthermore, the computational model that best accounts for the data
187 (when considering all participants together) is the one that incorporates the *compare-then-integrate*
188 framework in addition to the *integrate-then-compare* framework, along with differential evidence
189 accumulation rates according to salience condition. Grouping participants by risk preference
190 reveals that both groups consider individual attributes in their choices, but they do so in addition
191 to different overall strategies (*compare-then-integrate* for risk-averse and *integrate-then-compare*
192 for risk-neutral).

193

194 **Methods**

195 *Ethics approval*

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

198

199 ***Participants***

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

204

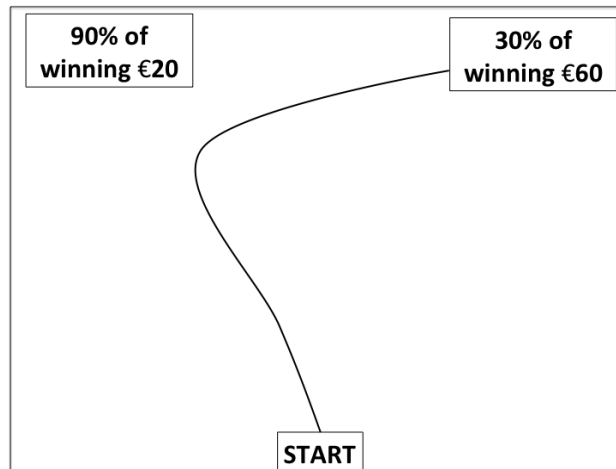
205 ***Stimuli and procedure***

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

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

222 response buttons appeared (one at the upper-left and one at the upper-right of the screen) and
223 remained on the screen until a response was entered.

224



225

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

232

233 ***Behavioral and kinematic measures***

234 Choice and response time (RT, from when participants pressed *START* until they reached
235 and pressed one of the response buttons) were recorded for each trial, as were the x and y
236 coordinates of the mouse trajectories (with a sampling rate of approximately 70Hz). For all
237 analyses reported below, we converted RT to seconds and ignored outlier trials (defined as having
238 $\log(\text{RT})$ greater than the median $\pm 3x$ the median average deviation, within participant). With
239 respect to mouse movement, we focused on the *maximum deviation* (MD) of the trajectories, which
240 indexes choice uncertainty and the competition between response alternatives (Hehman et al.,

241 2015; Spivey et al., 2005). The MD is the maximum shortest distance between each point on the
242 observed mouse trajectory and an ideal straight line connecting the start button to the response
243 button. The closer the mouse trajectory is to this ideal line, the smaller the MD will be, indicating
244 a higher confidence in the choice. For each of the regression analyses that we report below, we
245 used mixed effects models with random slopes and intercepts for each participant in addition to
246 the regressors of interest.

247

248 *Drift-diffusion model-based analysis*

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

261 We followed the approach used by Lee and Hare (Lee & Hare, 2022) and considered three
262 main models. Model 1 (*expected value DDM* or *evDDM*) is based on comparisons of expected
263 value (EV). Model 2 (*multi-attribute DDM* or *maDDM*) is based on independent comparisons of

264 the monetary amount (X) and probability (P) attributes. Model 3 (*multi-attribute DDM plus*
 265 *expected value* or *ev+maDDM*) is based on comparisons of both individual attributes X and P and
 266 EV. We also included variants of Models 1-3 in which the rates of evidence accumulation can
 267 differ as a function of salience condition (Model 4: *multi-attribute DDM plus salience* or
 268 *maDDM+sal*, Model 5: *expected value DDM plus salience* or *evDDM+sal*, Model 6: *expected*
 269 *value DDM plus salience* or *ev+maDDM+sal*). These latter models reflect a key assumption of
 270 our design, that the salience of attributes influences evidence accumulation. The mathematical
 271 details of each model are provided below.

272

273 *Model 1: expected value DDM (evDDM)*

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

279

$$DV = EV_R - EV_S$$

280

$$drift = d^V DV$$

281

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

282

$$\varepsilon \sim N(0, \sigma^2)$$

283

$$e_0 = 0$$

284 where EV_R and EV_S are independent variables, and d^V and σ^2 are free parameters to be estimated
 285 to capture the individual-specific rate of evidence accumulation (drift) and level of noise in the
 286 accumulation process (diffusion), respectively. Evidence accumulation terminates when e reaches

287 a response boundary $\in \{\theta, -\theta\}$, with the sign of the final value of e determining the chosen option
 288 (arbitrarily defined as positive for the riskier option, negative for the safer option) and the final
 289 value of t determining the response time (RT).

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

$$293 \quad p \stackrel{\text{def}}{=} p(\text{ch} = \text{riskier}) = \frac{1}{1 + e^{\frac{-2 * \text{drift}}{\sigma^2}}}$$

$$294 \quad E[RT] = \frac{2p - 1}{\text{drift}} + NDT$$

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

299

300 *Model 2: multi-attribute DDM (maDDM)*

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

$$304 \quad DX = X_R - X_S$$

$$305 \quad DP = P_R - P_S$$

$$306 \quad \text{drift} = d^X DX + d^P DP$$

307 where X_R , X_S , P_R , and P_S are independent variables, d^X and d^P are free parameters to capture the
 308 individual-specific rates of evidence accumulation for X and for P, and σ^2 captures the noise in the
 309 overall evidence accumulation process.

310

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

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

$$323 \quad drift = d^V DV + d^X DX + d^P DP$$

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

324

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

326 The fourth model is similar to Model 1, except that now evidence accumulation rates can
 327 differ according to which option is affiliated with the most salient attribute on each trial. The idea
 328 here is that whichever option has an attribute that is salient on a given trial will capture more
 329 attention and thus adjust the rate at which information is processed about that option relative to the

330 other option. The computational structure is otherwise identical to that of Models 1-3, and evidence
 331 accumulates as follows:

$$336 \quad drift = (d^V + d_r^V * risk) * EV_R - (d^V + d_s^V * safe) * EV_S$$

332 where d_r^V and d_s^V are free parameters to capture the individual-specific rates of incremental
 333 evidence accumulation for the riskier option when SAL = riskier and for the safer option when
 334 SAL = safer, respectively, $risk = 1$ if salience favors the riskier option (and 0 otherwise), and $safe$
 335 = 1 if salience favors the safer option (and 0 otherwise).

337

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

339 The fifth model is similar to Model 2, except that now evidence accumulation rates can
 340 differ according to which attribute is salient on each trial. The idea here is that whichever attribute
 341 is salient on a given trial will capture more attention and thus adjust the rate at which information
 342 is processed about that attribute relative to when it is not salient. The computational structure is
 343 otherwise identical to that of Models 1-4, and evidence accumulates as follows:

$$349 \quad drift = (d_r^X DX + d_r^P DP) * risk + (d_s^X DX + d_s^P DP) * safe$$

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

350

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

352 The six model is essentially a hybrid of Modes 4 and 5. The computational structure is
 353 otherwise identical to that of Models 1-5, and evidence accumulates as follows:

$$355 \quad drift = (d^V + d_r^V * risk) * EV_R - (d^V + d_s^V * safe) * EV_S + (d_r^X DX + d_r^P DP) * risk$$

$$356 \quad + (d_s^X DX + d_s^P DP) * safe$$

354

357 We note that our model formulations do not contain a free parameter to represent a *starting*
 358 *point bias* in the evidence accumulation process. This parameter is popular in drift-diffusion
 359 modeling studies, as it allows for the possibility that one of the responses may be a sort of default
 360 option for a participant before the specific options are even presented. Previous studies on risky
 361 choice have found a starting point bias related to loss aversion (Clay et al., 2017; Sheng et al.,
 362 2020; Zhao et al., 2020). Although we do not explore loss aversion in this work, we thought it
 363 might be possible that the starting point bias parameter could serve to capture the risk-aversion
 364 tendencies that we found in our data. We therefore performed quantitative comparisons of our set
 365 of models with this additional parameter versus without, using formulations provided in previous
 366 studies (Grasman et al., 2009; Lopez-Persem et al., 2016). The models performed better without
 367 the starting-point bias parameter. We therefore decided to simplify our analysis by excluding this
 368 parameter (or equivalently, fixing it to zero). We also did this (for the same reason) for an optional
 369 parameter that allows for a fixed component of the drift rate (i.e., a drift component independent
 370 of the trial-specific option values).

371 Using the VBA toolbox in Matlab (see below) to fit and compare models allows us to
 372 simultaneously fit other choice variables in addition to those included in the DDM (choice
 373 probability and RT). VBA simultaneously optimizes parameters over a set of analytical equations,

374 such as those listed above for choice probability and mean RT. Importantly, we can just as easily
375 perform our model comparison while fitting additional equations. To that end, we fit generalized
376 predictions about the relationship between the evidence accumulation (drift) rate and maximum
377 mouse trajectory deviation (MD) in addition to choice probability and mean RT. We estimated
378 MD as a linear function of either expected value difference (ev), individual attribute differences
379 (ma), both (ev+ma), or expected value differences and individual attribute differences dependent
380 on salience condition, or both (ev+sal, ma+sal, ev+ma+sal, respectively). The formula that we
381 used to estimate MD under each model was:

$$382 \quad MD = \beta_0 + \beta_1 * drift$$

383

384 ***Model fitting procedure***

385 We fit each of the candidate models to the experimental data, then performed Bayesian
386 model comparison to determine which of the models (if any) performed significantly better than
387 the others across the population of participants. For this model fitting and comparison exercise, we
388 relied on the Variational Bayesian Analysis toolbox (VBA, available freely at [https://mbb-](https://mbb-team.github.io/VBA-toolbox/)
389 [team.github.io/VBA-toolbox/](https://mbb-team.github.io/VBA-toolbox/); (Daunizeau et al., 2014)) with Matlab R2022b. Within participant
390 and across trials, we entered the experimental variables {monetary amount, probability, and
391 expected value for each option; observed RT; salience condition} as input and {choice = 1 for the
392 riskier option, 0 for the safer option; RT; MD} as output. All monetary amounts were rescaled to
393 the range (0,1] in accord with the probability measures. We also entered the model-specific
394 mappings from input to output as outlined in the analytical formulas above. As we fixed the
395 threshold parameter θ to 1, the parameters to be fitted were the drift scalar (d), diffusion noise (σ^2),
396 and non-decision time (NDT) terms described above in the model formulations, plus the slope and

397 intercept parameters for MD. VBA requires prior estimates for the free parameters, for which we
398 set the mean and variance equal to: 1.6 and 37 for the positively constrained parameters (noise and
399 all drift scalars); 0.5 and 3.7 for NDT (constrained between 0 and 1); and 0 and 16 for the
400 unconstrained MD parameters. The theoretical drift rate, noise, and NDT parameters are always
401 positive; we thus constrained the search space of our model fitting algorithm to the positive domain
402 by replacing these parameters with the following calculation: $\log(1 + \exp(\text{parameter})) * 2.3$. VBA
403 then recovers an approximation to both the posterior density on unknown variables and the model
404 evidence (which is used for model comparison). We used the VBA_NLStateSpaceModel function
405 to fit the data for each participant individually, followed by the VBA_groupBMC function to
406 compare the results of the model fitting across models for the full group of participants.

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

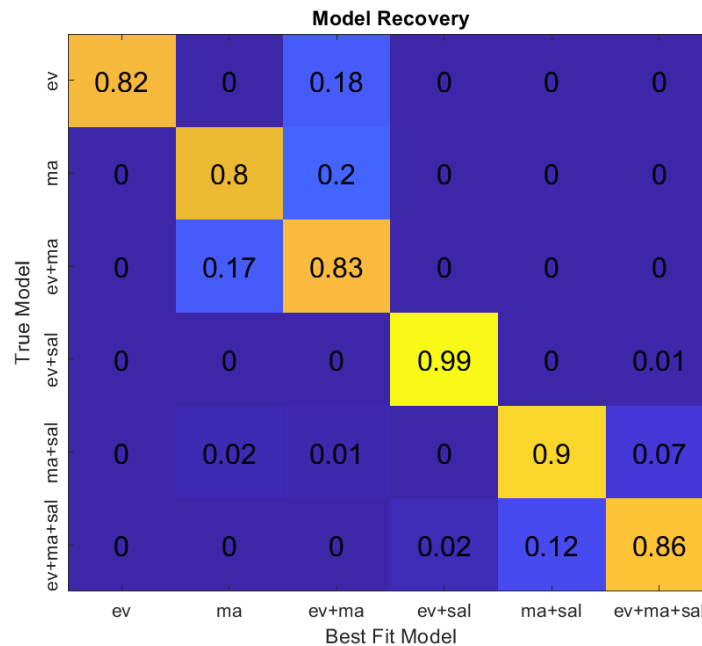
420 The VBA toolbox also allows models to be formally tested across what is known as
421 “families” based on fundamental similarities across all models within each family. We established
422 two types of family in our set of models. The first model family category represented our primary
423 research question: is evidence integrated then compared, compared then integrated, or some
424 combination of both. These families were thus: $ev = \{\text{Model 1, Model 4}\}$; $ma = \{\text{Model 2, Model}$
425 $5\}$; $ev+ma = \{\text{Model 3, Model 6}\}$. The second model family category represented our secondary
426 research question: does the salience of individual attributes impact evidence accumulation. These
427 families were thus: $DDM = \{\text{Models 1-3}\}$; $DDM+sal = \{\text{Models 4-6}\}$. We compared the aggregated
428 model performance across families using the *options.families* input to the *VBA_groupBMC*
429 function.

430

431 ***Model recoverability***

432 To verify that our model-fitting procedure is suitable for this specific analysis, we
433 performed a test of model recoverability. Specifically, we took as the model input the same
434 monetary amounts and probabilities from the choice trials that the participants were faced with.
435 We then simulated the set of choice probabilities, mean RTs, and MDs for each participant,
436 separately according to each of our models, using the actual participant-specific fitted parameters
437 for each model. Finally, we fit all simulated data (per participant) to each of our models and
438 performed the same formal model comparison as with our real experimental data. The results of
439 this procedure can be seen in Figure 2. This matrix shows, for each true generative model, the
440 percentage of participants (simulated under that model) that were attributed to each of the best fit
441 models by our model-fitting procedure. As shown in the matrix, model confusion was low and the
442 procedure attributed the true generating model as the best-fitting model for the vast majority of

443 participants (recovery accuracy: 82% for *evDDM*, 80% for *maDDM*, 83% for *ev+maDDM*, 99%
 444 for *evDDM+sal*, 90% for *maDDM+sal*, and 86% for *ev+maDDM+sal*). There was a small amount
 445 of confusion between the *ev+maDDM* and the *evDDM* and *maDDM*, which is to be expected since
 446 the *ev+maDDM* is essentially a combination of those other models.



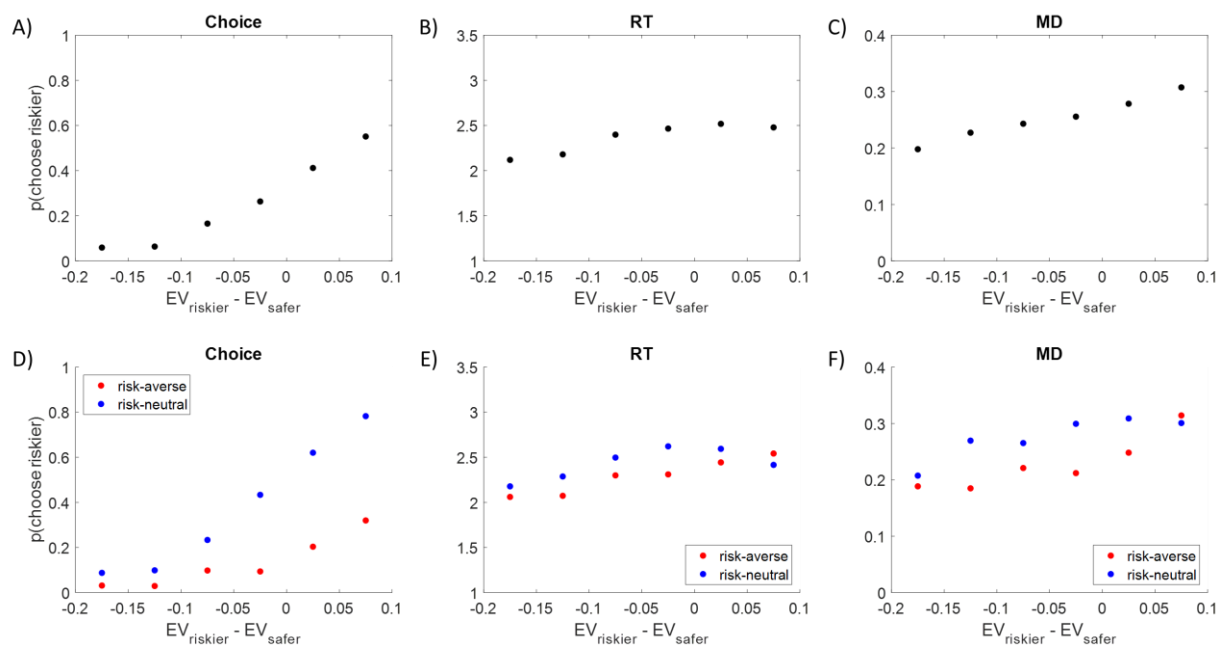
447
 448 **Figure 2. Model recovery analysis.** *The cells in each “confusion matrix” summarize the*
 449 *percentage of participants (simulated under each true model) for which our model-fitting*
 450 *procedure attributed each of the (best fit) models.*

451
 452 **Results**

453 ***Behavioral measures***

454 We first examined the three decision variables of interest (choice, response time or RT,
 455 and maximum deviation or MD) in a model-free manner by observing their relationships with the
 456 relative attractiveness of the riskier option compared to the safer option. Specifically, we considered
 457 the difference in the expected value (EV = monetary amount * probability) of the riskier option

458 minus that of the safer option. The closer this difference is to zero, the more difficult the choice is
 459 presumed to be. Pooling together all trials across all participants, we separated the data into bins
 460 of equal widths covering the full range of EV difference. Within each bin, we calculated the
 461 percentage of trials where the riskier option was chosen, the mean RT, and the mean MD. Our data
 462 seem to conform to standard psychometric findings, where choices are close to chance level (50%),
 463 RTs are longest, and MDs are largest when the decision variable is closest to zero. However, we
 464 found a clear skew in our data, where this equivalence point was shifted away from zero toward
 465 the right of the EV difference scale (Figure 3A-C). This indicates that our participants (on average)
 466 were averse to risk, as has often been reported in studies of risky choice (O'Donoghue &
 467 Somerville, 2018).



468

469 **Figure 3. Behavioral results.** A-C) Choice probability (of choosing the riskier option), response
 470 time (RT), and maximum mouse trajectory deviation (MD) plotted against EV difference (riskier
 471 minus safer), pooled across all participants. D-F) Choice probability, RT, and MD plotted against
 472 EV difference, pooled across participants after performing a median split by risk preference type.
 473 Each dot represents an average across all trials within EV difference bins of equal range.

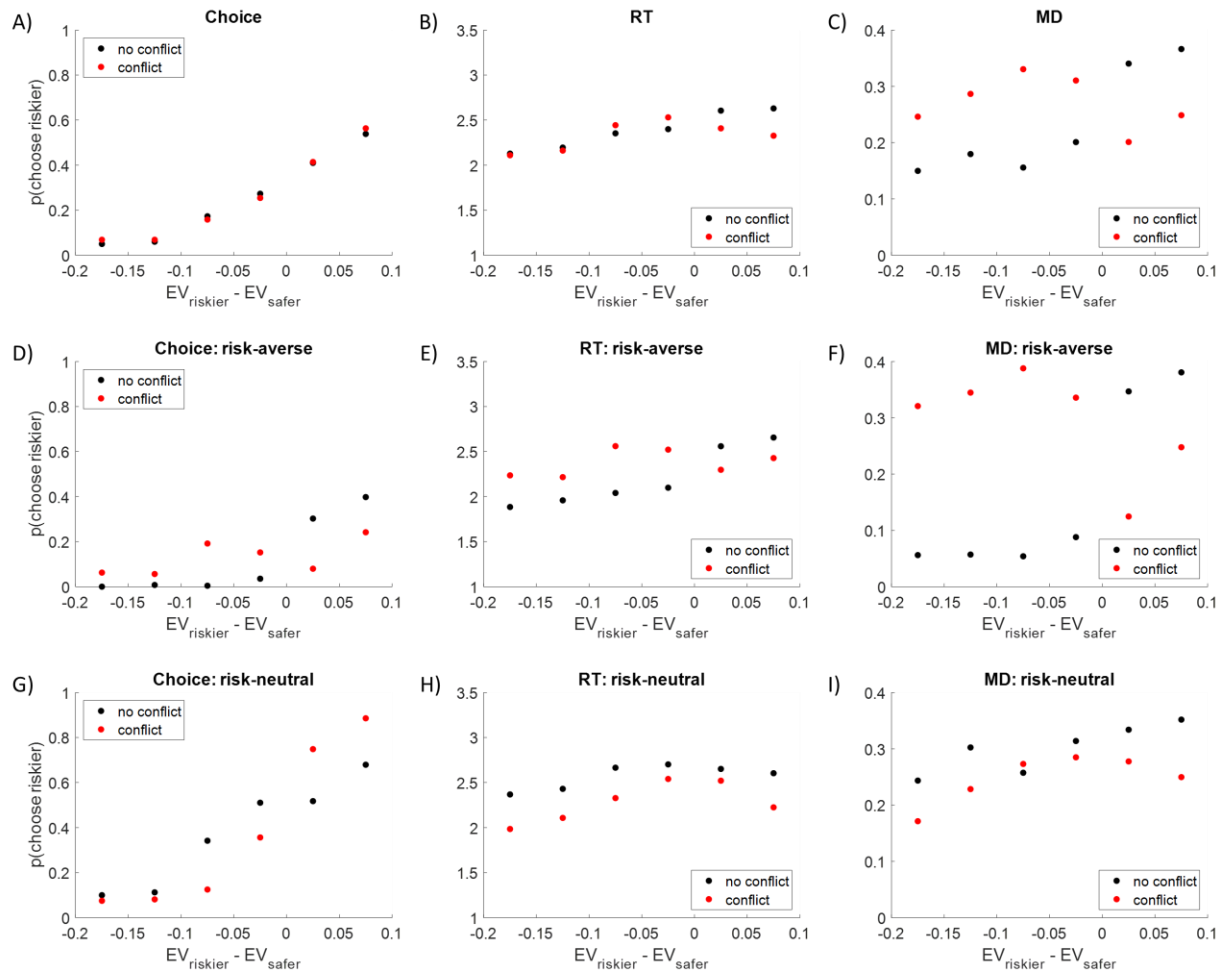
474

475 It is well known that people vary in terms of their risk preferences. Given that our data
476 clearly indicated that our participants (as a whole) were averse to risk, we checked if we could
477 reasonably split our participants into two groups: risk-neutral and risk-averse. To do this, we first
478 estimated a parameter *alpha* (α) that is commonly-used to capture risk aversion (cf, Prospect
479 Theory (Tversky & Kahneman, 1992)), separately for each participant: $X \leftarrow X^\alpha$ (X = monetary
480 amount). We used VBA to fit the basic prospect theory logistic model of choice probability for
481 each participant (including both α and the c parameter that captures probability distortion;
482 specifically, $EV = X * P$ became $EU = X^\alpha * \frac{P^c}{(P^c + (1-P)^c)^{\frac{1}{c}}}$ as in the original Prospect Theory
483 formulation). A value of α close to 1 indicates no aversion to risk, whereas a value of α close to 0
484 indicates extreme risk aversion. We thus created groups of participants whose estimated alpha
485 parameter was either less than or greater than the group median (0.4). We labeled these groups
486 “risk-averse” and “risk-neutral”, respectively. We did not find evidence for a “risk-seeking” group
487 (i.e., $\alpha > 1$) within our pool of participants. We then repeated the above qualitative analysis,
488 separately by group. Clearly this separation into groups was meaningful, as two distinct patterns
489 in the data emerged. Risk-averse participants rarely chose the riskier option unless the EV of the
490 riskier option was much greater than the EV of the safer option (Figure 3D in red). They also took
491 longer to decide and deviated more from a straight trajectory as the EV of the riskier option
492 increased (within the available range; Figure 3E-F in red). Risk-neutral participants showed the
493 patterns expected for people who choose based on simple economic calculations unaffected by
494 risk aversion. Their probability of choosing the riskier option also increased monotonically as a
495 function of EV difference (riskier - safer), but their point of neutrality ($p(\text{ch}) = 0.5$) was when EV
496 difference equaled zero (Figure 3D in blue). Furthermore, their RTs were longest and MDs were
497 largest on trials where EV difference was closest to zero (Figure 3E-F in blue).

498 To confirm the apparent group differences, we regressed choice (of the riskier option) on
499 EV difference (dV), log(RT) on abs(dV), and MD on abs(dV), separately for each dependent
500 variable and risk preference group. The relative magnitudes of the regression coefficients across
501 groups suggest that EV had a much greater influence on the choice probability and RT of the risk-
502 neutral participants relative to the risk-averse participants (coefficients for dV: **choice**: risk-averse
503 = 1.34, 95% CI = [0.92 1.75]; risk-neutral = 3.39, 95% CI = [2.88 3.90]; **RT**: risk-averse = -0.56,
504 95% CI = [-0.87 -0.26]; risk-neutral = -1.07, 95% CI = [-1.71 -0.43]), but there was no relationship
505 between dV and MD for either group (coefficients for dV: risk-averse = 0.03, 95% CI = [-0.33
506 0.26]; risk-neutral = -0.34, 95% CI = [-1.02 0.35]). Given the clear differences in group behavior,
507 we decided to also test for group differences in the model comparison analysis reported below.

508 Beyond the effects of EV difference, we hypothesized that choice behavior would differ
509 according to attribute salience. Specifically, we predicted that information processing about the
510 salient attribute on each trial would be facilitated relative to the less salient attribute. This should
511 lead to more extreme choice probability, faster RT, and smaller MD on trials where salience
512 aligned with EV difference (i.e., when the EV of the riskier option is higher and the salient attribute
513 is monetary amount, or when the EV of the safer option is higher and the salient attribute is
514 probability). We label such trials as *no conflict* trials. In the opposite situation, where salience
515 conflicts with EV difference (*conflict* trials), choice probability should be closer to 50% (i.e.,
516 chance level), RT should be slower, and mouse trajectories should deviate more. To test for this,
517 we split trials by conflict type (no or yes) and repeated the analysis reported above. Overall, we
518 found no difference in choice probability (Figure 4A), but a shift in the peak of the RT and MD
519 distributions (Figure 4B-C). Expecting to find group differences (risk-averse versus risk-neutral),
520 we repeated this conflict analysis while splitting the data by group. With the risk-averse

521 participants, we found the anticipated patterns: for trials where the safer EV was higher, conflict
522 increased the probability of choosing the riskier option (towards chance level) and increased both
523 RT and MD; for trials where the riskier EV was higher, conflict decreased the probability of
524 choosing the riskier option (away from chance level) and decreased both RT and MD (Figure 4D-
525 F). However, with the risk-neutral participants, we found the opposite patterns: for trials where the
526 safer EV was higher, conflict decreased the probability of choosing the riskier option (away from
527 chance level) and decreased both RT and MD; for trials where the riskier EV was higher, conflict
528 increased the probability of choosing the riskier option (away from chance level) and decreased
529 both RT and MD (Figure 4G-I). Here, the behavioral data are internally consistent, in the sense
530 that RT and MD both decreased whenever choice probability moved away from chance level and
531 RT and MD both increased whenever choice probability moved towards chance level. But salience
532 seemed to affect the risk-neutral participants in a way opposite to what we predicted. It is likely
533 that the options we labeled as salient were indeed salient even for this group, based on the
534 behavioral effects. However, it seems like those options were salient not because of the high
535 magnitude attributes but rather the low ones (because on average, when our options had a higher-
536 than-average level of one attribute, they had a lower-than-average level of the other). In other
537 words, risk-averse participants might focus more on probability, except when monetary amount is
538 particularly high. Risk-neutral participants, in contrast, might focus more on monetary amount,
539 except when probability is particularly low. Thus, it seems that high monetary amounts are salient
540 for risk-averse people, and low probabilities are salient for risk-neutral people.



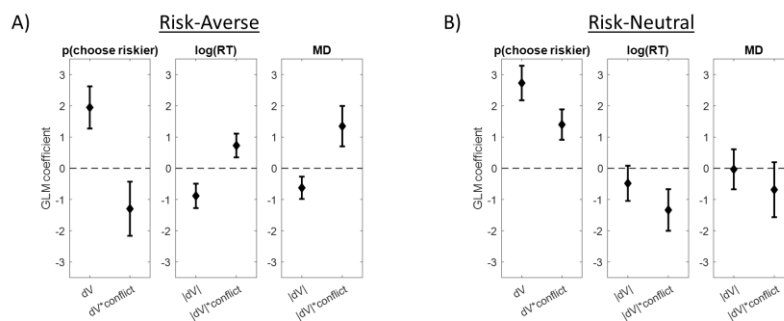
541

542 **Figure 4. Impact of conflict on choice behavior.** Choice probability (of choosing the riskier
 543 option), response time (RT), and maximum mouse trajectory deviation (MD) plotted against EV
 544 difference (riskier minus safer), pooled across all participants (plots A-C), risk-averse participants
 545 (plots D-F), and risk-neutral participants (plots G-I). Each plot shows the data separated by trial
 546 type (conflict versus no conflict). Each dot represents an average across all trials within EV
 547 difference bins of equal range.

548

549 To confirm the group differences, we regressed choice on $dV + dV \cdot \text{conflict}$, $\log(\text{RT})$ on
 550 $\text{abs}(dV) + \text{abs}(dV) \cdot \text{conflict}$, and MD on $\text{abs}(dV) + \text{abs}(dV) \cdot \text{conflict}$, separately for each
 551 dependent variable and risk preference group (where conflict is an indicator variable = 1 on conflict
 552 trials and = 0 on no conflict trials). The regression coefficients for dV were qualitatively similar

553 across groups (**choice**: risk-averse = 1.95, 95% CI = [1.27 2.62]; risk-neutral = 2.73, 95% CI =
 554 [2.18 3.28]; **RT**: risk-averse = -0.88, 95% CI = [-1.27 -0.49]; risk-neutral = -0.48, 95% CI = [-1.04
 555 0.08]; **MD**: risk-averse = -0.63, 95% CI = [-0.98 -0.27]; risk-neutral = -0.03, 95% CI = [-0.67
 556 0.61]; Figure 5). In contrast, the regression coefficients for $dV \cdot \text{conflict}$ were qualitatively opposite
 557 across groups (**choice**: risk-averse = -1.30, 95% CI = [-2.16 -0.43]; risk-neutral = 1.40, 95% CI =
 558 [0.91 1.89]; **RT**: risk-averse = 0.73, 95% CI = [0.35 1.11]; risk-neutral = -1.34, 95% CI = [-2.00 -
 559 0.67]; **MD**: risk-averse = 1.35, 95% CI = [0.70 1.99]; risk-neutral = -0.69, 95% CI = [-1.57 0.19];
 560 Figure 5).



561

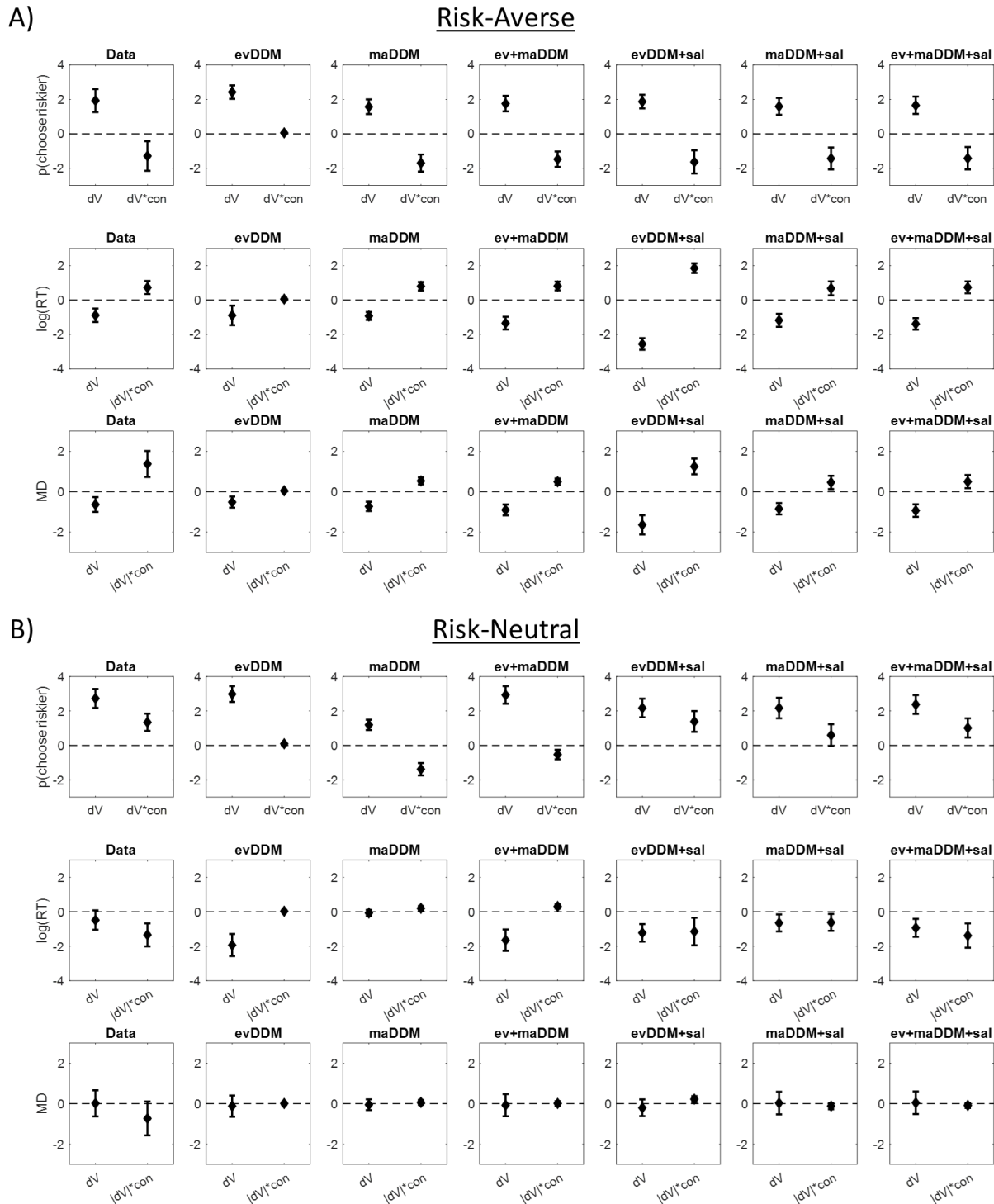
562 **Figure 5. Impact of expected value difference and conflict across risk preference groups.** *The*
 563 *effects of expected value difference ($dV = EV$ of riskier option – EV of safer option) and dV on*
 564 *conflict trials ($dV \cdot \text{conflict}$) on choice probability (for the riskier option), $\log(RT)$, and maximum*
 565 *deviation (MD) for risk-averse (plot A) and risk-neutral participants (plot B); dV is unsigned for*
 566 *RT and MD ; diamonds represent fixed effects regression coefficients; error bars represent 95%*
 567 *confidence intervals.*

568

569 **Qualitative Model Predictions**

570 The DDM variants that we compare make distinguishable predictions regarding the impact
 571 of EV difference and conflict on choice behavior, when separately considering risk-averse and
 572 risk-neutral participants. We show in Figure 6 the qualitative predictions that each model (*evDDM*,
 573 *maDDM*, *ev+maDDM*, *evDDM+sal*, *maDDM+sal*, and *ev+maDDM+sal*, each simulated under

574 its participant-specific best-fitting parameters) makes with respect to the effects of EV difference
575 (dV; riskier minus safer) and dV in *conflict* trials on choice probability (for the riskier option), RT,
576 and MD, and how this compares to the empirical data. To generate the synthetic data, we used the
577 same choice trials that participants faced, along with each participant's best-fitting parameters for
578 each of the four models. Next, we performed mixed effects regressions of choice (binomial) on
579 dV and dV*conflict, and of log(RT) and MD (linear) on |dV| and |dV|*conflict, pooling together
580 data from all simulated participants and including participants as random effects. For the risk-
581 averse group, all the models except for the *evDDM* are able to account for the qualitative patterns
582 of the associations between dV (with and without conflict) and choice probability, RT, and MD
583 (Figure 6A). For the risk-neutral group, only the models with a parameter related to salience
584 (*evDDM+sal*, *maDDM+sal*, and *ev+maDDM+sal*) are able to account for the relative magnitudes
585 and directionality of the associations between dV (with and without conflict) and choice
586 probability, RT, and MD (Figure 6B). Note that what is important here is the qualitative patterns
587 of the coefficients for dV and dV*conflict *within* each data source, not the absolute magnitudes or
588 comparisons across data sources.



589

590 **Figure 6. Model predictions.** *Qualitative predictions of the effects of expected value difference*
 591 *($dV = EV$ of riskier option – EV of safer option) and dV on conflict trials (dV *conflict) on choice*
 592 *probability (for the riskier option), $\log(RT)$, and maximum deviation (MD) in the empirical*

593 (column 1) and simulated data (columns 2-7; shown for responses simulated using the best-fitting
594 parameters for each model); dV is unsigned for RT and MD; diamonds represent fixed effects
595 regression coefficients; error bars represent 95% confidence intervals. Panel A shows the risk-
596 averse group, panel B shows the risk-neutral group.

597

598 ***Model comparison***

599 Our primary interest when conducting a model comparison of the DDM variants was in
600 knowing whether risky decisions were made purely based on comparisons of the expected value
601 (EV) of the available options, on direct comparisons of each of the individual attributes (monetary
602 amount X and probability P), or on either EV or individual attributes with an additional influence
603 of the most salient attribute on each trial. We separated this into two core research questions: 1) if
604 people integrate evidenced before comparing it, compare evidence before integrating it, or both;
605 2) if the salience of individual attributes influence evidence accumulation. We tested each of these
606 questions separately by performing model family comparisons based on the core model features
607 reflective of each question. In brief, the model family approach consists in pooling together model
608 evidence for models that share core components, to test those specific components against
609 competitors (while setting aside other differences between models within each family). This
610 approach is more robust than testing individual models when they could be considered to be
611 variants of subclasses of similar models. As we have two main research questions, and each
612 individual model contains features relevant to either question, we classified our models into family
613 sets in two different ways. The first model family classification separates the models by evidence
614 accumulation mechanism: Models 1 and 4 both rely on comparisons of EV; Models 2 and 5 both
615 rely on comparisons of individual attributes; and Models 3 and 6 both rely on comparisons of both
616 EV and individual attributes. We examined this family classification with respect to research

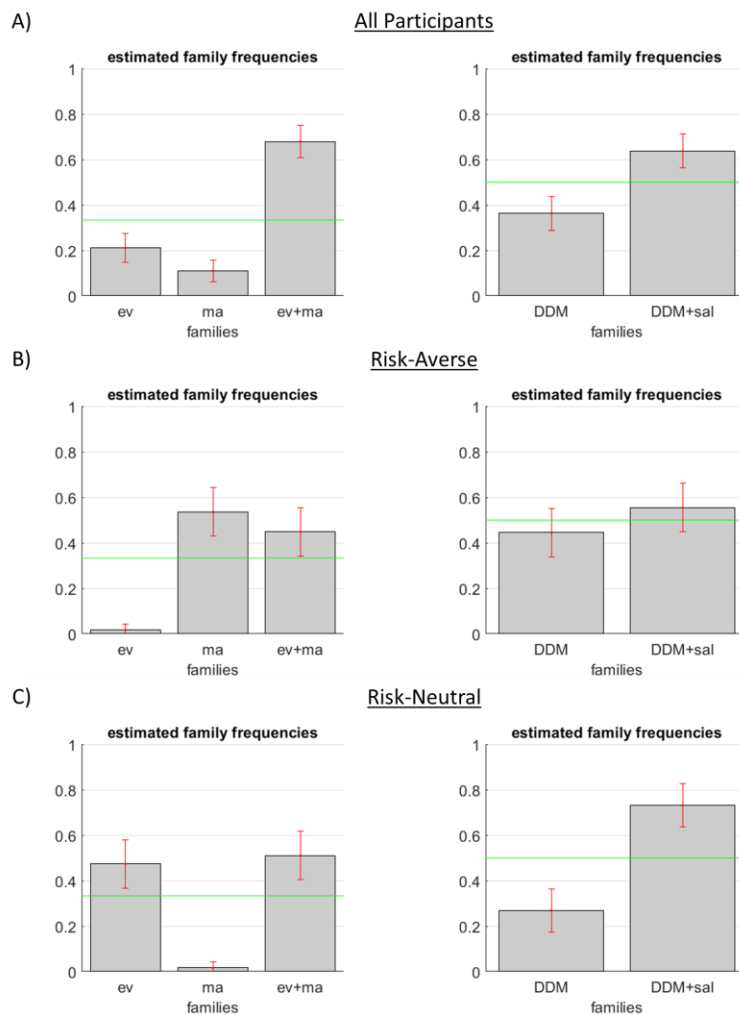
617 question 1 above. The second model family classification separates the models by the impact of
618 attribute salience: Models 1-3 are not impacted by salience and Models 4-6 are. We examined this
619 family classification with respect to research question 2 above.

620 For question 1, we found that the ev+ma model family that uses comparisons of both
621 individual attributes and EV dominated (estimated family frequency = 0.68; Figure 7). Testing the
622 risk-averse group separately, we found that both families that incorporated comparisons of
623 individual attributes dominated the family that only incorporated comparisons of EV (estimated
624 family frequencies: ma = 0.54, ev+ma = 0.45; Figure 7). Testing the risk-neutral group separately,
625 we found that both families that incorporated comparisons of EV dominated the family that only
626 incorporated comparisons of individual attributes (estimated family frequencies: ev = 0.47, ev+ma
627 = 0.51; Figure 7). Thus, we can conclude that risk-averse participants mostly rely on a compare-
628 then-integrate strategy and risk-neutral participants mostly rely on an integrate-then-compare
629 strategy, but half of the participants in each group seem to use a mixed strategy by considering
630 both individual attributes and EV.

631 For question 2, we found that the DDM+sal model family dominated (estimated family
632 frequency = 0.64; Figure 7). Testing the risk-averse group separately, we found that the DDM+sal
633 family performed best (estimated family frequency = 0.55; Figure 7). Testing the risk-neutral
634 group separately, we found that the DDM+sal family dominated (estimated family frequency =
635 0.73). We can thus conclude that most participants are affected by the salience of individual
636 attributes. Interestingly, the participants who mostly compare EV across options (the risk-neutral
637 group) seem to be influenced more by differences in attribute salience. This provides clear
638 evidence that even those who seem to choose based on classical economic theory (i.e., to maximize

639 EV; Figure 7) nevertheless pay attention to the values of the individual attributes as a function of
 640 their salience.

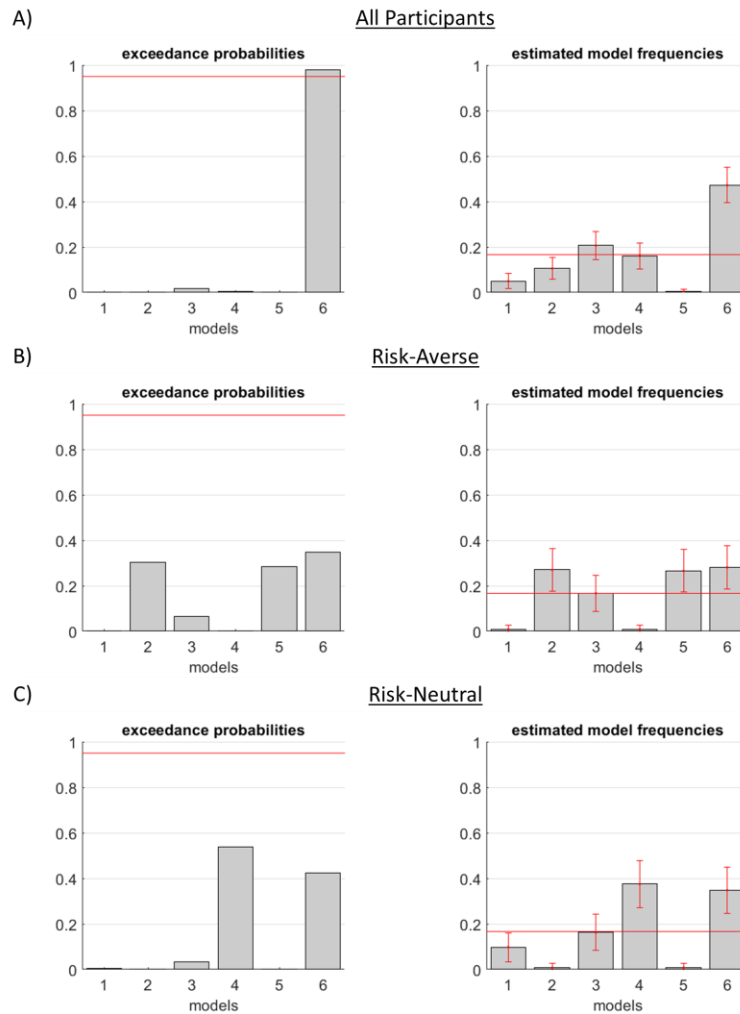
641 To summarize, both our analyses indicate that participants consider individual attributes
 642 when making their choices, possibly in combination with EV comparisons.



643
 644 **Figure 7. Model family comparison.** *Estimated frequencies for model families based on evidence*
 645 *accumulation strategies (EV, individual attributes, or both; left column) or influence of attribute*
 646 *salience (not present or present; right column). Row A shows all participants, row B shows risk-*
 647 *averse participants only, and row C shows risk-neutral participants only. Green lines indicate*
 648 *chance level of family frequency if families were equally probable a priori.*

649

650 We next performed a standard quantitative model comparison that included all our
651 individual models (Models 1-6). Across all participants, Model 6 (*ev+maDDM+sal*) dominated
652 (estimated model frequency = 0.47, exceedance probability = 0.98; Figure 8A). Model frequency
653 is defined as the number of participants with more evidence in favor of a particular model, and
654 exceedance probability quantifies the likelihood that a particular model accounts for the data better
655 than the other models (Stephan et al., 2009). Given the results of the model family comparisons
656 reported above, it is not surprising that Model 6 won the individual model comparison, as it is the
657 only model that is a member of both winning families. Repeating the individual model comparison
658 for the risk-averse group only, we found that Models 2, 5, and 6 (*maDDM*, *maDDM+sal*, and
659 *ev+maDDM+sal*) each performed above chance level, but none of these three significantly
660 outperformed the other (estimated model frequency: M2 = 0.27, M5 = 0.27, M6 = 0.28; exceedance
661 probability: M2 = 0.30, M5 = 0.28, M6 = 0.35; Figure 8B). Note that each of the best-performing
662 models relies on comparisons of individual attributes. Repeating the model comparison for the
663 risk-neutral group only, we found that Models 4 and 6 (*evDDM+sal* and *ev+maDDM+sal*) each
664 performed above chance level, but neither significantly outperformed the other (estimated model
665 frequency: M4 = 0.37, M6 = 0.35; exceedance probability: M4 = 0.54, M6 = 0.42; Figure 8C).
666 Note that each of the best-performing models relies on the influence of individual attributes
667 according to their salience. Although different models performed best for the different groups, all
668 best-performing models required information about individual attributes in one way or another.



669

670 **Figure 8. Model comparison.** Exceedance probabilities (left column) and estimated model
 671 frequencies across participants (right column) for each model. Row A shows all participants, row
 672 B shows risk-averse participants only, and row C shows risk-neutral participants only. Red lines
 673 indicate 95% threshold for exceedance probabilities (left plots) or chance level of model frequency
 674 if models were equally probable a priori (right plots).

675

676 To more directly test whether both groups relied on information about both EV and
 677 individual attributes, independent of the salience effect, we performed a model comparison of
 678 Models 1-3 only (*evDDM*, *maDDM*, and *ev+maDDM*). We found that Model 3 decidedly
 679 dominated across all participants, with an estimated model frequency of 0.93 and an exceedance

680 probability of 1. Repeating this comparison for the risk-averse group only, Model 3 won the
681 competition (estimated model frequency = 0.64, exceedance probability = 0.91). Repeating this
682 comparison for the risk-neutral group only, Model 3 decidedly dominated (estimated model
683 frequency = 0.86, exceedance probability = 1). Thus, it appears that even those participants who
684 mostly rely on comparisons of EV when deciding also rely on additional information based on
685 comparisons of individual attributes. This aligns with previous findings (Lee & Hare, 2022).

686 Finally, we repeated all of the model comparisons reported above, this time excluding the
687 equations for maximum deviation (MD). All results were nearly identical.

688

689 **Discussion**

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

700 Our analyses of behavioral and kinematic indexes of response probabilities, response times
701 (RTs), and curvatures of mouse trajectories during decisions indicate three main findings. First,
702 participants performed the task properly, as shown by the fact that their response probabilities are

703 significantly modulated by the EV of the options within each choice pair. Second, participants
704 could be categorized into distinct groups based on risk preference type: risk-averse and risk-
705 neutral. Third, attribute salience significantly affected response probability as well as decision
706 dynamics (as evident in both RT and response trajectory curvature), but in an opposite direction
707 for the two risk preference groups. When salience conflicted with the higher EV option, risk-averse
708 participants were more likely to choose the salient option, whereas risk-neutral participants were
709 less likely to choose the salient option. Furthermore, both groups were faster to respond when
710 conflict (or lack of conflict) caused their choice probabilities to move away from chance level. On
711 these trials, participants also moved the mouse with a more direct trajectory – which is an index
712 of increased choice confidence and decreased attraction from the non-selected alternative (Hehman
713 et al., 2015; Spivey et al., 2005). Note that the RT and trajectory curvature results are consistent
714 with the different choice preferences of the two groups.

715 This pattern of results can perhaps be explained by the fact that risk-averse participants (by
716 definition) prefer options with higher probabilities, whereas risk-neutral participants (by
717 definition) mostly consider EV (or perhaps prefer higher monetary amounts). By design, on trials
718 where salience was for the riskier option, such options included both an exceptionally large
719 monetary amount and an exceptionally small probability. It seems that risk-averse participants,
720 who usually pay more attention to probability, paid particular attention to the large monetary
721 amount when it was salient, thus making the riskier option more attractive (hence the higher choice
722 probability when EV favored the safer option but salience favored the riskier option) and the choice
723 more difficult (hence the slower RT and more deviant response trajectory). The opposite applies
724 for trials where the large probability was salient: the riskier option became less attractive (hence
725 the lower choice probability when EV favored the riskier option but salience favored the safer

726 option) and the choice easier (hence the faster RT and more direct response trajectory). Conversely,
727 risk-neutral participants seem to have paid particular attention to the small probability when SAL
728 = riskier and the small monetary amount when SAL = safer, thus making the corresponding options
729 (with the apparently salient small-valued attributes) less attractive. Thus, for these participants,
730 conflict between EV difference and salience (as we defined it, according to the largest attribute
731 value) actually made the choices easier (hence the steeper psychometric choice curve, faster RT,
732 and more direct response trajectory on conflict trials). Although this divergence of the attribute
733 salience effect across risk preference types was not something we predicted, we believe that the
734 overall pattern of results clearly shows that salience exerted an influence on choice behavior and
735 decision dynamics.

736 Taken together, these results show that participants are sensitive to both the EV of the
737 different options and the salience of the different attributes during their choices. The above results
738 lend some support to conceptual models that highlight separate, within-attribute comparisons, but
739 cannot fully distinguish whether these attribute comparisons are alternative or simultaneous to EV
740 comparisons (as envisaged by the combined model).

741 To address this last question more directly, we designed and systematically compared six
742 versions of drift-diffusion model (DDM) that incorporate different hypotheses about how multi-
743 attribute decisions are made: an *integrate-then-compare model* (Model 1: *evDDM*) that only allows
744 EV comparisons, a *compare-then-integrate model* (Model 2: *maDDM*) that only allows separate
745 comparisons of individual attributes, a *combined-comparison model* (Model 3: *ev+maDDM*) that
746 allows both EV and attribute comparisons, a variant of the *integrate-then-compare model* that
747 allows evidence to accumulate at different rates depending on which option contains the salient
748 attribute on a given trial (Model 4: *evDDM+sal*), a variant of the *compare-then-integrate model*

749 that allows evidence to accumulate at different rates depending on which attribute is salient on a
750 given trial (Model 5: *maDDM+sal*), and a variant of the *combined-comparison model* that allows
751 evidence to accumulate at different rates depending on which option contains the salient attribute
752 on a given trial or on which attribute is salient on a given trial (Model 6: *ev+maDDM+sal*).

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

767 Salience is understood to impact the cognitive processes involved in decision-making
768 through its ability to attract and capture attention. Attention-related arousal has been shown to
769 accompany the presentation of offers with exceptionally high monetary amounts (Leuker et al.,
770 2019). When a decision set contains a relatively high numerical magnitude for one of the options
771 or attributes, the attention that it captures is thought to cause the decision-relevant information

772 about that option or attribute to be weighted more heavily (Bordalo et al., 2012; Tsetsos et al.,
773 2012). The idea that attention leads to differential weighting has been computationally
774 demonstrated in previous work based on the so-called *attentional drift-diffusion model* (aDDM;
775 (Krajbich et al., 2010; Smith & Krajbich, 2019)). Under the aDDM, the evidence accumulation
776 rate for the option that holds the attention of the decision-maker at any point in time (assumed to
777 be the option that is visually fixated) is enhanced. This work has recently been extended to include
778 attention towards a particular attribute in addition to attention towards a particular option (Yang
779 & Krajbich, 2022). Our *evDDM+sal* and *maDDM+sal* models align well with the aDDM
780 framework, in that attention (whether assumed by monitoring visual fixations or the highest
781 numerical magnitudes) changes evidence accumulation rates. For our risk-averse group, it seems
782 that the highest numerical magnitudes were the most salient. For our risk-neutral group, it seems
783 that it was perhaps the *lowest* numerical magnitudes that were the most salient, rather than the
784 highest. This would be consistent with increased evidence accumulation for the “worse” attribute
785 (for the risk-neutral group) if these participants were choosing which option to reject rather than
786 which to accept, which has been demonstrated in previous aDDM work (Sepulveda et al., 2020).

787 In sum, our results, based on both behavioral measures and drift-diffusion models, suggest
788 that risky decisions are resolved differently for different types of people. For risk-averse people,
789 such decisions seem to be resolved by running in parallel multiple competitions between the
790 individual attributes – possibly in combination with an additional competition between expected
791 values – and then integrating the partial results of the separate competitions afterwards (Hunt et
792 al., 2014; Roe et al., 2001; Turner et al., 2018; Usher & McClelland, 2004). For risk-neutral people,
793 risky decisions seem to be resolved by a competition between expected values but influenced by
794 the salience of individual attributes. These results stand in contrast with the assumption of standard

795 economic theory that choices require a unique comparison of expected values, and suggests that
796 at the cognitive level, decision processes might be more distributed than commonly assumed.
797 Furthermore, our results show that choice behavior can be altered when one attribute for one option
798 is particularly salient. Finally, and intriguingly, individual differences in risk preference
799 correspond to an opposite pattern in the effects of attribute salience, and these differences manifest
800 differential evidence accumulation rates for either individual attributes (for risk-averse people) or
801 options (for risk-neutral people) according to trial type and risk preference trait.

802 Data and Code Availability

803 The data and analysis code used in preparation of this manuscript are publicly available on the
804 Open Science Framework at <https://osf.io/7pu98/>.

805

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959

Supplementary Materials

for

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

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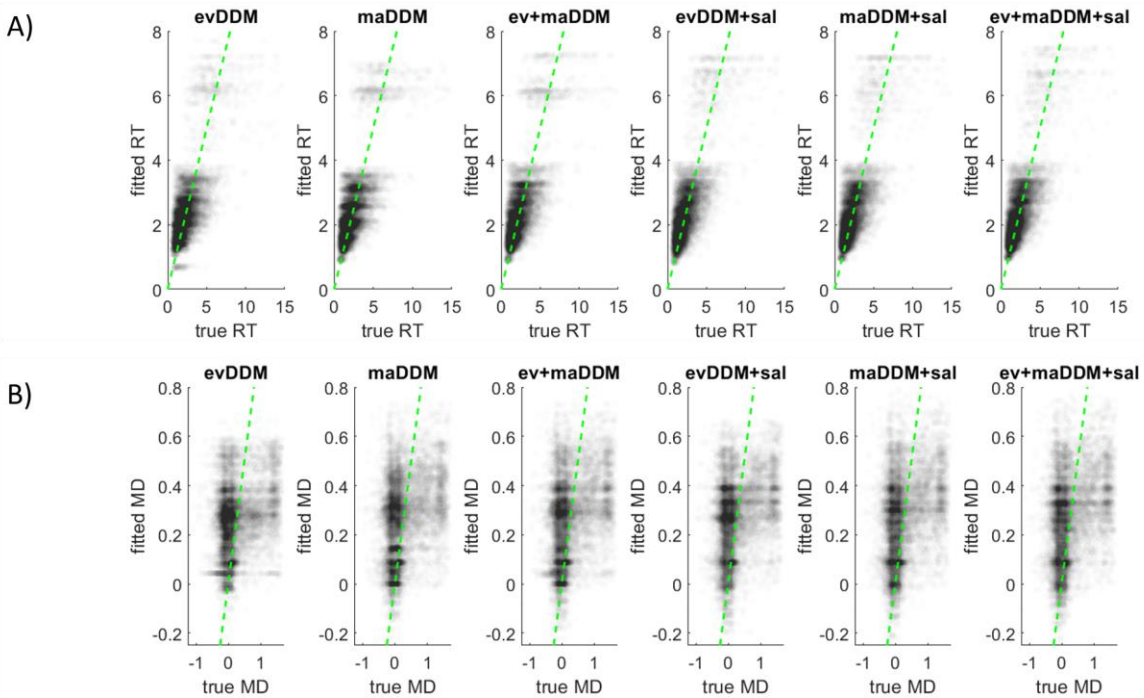
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Posterior predictive checks

Here we provide posterior predictive checks that demonstrate how well the models were able to fit the data. Overall, the models did a good job of predicting the data. Note, however, that the empirical MD had a highly skewed distribution, a pattern that the models (based on our simple linear formulation of MD) could not replicate. Also, recall that we fit MD using a very simple linear model in addition to the primary drift-diffusion model analysis (based on more advanced equations for choice probability and mean RT), so one might expect the fits for MD to be worse than those for the other variable.

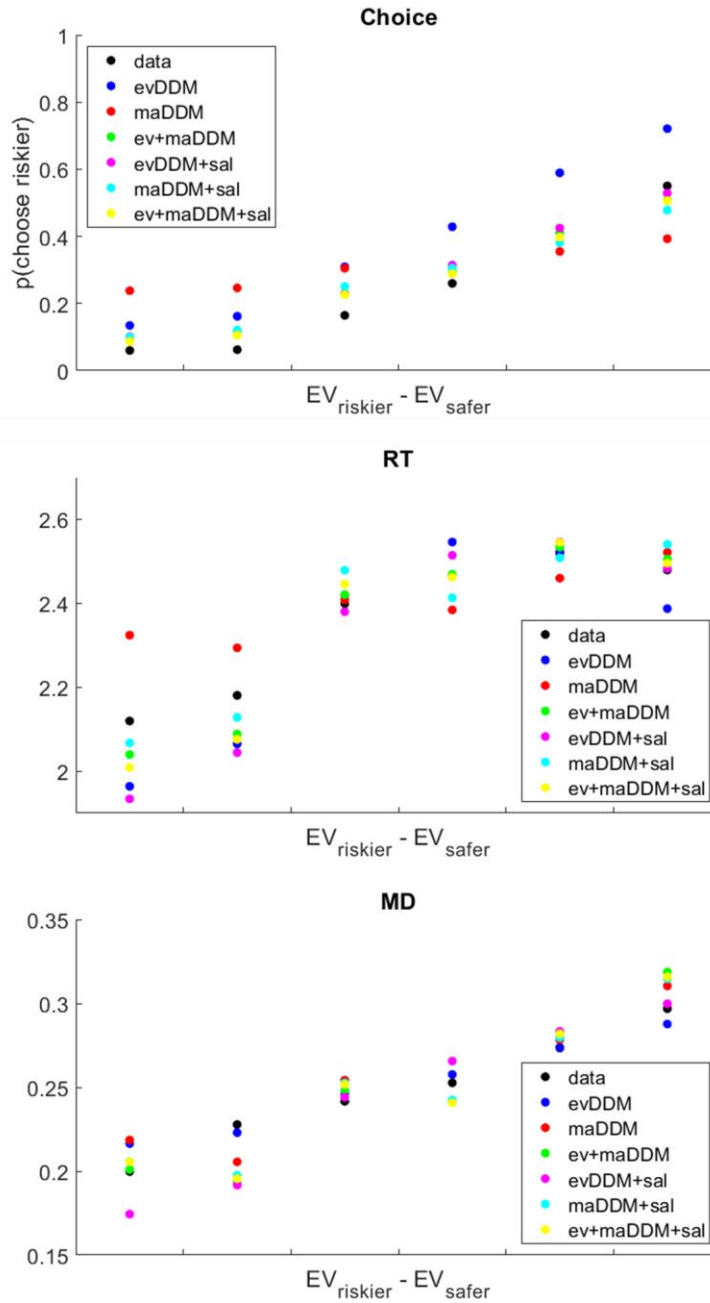


979

980 **Figure S2. Posterior predictive checks.** A) Under each model, the predicted fitted RT is plotted
 981 against the empirical true RT. B) Under each model, the predicted fitted MD is plotted against the
 982 empirical true MD. Each dot represents one trial, pooled across participants. The green dashed
 983 line indicates the ideal perfect correspondence between true and fitted data.

984

985 We also repeated the qualitative analysis as reported at the beginning of the Results section
 986 in the main text, this time for both the real data and the data predicted under each model. The
 987 models all seem to do a fair job of predicting all variables (choice, RT, and MD). However, the
 988 *ev+maDDM*, *evDDM+sal*, *maDDM+sal*, and *ev+maDDM+sal* seem to predict the data better
 989 than the *evDDM* and *maDDM*, which aligns with the fact that they performed better in the
 990 quantitative model comparison.



991

992 **Figure S2. Posterior predictive checks.** *Binned behavioral plots as in Figure 3 in the main*
 993 *manuscript. Here we show the true data (black dots) along with the model output data under each*
 994 *model (color code).*