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Strategy selection in decisions from givens: Deciding at a glance?[☆]

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☆ The stimuli, raw data, and model code can be retrieved via https://osf.io/2znxf.

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Abstract

People deciding between alternatives have at their disposal a toolbox containing both compensatory strategies, which take into account all available attributes of those alternatives, and noncompensatory strategies, which consider only some of the attributes. It is commonly assumed that noncompensatory strategies play only a minor role in *decisions from givens*, where attribute information is openly presented, because all attributes can be processed automatically "at a glance." Based on a literature review, however, I establish that previous studies on strategy selection in decisions from givens have yielded highly heterogeneous findings, including evidence of widespread use of noncompensatory strategies. Drawing on insights from visual attention research on subitizing, I argue that this heterogeneity might be due to differences across studies in the number of attributes and in whether the same or different symbols are used to represent high/low attribute values across attributes. I tested the impact of these factors in two experiments with decisions from givens in which both the number of attributes shown for each alternative and the coding of attribute values was manipulated. An analysis of participants' strategy use with a Bayesian multimethod approach (taking into account both decisions and response-time patterns) showed that a noncompensatory strategy was more frequently selected in conditions with a higher number of attributes; the type of attribute coding scheme did not affect strategy selection. Using a compensatory strategy in the conditions with eight (vs. four) attributes was associated with rather long response times and a high rate of strategy execution errors. The results suggest that decisions from givens can incur cognitive costs that prohibit reliance on automatic compensatory decision making and that can favor the adaptive selection of a noncompensatory strategy.

Keywords: Decision strategies, Heuristics, Strategy selection, Adaptive decision making, Cognitive costs, Subitizing, Bayesian cognitive modeling

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1. Introduction

Decision making is highly variable. People decide differently depending on the number and nature of alternatives available, how they are asked about their preferences (e.g., rating vs. choice), and how they learn about the alternatives, to name but a few factors (e.g., Hertwig et al., 2004; Lichtenstein & Slovic, 2006; Pachur & Olsson, 2012; Payne, 1982; Trueblood et al., 2013). It is often assumed that this variability is due to people being able to choose from a repertoire of decision strategies according to the context (e.g., Brown, 2002; Gigerenzer et al., 1999; Krefeld-Schwalb et al., 2019; Payne et al., 1993; Siegler, 1999; but see Glöckner et al., 2014). Some strategies involve integrating the information on all available attributes, either weighting each attribute depending on its importance or weighting all attributes equally. These strategies are *compensatory*: Because all attributes are taken into account, a high value on one attribute can compensate for a low value on another. Other strategies simplify the process by dispensing with integration and relying instead on one-reason decision making. These strategies are *noncompensatory*, in the sense that a decision based on one attribute cannot be reversed based on information about other attributes (Einhorn, 1970). Such simplifying heuristics have been proposed as one way by which the mind can achieve "bounded rationality": using efficient and effort-reducing mental tools to make good decisions (Gigerenzer et al., 2011; Simon, 1990; see also Kahneman, 2003; Shah & Oppenheimer, 2008).

Research has identified a number of factors that might shape selection from the "adaptive toolbox" of decision strategies. One is the structure of the environment. In domains with a skewed distribution of attribute importance—that is, where one attribute is much more important than the others—a noncompensatory strategy is appropriate. When the distribution of attribute importance is less skewed, or when the relative importance of the attributes is simply unknown, an equal weighting strategy is called for (e.g., Mata et al., 2007; Pachur & Marinello, 2013; Rieskamp & Otto, 2006). Constraints imposed by the context of the decision may also play a role; for instance, people rely more on noncompensatory strategies when under time pressure (Oh et al., 2016; Payne et al., 1988; Rieskamp & Hoffrage, 2008) or in dual-task settings (Bröder & Schiffer, 2003b, 2006).

But strategy selection may also depend on characteristics of the attribute information. A key emphasis of previous work in this regard has been on the cognitive costs of information search and acquisition. In *decisions from memory*, the attribute values are stored in memory; this information has to be searched and retrieved to make a decision. In *decisions from givens*, in contrast, all attribute values are openly provided and search costs are assumed to be low (e.g., Glöckner & Betsch, 2008). Gigerenzer and Todd (1999) proposed that "experiments in which search is obviated are unsuitable for testing models of ecological and bounded rationality that rely on limited information search as a central component" (p. 23). On this account, tools of bounded rationality play only a minor role in decisions from givens (unless, as discussed in the previous paragraph, the distribution of attribute importance renders them appropriate).

The thesis that search costs are a key determinant of strategy selection has garnered substantial support. Several studies have found that in decisions from memory a considerable proportion of people rely on noncompensatory strategies (e.g., Bröder & Schiffer, 2003b; Dummel & Rummel, 2016; Persson & Rieskamp, 2009; Platzer & Bröder, 2013; but see Glöckner & Bröder, 2011; Heck & Erdfelder, 2017), whereas in decisions from givens a large majority of people use compensatory strategies (e.g., Bröder & Schiffer, 2003b, 2006; Glöckner & Betsch, 2008; Pachur & Olsson, 2012). In addition, other factors that are assumed to lower the costs of information search—such as presenting the alternatives' values on each attribute side by side (Söllner et al., 2013) or making less important information perceptually salient (Platzer & Bröder, 2012)—have been shown to increase reliance on compensatory strategies.

Puzzlingly, however, some studies on decisions from givens have observed a pronounced reliance on noncompensatory strategies (e.g., Bergert & Nosofsky, 2007; Dummel et al., 2016; Garcia-Retamero & Dhami, 2009; Pachur & Marinello, 2013). Why do people sometimes use simple heuristics even when all attribute information is provided openly? In this article, I will highlight a previously neglected factor: the costs associated with integrating the attribute information (but see Bröder & Schiffer, 2003b).[1] That is, I will consider not only the effort required to search and acquire the information, but also the costs of aggregating it across attributes—costs incurred by compensatory strategies but not by noncompensatory strategies. As laid out in more detail below, previous studies that found clear evidence for the use of noncompensatory strategies in decisions from givens used materials that—due to the number and coding of attributes—involved high costs for information integration or generated previously overlooked search costs. No investigation, however, has directly manipulated the number of attributes and the attribute coding within the same experiment while keeping all other factors constant. Here, I report two experiments that implement such a design.

In the following, I first describe compensatory and noncompensatory decision strategies in more detail and present a systematic literature review on strategy selection in decisions from givens, highlighting a large heterogeneity in findings. I then delineate a conceptual framework describing how the number and coding of attributes might affect strategy selection, which may help to explain this heterogeneity. Finally, I describe a novel Bayesian multimethod approach to strategy classification that draws on both decision and response-time data, and I report two experiments that use this approach to test the impact of the number of attributes and the type of attribute coding on people's selection of compensatory and noncompensatory strategies.

1.1. Strategies in the adaptive toolbox

Various models of strategies have been proposed to characterize different types of information processing underlying people's decisions. An important distinction is whether the strategies are compensatory or noncompensatory.

1.1.1. Compensatory strategies

In compensatory strategies, all attributes are taken into account to make a decision, such that a positive value (i.e., that supports the alternative in question) on one attribute can be compensated by a negative value (i.e., that speaks against that alternative) on another attribute, or a combination of other attributes. A frequently studied compensatory strategy is the *weighted-additive strategy* (WADD; Payne et al., 1993). In WADD, the attribute values are multiplied by the respective importance weights of the attributes, the weighted

[1] Bröder and Schiffer (2003b) compared strategy selection for attributes presented in verbal versus pictorial format (see also Juslin et al., 2003). Although it was originally assumed that a pictorial format would foster the use of compensatory strategies because it facilitates information integration, subsequent research by Platzer and Bröder (2012) demonstrated that these effects were in fact due to differences in salience—that is, the mode of presentation affected the acquisition rather than the integration of attributes.

Table 1
Overview of Studies on Decisions From Givens That Classified Individual Participants as Users of Noncompensatory or Compensatory Strategies.

Studies	Number of attributes	Attribute coding scheme	Users of a noncompensatory (compensatory) strategy
Pachur & Olsson (2012, Exp. 1)[a]	4	Varied	0% (85%)
Hilbig & Moshagen (2014)	4	Uniform	3.8% (87%)
Pachur & Olsson (2012, Exp. 2)[a]	4	Varied	5% (85%)
Glöckner & Betsch (2012)	4	Uniform	5% (95%)
Söllner et al. (2013, Exp. 3)[b]	4	Uniform	8% (92%)
Heck et al. (2017)	4	Uniform	8.7% (78.8%)
Söllner et al. (2013, Exp. 3)[c]	4	Uniform	10% (90%)
Söllner et al. (2013, Exp. 2)[d]	4	Uniform	11% (89%)
Glöckner & Betsch (2008, Exp. 1)	3	Uniform	13% (74%)
Glöckner et al. (2014, Exp. 1)[e]	4	Uniform	14% (86%)
Söllner et al. (2013, Exp. 1)[d]	4	Uniform	14% (86%)
Bröder (2000, Exp. 4)[f]	4	Uniform	15% (85%)
Ayal & Hochman (2009, Study 2)	3	Uniform	18% (72%)
Bröder (2000, Exp. 2)[g]	4	Uniform	20% (80%)
Glöckner & Betsch (2008, Exp. 3)	6	Uniform	21% (79%)
Newell & Lee (2011, Exp. 1)[h]	5	Varied	42.6% (35.1%)
Dummel et al. (2016, Exp. 1b)[i]	4	Varied	43% (54%)
Shevchenko & Bröder (2018)[j]	5	Uniform	43% (57%)
Bröder & Schiffer (2003b, Exp. 2)	4	Varied	44% (48%)
Dummel et al. (2016, Exp. 2)[i]	4	Varied	50% (50%)
Bryant (2014, Exp. 1)[k]	4	Varied	52.1% (45.8%)
Dummel et al. (2016, Exp. 3)[i]	4	Varied	54% (42%)
Dummel et al. (2016, Exp. 1a)[i]	4	Varied	62% (34%)
Pachur & Marinello (2013)[l]	8	Varied	64.5% (32.2%)
Bryant (2014, Exp. 2)[m]	4	Varied	68.1% (26.6%)
Bergert & Nosofsky (2007, Exp. 1)	6	Varied	73.7% (24.6%)
Bergert & Nosofsky (2007, Exp. 2)	6	Varied	80% (20%)
Garcia-Retamero & Dhami (2009)[l]	8	Varied	81% (14%)

Note. Studies are ordered by increasing proportion of users of a noncompensatory strategy.
[a] Learning by comparison condition
[b] Adjusted matrix condition
[c] Random row matrix condition
[d] Matrix condition
[e] Compensatory condition
[f] Conditions 1 and 2 (i.e., simultaneous cue display)
[g] Low cue dispersion condition
[h] Text and image conditions combined
[i] Test phase 1
[j] Neutral mood condition with open information board
[k] Control condition
[l] Expert groups
[m] Across low- and high-salience conditions

attribute values are summed up for each alternative, and the alternative with the higher sum is chosen. A somewhat simplified compensatory strategy is the *equal-weight strategy* (EQW; Dawes, 1979). EQW determines the number of positive attribute values for each alternative and chooses the alternative with the higher sum. A key feature of compensatory strategies is that they integrate across multiple attributes to make a decision. Several investigations have found evidence that weighted compensatory processing can, at least sometimes, be implemented in an automatic fashion (e.g., Brusovansky et al., 2018; Glöckner & Betsch, 2008; Glöckner et al., 2014; Söllner et al., 2013).

1.1.2. Noncompensatory strategies

Noncompensatory strategies inspect only a part of the information; it is therefore possible that a low value on one attribute cannot be compensated by high values on other attributes. A prominent model is the *take-the-best heuristic* (TTB; Gigerenzer & Goldstein, 1996), where attributes are inspected sequentially in descending order of importance and the alternatives are compared on each attribute; as soon as the alternatives differ on a given attribute, information search is stopped and the alternative with a positive value on that attribute is chosen (for an investigation of the neural underpinnings of using TTB, see Dimov et al., 2020; Khader et al., 2016). Importantly, unlike WADD and EQW, TTB does not integrate multiple attribute values. It thereby incurs not only lower search costs but also low costs of integration.

1.2. Strategy selection in decisions from givens: No need to be frugal?

When do people rely on compensatory and noncompensatory strategies? As summarized by Glöckner and Hodges (2011), “[i]f the information about the city (cue value) is directly presented to the person, for instance on a computer screen, this would be considered an inference from the givens […]. In contrast, if cue values have to be retrieved from memory this is referred to as inferences from memory."[2] (p. 181) Locating and accessing information stored in memory is associated with costs (Anderson, 1991) and retrieving information from memory is commonly considered to be cognitively more effortful than simply reading it off an external source (e.g., a computer screen). Consistent with this assumption, Gigerenzer and Todd (1999) proposed that people use noncompensatory strategies mainly in decisions from memory, where search costs are relatively high, but rarely use them in decisions from givens, where search costs are low (unless the distribution of attribute importance is skewed). A seminal investigation by Bröder and Schiffer (2003b) tested this hypothesis. Participants either retrieved previously learned attribute information about alternatives to make a decision (thus making a decision from memory) or made a decision based on attribute information shown on a computer screen (thus making a decision from givens). 44% of participants in the decisions-from-memory condition were classified as users of TTB. This proportion dropped to 20% in the decisions-from-givens condition (see also Bröder & Schiffer, 2006). These findings offered support for the idea that people tend not to use simple heuristics when the costs of information search are low.[3] Several subsequent studies replicated the finding that few people rely on simple strategies when attribute information is provided openly (e.g., Bröder et al., 2010; Glöckner & Betsch, 2008; Heck et al., 2017; Hilbig & Moshagen, 2014; Pachur & Olsson, 2012).[4]

1.3. A possible role of costs of information integration in strategy selection

Not all studies on decisions from givens come to the same conclusion, however. Table 1 shows the results of a systematic literature review of studies on decisions from givens that classified participants as users of noncompensatory or compensatory strategies (for a detailed description of the literature search and inclusion criteria, see Appendix A). As can be seen, there is immense variability in the observed reliance on a noncompensatory strategy, ranging from as low as 0% to as high as 81%. For instance, Bergert and Nosofsky (2007) showed their participants pairs of pictures of insects that varied on various features (e.g., body, eyes, legs, antennae) and asked them which insect was more poisonous. Participants first completed a training phase in which they received feedback about their decisions (thus allowing them to learn about the importance of each feature), then completed a test phase that included new insects. Computational modeling indicated that the noncompensatory TTB strategy was clearly better at capturing participants' decisions in the test phase than was a compensatory strategy, even though the search costs were low. Using similar material and a similar paradigm, Nosofsky and Bergert (2007) and Dummel et al. (2016) likewise found clear evidence of noncompensatory processing. Pachur and Marinello (2013) modeled airport custom officers' decisions on passenger screening, which were based on passenger profiles (e.g., gender, age, flight origin, amount of luggage) presented on a computer screen as verbal descriptions. The responses of almost two thirds of the officers were better described by TTB than by a compensatory strategy. These results parallel those obtained in Garcia-Retamero and Dhami's (2009) study on police officers and incarcerated burglars, who were asked to judge the risk that houses with different characteristics (e.g., location, type of garden, signs of care) would be burgled. Given that in all of these studies the attribute information was openly presented to participants and the search costs were thus low, why did many people nevertheless opt for a noncompensatory strategy?

Factors that may contribute to the variability in inferred strategy use across studies are natural differences in the participants recruited for the studies as well as variability in how strategy use was inferred. For instance, some analyses compared the proportion of correctly predicted choices of different strategies (e.g., Garcia-Retamero & Dhami, 2009), others used likelihood-based measures of model performance (e.g., Bergert & Nosofsky, 2007; Pachur & Olsson, 2012), and still others used Bayes factors (Heck et al., 2017). As another, potentially more important reason, I propose that the variability might be due to the relatively high number of attributes as well as the type of coding of positive (vs. negative) attribute values in some of the studies. Here, a distinction can be made between *uniform coding*, where positive/negative values are represented by the same symbols (e.g., +/− or ✓/×) across all attributes, and *varied coding*, where the coding scheme differs across attributes (e.g., "brown/green" vs. "round/wedge"). Fig. 1 shows examples of visual displays used to present attribute information in decisions from givens; the displays differ in various ways, including the number and type of coding of attributes. Table 1 also reports the number of attributes and the type of attribute coding used in the studies considered in the systematic overview. Studies in which the proportion of users of a noncompensatory strategy tended to be low typically showed participants a low number of attributes and used uniform coding. Studies that observed a higher proportion of users of a noncompensatory strategy, by contrast, usually showed participants a large number of attributes and used varied coding.

Why might the number of attributes and the type of attribute coding affect whether people use compensatory or noncompensatory strategies? First, a higher number of attributes may lead to higher search costs—although it is commonly assumed that these costs are low when information is openly presented (e.g., Glöckner & Betsch, 2008). Second, the number of attributes and the type of attribute coding could impact the costs incurred by integrating information, an aspect that has previously been neglected in decisions from

[2] Note that even if attribute information is presented openly on the screen, additional cognitive processes—often involving access to long-term memory—may be required to interpret the values as positive or negative ones.

[3] Several studies have shown that decision makers classified as users of TTB based on their decisions do not completely ignore attributes after the first discriminating attribute, as this information seems to affect response times and subjective confidence (Dummel & Rummel, 2016; Dummel et al., 2016; Söllner & Bröder, 2016).

[4] That search costs are important for strategy selection is also supported in studies by Platzer et al. (2014) and Platzer and Bröder (2012) on decisions from memory. These studies showed that although people tend to use a noncompensatory strategy for decisions from memory—arguably because the search costs are relatively high—their use of compensatory strategies increases when the search costs of less important attributes are alleviated by making those attributes more salient.

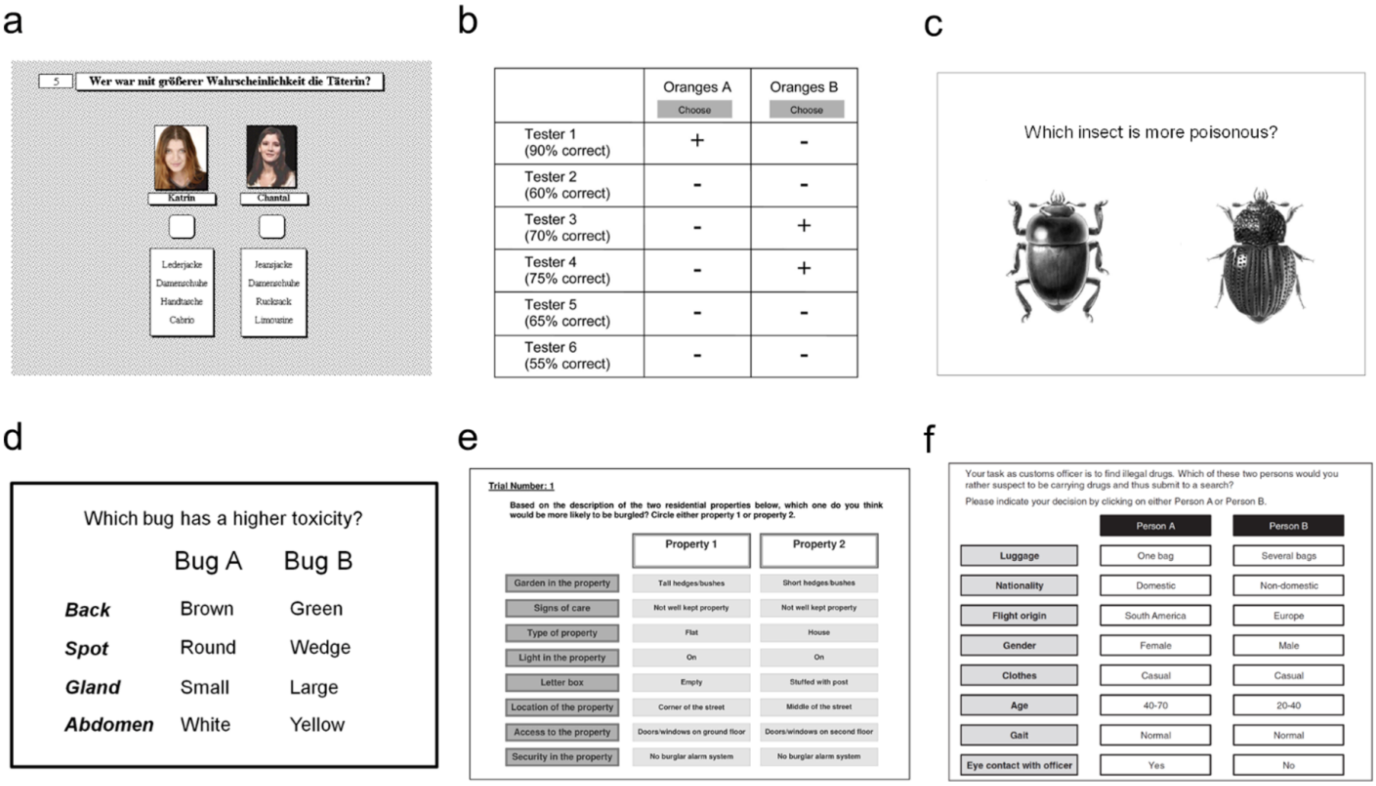


Fig. 1. Examples of material used in studies on decisions from givens. (a) is from Bröder and Schiffer (2003b), (b) is from Glöckner and Betsch (2008), (c) is from Bergert and Nosofsky (2007), (d) is from Pachur and Olsson (2012), (e) is from Garcia-Retamero and Dhami (2009) and (f) is from Pachur and Marinello (2013).

givens (but see Bobadilla-Suarez & Love, 2018; Bröder & Schifffer, 2003b). Note that in the set-ups commonly used in studies on decisions from givens (see Fig. 1), information integration—incurred by compensatory but not by noncompensatory strategies—usually requires a visual assessment of the number of positive versus negative attribute values for each alternative. As is known from studies in attention research, visual enumeration can be accomplished by two qualitatively different types of processes. One process, *subitizing*, allows for the automatic, fast, and highly accurate assessment of the number of objects (Kaufman et al., 1949); subitizing only occurs, however, when no more than about four objects are present. Otherwise, people use a controlled, sequential, more effortful, and slower process: *counting*. A prominent explanation of subitizing makes reference to internal tags, called "fingers of instantiation," or FINSTs. These FINSTs allow the mental system to simultaneously track and process individual objects in a parallel and preattentive fashion, and their number is assumed to be limited to about four (Trick & Pylyshyn, 1993, 1994; for other proposals, see, e.g., Gallistel & Gelman, 1992; Mandler & Shebo, 1982).

Here I propose that in decisions from givens compensatory decision strategies could exploit subitizing to integrate evidence for each alternative from a set of attributes in a quick and relatively effortless fashion. This applies in particular to EQW, which relies—in a similar way as the typical enumeration studies on subitizing—on the unweighted number of positive (vs. negative) attribute values. From the theoretical perspective on subitizing (FINST theory; Trick & Pylyshyn, 1993), however, there is nothing to rule out the possibility that subitizing can also implement a weighted summation. If so, compensatory strategies—whether EQW or WADD—might be predominant with a relatively low number of attributes, as subitizing can be used to gauge the (weighted) number of positive versus negative attributes for each alternative (assuming that evidence is integrated for each alternative separately). With a relatively high number of attributes, by contrast, there will be fewer cases where subitizing is possible; instead, more effortful processes will be necessary to integrate across attributes. In that case, noncompensatory strategies such as TTB, which do not require the integration of multiple attributes, could be more attractive because they avoid the higher costs incurred by counting. Alternatively, people might select a compensatory strategy even when the number of attributes is relatively high and attributes cannot be integrated by means of subitizing; to do so, however, they would need to revert to a serial, slow, and perhaps more error-prone counting process.

To avoid misunderstandings: The purpose of invoking the notion of subitizing in the present work is not to propose an alternative strategy of automatic compensatory decision making (e.g., Glöckner & Betsch, 2008). Instead, the argument is that subitizing might serve to implement the subprocess of integration that is part of compensatory decision strategies; if so, the known limits of subitizing might point to differences in the cognitive costs incurred by compensatory strategies for different types of stimuli and thus also point to boundary conditions of quick, holistic compensatory processing in decisions from givens—an aspect that has received only scant attention in decision research so far.

Some previous studies examined the influence of the number of attributes on aspects of information processing (for overviews, see Ford et al., 1989, and Payne et al., 1993). Although the findings are mixed, there is some evidence that—consistent with the thesis presented here—in tasks with a higher number of attributes, information processing is more simplified (Biggs et al., 1985; Sundström, 1987; but see Payne, 1976). None of the investigations, however, modeled strategy selection directly or aimed at elaborating on the type of costs incurred given the number of attributes.

By the same token as for the number of attributes, strategy selection might also be influenced by the type of attribute coding due to subitizing. People seem to subitize not only depending on the number of objects, but also depending on the degree to which visual properties that distinguish the target objects from other objects are a “pop-out feature” (Trick & Pylyshyn, 1994, p. 97) that make a low-level grouping of the target objects possible. For instance, groups of positive and negative attribute values might pop out more readily with uniform coding (e.g., “✓, ×, ✓, ✓, ✓, ×, ✓”) than with varied coding (e.g., “higher, lesser, larger, stronger, inferior, better”; cf. Bobadilla-Suarez & Love, 2018). This might occur because FINSTs are only assigned to objects that share certain features (Trick & Pylyshyn, 1993). Note that according to FINST theory, the objects remain individually represented and trackable; a pop-out effect therefore does not mean that they are chunked together. Trick and Pylyshyn (1993) found evidence for subitizing when target objects were easily discriminable from nontargets, but not when target objects did not pop out against nontargets. Applied to attribute information in decisions from givens, this might mean that integration across multiple attributes incurs lower costs with uniform than with varied coding. As a consequence, the use of compensatory strategies might be more pronounced in the former than in the latter.

Evidence consistent with the notion that varied and uniform coding incur different integration costs comes from a study by Bobadilla-Suarez and Love (2018). The authors instructed participants to use the compensatory EQW and manipulated whether the decision had to be made with or without time pressure. Participants executed the strategy equally well in both time pressure conditions when (all seven) attributes were shown in a uniform coding format (Experiment 1), but they made more errors under time pressure when coding was varied (Experiment 2). In addition, response times for implementing EQW were much longer with varied than with uniform coding (in the condition without time pressure). The authors proposed that these results reflect that the uniform, but not the varied, coding format allows for a quick, holistic integration of the attribute information; based on the reasoning developed above, this might be because uniform coding helped the relevant attribute values to pop out, and thus make subitizing possible.

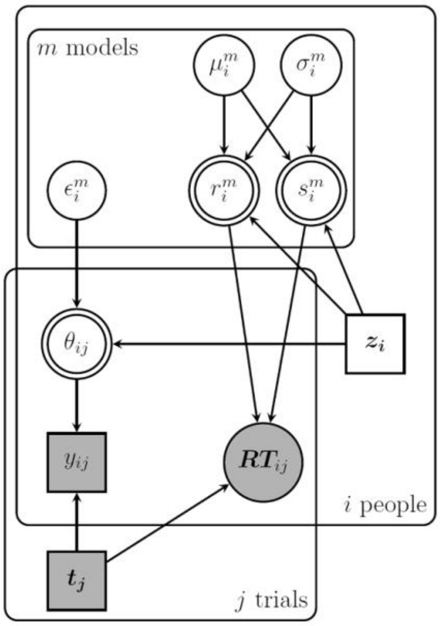
Note that the distinction between varied and uniform coding differs from previous suggestions of how attribute format might influence strategy selection. The authors of two studies that distinguished between a “presence–absence” format (e.g., fever present vs. not present) and an “alternative” format (e.g., brown vs. green eyes; Bröder et al., 2010; Platzer & Bröder, 2013) argued that learning the attribute direction (i.e., whether an attribute value provides positive or negative evidence for an alternative) is more difficult with the alternative format than with the presence–absence format (because the attribute direction is more ambiguous with the former). Yet this distinction is in principle orthogonal to the distinction between uniform and varied coding. In previous studies, uniform coding has often been used in combination with a presence–absence format, and varied coding with an alternative format. But this does not need to be the case; in the experiments I report here, the attribute values were always presented in an alternative format, while varying whether a uniform or a varied coding scheme was used. Finally, Söllner et al. (2013) distinguished the commonly used matrix format (where attributes are presented by alternatives in a grid) from a map format, in which each attribute has its specific location on a two-dimensional map. However, these different attribute formats are thought to impact the accessibility of the attribute information (e.g., Platzer & Bröder, 2013; Söllner et al., 2013) and thus the costs of information search, not the costs of integration.

Although the patterns of results in Table 1 suggest that strategy selection may be influenced by the number of attributes and the type of attribute coding, no study has yet systematically examined the use of noncompensatory and compensatory strategies while varying both factors within the same experimental paradigm, holding everything else (e.g., distribution of attribute importance, type of stimuli) constant. In fact, in the studies listed in Table 1, the number of attributes and the type of attribute coding have been confounded to some extent, because the studies with a rather low number of attributes also tended to use a uniform coding scheme. It is therefore currently unclear whether both factors play a role, or only one of them, or whether attribute coding comes into play only when the number of attributes is relatively high.

To address these questions, below I report two experiments that manipulate both the number and type of coding of attributes. In these experiments, great care is taken to create situations in which, according to previous literature, search costs should be low. For instance, it is commonly assumed that search costs are low when all attribute information is openly presented onscreen, thus allowing for a holistic assessment of the alternatives (Glöckner & Betsch, 2008); search costs are also thought to be low when the attributes are presented in a structured fashion (Söllner et al., 2013). Furthermore, participants received intense training on the meaning of the attribute values so that they would be able to retrieve this information from memory efficiently. However, it may be impossible to eliminate search costs entirely, or to conclusively disentangle costs of search and integration. For instance, when integration is implemented by counting, attention moves sequentially from one attribute to the next, even if all information is directly accessible (or has already been acquired). It therefore cannot be ruled out that search costs may also contribute to possible effects on strategy selection.

To summarize: It has previously been assumed that, due to the importance of search costs in strategy selection, noncompensatory strategies play only a minor role in decisions from givens, where all information is openly presented on the screen and search costs are thought to be low. However, my systematic review of strategy selection in decisions from givens revealed a highly heterogeneous picture, with the percentage of users of a noncompensatory strategy ranging from 0% to 81%. I argue that this heterogeneity might be due to variability between studies in the number of attributes used and how attribute values are coded. Insights on enumeration processes from visual attention research suggest that both factors might affect the costs of integrating attributes incurred by compensatory strategies. When the number of attributes is low enough, the decision maker could use subitizing to integrate the number of positive (vs. negative) attributes of the alternatives, and thus predominantly rely on a compensatory strategy. Moreover, integration costs could be low only when positive and negative attributes pop out as easily separable groups of stimuli. When these conditions are not met and integration costs are thus relatively high, people instead may turn to a noncompensatory strategy.

Below I report two experiments that manipulated these factors while keeping search costs minimal. Experiment 2 is basically a replication of Experiment 1 with an increased sample size, additional measures to reduce search costs and to increase motivation, and a



$$
\begin{array}{rcl}
z & \sim & \text{Categorical}\left(\frac{1}{4},\frac{1}{4},\frac{1}{4},\frac{1}{4}\right) \\
\epsilon_i^m & \sim & \text{Uniform}(0,1) \\
\theta_{ij} & = & \begin{cases} \mathcal{H}_m(\boldsymbol{t}_j)\,(1-\epsilon_i^m)+\frac{1}{2}\epsilon_i^m & \text{if } z \in \{\text{ttb, eqw, wadd}\} \\ \frac{1}{2} & \text{if } z = \text{guessing} \end{cases} \\
y_{ij} & \sim & \text{Bernoulli}(\theta_{ij}) \\
RT_{ij} & \sim & \text{Gamma}(s_i^m, r_i^m) \\
r_i^m & \leftarrow & \frac{\mu_i^m}{(\sigma_i^m)^2} \\
s_i^m & \leftarrow & \frac{(\mu_i^m)^2}{(\sigma_i^m)^2} \\
\mu_i^m & \sim & \begin{cases} \text{Uniform}(0,25000)\colon \mu^m_{i,type(j)=1} < \ldots < \mu^m_{i,type(j)=K} & \text{if } z = \text{ttb} \\ \text{Uniform}(0,25000)\colon \mu^m_{i,type(j)=1} = \ldots = \mu^m_{i,type(j)=K} & \text{if } z \in \{\text{eqw, wadd, guessing}\} \end{cases} \\
\sigma_i^m & \sim & \text{Uniform}(0,25000)
\end{array}
$$

Fig. 2. Graphical model of the Bayesian latent-mixture approach for inferring strategy use based on decision and response-time data.

refined set of decision problems. In both experiments, participants were asked to make decisions about alternatives (diamonds) whose attribute information was presented openly onscreen, neatly structured by alternatives and attributes; also the importance weights of the attributes were presented openly onscreen. In an extensive learning phase designed to keep search costs low, participants learned the meaning of the symbols representing the attribute values. The alternatives were described using either four or eight attributes, and positive and negative attribute values were shown in either a uniform or a varied coding scheme.[5] I assume that attribute information for each alternative can be integrated relatively effortlessly with up to four attributes (by means of subitizing), even with a varied coding scheme, as the individual FINSTs also track distinct objects. Therefore, I predict that people will predominantly use compensatory strategies in the conditions with four attributes, independently of the type of attribute coding. With eight attributes, however, integration by subitizing is less likely because there will be more cases where the number of positive attribute values exceeds four; people will therefore select TTB and/or guess more. I predict the highest rate of selection of TTB in the condition with eight attributes and varied attribute coding, where the costs of information integration are likely to be highest. I also explored patterns of response times: In the conditions with four attributes, the response times of users of a compensatory strategy are expected to be approximately as short as those of users of a noncompensatory strategy due to the automatic processing of subitizing. In the conditions with eight attributes, in contrast, the response times of users of compensatory strategies should be considerably slower, reflecting a higher prevalence of more controlled processing.

People's strategy selection was inferred with a Bayesian modeling approach that considers both their decisions and patterns in response times. This approach is described in more detail in the next section.

2. Bayesian multimethod strategy classification

Participants were classified as using the compensatory WADD or EQW, using the noncompensatory TTB, or guessing, via a multimethod Bayesian latent-mixture approach that builds on Lee et al. (2019; see also Lee, 2016). Based on the (mis)match between each strategy's predicted decision and the participant's actual decisions, as well as the predicted response-time pattern and the participant's actual response-time pattern in the decision task, I estimated a posterior probability—informed by the data—that the person had used each of the tested strategies. This multimethod approach takes into account that the models differ not only in terms of the decisions they predict, but also in terms of the predicted pattern of response time—thus doing more justice to the predictions of the strategies than considering only people's decisions.

The graphical model of the approach is shown in Fig. 2, with nodes representing parameters and data, and the graph structure indicating how the parameters are assumed to generate the data. Each trial j presents a decision problem, consisting of a pair of alternatives with attribute profiles. The decision at a given problem j is represented by the y_j node, which is 1 if the first alternative in a pair is picked and 0 if the second alternative is picked. The node for the decision is represented by a square, to reflect that the data is discrete. The model assumes that the data were generated by a person's use of strategy m. It also assumes that the use of strategy m is associated with making an executing error with probability ε_m, in which case a decision is made by guessing.

The response time at decision problem j is represented by the RT_j node, which is a circle to reflect that response times are continuous. The response time for strategy m at a given problem is assumed to be drawn from a gamma distribution. For ease of interpretation, the s and r parameters of the gamma distribution are reparameterized into mean μ and standard deviation σ (see right

[5] These two levels for the number of attributes were chosen to reflect both the lower and upper bounds of the numbers commonly used in previous studies on decisions from givens.

side of Fig. 2 for details). Because the different strategies partly predict different patterns of response times, μ and σ are estimated separately for each strategy. In order to differentiate these predictions, types of decision problems are distinguished that differ in terms of when TTB predicts search to be stopped—and thus how fast a decision is made (such a distinction has also been made by, e.g., Bröder & Gaissmaier, 2007; Dummel & Rummel, 2016; Fechner et al., 2018; Fechner et al., 2019; Khader et al., 2013; Khader et al., 2016; Nosofsky & Bergert, 2007).[6] Specifically, due to TTB's stopping rule, response times for decision problems in which the most important attribute discriminates between the alternatives (type 1) should be faster than those for problems in which only the second most important attribute in the attribute hierarchy discriminates (type 2), which should in turn be faster than those for decisions on problems in which the third most important attribute discriminates (type 3), etc. To reflect this prediction, for TTB the parameters μ and σ are estimated separately for the K different types of decision problems in the model, with the order constraint $\mu_{\text{type 1}}$ (i.e., first attribute discriminates) $< \ldots < \mu_{\text{type } K}$ (i.e., the K^{th} attribute discriminates). For WADD and EQW, no differences between different types of decision problems are usually predicted (e.g., Bröder & Gaissmaier, 2007; Fechner et al., 2018), and this assumption was adopted here (I also tested variants of WADD and EQW that assumed that response times differ across types of decision problems, but they were outperformed by the simpler variants; see below).

The predicted probability of choosing alternative A in a given decision problem is represented by θ_j. For guessing, θ_j is 0.5. If WADD, EQW, or TTB is selected, the probability of choosing alternative A depends on the predicted decisions of the respective strategy m and the estimated execution error ε_m. Following Lee et al. (2019), the decision predicted by strategy m on decision problem j is represented in Fig. 2 as $\mathcal{H}_m(t_j)$. To derive $\mathcal{H}$ for WADD and TTB, I used the importance weights provided to participants on the screen at each trial to weight the attributes and order them, respectively. The strategy used to account for the data is determined by the categorical strategy node z; it can take on values 1, 2, 3, and 4, representing WADD, EQW, TTB, and guessing, respectively. The posterior distribution of z, which is estimated for each participant, can be viewed as an indicator of the relative evidence for each strategy and is the basis for inferring which strategy a person is most likely to have used (i.e., for strategy classification). The assumptions about the prior distributions for the different parameters are specified in Fig. 2.

I conducted several robustness checks for the results and assumptions in the strategy classification model. First, participants' strategy selection was also inferred using a classification model that used the decision data only. As reported in Appendix B, this led to qualitatively very similar results. Second, in order to identify the best-performing variants of the compensatory strategies, I conducted a model comparison between variants for which the same response time was predicted across all problem types and variants for which the response time was predicted to be faster in problem types where the evidence differentiated more strongly, on average (across the decision problems of the problem type), between the alternatives.[7] Note that as the latter variants estimate a separate response time for each problem type, they have higher model complexity. In this model comparison, reported in Appendix C, the variants predicting the same response time across all problem types were clearly superior, indicating that they provide a better balance between model fit and complexity. Note, however, that this does not mean that response times of compensatory mechanisms are generally insensitive to the amount of evidence in a decision problem; instead, as the problem types were not specifically designed as a function of differences in evidence (but were defined based on TTB's stopping rule), the existing differences between the problem types might simply not have been large enough to warrant a higher model complexity.

Third, for modeling decisions with WADD, it has been proposed that the probability of choosing an alternative might be sensitive to the relative amount of evidence present, such that there is less "error" when the difference in evidence between the alternatives in a decision problem is larger than when it is smaller (Lee, 2016; Heck et al., 2017; Hilbig & Moshagen, 2014). As reported in Appendix D, variants of WADD and EQW with a constant error (as assumed in Fig. 2) outperformed variants equipped with Luce's choice rule or softmax.

3. Experiment 1

3.1. Method

3.1.1. Participants

The experiment involved a total of 80 participants (62 women, 18 men; mean age 25.28 years, $SD = 5.84$, range = 17–49 years); most were students at the University of Basel. They were compensated either with credit points or 10 Swiss francs; additionally, they could take part in a raffle that paid out 100 Swiss francs to each of five randomly drawn participants.

[6] For an alternative distinction of problem types that focuses on whether the different strategies predict the same or opposing decisions, see, for instance, Bröder and Schiffer (2003a), Hilbig and Moshagen (2014), Lee (2016), and Heck et al. (2017).

[7] There is evidence that the larger the difference in evidence between alternatives, the faster responses will be (e.g., Moyer & Landauer, 1967). Therefore, one may argue that the predicted response time of compensatory mechanisms should reflect such differences. Although one could implement such a model within the current framework, it would be highly complex (and thus unlikely to perform well in the Bayesian strategy classification model) because a separate (though ordered) response time would be predicted for each level of evidence difference. In order to keep the level of model complexity for TTB and the compensatory strategies in comparable ranges, I use a distinction of problem types that is theoretically grounded in TTB. Alternatively, a compensatory strategy with response-time predictions that are sensitive to evidence differences between alternatives could be implemented as an evidence accumulation model (e.g., Busemeyer & Townsend, 1993; Glöckner et al., 2014), but this would require a very different modeling framework, limiting comparability with the implementation of TTB.

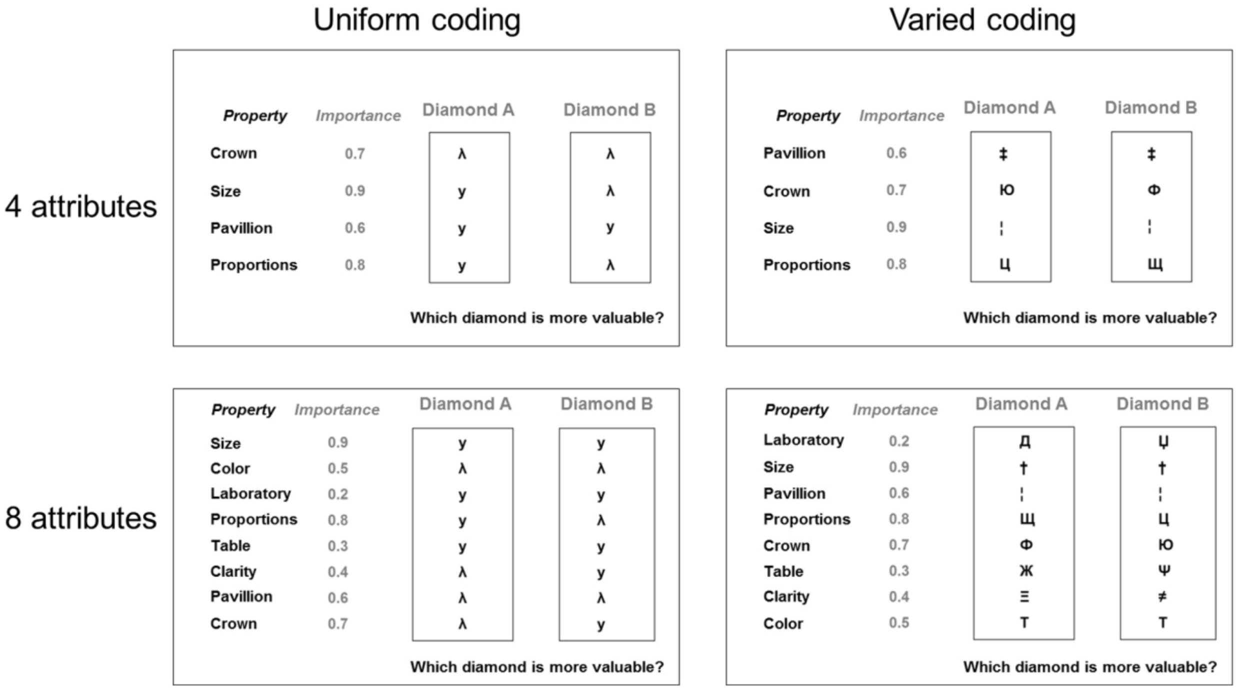


Fig. 3. Illustration of the screen set-up in the decision task, separately for the four conditions.

3.1.2. Design and material

Participants were randomly assigned to the conditions of a 2 (number of attributes: 4 vs. 8) × 2 (attribute coding: uniform vs. varied) design, with 20 participants in each condition. The task material consisted of diamonds of different values (adapted from Mata et al., 2007). The diamonds were characterized on binary attributes that were of varying importance in determining the value. The attributes, ordered from most to least important, were size, overall proportions, crown proportions, pavilion proportions, color, clarity, size of table, and certification laboratory. The ranking of the attributes reflected their predictive strength for the value of real diamonds (cf. Mata et al., 2007).

In the conditions with four attributes, the diamonds were characterized by the four most important attributes. Participants saw 120 pairs of diamonds and were asked to pick the more valuable one in each pair. These decision problems consisted of all 120 possible pair comparisons of the 16 diamonds with different (binary) attribute profiles. There were 64, 32, 16, and 8 pairs in which the first discriminating attribute was the first, second, third, or fourth attribute in the importance hierarchy, respectively. That is, in the conditions with four attributes, there were four different types of decision problems. In 36 of the decision problems, EQW and TTB predicted different decisions; in 26 problems, EQW and WADD predicted different decisions; and in 10 problems, WADD and TTB predicted different decisions.

In the condition with eight attributes, I first generated all 32,640 possible pairs of all $2^8 = 256$ possible alternatives. Because the primary interest was in distinguishing the use of noncompensatory versus compensatory strategies, I then identified the pairs in which TTB would arrive at a different decision than the compensatory strategies WADD and EQW. From these pairs, I randomly selected 40 pairs in which the first attribute in the attribute hierarchy was the first discriminating attribute, then did the same for the second and third attribute. In the condition with eight attributes, there were thus three different types of decision problems. Note that whereas TTB predicted a different decision than did WADD and EQW on all of the 120 decision problems, WADD and EQW always predicted the same decision; I therefore do not distinguish between these two compensatory strategies in the conditions with eight attributes (and the z node could take on only values from 1 to 3). Experiment 2 allows for a distinction between WADD and EQW also in these conditions.

Each attribute was assigned an importance weight (with higher numbers indicating higher importance) varying between 0.6 and 0.9 (in steps of 0.1) in the condition with four attributes, and between 0.2 and 0.9 (in steps of 0.1) in the condition with eight attributes. The ranking of the attributes was fixed across participants. The importance weights were openly presented onscreen next to the attribute names. Fig. 3 shows screenshots of the decision task in the different conditions.

Positive and negative attribute values, providing evidence for the diamond being of higher and lower value, respectively, were indicated by different symbols. Participants learned the meaning of the symbols in an extensive learning task preceding the decision task (see below for details). In the conditions with uniform coding, the same symbol pair was used across all attributes. In the con-ditions with varied attribute coding, each attribute had its own symbol pair for positive and negative values. Whereas the symbols indicating positive and negative values within an attribute were similar (e.g., ‡ vs. †), for different attributes the symbols were dissimilar (e.g., ‡ vs. Φ). Table 2 shows the symbols used. The symbol pairs were assigned randomly to the different attributes for each

Table 2
Symbol Pairs Used to Represent Positive and Negative Attribute Values in the Different Conditions.

Symbol 1	Symbol 2	Condition in which the symbol pair was used	
		Number of attributes	Attribute coding scheme
У	λ	4, 8	Uniform
‡	†	4, 8	Varied
Φ	Ю	4, 8	Varied
¦	- -	4, 8	Varied
Щ	Ц	4, 8	Varied
Џ	Д	8	Varied
T	П	8	Varied
Ξ	≠	8	Varied
Ж	Ψ	8	Varied

Table 3
Average Number of Trials Completed in the Learning Task Before the Learning Criterion Was Reached, by Condition.

	Number of attributes	Experiment 1		Experiment 2	
		Attribute coding scheme			
		Uniform	Varied	Uniform	Varied
Part 1	4	19.80 (5.55)	22.20 (5.76)	28.12 (5.41)	31.40 (7.73)
(initial learning)	8	37.85 (9.79)	49.05 (12.42)	60.88 (23.57)	74.15 (23.04)
Part 2 (consolidation)	4	16.70 (1.84)	16.20 (0.94)	26.02 (5.19)	26.05 (6.11)
	8	32.55 (2.46)	32.30 (1.34)	50.38 (6.76)	60.55 (22.12)

Note. The minimum necessary number of trials in the condition with four attributes (eight attributes) was 16 (32) and 24 (48) trials in Experiments 1 and 2, respectively. Standard deviations are shown in parentheses.

participant. In both the uniform and the varied coding conditions, which symbol in each pair represented a positive or a negative attribute value was also assigned randomly for each participant.

3.1.3. Procedure

All tasks were programmed in E-Prime 2.0 and presented on a computer screen. Depending on the condition, participants took 60–90 min to complete the experiment.

In the first part of the experiment, participants learned which symbol represented a positive and which represented a negative value for each attribute. This *learning task* started with a written description (on the computer screen) of each attribute and why it was an indicator of the value of a diamond. Participants were then presented with a randomly chosen attribute and its assigned symbol pair and asked to indicate, by clicking on the respective box on the screen, which symbol represented a positive value, initially by guessing. This was followed by feedback (“Correct” or “Incorrect”); then a next, randomly chosen attribute was presented, until all attributes had been presented. Then there was another cycle of attribute presentations (with the attributes presented in a new random order). This process continued until the participant had responded correctly to all attributes four times in a row. This was followed by an unrelated distraction task that took around 30 min. Then the participants were presented with the learning task again (consolidation phase), with the same accuracy criterion for completing the task as in the initial learning phase. The goal of this intensive training was to ensure that participants were able to recall the coding of each attribute with high ease and accuracy, thus keeping search costs low.

After successfully completing both phases of the learning task, participants were presented with a *decision task*, involving 120 profile pairs of diamonds shown in random order (with a different random order for each participant). The two diamonds in each pair were randomly assigned to the left and right sides of the screen. The order of the attributes presented onscreen was also random at each trial (i.e., the attributes were not ordered by importance). For each pair, participants were instructed to pick the diamond they thought was more valuable, given the attribute profile, by pressing either the F1 key (for diamond A in the pair) or the F12 key (for diamond B) on the keyboard. Consistent with previous studies (e.g., Bröder & Schiffer, 2003b; Mata et al., 2007), neither a definition of a “correct” decision nor any accuracy feedback was provided in order to avoid unnecessarily constraining participants’ strategy selection. Participants worked at their own pace.

3.2. Results

3.2.1. Learning the attribute coding scheme

As described above, participants had to correctly indicate which symbol represented a positive attribute value for all attributes four times in a row before they could finish the learning phase. This means that the minimum number of trials was 16 in the conditions with four attributes and 32 in the conditions with eight (if the correct symbol was guessed in the first trial). Table 3 shows that in the conditions with uniform coding, participants required only slightly more than the minimum number of trials to reach the learning criterion for the first time. In the conditions with varied coding, the number of required learning trials was slightly higher. Most

Table 4
Median of the Median (Across Trials) Response Times (in Milliseconds) in the Consolidation Phase of the Learning Task.

	Number of attributes	Experiment 1		Experiment 2	
		Attribute coding scheme			
		Uniform	Varied	Uniform	Varied
Fluency	4	846.3 (304.4)	975.0 (400.0)	690.8 (193.5)	754.5 (234.8)
	8	810.3 (139.9)	942.5 (419.6)	662.5 (206.1)	857.8 (297.6)

Note. Interquartile ranges are shown in parentheses.

importantly, participants had retained the coding scheme almost perfectly in the consolidation phase (which occurred about 30 min after the initial learning phase); in fact, 74 of the 80 participants (92.5%) did not require any additional cycle to meet the learning criterion again. Table 4 reports participants' response times in the consolidation phase of the learning task, making it possible to compare the memory accessibility of the coding scheme across the conditions (note that the response times cannot be taken as a pure measure of memory fluency as they also reflect the motor component of moving to the respective box and clicking on it). A Bayesian ANOVA of the log-transformed response times indicated only anecdotal evidence for a main effect of coding scheme (Bayes factor, BF, of the alternative over the null hypothesis, $\mathrm{BF}_{10} = 1.438$), and moderate evidence against both a main effect of the number of attributes ($\mathrm{BF}_{10} = 0.247$) and an interaction of the two factors ($\mathrm{BF}_{10} = 0.117$). This suggests that the extensive learning phase enabled participants to recall the coding scheme equally fast across the coding conditions, even when the material was relatively complex. It is thus plausible that participants required little effort to assess whether each attribute provided positive or negative evidence for each alternative, and that the search costs of this information were therefore low.

3.2.2. Strategy classification

In the analysis of the decision task data, trials in which responses faster than 200 ms (52 trials) or slower than 60,000 ms (19 trials) were excluded (0.7% of all trials) as they are too short to be based on a processing of the attribute values or unlikely to reflect the actual decision processes (e.g., because the participant was distracted; Whelan, 2008).[8] The Bayesian strategy classification model for inferring strategy use in the decision task was estimated using JAGS (Plummer, 2003). I ran 80,000 samples on each of 10 chains, with a burn-in of 2,000 samples. To reduce autocorrelations, only every 20th sample was recorded. Convergence of the chains was checked with the $\hat{R}$ statistic (Brooks & Gelman, 1998). The descriptive adequacy of the model was assessed using posterior predictive checks (e.g., Lee & Wagenmakers, 2014). The model captured participants' decisions on average (across participants) 85.9% ($SD = 11.7$) of the time (excluding the two participants classified as guessing; see below). As demonstrated in Fig. A4 in Appendix E—which shows the empirical and the estimated response-time pattern of the inferred strategy for each participant (based on the mean of the posterior distributions of the estimated μ parameter for the inferred strategy)—the response times for the different types of decision problems were captured well overall. Fig. A4 also reports the estimated strategy execution error rate ε for the most likely strategy for each participant (to which we turn below).

Fig. 4 shows, for each of the four conditions, the posterior distributions of the z strategy parameter for each participant. The posterior distribution represents an estimate of the posterior probability that the respective strategy was used by the participant. The posterior probabilities can be interpreted as Bayes factors (Kass & Raftery, 1995) at the level of individual participants and automatically balance goodness-of-fit with all forms of model complexity. In the figure, for each participant (shown on the x-axis) the posterior probability that the strategy was used is represented by the size of the circle for a given strategy (shown on the y-axis). Classifying each participant as a user of the strategy for which the posterior distribution was highest, the figure also reports the percentage of participants assigned to each strategy at the right margin of each panel.

Did participants' strategy use differ depending on the number of attributes and the type of attribute coding? As predicted, in the conditions with four attributes, a large majority of participants (35 out of 40; 87.5%) were classified as using one of the two compensatory strategies, WADD and EQW. Only few participants were inferred to have used TTB (5 out of 40; 12.5%).[9] This pattern was relatively unaffected by whether the attributes were presented in a uniform or a varied coding scheme. Strategy selection was different in the conditions with eight attributes, with clear indications that participants simplified the decision process, either by selecting TTB or by guessing (note that due to the design of the decision problems, no distinction is made here between WADD and EQW). In the condition with varied attribute coding—where costs were likely to be highest—the majority of participants (12 out of 20; 60%) were inferred to have used TTB, and the percentage of users of a compensatory strategy dropped to 35% (7 out of 20). An additional phase-wise strategy classification analysis, reported in the Supplemental Material (both for Experiment 1 and 2), suggests

[8] One may argue that 60,000 ms is an unusually long time. However, I did not want to exclude the possibility that some participants sometimes seriously engaged in deliberate mental calculation to make a decision, and with a total of eight attributes that might take quite some time. The value of the upper cut-off should be considered as a pragmatic one; the strategy selection results were robust with alternative cut-off values or with no cut-off at all.

[9] One might wonder whether the higher proportion of users classified as using a compensatory strategy could be due to the strategy comparison involving two compensatory strategies but just one noncompensatory strategy. An analysis reported in the Supplemental Material shows that exactly the same number of participants were classified as using a compensatory strategy when the comparison involved only one compensatory strategy (WADD).

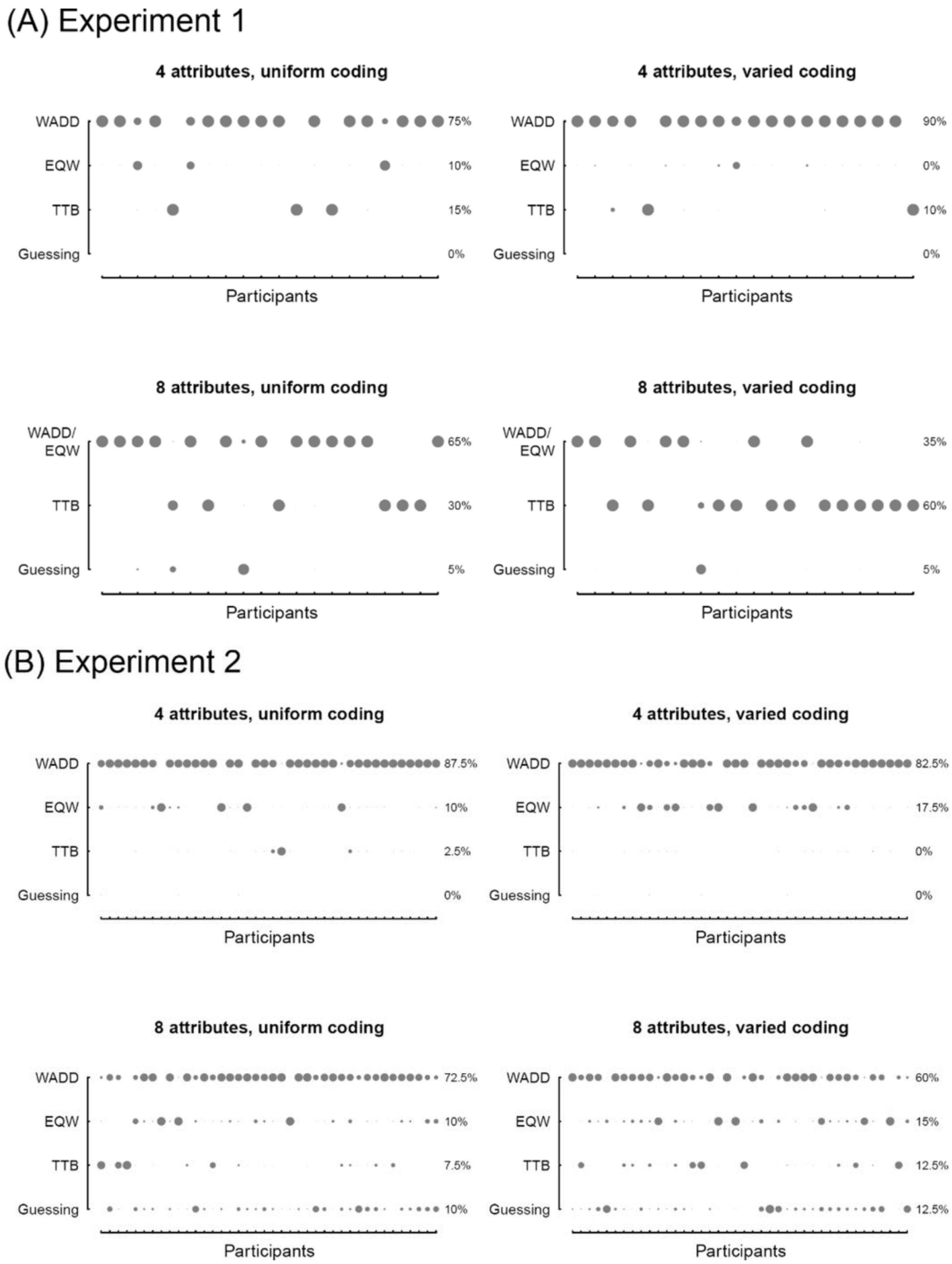


Fig. 4. Results of the Bayesian strategy classification, separately for the different conditions in Experiment 1 (A) and Experiment 2 (B). The size of the points represents the amount of evidence for each of the four strategies (weighted additive, WADD; equal weight, EQW; take-the-best, TTB; and guessing) for each participant, based on the posterior distribution of the strategy parameter z. The numbers at the right margin indicate, for each strategy, the percentage of participants for whom the posterior probability of using that strategy was highest.

that the pattern of strategy selection was relatively stable across the 120 trials of the decision task (cf. Lee & Gluck, 2021; Lee et al., 2019).

The differences in the number of participants classified as users of the different strategies were examined statistically using Bayesian log-linear regression with an uninformative prior, conducted with the `conting` package in R (Overstall & King, 2014). In this

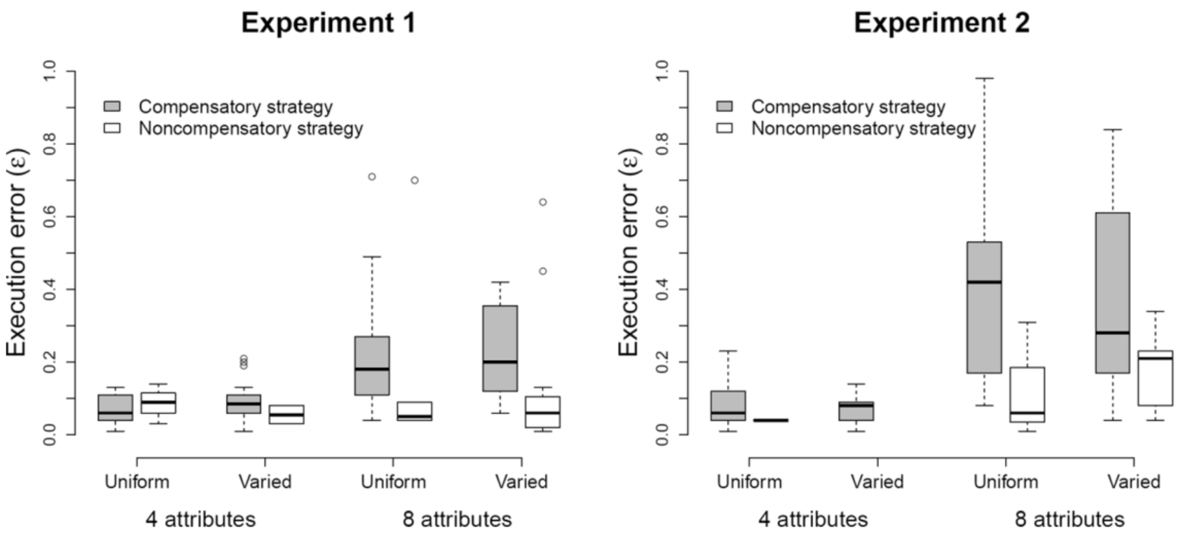


Fig. 5. Boxplots of the estimated strategy execution errors for the individual participants' inferred strategies in the different conditions in Experiment 1 (left) and Experiment 2 (right), separately for users of a compensatory vs. a noncompensatory strategy (note that in the condition with four attributes and varied coding in Experiment 2, no participant was inferred to use a noncompensatory strategy).

analysis, the best-performing model was the one that only retained the two-way interaction between strategy (compensatory vs. noncompensatory) and number of attributes (4 vs. 8) and had a posterior probability of 0.667. This model was 3.61 (i.e., Bayes factor = $0.667/0.185$) times more likely than the model that also included the interaction between strategy and attribute coding (varied vs. uniform) and 95.3 times (i.e., Bayes factor = $0.667/0.007$) more likely than the model that also included the three-way interaction between strategy, number of attributes, and attribute coding. A follow-up analysis with a Bayesian contingency table (conducted with JASP; JASP Team, 2020) showed strong evidence for the null hypothesis that attribute coding did not affect strategy use in the conditions with four attributes ($\mathrm{BF}_{10} = 0.096$) and moderate evidence in the conditions with eight attributes ($\mathrm{BF}_{10} = 0.248$).

The left panel of Fig. 5 plots the estimated strategy execution errors ε (see Fig. 2) of the users of a compensatory versus a non-compensatory strategy in the different conditions, as they may hint as the difficulty of implementing the strategies; the results are based on the estimated parameter ε of that strategy to which each participant was classified. There were considerable differences between the strategies across the conditions. Specifically, the execution error of users of a compensatory strategy nominally more than doubled between the conditions with four and the conditions with eight attributes ($Md = 0.08$ vs. 0.19); for users of the non-compensatory strategy, the execution errors were very similar across the two sets of conditions ($Ms = 0.08$ vs. 0.06). These differences are further discussed in terms of the adaptivity of participants' strategy selection in the General Discussion.

To summarize: In line with the idea that information integration can be implemented by subitizing when the number of attributes is relatively low, most participants selected a compensatory strategy in the conditions with four attributes. This was unaffected by how attributes were coded. With eight attributes, however, people increasingly turned to the noncompensatory TTB, and when attributes were coded with a varied format, the majority of participants relied on TTB. The number of attributes but not the type of attribute coding credibly affected strategy use. The participants who relied on a compensatory strategy in the conditions with eight attributes incurred a larger error in executing the strategy. The results demonstrate that even when attributes are provided openly in a structured format onscreen and the meaning of the attribute symbols is readily available in memory, tools of bounded rationality have a place in people's decision making. These tools come into play when compensatory strategies incur high mental costs that make them unattractive and error-prone. The results support the idea that the heterogeneity observed in previous studies on strategy selection in decisions from givens (Table 1) may be due (at least in part) to variability in the number of attributes.

3.2.3. Response times

Participants' response times can provide further insights into their strategy use and integration of information. I first describe the response times generally across the different conditions and then distinguish participants by inferred strategy use. For the analyses, each participant's median (across decision problems) response time was determined, thus addressing the typical skew in the response time distributions. The results for the different conditions are shown in the left panel of Fig. 6. Decisions were considerably faster when the alternatives were described on four rather than eight attributes ($Md = 4{,}514$ ms, $IQR = 1{,}999$ vs. $Md = 9{,}269$ ms, $IQR = 10{,}695$); the difference in response times between the uniform and varied coding conditions was considerably smaller by comparison ($Md = 5{,}193$ ms, $IQR = 5{,}702$ vs. $Md = 4{,}905$ ms, $IQR = 5{,}265$). Corroborating the visual impression from Fig. 6, in a Bayesian ANOVA (of the log-transformed response times) a model with only the number of attributes as a main effect was preferred to the baseline model by a Bayes factor of 282.82, and to a model with attribute coding as an additional main effect by a Bayes factor of $282.82/75.17 = 3.76$. The baseline model was preferred to a model with only attribute coding as a main effect by a Bayes factor of 3.83. Finally, the model with the number of attributes as the only main effect was preferred to a model that included the interaction between the number of attributes and attribute coding by a Bayes factor of $282.82/70.42 = 4.01$. The data thus provide extreme evidence that the number of

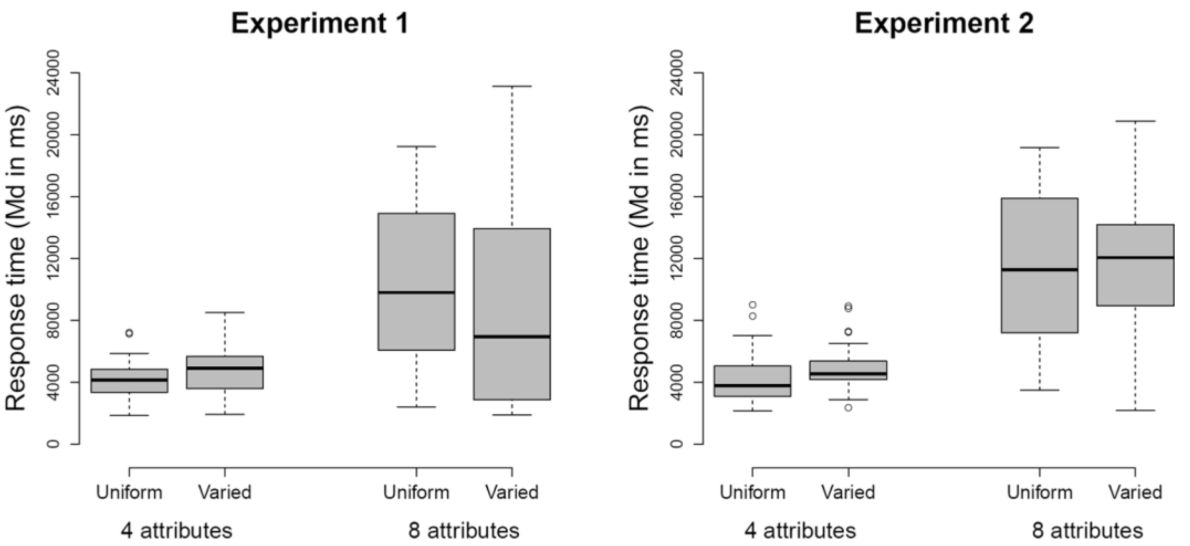


Fig. 6. Boxplots of the response times (based on each participant's median response times across the decision problems) in the decision task in the different conditions in Experiments 1 and 2.

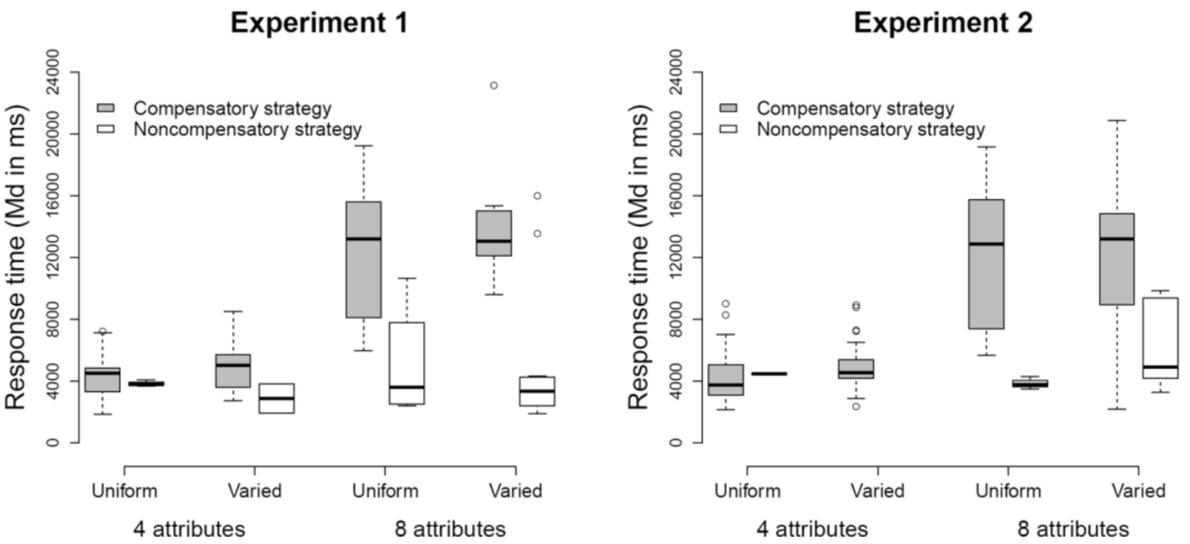


Fig. 7. Boxplots of the response times (based on each participant's median response times across the decision problems) in the different conditions, by inferred strategy use.

attributes affected the response times, and moderate evidence against both an effect of attribute coding and an effect of the number of attributes depending on the attribute coding scheme.

Next, the response times were analyzed as a function of whether a participant was inferred (based on the strategy classification model) to have used a compensatory or a noncompensatory strategy. This analysis is informative for at least two reasons. First, a comparison of response times for different strategy users across the conditions with four versus eight attributes addresses a process prediction of the strategies that did not enter the strategy classification model (Fig. 2). For TTB, the number of inspected attributes is similar across the conditions with four and eight attributes—namely 1.73 and 2 attributes (on average across decision problems), respectively. The response times of TTB users should therefore not differ between these two conditions. For users of the compensatory strategies WADD and EQW, response times should be longer when eight rather than four attributes have to be integrated, at least when assuming a deliberate integration process (as expected in the conditions with eight attributes). Second, a response-time analysis by strategy use indicates to what extent it might be reasonable to assume that compensatory processing is implemented by an automatic mechanism, as suggested by the notion of subitizing and as has been proposed for decision making more generally (e.g., Brusovansky et al., 2018; Glöckner & Betsch, 2008). If this is the case, there should be only small (if any) differences in the absolute levels of response times between users of a compensatory strategy and users of a noncompensatory strategy, and this should hold in the conditions with four attributes (where subitizing is possible) in particular.

Fig. 7 shows the response times in the different conditions, separately for users of compensatory and noncompensatory strategies (excluding participants classified as guessing). A Bayesian ANOVA (of the log-transformed response times) revealed that a model with only strategy use (compensatory vs. noncompensatory) as main effect was preferred to the baseline model by a Bayes factor of 23.97, providing strong evidence that users of a compensatory strategy took longer to make decisions than did users of a noncompensatory strategy. Importantly, a model that included not only main effects of the number of attributes and strategy use but also the interaction of the two was preferred to a model that included only the main effects by a Bayes factor of $(4.147 \times 10^9)/(9.598 \times 10^7) = 43.21$; there was thus very strong evidence that differences in response times between users of compensatory and noncompensatory strategies varied as a function of the number of attributes. This interaction corroborates the impression from Fig. 7 that while the response times of TTB users were unaffected by the number of attributes, the response times of compensatory strategy users were longer when the alternatives were described on eight rather than four attributes. Overall, the results support the process assumption that users of TTB implement a stopping rule that limits information search, whereas users of the compensatory strategies process all (or most of) the information available. One limiting aspect of this analysis, however, is that in the conditions with four attributes only five participants were classified as users of TTB.

What about the idea that attribute values are automatically integrated in compensatory strategies (e.g., Glöckner & Betsch, 2008)? Although absolute levels in response times should be interpreted with caution (response times are the result of many different types of processing and depend on the underlying process assumptions; see Dimov et al., 2020; Marewski & Mehlhorn, 2011), the left panel of Fig. 7 shows that in the conditions with four attributes the response times of users of a compensatory strategy were similar to those of users of the noncompensatory TTB, which does not integrate attribute information. When there were four attributes, information was thus integrated quickly. In the conditions with eight attributes, by contrast, the response times of the users of a compensatory strategy were more than three times longer than in the conditions with four attributes—while the number of attributes merely doubled. This suggests that compensatory strategies may entail qualitatively different processes of information integration depending on the number of attributes. Specifically, the amount of evidence for an alternative—in terms of the (weighted) number of positive or negative attributes—could be determined by subitizing with four attributes, but more effortful, controlled processes were required with eight attributes, as reflected in considerably longer response times.

4. Experiment 2

The purpose of Experiment 2 was to replicate and extend the findings of Experiment 1 using an increased sample size and additional measures to mitigate the possible effects of fatigue and reduce remaining search costs on strategy selection. Specifically, in the decision task participants were given the opportunity to take a break after blocks of 40 trials. In addition, the learning of the attribute coding scheme was further intensified by requiring participants to give six rather than four correct responses in a row before they could proceed to the decision task. Finally, in the conditions with eight attributes the decision problems were revised such that they now allowed for a distinction between WADD and EQW (while at the same time necessarily reducing the discriminability between TTB and the compensatory strategies).

4.1. Method

4.1.1. Participants

The experiment was conducted at the Max Planck Institute for Human Development in Berlin. It involved a total of 160 participants (96 women, 64 men; mean age 27.22 years, $SD = 5.33$, range = 18–40 years), recruited from the institute's internal participant database. Participants received a compensation of €23.

4.1.2. Design and material

The design was the same as in Experiment 1: Participants were randomly assigned to the conditions of a 2 (number of attributes: 4 vs. 8) × 2 (attribute coding: uniform vs. varied) design, but now with 40 participants in each condition. The same material was used as in Experiment 1, except that for the conditions with eight attributes the decision problems allowed for a distinction between WADD and EQW. To that end, for the conditions with eight attributes I matched the first four attributes in the attribute hierarchy to the attribute profiles of the 120 decision problems in the conditions with four attributes. This approach ensured that TTB makes the same predictions as in the condition with four attributes. That is, there were again 64, 32, 16, and 8 pairs in which the first discriminating attribute was the first, second, third, or fourth attribute in the importance hierarchy, respectively. In selecting the extensions (i.e., the attribute values for attributes five to eight in the importance hierarchy) of these "base" profiles, the goal was to achieve high discriminability between EQW and WADD while at the same time ensuring discriminability of these strategies from TTB and minimizing cases where a "guessing" decision is predicted. I first created all $16^2 = 256$ combinations of the 16 different four-attribute profiles (one for alternative A and one for alternative B) and added these as extensions to each of the 120 base pairs of attribute profiles. Of the resulting decision problems, I retained those in which WADD and EQW made an unambiguous prediction (i.e., guessing predictions were excluded) and differed in their predicted decision. For each of the 18 base pairs of attribute profiles where there was at least one extension with which, when combined with the base pair, WADD predicted a different decision than did TTB, one of extensions was selected randomly. The same was done for 101 of the remaining base pairs in which EQW predicted a different decision than did TTB. There was one base pair (namely, [1 1 1 1] vs. [0 0 0 0]) for which no extension existed with which at least one of the compensatory strategies would make an unambiguous prediction that differed from the decision predicted by TTB. This base pair was extended with the profile [0 0 0 0] vs. [1 1 1 1], because with this extension EQW predicted guessing whereas TTB and WADD predicted the choice of alternative A. In the final set of decision problems, WADD and EQW made different predictions on all problems, WADD made different predictions than did TTB in 18 cases, and EQW made different predictions than TTB did in 102 cases.

4.1.3. Procedure

Except for two modifications, the procedure was identical to that in Experiment 1. First, participants had to give the correct response to all attributes six (instead of four) times in a row to complete the learning task, both in the initial learning phase and in the consolidation phase. In addition, they were told that they would need to retrieve the information quickly and that they should therefore respond swiftly during the learning task. Second, in the decision task participants were explicitly given the opportunity to take a short break after each block of 40 trials.

4.2. Results

4.2.1. Learning the attribute coding scheme

The number of trials that participants required to finish the learning task and their median (across trials) response times in the consolidation phase of the learning task are reported in Tables 3 and 4, respectively (note that the minimum necessary number of trials was higher in Experiment 2 than in Experiment 1; see note to Table 3 for details). Although the response times were somewhat faster than in Experiment 1 (possibly reflecting both the instruction to respond quickly and the intensified training), the overall pattern was similar: A Bayesian ANOVA of the log-transformed response times indicated only anecdotal evidence for a main effect of coding scheme ($\mathrm{BF}_{10} = 1.907$), moderate evidence against a main effect of the number of attributes ($\mathrm{BF}_{10} = 0.223$), and anecdotal evidence against an interaction of the two factors ($\mathrm{BF}_{10} = 0.448$). As in Experiment 1, participants could thus recall the attribute coding scheme equally fast across conditions, even when the material was relatively complex.

4.2.2. Strategy classification

As in Experiment 1, trials in the decision task in which responses were faster than 200 ms (6 trials) or slower than 60,000 ms (82 trials) were excluded (0.4% of all trials). The Bayesian strategy classification model was estimated using the same procedure and settings as in Experiment 1. Posterior predictive checks showed that the model captured participants' decisions on average (across participants) 76.4% ($SD = 14.4$) of the time (excluding the nine participants classified as guessing; see below).[10] As can be seen from Figs. A5 and A6 in Appendix E, the individual participants' empirical response times for the different types of decision problems were captured well overall.

The lower panel of Fig. 4 shows the posterior distributions of the z strategy parameter of the strategy classification model for each participant. In all conditions, the proportion of users of a compensatory strategy was higher than in Experiment 2 than in Experiment 1 (4 attributes: 90% vs. 87.5%; 8 attributes: 78.8% vs. 50%), and the proportion of users of TTB was considerably lower (4 attributes: 1.25% vs. 12.5%; 8 attributes: 10% vs. 45%). In fact, reliance on compensatory strategies was now predominant in all conditions, even in the condition with eight attributes and varied cue coding. In other words, the finding in Experiment 1 that in that condition TTB was the most frequent strategy was not replicated. Several factors might have contributed to the generally higher reliance on a compensatory strategy in Experiment 2: the introduction of breaks during the decision task; lower search costs due to intensified learning of the attribute coding scheme; differences in the population from which participants were sampled; differences between the labs in Switzerland and Germany; and the fact that decision problems used in the conditions with eight attributes discriminated less well between TTB and the compensatory strategy than in Experiment 1. Further, in the conditions with eight attributes the proportion of participants classified as guessing was somewhat higher than in Experiment 1; this could be due either to more unsystematic responding or to some people using idiosyncratic strategies that are not well captured by WADD, EQW, or TTB. Overall, however, a pattern similar to that observed in Experiment 1 emerged across the conditions: the proportion of participants classified as using TTB was nominally highest in the condition with eight attributes and varied coding (5 out of 40; 12.5%), and it was higher in the conditions with eight attributes (8 out of 80; 10%) than in the conditions with four attributes (1 out of 80; 1.25%).

The differences in the number of participants classified as users of the different strategies were again examined statistically using Bayesian log-linear regression. As in Experiment 1, the best-performing model retained the two-way interaction between strategy (compensatory vs. noncompensatory) and number of attributes (4 vs. 8) and had a posterior probability of 0.690. This model was 6.5 (i.e., Bayes factor $= 0.690/0.106$) times more likely than the model that also included the interaction between strategy and attribute coding (varied vs. uniform) and 94.5 times (i.e., Bayes factor $= 0.690/0.007$) more likely than the model that also included the three-way interaction between strategy, number of attributes, and attribute coding. A follow-up analysis with a Bayesian contingency table (conducted with JASP) showed moderate evidence for the null hypothesis that attribute coding did not affect strategy use in the conditions with four attributes ($\mathrm{BF}_{10} = 0.28$) but anecdotal evidence for an effect of attribute coding in the conditions with eight attributes ($\mathrm{BF}_{10} = 2.40$).

In contrast to Experiment 1, Experiment 2 also allowed for a distinction between use of WADD and EQW in the conditions with eight attributes. As Fig. 4 shows, the overwhelming majority of users of a compensatory strategy were classified as using WADD here, as in the conditions with four attributes. A second observation is that the decrease in the use of compensatory strategies in the conditions with eight attributes applies particularly to WADD; the use of EQW remained relatively stable across all conditions. In a Bayesian log-linear regression of the frequencies of WADD users, the best-performing model retained the interaction between strategy

[10] The likely reason for the lower percentage in the posterior predictive checks than in Experiment 1 is that in Experiment 2, as reported below, a higher number of participants were classified as using a compensatory strategy, for which the execution error was higher than for the noncompensatory TTB. With a higher execution error, a higher number of decisions is determined randomly, naturally decreasing the proportion of overlapping decisions between model and data.

(WADD vs. other strategies) and number of attributes, and had a posterior probability of 0.643; in the corresponding analysis for the frequencies of EQW users, by contrast, the best-performing model retained only the effect of strategy, and had a posterior probability of 0.634 (the posterior probability of the model containing the interaction between strategy and number of attributes was only 0.111).

The right panel of Fig. 5 shows that, as in Experiment 1, the strategy execution errors (ε parameter; Fig. 2) differed considerably between users of a compensatory versus a noncompensatory strategy (note that no participant was classified as using a noncompensatory strategy in the condition with four attributes and varied attribute coding). As in Experiment 1, the execution error of users of a compensatory strategy was generally higher and increased more strongly between the conditions with four and the conditions with eight attributes ($Mds = 0.08$ vs. 0.29) than that of users of the noncompensatory TTB ($Mds = 0.04$ vs. 0.14).

4.2.3 Response times

Overall, the pattern of response times was highly similar to that in Experiment 1. Plotted in the right panel of Fig. 6, decisions were considerably faster when the alternatives were described on four rather than eight attributes ($Md =$ 4,351 ms, $IQR =$ 1,832 vs. $Md =$ 11,958 ms, $IQR =$ 7,083); the difference in response times between the uniform and varied coding conditions was considerably smaller by comparison ($Md =$ 5,789 ms, $IQR =$ 7,339 vs. $Md =$ 6,369 ms, $IQR =$ 7,499). In a Bayesian ANOVA (of the log-transformed response times) a model with only the number of attributes as main effect was preferred to the baseline model by a Bayes factor of 4.022 × 1025; and to a model with attribute coding as an additional main effect by a Bayes factor of $(4.022 \times 10^{25})/(2.222 \times 10^{25}) = 1.81$. The baseline model was preferred to a model with only attribute coding as a main effect by a Bayes factor of 3.40. Finally, the model with the number of attributes as the only main effect was preferred to a model that included the interaction between the number of attributes and attribute coding by a Bayes factor of $(4.022 \times 10^{25})/(7.136 \times 10^{24}) =$ 5.63. The data thus provide extreme evidence that the number of attributes affected the response times, and moderate evidence against both an effect of attribute coding and the hypothesis that the effect of the number of attributes depended on the attribute coding scheme.

The right panel of Fig. 7 shows that, as in Experiment 1, the response times of users of a compensatory strategy were longer than those of users of a noncompensatory strategy. In addition, users of a compensatory strategy took considerably longer to make a decision in the conditions with eight than with four attributes; this increase was much less pronounced for users of a noncompensatory strategy. Notwithstanding the limitation that only a small number of participants were classified as using a noncompensatory strategy, these patterns were evaluated statistically with a Bayesian ANOVA. In this analysis the baseline model was preferred to the model with only strategy use (compensatory vs. noncompensatory) as a main effect by a Bayes factor of $1/0.737 = 1.356$; as in Experiment 1, however, a model that included not only the main effects of strategy use and the number of attributes but also the interaction of these factors was supported over the model that included only the main effects by a Bayes factor of $(1.282 \times 10^{28})/(1.059 \times 10^{27}) = 12.1$; there was thus again strong evidence that the differences in response times between users of compensatory and noncompensatory strategies differed between the conditions with four and eight attributes.

An additional analysis for the users classified as using a compensatory strategy showed that the considerable increase in response time from the conditions with four to the conditions with eight attributes held for both WADD users ($Mds =$ 4,510.3 vs. 13,338 ms, $IQRs =$ 1,863.5 vs. 6,790.5) and EQW users ($Mds =$ 3,204.5 vs. 7,706 ms, $IQRs =$ 962.25 vs. 3,943.88). In a Bayesian ANOVA of the log-transformed response times (with number of attributes and attribute coding as factors), there was strong evidence for a main effect of the number of attributes for both the WADD users (with a Bayes factor of 1.023×10^{25} over the baseline model) and the EQW users (with a Bayes factor of 39,704.86 over the baseline model). That is, even if the proportion of EQW users was similar across all conditions (lower part of Fig. 4), it seems unlikely that they relied on fast subitizing to integrate the information throughout; instead, the EQW users arguably reverted to serial counting in the conditions with eight attributes.

Despite the similarity of the response-time patterns in Experiments 1 and 2, Fig. 6 also reveals an important difference between the experiments: In the condition with eight attributes and varied coding, response times were considerably longer in Experiment 2 than in Experiment 1. Bayesian t-tests (conducted with JASP) comparing the (log-transformed) response times between the experiments indicated moderate evidence against a difference between the experiments for the conditions with four attributes (uniform coding: $\mathrm{BF}_{10} = 0.211$; varied coding: $\mathrm{BF}_{10} =$ 0.286), and anecdotal evidence for the null hypothesis in the condition with eight attributes and uniform coding ($\mathrm{BF}_{10} = 0.537$), but strong evidence for a difference between the experiments for the condition with eight attributes and varied coding ($\mathrm{BF}_{10} = 10.739$). This underscores that participants tended to respond differently in Experiment 2 than in Experiment 1 when the cognitive costs incurred by the attribute information increased. In addition to some participants turning to a noncompensatory strategy, the majority of participants seemed to invest more effort, reflected in longer response times, and attempted to engage in a compensatory strategy.

Overall, the results show that people are in principle able to apply a compensatory strategy even under conditions with high cognitive costs; however, rather than a fast, intuitive process that allows them to decide "at a glance," a considerable amount of cognitive effort seems to be necessary. In addition, despite the increased effort expended, participants frequently made errors in executing the compensatory strategy.

5. General Discussion

One influential idea to account for the flexibility of human decision making is that the mind selects from an adaptive toolbox a strategy for a given task such that the cognitive effort required is aligned to the available cognitive resources (e.g., Beach & Mitchell, 1978; Gigerenzer et al., 2011; Lieder & Griffith, 2020; Payne et al., 1993; but see Glöckner et al., 2014). Strategy selection should therefore be sensitive to the mental costs that the attribute information imposes on the operations of a strategy. It has previously been hypothesized that because all information is openly provided in decisions from givens, there is no need for noncompensatory strategies; people instead tend to select compensatory strategies (Gigerenzer & Todd, 1999; Glöckner & Betsch, 2008; Platzer & Bröder, 2013; Söllner et al., 2013). Based on a review of previous studies on strategy selection in decisions from givens, I have shown that results are very mixed, and that in some studies people tended to select a noncompensatory strategy. Drawing on insights from visual attention research on subitzing in enumeration tasks (e.g., Trick & Pylyshyn, 1993, 1994), I proposed that this heterogeneity in findings might be due to variation in both the number of attributes involved and the type of attribute coding—factors that might affect the costs of attribute search and integration.

To test this thesis, I conducted two experiments in which both the number of attributes and the type of attribute coding were manipulated. Search costs were kept to a minimum by presenting attribute information openly and in a clearly structured manner, and by teaching participants to decode positive and negative attribute values in an extensive learning phase. In both experiments, participants predominantly relied on a compensatory strategy when there were only four attributes, irrespective of attribute coding; the selection of TTB increased when there were eight attributes, and the proportion of TTB users was highest with eight attributes and varied attribute coding (although only the number of attributes had a credible effect on strategy use). In Experiment 1, TTB was the most frequently selected strategy in that condition. With intensified learning of the attribute coding scheme and measures to reduce fatigue in Experiment 2, participants predominantly selected a compensatory strategy across all conditions (note that the lower discriminability here between compensatory and noncompensatory strategies and differences in the participant pool may also have contributed to the differences between experiments). Yet participants who selected a compensatory strategy in this situation incurred costs, with both considerably longer response times and higher errors in strategy execution than users of a noncompensatory strategy.[11] The rather long response times of users of a compensatory strategy in the conditions with eight attributes (median > 9 s) suggest that participants did not rely on holistic, automatic processing that would enable them to decide "at a glance." Instead, they likely relied on serial and deliberate processing. Overall, of the two potential factors investigated here—which have often been confounded in previous studies (see Table 1)—it was mainly the number of attributes that influenced strategy selection in both experiments; there was evidence that the type of attribute coding did not have an effect on strategy selection and that it did not interact with the number of attributes. From the perspective of FINST theory, the finding that the type of attribute coding had little impact on strategy selection may suggest that FINSTs can be assigned rather flexibly and not only to objects that share certain features (as hypothesized by Trick & Pylyshyn, 1993).

The present results establish that, unlike previously assumed (Gigerenzer & Todd, 1999), noncompensatory strategies can be a relevant tool even in decisions from givens. Further, cognitive costs seem to affect decision making even when all attribute values and attribute weights are openly presented and search costs are thus kept low. With a higher number of attributes, it is less likely that the amount of supporting evidence for an alternative can be enumerated by subitizing and grasped at a glance; instead, the individual pieces of evidence have to be unpacked and integrated sequentially. This makes using a compensatory strategy more effortful. Although an association between noncompensatory processing and a high number of attributes had been noted previously (see Ford et al., 1989), several of these studies used information boards, incurring high search costs, and thus did not represent decisions from givens.

In contrast to most previous studies involving varied attribute coding (e.g., Bröder & Schiffer, 2003b; Newell & Lee, 2011; Pachur & Marinello, 2013), the present study used artificial rather than natural—and thus familiar—symbols. As a result, more cognitive operations may have been required to decode the information than in previous studies. Costs of decoding the attribute values as positive or negative may also have contributed to the generally lower reliance on TTB in Experiment 2 than Experiment 1; specifically, the extended learning phase in Experiment 2 may have facilitated decoding during the decision task and thus lowered cognitive costs. Future research could investigate the extent to which the "naturalness" of the coding of positive and negative attribute values (e.g., "+" and "−" may be particularly intuitive codes) might foster reliance on compensatory decision making. An intriguing observation is that many of the studies in Table 1 that reported a high reliance on compensatory strategies (e.g., Ayal & Hochman, 2009; Bröder, 2000; Glöckner & Betsch, 2008, 2012; Heck et al., 2017; Hilbig & Moshagen, 2014; Söllner et al., 2013) presented positive and negative attribute values as "+" and "−" signs.

The work presented in this article makes a number of contributions to the literature. First, the findings suggest an explanation for the perplexingly mixed results of previous studies on strategy selection in decisions from givens (Table 1). In light of the present findings, one likely contributing factor is that the studies that found a surprisingly high proportion of users of a noncompensatory strategy (e.g., Garcia-Retamero & Dhami, 2009; Bergert & Nosofsky, 2007; Pachur & Marinello, 2013) involved a rather high number of attributes—that despite being openly available onscreen, led to relatively high costs of information search and integration. The fact that these studies also tended to use varied attribute coding may be of lesser importance. Second, the results indicate that the costs associated with integrating information may influence the selection of compensatory and noncompensatory strategies—a factor that has thus far been largely overlooked. Third, the results help to link decision-making research with other fields of cognitive psychology, in particular visual attention and number processing; to my knowledge, this is the first time that the concept of subitizing has been applied to understand the selection of strategies in decision making. Fourth, by modifying Lee et al.'s (2019) Bayesian multimethod

[11] One possible objection to the high execution error estimated for users of a compensatory strategy in the conditions with eight attributes is that assuming a compensatory strategy that integrates all attributes might be unrealistic here. The high estimated execution error might thus reflect a lack of model fit rather than unsystematic behavior on the part of the participants. In order to explore this possibility, Appendix F reports an analysis in which a truncated version of WADD, that takes into account only the four most important attributes, is added to the set of candidate strategies. Although this truncated WADD captured the responses of some participants (in particular in Experiment 2), the estimated strategy execution error for these participants was of a similar magnitude as for participants classified as using the nontruncated version of WADD.

approach I have illustrated how decisions and response-time patterns can be combined seamlessly using a Bayesian framework to infer strategy use (for a related endeavor using a maximum-likelihood approach, see Glöckner, 2009). I now turn to implications of the present findings.

5.1. Is people's strategy selection adaptive?

A key assumption underlying the notion that people have a repertoire of decision-making strategies at their disposal is that strategy selection is guided by the goal of adaptivity. To what extent might the shift to the noncompensatory TTB in more effortful conditions indeed be viewed as adaptive? Unless the distribution of attribute importance is very skewed (and assuming that the importance weights of the attributes are known), using a noncompensatory strategy decreases accuracy relative to using a compensatory strategy. This also holds for the environments in the present experiments, where the distribution of importance weights was relatively flat. But how much accuracy is compromised when using TTB? As it turns out, TTB is an effective way to simplify the decision process: Defining the "correct" decision as choosing the alternative with the highest weighted (by importance weight) sum of attributes, TTB is correct in 92.4% and 83.7% of the cases in environments with four and eight attributes, respectively.[12] This means that, faced with increasing cognitive costs, TTB users relied on a strategy that circumvented integration while still allowing for good decision quality—instead of risking more processing errors while trying to apply a compensatory strategy, or reverting to guessing.[13]

Note that in both experiments there were clear indications that a compensatory strategy and TTB incurred differential costs across conditions. First, as illustrated in Fig. 7, in both experiments the response times for users of a compensatory strategy were considerably slower when they saw eight, rather than four, attributes, whereas the response times for TTB users were relatively fast irrespective of the number of attributes. Second, the estimated execution errors for participants' inferred strategies (shown in Fig. 5) suggest that applying a compensatory strategy is cognitively more taxing when there were eight rather than four attributes, whereas for applying the noncompensatory TTB the number of attributes has no effect.

In sum, in the conditions in which cognitive costs are likely to be high, using TTB helped participants to avoid both longer response times and increased execution errors. For several participants, this was apparently sufficiently attractive to sacrifice some decision accuracy. In that sense, the shift to TTB in the conditions with a higher number of attributes can be viewed as an adaptive response to the cognitive requirements posed by the decision environment. Whether the same applies to the finding that in the conditions with eight attributes participants relied more strongly on compensatory strategies in Experiment 2 than in Experiment 1 can certainly be debated, given that participants incurred considerable costs in terms of longer response times and higher execution errors.

An interesting avenue for future research will be to simulate and formalize the cognitive costs of compensatory and noncompensatory strategies under the task conditions examined here in a cognitive architecture such as ACT-R. Fechner et al. (2018; see also Fechner et al., 2019) used ACT-R to analyze the cognitive costs (in terms of response time and execution error) of compensatory and noncompensatory strategies in decisions from givens under different search requirements. This approach could be extended to include a possible role of subitizing (see Peterson & Simon, 2000, for an implementation in ACT-R) to conduct the integration processes in compensatory decision strategies; and to simulate the contribution of subitizing to decision making with compensatory strategies under different task conditions (number of attributes, type of attribute coding).

5.2. Merits of an adaptive perspective on strategy selection

Simple, noncompensatory heuristics and compensatory processes have sometimes been pitted against each other as general accounts of decision making (e.g., Bröder, 2000; Glöckner et al., 2014). The results presented here illustrate that rather than juxtaposing noncompensatory and compensatory mechanisms, it may be more instructive to elaborate their cognitive requirements and identify the conditions under which each mechanism represents an adaptive solution for a cognitive system with natural bounds. If search and integration costs are negligible (e.g., because the information is presented in an appropriate manner) or sufficient motivation and time are available, if the importance weights are unknown or it is known that the distribution of the importance weights is not skewed, compensatory strategies are appropriate tools. In fact, under low search and integration costs, compensatory strategies might even be implemented by a fast and automatic mechanism (e.g., Brusovansky et al., 2018; Glöckner & Betsch, 2008). In situations incurring more substantial search and integration costs, however, decision making based on automatic compensatory integration seems to be beyond the capacity of the human mind. Noncompensatory strategies offer an effective way to reduce these costs, being implementable with reasonable execution error and with only a low risk of substantial decreases in decision accuracy.

Consistent with the idea that people adjust their strategy selection adaptively, they are more likely to use TTB when the task incurs costs (due to search, Bröder & Schiffer, 2003b; or integration, as arguably demonstrated in the present study) or when the available

[12] These accuracy levels were calculated using *all* possible decision problems for environments of alternatives with four (120 problems) and eight (32,640 problems) attributes. For the situation with eight attributes, I did not use the set of problems used in the experiments because they represented selected sets of problems (e.g., in Experiment 1 the problems were selected such that TTB and WADD always made the opposite decisions, facilitating their distinction in the model comparison).

[13] I do not claim here that people necessarily knew the accuracy of the strategies. Participants were not told what a "correct" decision would be, nor were they given feedback on the accuracy of their decisions. However, there is evidence that people have a general understanding of the link between the distribution of importance weights and strategy use. Mata et al. (2007) found that people adjust their strategy selection to the distribution of attribute weights even in the absence of explicit feedback about the accuracy of their decisions.

cognitive resources are constrained—due, for instance, to cognitive aging (Mata et al., 2007; Pachur et al., 2009), dual task constraints (Bröder & Schiffer, 2006), or time pressure (Payne et al., 1988; Rieskamp & Hoffrage, 2008). An adaptive perspective such as the one taken here helps to account for the variability in differences in information processing—as captured by different decision strategies—across contexts.

It should be noted that previous work on automatic compensatory decision making has specified some conditions under which quick integration is possible. For instance, Glöckner and Betsch (2008) highlighted that automatic decision processes can be expected to operate only when attribute information is readily visible and a holistic inspection is not obstructed—for instance, due to the use of Mouselab (Payne et al., 1993) or other information board procedures. Importantly, however, these boundary conditions are usually not discussed in terms of adaptive decision making. In addition, from the perspective of a single, automatic decision mechanism it is not clear how the human mind might simplify processing under higher cognitive costs (e.g., by considering fewer attributes) or how processing in decisions from givens would be affected by the manipulations of the task factors investigated here.

5.3. Practical implications

The present results also have implications for choice architects aiming to present decision alternatives and attribute information in ways that improve decision making (e.g., Johnson, 2021). In environments where compensatory strategies in principle yield the highest accuracy, the use of these strategies could be fostered via choice architectures that present manageable costs of integration and information search. For instance, when showing people different types of health insurance (e.g., Li et al., 2015), it might be helpful to focus on a handful of important attributes, or on the attributes that actually differentiate between alternatives. In addition, whether the alternatives score high or low on attributes could be indicated by the same symbols across attributes (i.e., uniform coding), further facilitating the acquisition and integration of information. This approach is implemented on food labels that use traffic light symbols to indicate values across all attributes (e.g., fat, saturated fat, sugars, and salt content). Choice architectures using this type of format might help people to successfully use compensatory strategies.

6. Conclusion

According to Herbert Simon's influential notion of bounded rationality (Simon, 1990), the route to successful decision making for a mind with naturally constrained capacities is to select strategies that incur manageable costs but still yield good decisions. In order to successfully study people's decision making, researchers thus need to understand both the capacities of the mind and the costs generated by task characteristics. Borrowing insights from research on visual attention, the present work highlights that the human mind seems to be able to accomplish compensatory information processing without much effort when attribute information is presented in specific ways; beyond these bounds, processing incurs considerably higher cognitive costs and alternative, heuristic strategies become attractive. By showing that people's use of compensatory strategies is indeed sensitive to these characteristics in decisions from givens, this investigation helps to more precisely demarcate the bounds of rationality, as well as to identify where the tools of bounded rationality are applied.

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.

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Appendix A

Description of the Literature Search for Studies on Strategy Selection in Decisions from Givens.

To identify studies that assessed the use of compensatory and noncompensatory strategies in decisions from givens, I conducted a literature search in ISI Web of Science (December 2019). A first search included the keywords "strategy selection," "strategy use," or "strategy classification" and "take-the-best," "noncompensatory," "non-compensatory" or "lexicographic." A second search identified all articles that cite Gigerenzer and Goldstein (1996)—the seminal article on the take-the-best heuristic—and all articles that cite Bröder and Schiffer (2003b)—the seminal article comparing strategy use in decisions from givens and decisions from memory. These searches yielded 1,473 distinct articles, each of which was then individually screened. Studies were included if they met the following criteria: (a) all attribute information was openly provided to participants, (b) the task involved a two-alternative paired-comparison task, (c) the attributes were binary, (d) the attribute values of the alternatives were conveniently shown next to each other (thus keeping search costs down), (e) and participants were individually classified as users of a compensatory or a noncompensatory strategy. Studies were excluded if they applied severe time pressure (the instruction to be fast but also as accurate as possible was not regarded as severe time pressure) or provided accuracy feedback throughout the experiment. The study by Lee and Cummins (2004) was not included because the presentation of the cues was rather untypical (molecules of a specific color moving around in a canister), making it difficult to compare the results to those of the other studies. Moreover, not all participants were classified as using a compensatory or noncompensatory strategy (it was only indicated how many participants made decisions that were perfectly in line with the predictions of a compensatory or a noncompensatory strategy). In total, 28 studies from 17 articles were included in the analysis.

For Garcia-Retamero and Dhami (2009) and Pachur and Marinello (2013) only the results for the expert groups were included in order to minimize any influence of lack of knowledge about attribute importance. In studies that also tested the parallel constraint satisfaction (PCS) model (Glöckner et al., 2014; Söllner et al., 2013), PCS was counted as a compensatory strategy (note that although PCS implements a weighted additive integration, its predictions do not completely overlap with those of WADD). From Pachur and Olsson (2012), the learning by comparison condition was included because it is the typical type of learning used in experiments in which participants are taught the attribute hierarchy. The strategy classification of Bergert and Nosofsky (2007) was based on the BIC values provided for each participant. For Heck et al. (2017), the proportions of strategy users refer to the classification based on Bayes factors. For Hilbig and Moshagen (2014), the results refer to the classification based on the generalized approach.

Appendix B

Strategy Classification Based on Decision Data Only.

To what extent do the conclusions about strategy use in the different conditions depend on both people's decisions and their response-time patterns being taken into account in the modeling approach? To find out, I implemented a model that only considered people's decisions, using the data from Experiment 1 for illustrative purposes. Fig. A1 shows the results; although the distributions across the strategies differed somewhat compared to the decisions-and-response-times model, the general conclusions are robust: The clear majority of participants were classified as users of WADD or EQW when the number of attributes was low, TTB use increased slightly in the condition with eight attributes and uniform coding, and the majority of participants were classified as users of TTB in the condition with eight attributes and varied coding.

In total, there were five participants for whom strategy classification differed between the decisions-only and the decisions-and-response-times models (#8, #23, #26, #27, #68). Most of them were classified as using TTB by the decision-only model, but as using WADD by the decision-and-response-times model. As can be gleaned from Fig. A4 in Appendix E, this shift likely occurred because the participants' response-time patterns were not consistent with TTB's prediction of increasing response time when the first discriminating attribute was lower in the importance hierarchy.

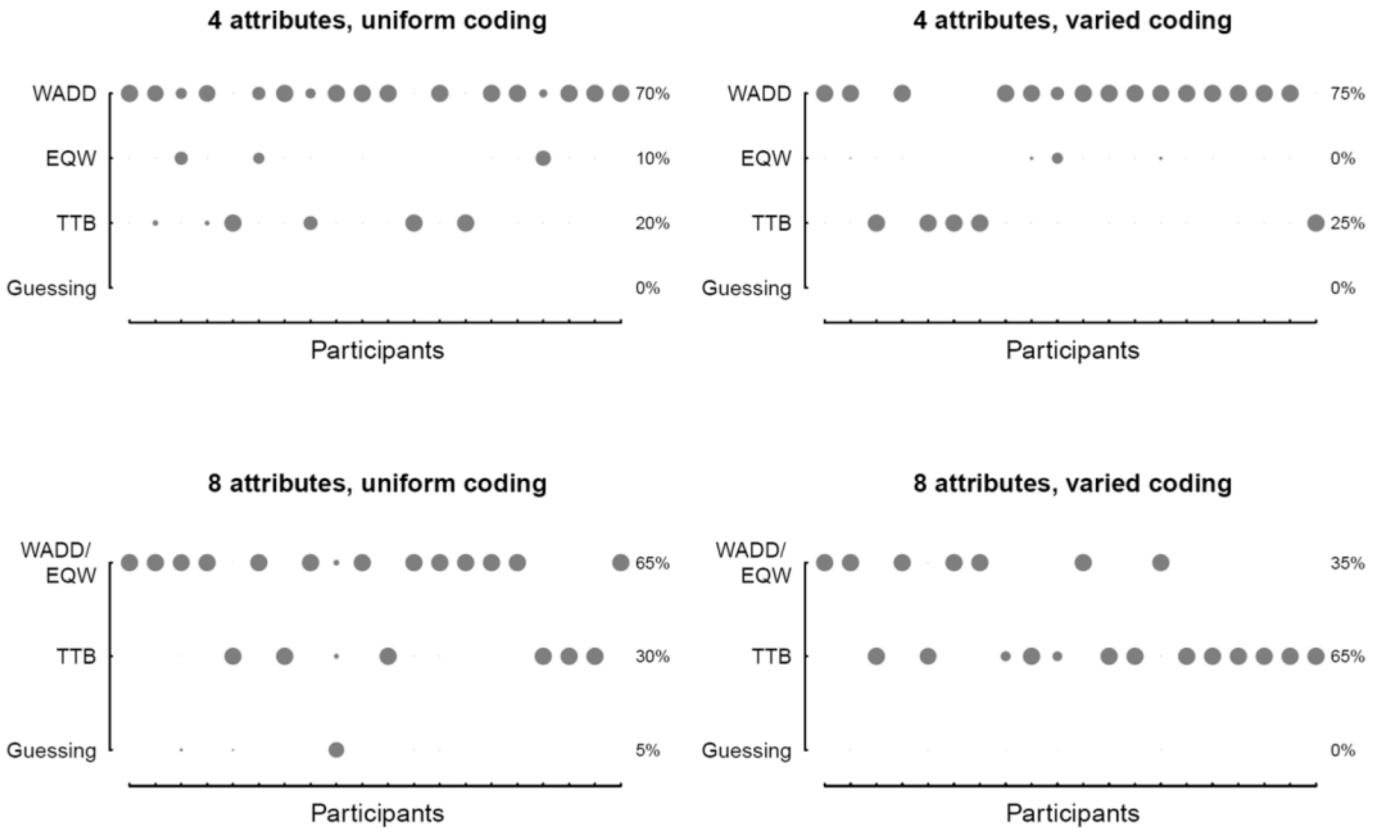

Fig. A1. Strategy classification for the data in Experiment 1 based on participants' decisions only. The numbers at the right margin indicate, for each strategy, the percentage of participants for whom the posterior probability of the respective strategy was highest.

Appendix C

Comparison of Compensatory Strategies with Different Response-Time Predictions.

As described in Section 2, the strategy-classification approach considered both people's decisions and the pattern of response times (i.e., whether response times depend on the position of the first discriminating attribute in the importance hierarchy). By including both types of dependent variables, this approach takes into account a process prediction of TTB: According to TTB, attributes are inspected sequentially and inspection is terminated as soon as an attribute discriminates between the alternatives. Therefore, the earlier in the importance hierarchy that an attribute discriminates, the faster response times should be. Given that compensatory strategies do not have a stopping rule and thus always consider all attributes, it is typically assumed that their response times do not differ between these types of decision problems (e.g., Bröder & Gaissmaier, 2007; Fechner et al., 2018). However, they might be faster when the differences between the alternatives are larger than when they are smaller (e.g., Glöckner et al., 2014). This pattern follows from the PCS model, a connectionist model describing an automatic, weighted additive (and thus compensatory) integration process, and also from other evidence accumulation models of decision making (e.g., sequential sampling models; see Ratcliff et al., 2016). If the amount of evidence differs, on average, between the types of problems that differ in terms of the first discriminating attribute, it might be important to take such differences into account.

To explore this possibility, I conducted a model comparison using the data from Experiment 1. An analysis showed that there were indeed some differences between the problem types in terms of the average superiority of the better alternative—at least for the conditions with four attributes. This held for both WADD and EQW. The evidence differences were calculated as the average (across the decision problems of each type) difference between the summed evidence determined by each strategy for alternative A and for alternative B. In the conditions with four attributes, for WADD these average differences were 1.03, 0.86, 0.70, and 0.60 for decision problems where the first discriminating attribute was the first, second, third, and fourth, respectively. For EQW the respective differences were 1.25, 1.13, 1, and 1. In the conditions with eight attributes, the differences between the problem types were much smaller: For WADD they were 0.30, 0.32, and 0.27 for decision problems where the first discriminating attribute was the first, second, and third, respectively. For EQW the respective differences were 1.11, 1.03, and 1.13. Because the differences in evidence between the problem types in the conditions with eight attributes were rather small, the following analyses focus on the conditions with four attributes. (To put these evidence differences into perspective, for WADD the differences ranged from 0–3 and from 0–0.9 in the conditions with four and eight attributes, respectively; for EQW, from 0–4 and from 0–3.).

Using the same Bayesian latent-mixture strategy classification approach as in the main analyses, I tested variants of WADD and EQW in which the differences between the problem types were taken into account in predicting response-time patterns. Specifically, I compared variants of WADD and EQW that assumed no differences in response times across problems types with variants that did allow for differences in response times. These variants assumed that decisions were faster for the type of decision problems for which the respective strategy computed, on average, larger differences in evidence between the alternatives than for those where the evidence differences were, on average, smaller, by using order constraints on the μ parameter. As these models implement a notion inherent in evidence accumulation models, I refer to them as $\mathrm{WADD}_{\mathrm{EAM}}$ and $\mathrm{EQW}_{\mathrm{EAM}}$. For completeness, I also included guessing in the strategy classification. As can be seen from Fig. A2, $\mathrm{WADD}_{\mathrm{EAM}}$ and $\mathrm{EQW}_{\mathrm{EAM}}$ were clearly outperformed by the variants assuming no differences between the types of decision problems. Thus, the higher complexity of the models allowing for such differences was not matched by a proportional increase in descriptive validity. This result should not be interpreted as indicating that the response times of compensatory mechanisms are generally insensitive to differences in evidence between alternatives. It merely indicates that taking the evidence differences between problem types into account does not seem to pay off in the present case.

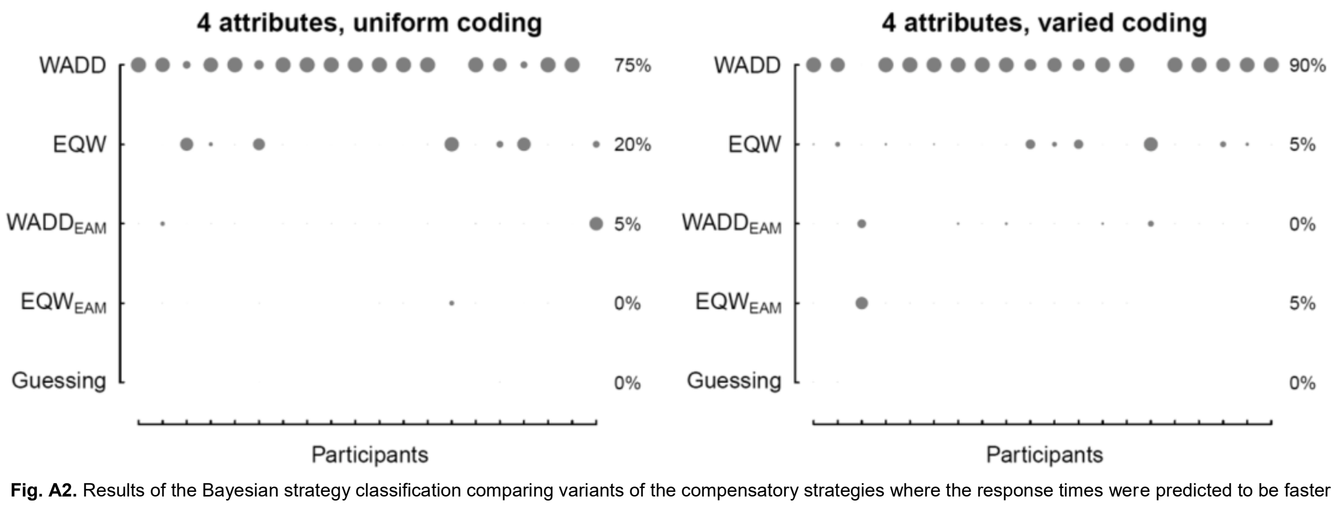

Fig. A2. Results of the Bayesian strategy classification comparing variants of the compensatory strategies where the response times were predicted to be faster for problem types in which the evidence differentiated between the alternatives, on average, more strongly ($\mathrm{WADD}_{\mathrm{EAM}}$ and $\mathrm{EQW}_{\mathrm{EAM}}$) or were predicted to be the same across problem types (WADD and EQW), and guessing. The comparison was conducted only for the conditions with four attributes; in the conditions with eight attributes the problem types barely differed in terms of the how much evidence differentiated between the alternatives. The numbers at the right margin indicate, for each strategy, the percentage of participants for whom the posterior probability of the respective strategy was highest.

Appendix D

Comparison of Variants of WADD with Different Stochastic Choice Rules.

Traditionally, in models of strategies for multi-attribute decision making the probabilistic nature of people's choices is taken into account by assuming a constant execution error (e.g., Bröder & Schiffer, 2003a; Glöckner, 2009). However, it has also been suggested that—similar to, for instance, risky choice (Rieskamp, 2008; see also Mosteller & Nogee, 1951)—the probability of choosing an alternative depends on the relative amount of evidence for it. Hilbig and Moshagen (2014), as well as Lee (2016), proposed and tested a model of WADD in which the execution error in a decision problem is larger when the evidence difference between alternatives is smaller than when the difference is larger (see also Heck et al., 2017). I examined the idea of evidence-sensitive execution errors for the decision data from Experiment 1. Using the same Bayesian strategy classification approach as in the main analyses, I compared WADD with a constant execution error (as defined in Fig. 2) with two variants of WADD that were sensitive to the amount of evidence. In the first variant, the probability of choosing an alternative A over an alternative B is determined by Luce's choice rule (Luce, 1959), based on the evidence for alternatives A and B, established by summing up the attribute values of each alternative (i.e., a^{A} and a^{B}), each weighted by the respective attribute weight w:

$$p(A; A, B) = \frac{(\sum_{i=1}^{n} a_i^A w_i)^{\gamma}}{(\sum_{i=1}^{n} a_i^A w_i)^{\gamma} + (\sum_{i=1}^{n} a_i^B w_i)^{\gamma}} \tag{A1}$$

The sensitivity parameter γ ($\geq$0) governs how sensitive the probability of selecting alternative A is to the differences in evidence for alternatives A and B. When $\gamma = 0$, choices are random; with higher values of γ, the predicted probability is increasingly deterministic in favor of the alternative with higher evidence.

In the second variant, $\mathrm{WADD}_{\mathrm{softmax}}$, the probability of selecting alternative A is determined by the softmax choice rule (e.g., Sutton & Barto, 2018), in which the difference in evidence for alternatives A and B enters an exponential function:

$$p(A; A, B) = \frac{1}{1 + \exp(-\varphi(\sum_{i=1}^{n} a_i^A w_i - \sum_{i=1}^{n} a_i^B w_i))} \tag{A2}$$

Here, a response sensitivity parameter φ ($\geq$0) governs the extent to which the decision deterministically follows the difference between the alternatives in evidence. When $\varphi = 0$, choices are random; with higher values of φ, the predicted probability is increasingly deterministic in favor of the alternative with higher evidence. For completeness, I also included guessing in the strategy competition.

Fig. A3 shows the results of the model comparison. As can be seen—and echoing earlier comparisons of variants of WADD with different stochastic choice rules (Heck et al., 2017; Hilbig & Moshagen, 2014; Lee, 2016)—the variant with a constant error across all

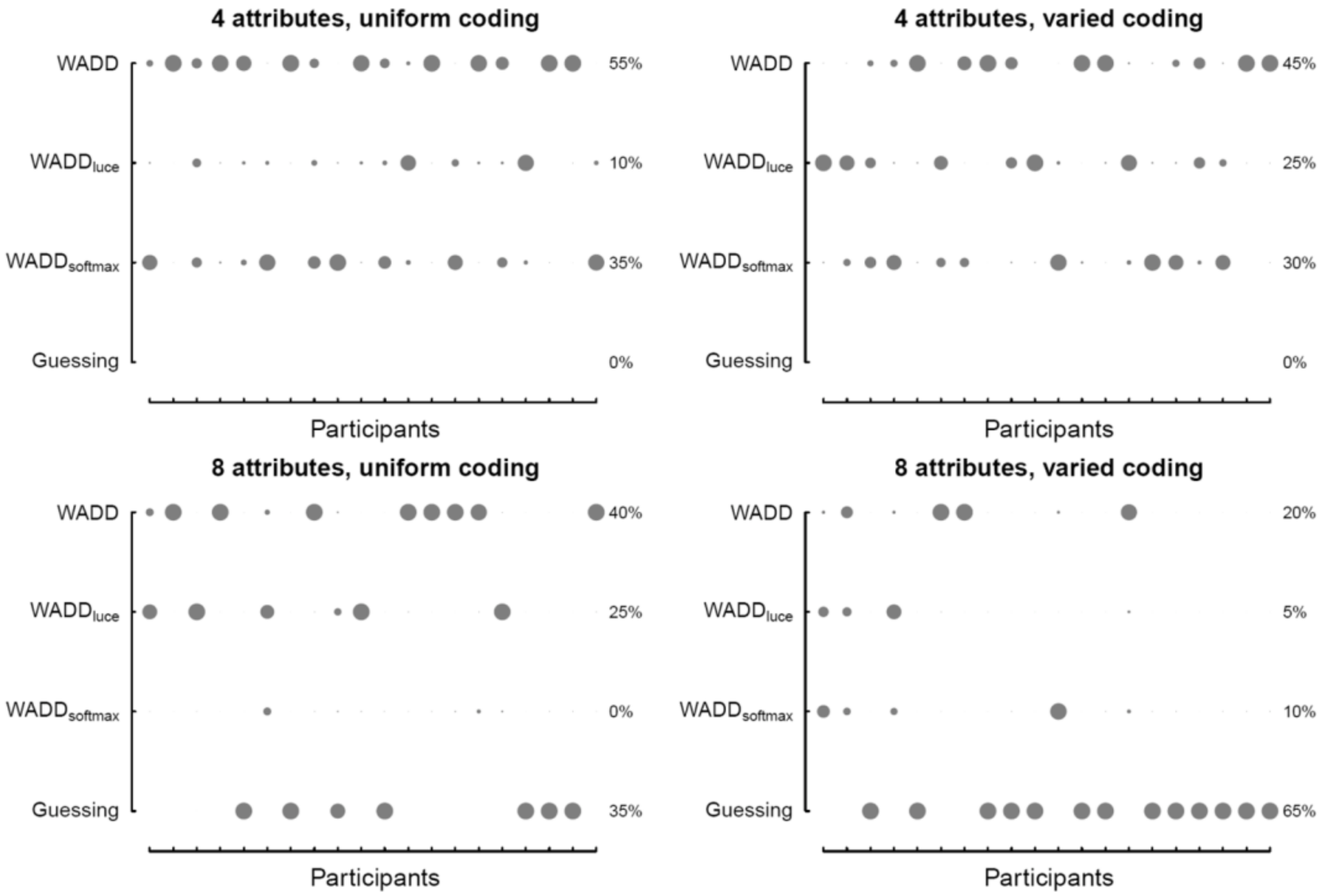

Fig. A3. Comparison of variants of WADD with different stochastic choice rules and guessing on the decision data from Experiment 1. The numbers at the right margin indicate, for each strategy, the percentage of participants for whom the posterior probability of the respective strategy was highest.

decision problems performed best (note that in the conditions with eight attributes relatively high proportions of participants were classified as guessing, reflecting that—as shown in Fig. 4 in the main analyses—participants were more likely to rely on TTB here). This variant was therefore considered in the strategy classification in the main analyses.

Appendix E

See Figs. A4-A6.

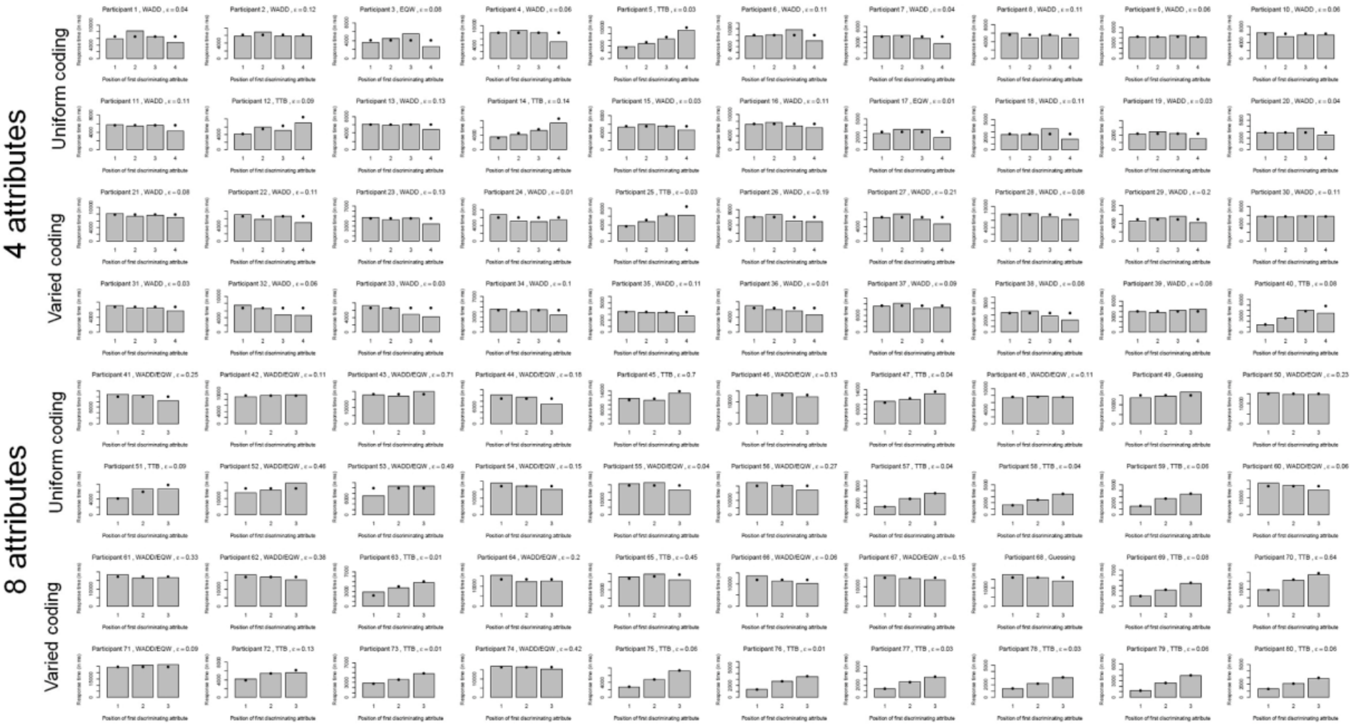

Fig. A4. Mean (across decision problems) response time in Experiment 1 of each participant and depending on which attribute in the importance hierarchy was the first discriminating attribute. The inferred strategy use and the estimated execution error ε_m for that strategy are also shown for each participant. The dots represent the estimated response times, μ, of the inferred strategy. The parameter estimates are based on the mean of the parameter posterior distribution of the respective parameter.

Fig. A5. Mean (across decision problems) response time in Experiment 2 for the conditions with four attributes. For a more details, see caption of Fig. A4.

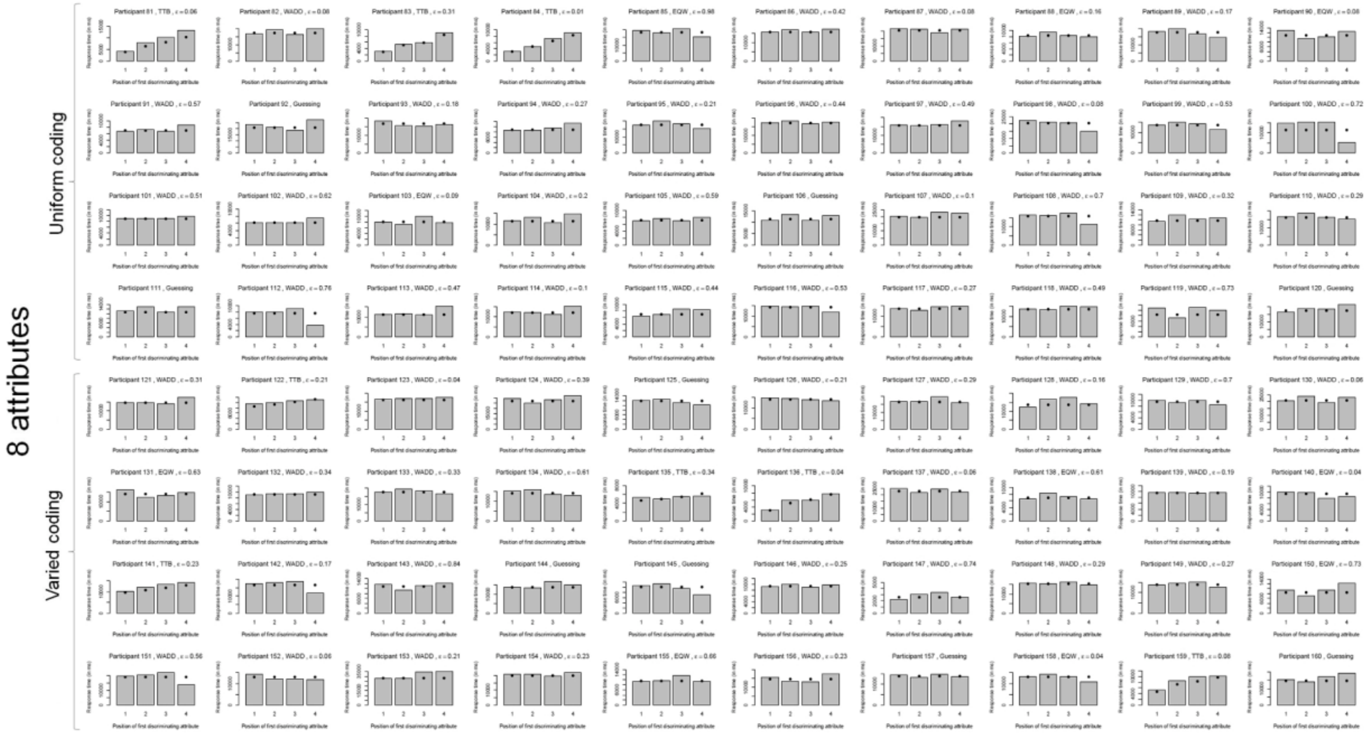

Fig. A6. Mean (across decision problems) response time in Experiment 2 for the conditions with eight attributes. For a more details, see caption of Fig. A4.

Appendix F

Testing WADD with Truncated Search.

In the condition with eight attributes, rather than switching to TTB, another possible way to reduce cognitive effort could be to switch to a strategy that integrates across multiple attributes but considers only part of the information.[14] In order to explore this possibility, I reran the strategy classification analyses with an additional variant of WADD that considers only the four most important attributes (truncated weighted additive strategy; truncWADD). Fig. A7 shows the results for Experiment 1 (upper panel) and Experiment 2 (lower panel). In Experiment 1, one participant in the condition with uniform coding and two participants in the condition with varied coding who were previously classified as users of TTB were classified as users of truncWADD. In Experiment 2, a considerably higher proportion of participants was classified as using truncWADD, and its addition to the set of candidate strategies affected the classification to the other strategies in a much less specific way than in Experiment 1, with the proportion of participants being reduced similarly across all strategy categories. One possible reason for this difference in the relative performance of truncWADD between Experiments 1 and 2 is that this strategy was less differentiated from the other strategies in Experiment 2 than in Experiment 1. In Experiment 1, truncWADD predicted different decisions than did WADD, EQW, and TTB in 108, 108, and 14 problems, respectively; in Experiment 2, this was the case in only 8, 9, and 10 problems.

Overall, this exploratory analysis suggests that reliance on noncompensatory processing under conditions with higher cognitive costs might take forms other than using a lexicographic strategy like TTB (note that although truncWADD considers the subset of attributes considered in a compensatory fashion, it represents a noncompensatory strategy; Dieckmann & Rieskamp, 2007). Future work might thus consider noncompensatory strategies other than lexicographic ones (see Oh et al., 2016).

To test the possibility that the high estimated strategy execution error of users of a compensatory strategy reported in the main text (Fig. 5) might be due to the non-inclusion of truncWADD, Tables A1 and A2 report the estimated execution error for the inferred

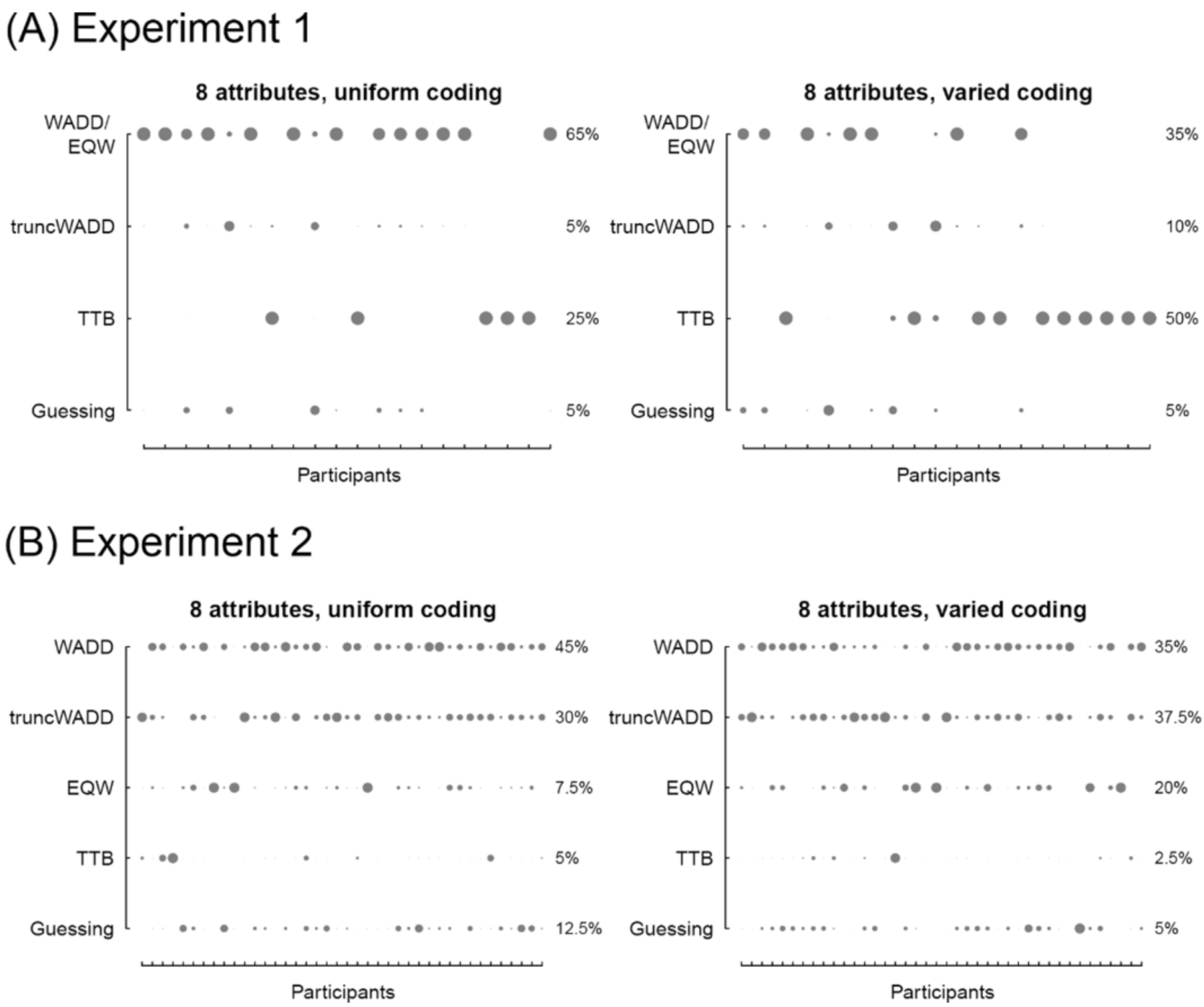

Fig. A7. Strategy classification for the decisions in the 8-attribute conditions in Experiment 1 (upper panel) and Experiment 2 (lower panel) when also including a truncated version of WADD (truncWADD) that considers only the four (of eight) most important attributes. The numbers at the right margin indicate, for each strategy, the percentage of participants for whom the posterior probability of the respective strategy was highest.

[14] I thank an anonymous reviewer for this suggestion.

strategies in Experiment 2.[15] Table A1 reports the results of the analysis in which truncWADD is included; Table A2 reports the results of the analysis in which truncWADD is not included. As can be seen, including truncWADD did not lead to a lower estimated execution error for users of a compensatory strategy. Overall, this indicates that the high execution error estimated for users of a compensatory strategy in the conditions with eight attributes is not an artefact of including an unrealistic strategy in the strategy classification.

Table A1
Estimated Strategy Execution Error (ε Parameter) for the Conditions with Eight Attributes in Experiment 2 When Also Including the Truncated WADD Strategy in the Strategy Classification.

				95% CI	
Strategy	*M*	*SD*	*n*	Lower Bound	Upper Bound
EQW	0.436	0.355	11	0.198	0.675
Guessing	0.500	0.000	7	0.500	0.500
truncWADD	0.467	0.223	27	0.379	0.556
TTB	0.120	0.165	3	0	0.530
WADD	0.342	0.242	32	0.255	0.430

Table A2
Estimated Strategy Execution Error (ε Parameter) for the Conditions with Eight Attributes in Experiment 2 When Not Including the Truncated WADD Strategy in the Strategy Classification.

				95% CI	
Strategy	*M*	*SD*	*n*	Lower Bound	Upper Bound
EQW	0.402	0.354	10	0.149	0.655
Guessing	0.500	0.000	9	0.500	0.500
TTB	0.160	0.129	8	0.053	0.267
WADD	0.357	0.221	53	0.296	0.418

Appendix G. Supplementary material

Supplementary data to this article can be found online at http://hdl.handle.net/21.11116/0000-000A-7151-B.

References

(References marked with an asterisk indicate studies included in the systematic literature overview.)

Anderson, J. R. (1991). Is human cognition adaptive? *Behavioral and Brain Sciences*, *14*(3), 471–485. https://doi.org/10.1017/S0140525X00070801
*Ayal, S., & Hochman, G. (2009). Ignorance or integration: The cognitive processes underlying choice behavior. *Journal of Behavioral Decision Making*, *22*(4), 455–474. https://doi.org/10.1002/bdm.642
Beach, L. R., & Mitchell, T. R. (1978). A contingency model for the selection of decision strategies. *Academy of Management Review*, *3*(3), 439–449. https://doi.org/10.5465/amr.1978.4305717
*Bergert, F. B., & Nosofsky, R. M. (2007). A response-time approach to comparing generalized rational and take-the-best models of decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *33*(1), 107–129. https://doi.org/10.1037/0278-7393.33.1.107
Biggs, S. F., Bedard, J. C., Gaber, B. G., & Linsmeier, T. J. (1985). The effects of task size and similarity on the decision behavior of bank loan officers. *Management Science*, *31*(8), 970–987. https://doi.org/10.1287/mnsc.31.8.970
Bobadilla-Suarez, S., & Love, B. C. (2018). Fast or frugal, but not both: Decision heuristics under time pressure. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *44*(1), 24–33. https://doi.org/10.1037/xlm0000419
*Bröder, A. (2000). Assessing the empirical validity of the “Take-the-best” heuristic as a model of human probabilistic inference. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(5), 1332–1346. https://doi.org/10.1037/0278-7393.26.5.1332
Bröder, A., & Gaissmaier, W. (2007). Sequential processing of cues in memory-based multiattribute decisions. *Psychonomic Bulletin & Review*, *14*(5), 895–900. https://doi.org/10.3758/BF03194118
Bröder, A., Newell, B. R., & Platzer, C. (2010). Cue integration vs. exemplar-based reasoning in multi-attribute decisions from memory: A matter of cue representation. *Judgment and Decision Making*, *5*(5), 326–338.
Bröder, A., & Schiffer, S. (2003a). Bayesian strategy assessment in multi-attribute decision making. *Journal of Behavioral Decision Making*, *16*(3), 193–213. https://doi.org/10.1002/bdm.442
*Bröder, A., & Schiffer, S. (2003b). Take The Best versus simultaneous feature matching: Probabilistic inferences from memory and effects of representation format. *Journal of Experimental Psychology: General*, *132*(2), 277–293. https://doi.org/10.1037/0096-3445.132.2.277
Bröder, A., & Schiffer, S. (2006). Stimulus format and working memory in fast and frugal strategy selection. *Journal of Behavioral Decision Making*, *19*(4), 361–380. https://doi.org/10.1002/bdm.533
Brooks, S. P., & Gelman, A. (1998). General methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics*, *7*(4), 434–455. https://doi.org/10.1080/10618600.1998.10474787

[15] I focus on Experiment 2 here because only very few participants in Experiment 1 were classified as using truncWADD.

Brown, N. R. (2002). Encoding, representing, and estimating event frequencies: A multiple strategy perspective. In P. Sedlmeier & T. Betsch (Eds.), *Etc.: Frequency processing and cognition* (pp. 37–53). Oxford University Press.
Brusovansky, M., Glickman, M., & Usher, M. (2018). Fast and effective: Intuitive processes in complex decisions. *Psychonomic Bulletin & Review*, *25*(4), 1542–1548. https://doi.org/10.3758/s13423-018-1474-1
*Bryant, D. J. (2014). Strategy selection in cue-based decision making. *Canadian Journal of Experimental Psychology/Revue canadienne de psychologie expérimentale*, *68*(2), 97–110. https://doi.org/10.1037/cep0000020
Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review*, *100*(3), 432–459. https://doi.org/10.1037/0033-295X.100.3.432
Dawes, R. M. (1979). The robust beauty of improper linear models in decision making. *American Psychologist*, *34*(7), 571–582. https://doi.org/10.1037/0003-066X.34.7.571
Dieckmann, A., & Rieskamp, J. (2007). The influence of information redundancy on probabilistic inferences. *Memory & Cognition*, *35*, 1801–1813. https://doi.org/10.3758/BF03193511
Dimov, C., Khader, P. H., Marewski, J. N., & Pachur, T. (2020). How to model the neurocognitive dynamics of decision making: A methodological primer with ACT-R. *Behavior Research Methods*, *52*(2), 857–880. https://doi.org/10.3758/s13428-019-01286-2
Dummel, S., & Rummel, J. (2016). Take-the-best and the influence of decision-inconsistent attributes on decision confidence and choices in memory-based decisions. *Memory*, *24*(10), 1435–1443. https://doi.org/10.1080/09658211.2015.1117642
*Dummel, S., Rummel, J., & Voss, A. (2016). Additional information is not ignored: New evidence for information integration and inhibition in take-the-best decisions. *Acta Psychologica*, *163*, 167–184. https://doi.org/10.1016/j.actpsy.2015.12.001
Einhorn, H. J. (1970). The use of nonlinear, noncompensatory models in decision making. *Psychological Bulletin*, *73*(3), 221–230. https://doi.org/10.1037/h0028695
Fechner, H. B., Schooler, L. J., & Pachur, T. (2018). Cognitive costs of decision-making strategies: A resource demand decomposition with a cognitive architecture. *Cognition*, *170*, 102–122. https://doi.org/10.1016/j.cognition.2017.09.003
Fechner, H. B., Pachur, T., & Schooler, L. J. (2019). How does aging impact decision making? The contribution of cognitive decline and strategic compensation revealed in a cognitive architecture. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *45*(9), 1634–1663. https://doi.org/10.1037/xlm0000661
Ford, J. K., Schmitt, N., Schechtman, S. L., Hults, B. M., & Doherty, M. L. (1989). Process tracing methods: Contributions, problems, and neglected research questions. *Organizational Behavior and Human Decision Processes*, *43*(1), 75–117. https://doi.org/10.1016/0749-5978(89)90059-9
Gallistel, C. R., & Gelman, R. (1992). Preverbal and verbal counting and computation. *Cognition*, *44*(1–2), 43–74. https://doi.org/10.1016/0010-0277(92)90050-R
*Garcia-Retamero, R., & Dhami, M. K. (2009). Take-the-best in expert-novice decision strategies for residential burglary. *Psychonomic Bulletin & Review*, *16*(1), 163–169. https://doi.org/10.3758/PBR.16.1.163
Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*(4), 650–669. https://doi.org/10.1037/0033-295X.103.4.650
Gigerenzer, G., Hertwig, R., & Pachur, T. (Eds.) (2011). *Heuristics: The foundations of adaptive behavior*. Oxford University Press.
Gigerenzer, G., & Todd, P. M. (1999). Fast and frugal heuristics: The adaptive toolbox. In G. Gigerenzer, P. M. Todd, & the ABC Research Group, *Simple heuristics that make us smart* (pp. 3–34). Oxford University Press.
Gigerenzer, G., Todd, P. M., & The ABC Research Group. (1999). *Simple heuristics that make us smart*. Oxford University Press.
Glöckner, A. (2009). Investigating intuitive and deliberate processes statistically: The multiple-measure maximum likelihood strategy classification method. *Judgment and Decision Making*, *4*(3), 186–199.
*Glöckner, A., & Betsch, T. (2008). Multiple-reason decision making based on automatic processing. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *34*(5), 1055–1075. https://doi.org/10.1037/0278-7393.34.5.1055
*Glöckner, A., & Betsch, T. (2012). Decisions beyond boundaries: When more information is processed faster than less. *Acta Psychologica*, *139*(3), 532–542. https://doi.org/10.1016/j.actpsy.2012.01.009
Glöckner, A., & Bröder, A. (2011). Processing of recognition information and additional cues: A model-based analysis of choice, confidence, and response time. *Judgment and Decision Making*, *6*(1), 23–42.
*Glöckner, A., Hilbig, B. E., & Jekel, M. (2014). What is adaptive about adaptive decision making? A parallel constraint satisfaction account. *Cognition*, *133*(3), 641–666. https://doi.org/10.1016/j.cognition.2014.08.017
Glöckner, A., & Hodges, S. D. (2011). Parallel constraint satisfaction in memory-based decisions. Experimental *Psychology*, *58*(3), 180–195. https://doi.org/10.1027/1618-3169/a000084
Heck, D. W., & Erdfelder, E. (2017). Linking process and measurement models of recognition-based decisions. *Psychological Review*, *124*(4), 442–471. https://doi.org/10.1037/rev0000063
*Heck, D. W., Hilbig, B. E., & Moshagen, M. (2017). From information processing to decisions: Formalizing and comparing psychologically plausible choice models. *Cognitive Psychology*, *96*, 26–40. https://doi.org/10.1016/j.cogpsych.2017.05.003
Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, *15*(8), 534–539. https://doi.org/10.1111/j.0956-7976.2004.00715.x
*Hilbig, B. E., & Moshagen, M. (2014). Generalized outcome-based strategy classification: Comparing deterministic and probabilistic choice models. *Psychonomic Bulletin & Review, 21*(6), 1431–1443. https://doi.org/10.3758/s13423-014-0643-0
JASP Team. (2020). *JASP (Version 0.14.10)* [Computer software]. https://jasp-stats.org.
Johnson, E. J. (2021). The elements of choice: Why the way we decide matters. Riverhead Books.
Juslin, P., Olsson, H., & Olsson, A.-C. (2003). Exemplar effects in categorization and multiple-cue judgment. *Journal of Experimental Psychology: General, 132*(1), 133–156. https://doi.org/10.1037/0096-3445.132.1.133
Kahneman, D. (2003). A perspective on judgment and choice: Mapping bounded rationality. *American Psychologist, 58*(9), 697–720. https://doi.org/10.1037/0003-066X.58.9.697
Kass, R., & Raftery, A. (1995). Bayes factors. *Journal of the American Statistical Association, 90*(430), 773–795. https://doi.org/10.1080/01621459.1995.10476572
Kaufman, E. L., Lord, M. W., Reese, T. W., & Volkmann, J. (1949). The discrimination of visual number. *The American Journal of Psychology, 62*(4), 498–525. https://doi.org/10.2307/1418556
Khader, P. H., Pachur, T., & Jost, K. (2013). Automatic activation of attribute knowledge in heuristic inference from memory. *Psychonomic Bulletin & Review, 20*(2), 372–377. https://doi.org/10.3758/s13423-012-0334-7
Khader, P. H., Pachur, T., Weber, L. A. E., & Jost, K. (2016). Neural signatures of controlled and automatic retrieval processes in memory-based decision making. *Journal of Cognitive Neuroscience, 28*(1), 69–83. https://doi.org/10.1162/jocn_a_00882
Krefeld-Schwalb, A., Donkin, C., Newell, B. R., & Scheibehenne, B. (2019). Empirical comparison of the adjustable spanner and the adaptive toolbox models of choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 45*(7), 1151–1165. https://doi.org/10.1037/xlm0000641
Lee, M. D. (2016). Bayesian outcome-based strategy classification. *Behavior Research Methods, 48*(1), 29–41. https://doi.org/10.3758/s13428-014-0557-9
Lee, M. D., & Cummins, T. D. (2004). Evidence accumulation in decision making: Unifying the “take the best” and the “rational” models. *Psychonomic Bulletin & Review, 11*(2), 343–352. https://doi.org/10.3758/BF03196581
Lee, M. D., & Gluck, K. A. (2021). Modeling strategy switches in multi-attribute decision making. *Computational Brain & Behavior, 4*(2), 148–163. https://doi.org/10.1007/s42113-020-00092-w
Lee, M. D., Gluck, K. A., & Walsh, M. M. (2019). Understanding the complexity of simple decisions: Modeling multiple behaviors and switching strategies. *Decision, 6*(4), 335–368. https://doi.org/10.1037/dec0000105
Lee, M. D., & Wagenmakers, E.-J. (2014). Bayesian cognitive modeling: A practical course. *Cambridge University Press*. https://doi.org/10.1017/CBO9781139087759

Li, Y., Gao, J., Enkavi, A. Z., Zaval, L., Weber, E. U., & Johnson, E. J. (2015). Sound credit scores and financial decisions despite cognitive aging. *Proceedings of the National Academy of Sciences, 112*(1), 65–69. https://doi.org/10.1073/pnas.1413570112
Lichtenstein, S., & Slovic, P. (Eds.). (2006). *The construction of preference.* Cambridge University Press.
Lieder, F., & Griffiths, T. L. (2020). Resource-rational analysis: Understanding human cognition as the optimal use of limited computational resources. *Behavioral and Brain Sciences, 43*, Article E1. https://doi.org/10.1017/S0140525X1900061X
Luce, R. D. (1959). *Individual choice behavior.* New York: John Wiley.
Mandler, G., & Shebo, B. J. (1982). Subitizing: An analysis of its component processes. *Journal of Experimental Psychology: General, 111*(1), 1–22. https://doi.org/10.1037/0096-3445.111.1.1
Marewski, J. N., & Mehlhorn, K. (2011). Using the ACT-R architecture to specify 39 quantitative process models of decision making. *Judgment and Decision Making, 6*(6), 439–519.
Mata, R., Schooler, L. J., & Rieskamp, J. (2007). The aging decision maker: Cognitive aging and the adaptive selection of decision strategies. *Psychology and Aging, 22*(4), 796–810. https://doi.org/10.1037/0882-7974.22.4.796
Mosteller, F., & Nogee, P. (1951). An experimental measurement of utility. *Journal of Political Economy, 59*(5), 371–404. https://doi.org/10.1086/257106
Moyer, R. S., & Landauer, T. K. (1967). Time required for judgements of numerical inequality. *Nature, 215*(1967), 1519–1520. https://doi.org/10.1038/2151519a0
*Newell, B. R., & Lee, M. D. (2011). The right tool for the job? Comparing an evidence accumulation and a naïve strategy selection model of decision making. *Journal of Behavioral Decision Making, 24*, 456–481. https://doi.org/10.1002/bdm.703
Nosofsky, R. M., & Bergert, F. B. (2007). Limitations of exemplar models of multi-attribute probabilistic inference. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 33*(6), 999–1019. https://doi.org/10.1037/0278-7393.33.6.999
Oh, H., Beck, J. M., Zhu, P., Sommer, M. A., Ferrari, S., & Egner, T. (2016). Satisficing in split-second decision making is characterized by strategic cue discounting. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 42*(12), 1937–1956. https://doi.org/10.1037/xlm0000284
Overstall, A., & King, R. (2014). conting: An R package for Bayesian analysis of complete and incomplete contingency tables. *Journal of Statistical Software, 58*(7), 1–27. https://doi.org/10.18637/jss.v058.i07.
*Pachur, T., & Marinello, G. (2013). Expert intuitions: How to model the decision strategies of airport customs officers? *Acta Psychologica, 144*(1), 97–103. https://doi.org/10.1016/j.actpsy.2013.05.003
Pachur, T., Mata, R., & Schooler, L. J. (2009). Cognitive aging and the use of recognition in decision making. *Psychology and Aging, 24*(4), 901–915. https://doi.org/10.1037/a0017211
*Pachur, T., & Olsson, H. (2012). Type of learning task impacts performance and strategy selection in decision making. *Cognitive Psychology, 65*(2), 207–240. https://doi.org/10.1016/j.cogpsych.2012.03.003
Payne, J. W. (1976). Task complexity and contingent processing in decision making: An information search and protocol analysis. *Organizational Behavior and Human Performance, 16*(2), 366–387. https://doi.org/10.1016/0030-5073(76)90022-2
Payne, J. W. (1982). Contingent decision behavior. *Psychological Bulletin, 92*(2), 382–402. https://doi.org/10.1037/0033-2909.92.2.382
Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14*(3), 534–552. https://doi.org/10.1037/0278-7393.14.3.534
Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker.* Cambridge University Press.
Persson, M., & Rieskamp, J. (2009). Inferences from memory: Strategy- and exemplar-based judgment models compared. *Acta Psychologica, 130*(1), 25–37. https://doi.org/10.1016/j.actpsy.2008.09.010
Peterson, S., & Simon, T. J. (2000). Computational evidence for the subitizing phenomenon as an emergent property of the human cognitive architecture. *Cognitive Science, 24*(1), 93–122. https://doi.org/10.1207/s15516709cog2401_3
Platzer, C., & Bröder, A. (2012). Most people do not ignore salient invalid cues in memory-based decisions. *Psychonomic Bulletin & Review, 19*(4), 654–661. https://doi.org/10.3758/s13423-012-0248-4
Platzer, C., & Bröder, A. (2013). When the rule is ruled out: Exemplars and rules in decisions from memory. *Journal of Behavioral Decision Making, 26*(5), 429–441. https://doi.org/10.1002/bdm.1776
Platzer, C., Bröder, A., & Heck, D. W. (2014). Deciding with the eye: How the visually manipulated accessibility of information in memory influences decision behavior. *Memory & Cognition, 42*(4), 595–608. https://doi.org/10.3758/s13421-013-0380-z
Plummer, M. (2003). JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling. In K. Hornik, F. Leisch, & A. Zeileis (Eds.), *Proceedings of the 3rd International Workshop on Distributed Statistical Computing (DSC 2003)* (pp. 20–22). https://www.r-project.org/conferences/DSC-2003/.
Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion decision model: Current issues and history. *Trends in Cognitive Sciences, 20*(4), 260–281. https://doi.org/10.1016/j.tics.2016.01.007
Rieskamp, J. (2008). The probabilistic nature of preferential choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 34*(6), 1446–1465. https://doi.org/10.1037/a0013646
Rieskamp, J., & Hoffrage, U. (2008). Inferences under time pressure: How opportunity costs affect strategy selection. *Acta Psychologica*, *127*(2), 258–276. https://doi.org/10.1016/j.actpsy.2007.05.004
Rieskamp, J., & Otto, P. E. (2006). SSL: A theory of how people learn to select strategies. *Journal of Experimental Psychology: General, 135*(2), 207–236. https://doi.org/10.1037/0096-3445.135.2.207
Shah, A. K., & Oppenheimer, D. M. (2008). Heuristics made easy: An effort-reduction framework. *Psychological Bulletin, 134*(2), 207–222. https://doi.org/10.1037/0033-2909.134.2.207
*Shevchenko, Y., & Bröder, A. (2018). The effect of mood on integration of information in a multi-attribute decision task. *Acta Psychologica, 185*, 136–145. https://doi.org/10.1016/j.actpsy.2018.02.007
Siegler, R. S. (1999). Strategic development. *Trends in Cognitive Sciences, 3*(11), 430–435. https://doi.org/10.1016/S1364-6613(99)01372-8
Simon, H. A. (1990). Invariants of human behavior. *Annual Review of Psychology, 41*, 1–19. https://doi.org/10.1146/annurev.ps.41.020190.000245
Söllner, A., & Bröder, A. (2016). Toolbox or adjustable spanner? A critical comparison of two metaphors for adaptive decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 42*(2), 215–237. https://doi.org/10.1037/xlm0000162
*Söllner, A., Bröder, A., & Hilbig, B. E. (2013). Deliberation versus automaticity in decision making: Which presentation format features facilitate automatic decision making? *Judgment and Decision Making, 8*(3), 278–298.
Sundström, G. A. (1987). Information search and decision making: The effects of information displays. *Acta Psychologica, 65*(2), 165–179. https://doi.org/10.1016/0001-6918(87)90025-4
Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction* ((2nd ed.).). MIT Press.
Trick, L. M., & Pylyshyn, Z. W. (1993). What enumeration studies can show us about spatial attention: Evidence for limited capacity preattentive processing. *Journal of Experimental Psychology: Human Perception and Performance, 19*(2), 331–351. https://doi.org/10.1037/0096-1523.19.2.331
Trick, L. M., & Pylyshyn, Z. W. (1994). Why are small and large numbers enumerated differently? A limited-capacity preattentive stage in vision. *Psychological Review, 101*(1), 80–102. https://doi.org/10.1037/0033-295X.101.1.80
Trueblood, J. S., Brown, S. D., Heathcote, A., & Busemeyer, J. R. (2013). Not just for consumers: Context effects are fundamental to decision making. *Psychological Science, 24*(6), 901–908. https://doi.org/10.1177/0956797612464241
Whelan, R. (2008). Effective analysis of reaction time data. *The Psychological Record, 58*(3), 475–482. https://doi.org/10.1007/BF03395630