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Attention and attribute overlap in preferential choice

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ABSTRACT
Attributes that are common, or overlapping, across alternatives in two-alternative forced preferential choice tasks are often non-diagnostic. In many settings, attending to and evaluating these attributes does not help the decision maker determine which of the available alternatives is the most desirable. For this reason, many existing behavioural theories propose that decision makers ignore common attributes while deliberating. Across six experiments, we find that decision makers do direct their attention selectively and ignore attributes that are not present in or associated with either of the available alternatives. However, they are as likely to attend to common attributes as they are to attend to attributes that are unique to a single alternative. These results suggest the need for novel theories of attention in preferential choice.

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Many everyday value-based decisions involve a choice between two or more alternatives defined on a set of attributes. These attributes determine the desirability of the alternatives, and in order to make the correct choice, decision makers need to attend to, and subsequently evaluate and aggregate, the decision attributes associated with the choice alternatives that they are deliberating over.

The aggregation of attribute values can be difficult, and this aspect of the decision process has been the focus of considerable scholarly enquiry (Busemeyer & Townsend, 1993; Dawes, 1979; Fishburn, 1967; Gigerenzer & Goldstein, 1996; Keeney & Raiffa, 1993; Stewart, Chater, & Brown, 2006; Tversky, 1972). Choosing the right attributes to attend to and evaluate is also, however, an important and difficult problem. The relevance of different attributes for the decision task can vary across choice sets. In order to make quick choices, decision makers need to direct their attention carefully, so that they process only the information that is relevant for making the choice.

In this paper we study attribute attention in two-alternative forced choice with binary attributes. Here attributes can be either present or absent in an alternative. Present attributes are attributes that the alternatives possess. For example, a diligent job candidate can have the attribute or quality of being hard working, and a luxurious resort can have the attribute of a swimming pool. Absent attributes are attributes that the alternative does not possess. It is possible that a certain, less diligent, job candidate is not especially hard working, or that a less luxurious resort does not have a swimming pool. If attributes are present in the alternatives then they can be either unique to a single alternative or common and overlapping across the two alternatives. The goal of these forced choice tasks is to select the alternative that is the most desirable, irrespective of the absolute desirability of the two alternatives. For this purpose, common attributes are often non-diagnostic. Particularly, when the values of the attributes in a choice problem are independent of each other, common attributes do not help the decision maker determine which of the available choice alternatives is more desirable. In these settings, focusing exclusively on unique attributes is necessary to ensure the quickest and least effortful decisions. Indeed, a number of existing theories of decision making have suggested that decision makers either completely ignore common attributes, or pay proportionally less attention to these attributes, compared to those that are unique in the available alternatives (Bordalo, Gennaioli, &

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Shleifer, 2012, 2013; Houston, Sherman, & Baker, 1989, 1991; Kőszegi & Szeidl, 2013).

How do decision makers select the attributes that they attend to in two-alternative binary-attribute forced choice tasks? Is attribute attention completely indiscriminate; that is, is each attribute equally likely to be attended to, regardless of whether it is common, unique, or absent across the alternatives? If not, then do decision makers focus their attention and attend to only unique attributes, or do they follow a simpler strategy that at times leads to inefficient decisions? Although attention is selective, a number of well-known findings in decision-making research suggest that attention allocation is not always completely efficient. Information that is irrelevant to the task at hand can at times become the focus of attention. This is perhaps best demonstrated through the dilution effect, which finds that judgments are sensitive to non-diagnostic information (LaBella & Koehler, 2004; McKenzie, Lee, & Chen, 2002; Nisbett, Zukier, & Lemley, 1981). Particularly, the presence of cues that are not correlated with the judgment criterion can reduce the weights placed on correlated diagnostic cues leading to weakened beliefs and reduced confidence in the judgment. Other work finds that numerical anchors, cues that are associated with favoured responses, dominance relationships between alternatives, and a number of other irrelevant features of the decision task can bias responses (Huber, Payne, & Puto, 1982; Nickerson, 1998; Tversky & Kahneman, 1974; see also Weber & Johnson, 2009 for a review).

In six experiments we test whether decision makers are able to successfully ignore common overlapping attributes, in simple binary forced choice. Our experiments involve three different measures of attribute attention and consider preferential choice problems from two separate domains. We find that decision makers do ignore absent attributes, indicating that their attention is selective. However, they are as likely to attend to common attributes as they are to unique attributes. This influences the quality of their decisions, so that decision makers typically take longer in choices involving both common and unique attributes than only unique attributes. Additionally we find that the observed attentional strategies in our forced choice tasks are similar to those used in free choice tasks, in which decision makers can choose not to select either of the two available alternatives. Common attributes are always diagnostic in free choice, suggesting that decision makers may be using a single attentional strategy for different types of choice, a strategy that is efficient when choice is free, but often inefficient when it is forced. We conclude this paper with a discussion of these efficiencies and their implications regarding the determinants of attribute attention in preferential choice.

Attention in multi-attribute choice

Consider a choice between a bag of chips and a banana, for an afternoon snack. Each of these alternatives can be described in terms of a set of attributes. For example, the chips can be seen as being "crunchy" and "savoury" whereas the banana can be seen as being "healthy" and "sweet". In choices such as these, decision makers determine the relative desirability of the choice alternatives by examining the desirability of their component attributes. If decision makers like crunchy and savoury snacks then they will choose chips. If on the other hand, they want something healthy or sweet, they will select bananas. This structure also applies to other types of choices. Thus, for example, a choice between two job candidates would be determined by the desirability of the component attributes of these candidates (attributes such as "hard working"), and a choice between two vacation resorts would be determined by the desirability of the component attributes of these resorts (attributes such as "swimming pool").

More generally, a two-alternative multi-attribute decision problem can be seen as a choice between alternatives $\boldsymbol{x}$ and $\boldsymbol{y}$, which are written as a vectors of n independent attributes, so that $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)$ and $\boldsymbol{y} = (y_1, y_2, \ldots, y_n)$. Each of these attributes has a certain desirability or value, V_i, with the overall desirability of an alternative equal to the sum of the desirability of its associated attributes (see Keeney & Raiffa, 1993, for an overview). In this paper we consider choices involving only binary attributes, where $x_i = 1$ if $\boldsymbol{x}$ is associated with attribute i and $x_i = 0$ if $\boldsymbol{x}$ is not associated with attribute i, and $y_i = 1$ if $\boldsymbol{y}$ is associated with attribute i and $y_i = 0$ if $\boldsymbol{y}$ is not associated with attribute i. For this setting we can write the set of the attributes associated with $\boldsymbol{x}$, as $A_x = \{i \mid x_i = 1\}$ and the set of the attributes associated with $\boldsymbol{y}$, as $A_y = \{i \mid y_i = 1\}$. Subsequently the desirability of $\boldsymbol{x}$ can be written as $U(x) = \sum_{i \in A_x} V_i$, and the desirability of $\boldsymbol{y}$ can be written as $U(y) = \sum_{i \in A_y} V_i$. The goal of the standard multi-attribute choice task is to select the choice alternative with the highest desirability, with $\boldsymbol{x}$

being the correct choice if $U(\boldsymbol{x}) > U(\boldsymbol{y})$ and $\boldsymbol{y}$ being the correct choice if $U(\boldsymbol{y}) > U(\boldsymbol{x})$.

In order to solve this task, the decision maker needs to attend to the attributes, determine their values, V_i, and then aggregate these values into a measure of the relative desirability of the two alternatives (see Bhatia, 2013; Roe, Busemeyer, & Townsend, 2001). A simple way to approach this would be to consider all n attributes equally. However, if attending to each attribute involves a cost (such as time), then this approach is inefficient. It is likely that many of the n attributes do not provide any information about which of the two alternatives is more desirable.

Which attributes should decision makers consider when attribute attention is costly? In two-alternative choices with binary attributes, where total value is additive in attributes, efficient attention can be easily characterized. Particularly, since decision makers only need to determine the most desirable of the alternatives—that is, whether $U(\boldsymbol{x}) > U(\boldsymbol{y})$ or $U(\boldsymbol{y}) > U(\boldsymbol{x})$—they should only consider attributes that are unique to the available alternatives—that is, attributes that are associated with only one of the available alternatives [attributes $i \in (A_x / A_y) \cup (A_y / A_x)$]. Common attributes that are associated with both of the alternatives (attributes i such that $i \in A_x \cap A_y$) are relevant for determining the absolute desirability of the alternatives, but not the relative desirability of the alternatives. Additionally, absent attributes that are associated with neither of the two alternatives (attributes i such that $i \notin A_x \cup A_y$) are clearly irrelevant to the decision.

More formally, we have $U(\boldsymbol{x}) > U(\boldsymbol{y})$ if and only if $\sum_{i \in A_x / A_y} V_i > \sum_{i \in A_y / A_x} V_i$, making evaluations of unique attributes both necessary and sufficient for determining the correct response in two-alternative forced choice. Knowing the value of V_i if i is associated with both the alternatives does not in any way help the decision maker determine $U(\boldsymbol{x}) > U(\boldsymbol{y})$ or $U(\boldsymbol{y}) > U(\boldsymbol{x})$. If an attribute i is common, V_i could take on any value and not influence which of the two alternatives is more desirable.

The above analysis uses insights from decision theory, which have guided the study of multi-attribute choice for many decades (Keeney & Raiffa, 1993). However we would obtain a similar characterization of efficient attention if we were to study the problem using Bayesian or information theoretic methods, which are typically used to examine information acquisition for experimental purposes (see Chaloner & Verdinelli, 1995; Kiefer, 1959 for work on optimal experimental design). These methods often characterize the usefulness of a piece of information (in this case, knowing the value of V_i for a particular i) in terms of its ability to discriminate between the hypotheses in consideration [$U(\boldsymbol{x}) > U(\boldsymbol{y})$ or $U(\boldsymbol{y}) > U(\boldsymbol{x})$]. According to these approaches, decision makers should attend to attributes only if knowing their values changes the posterior probabilities of the hypotheses or the relative likelihoods of the hypotheses. In the simple case studied here, these approaches would recommend that decision makers avoid sampling attributes associated with both available alternatives, as knowing the values of these common attributes would not change the decision maker's beliefs about which of the two alternatives is more desirable.

It is important to note that the above insights do not hold when the values of the attributes interact with each other—that is, when total value is not additive in attributes. For this reason we cannot claim that attending to common attributes is always inefficient. Nonetheless, the simple additive setting outlined here is the standard way of modelling multi-attribute choice and has been the focus of much enquiry in decision-making research (see Keeney & Raiffa, 1993). It is thus not surprising that a number of approaches have proposed, either explicitly or implicitly, that decision makers avoid attending to common attributes when making their decisions. For example, one of the best known lay decision-making strategies, Benjamin Franklin's rule, involves cancelling out and ignoring common attributes in pairwise choice (see Gigerenzer & Goldstein, 1999). Likewise, in the field of multi-criteria decision analysis, some strategies involve the use of attribute differences or ratios in the calculation of relative desirability, with attributes that are shared across alternatives playing little or no role in the decision (Triantaphyllou, 2013). From a behavioural perspective, some recent theories of economic choice have proposed that decision makers attend to attributes proportionally to the dispersion of the alternatives on the attributes. These strategies imply that common attributes, on which alternatives have zero dispersion, receive the least attention (Bordalo et al., 2012, 2013; Kőszegi & Szeidl, 2013). Likewise, psychological models such as the cancellation and focus heuristic suggest that decision makers cancel out and ignore common attributes in sequential choice (Houston et al., 1989, 1991). This can also be seen as being a property of the well-known additive difference model, in which attributes

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on which alternative differences fall below a certain threshold are ignored, though it is important to note that this model does not make explicit predictions regarding attention (Tversky, 1969; see also Leland, 1998; Rubinstein, 1988, for closely related models). Most of the above theories also predict that the amount of attention to common attributes should be equivalent to the amount of attention to absent attributes (as choice alternatives have equal amounts of both of these types of attributes).

Related claims have been made in multi-cue judgment research. Here scholars have suggested that the usefulness of a cue for a particular judgment depends on the ability of that cue to discriminate between alternatives. Decision makers who use cues that are present in most alternatives will typically be unable to distinguish two given alternatives from each other (Gigerenzer & Goldstein, 1999; Newell, Rakow, Weston, & Shanks, 2004; Rakow, Newell, Fayers, & Hersby, 2005). Although the focus of this work is on cue attention as a function of the statistical structure of the general decision making environment, rather than the specific choice set offered to the decision maker in a single trial (as in this paper), this work nonetheless supports the idea that attention towards common attributes is detrimental to the decision.

In this paper, we test whether decision makers do in fact ignore common attributes and focus only on unique attributes. In all of our experiments, we present decision makers with pairs of choice alternatives described by lists of attributes and ask decision makers to make choices between the two alternatives. These lists are structured so that attributes are associated with only one of the alternatives (and are thus unique) or both of the alternatives (and are thus common and overlapping). We also include attributes that are absent from both of the alternatives as a baseline measure for attribute attention. In four of our experiments, we measure attribute attention indirectly by the ability of decision makers to recall the attributes presented in these lists, after the lists have been displayed to them. In the remaining two experiments we measure attribute attention by using mouse clicks and viewing times, and overall decision times, respectively. Finally, although the first five of our experiments involve forced choices, in our sixth experiment we also include a free choice condition. Common attributes in free choices are always diagnostic, and an examination of attribute attention in free choice can test whether decision makers are able to successfully modify their attentional strategies based on the type of choice task that they are offered.

EXPERIMENT 1

In Experiment 1 we offered participants choices between two alternatives, defined on a set of attributes. After decision makers had seen the alternatives and the attributes, we tested whether they were better at recalling the attributes that were common, unique, or absent in their choice set. We used recall as a proxy for attribute attention, as attributes that are successfully recalled are ones that decision makers spent more time attending to and deliberating over. If attribute attention is indiscriminate, then the recall of an attribute should not depend on whether it is common, unique, or absent. If, on the other hand, attention is selective then we should expect systematic differences in the ability of participants to recall different attributes, based on their association with the available alternatives.

Method

Participants

One hundred participants were recruited through Amazon Mechanical Turk (59% male, $M_{age} = 30.55$ years, $SD = 8.57$) and performed the experiment online. All participants were English speakers living in the United States.

Materials and procedure

After giving informed consent, participants were presented with a single forced choice between two alternatives defined on binary attributes. Particularly, they were asked to imagine that they had to hire an employee for their company and that they had a choice between two applicants. The applicants were defined by 10 employment-related attributes, such as "intelligent", "motivated", and so on. The choice alternatives offered to the decision makers had one unique attribute each, one common attribute, and seven absent attributes.

The alternatives were presented in a table format, with the first column displaying the attributes and the second column indicating which of the attributes are associated with the alternative. If an attribute was associated with the alternative then there was an "X" in the table cell corresponding to that alternative's attribute. If not, then this cell was left empty. Participants were told that this "X" indicates that the

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candidate possesses that attribute whereas the absence of an "X" next to an attribute indicates that the candidate does not process that attribute. The order that the attributes and alternatives were presented in was randomized. Additionally, the attributes that were unique, common, or absent from the choice set were perfectly counterbalanced across participants, so that each attribute was associated with the first applicant, the second applicant, and both applicants an equal number of times. Note that this display format controls for display frequency: All attributes are listed an equal number of times, and common attributes are not mentioned more times than unique or absent attributes. Biases in attribute attention therefore cannot be attributed to differences in display frequency across different choice sets. Figure 1 shows an example of a choice display offered to participants.

After being shown the applicants and their component attributes, as in Figure 1, participants were taken to a new screen where they were asked to recall and list as many attributes presented in the previous screen as they could remember. They were explicitly told to list both the attributes associated with the applicants and the attributes not associated with the applicants (though they were not required to list these two sets of attributes in any particular order). After the attribute recall task was complete, participants proceeded to a final screen where they made their choices. Each participant answered only one question, and the entire experiment, including introduction and debriefing, took approximately five minutes.

Results

We found that participants were much more likely to recall the attributes that were associated with the available applicants (that is, unique and common attributes) than the attributes that were not associated with the available applicants (that is, absent attributes). Interestingly, Participant 85 explicitly mentioned this at the end of the study, as a way to justify his inability to recall all of the attributes. He said that he "only paid attention to the qualities the applicants had, not the ones they didn't". Overall, participants recalled an average of 91% of the unique attributes, 84% of the common attributes, and 15% of the absent attributes. The recall probabilities of the 10 attributes when they are unique, absent, and common are presented in Table 1.

We can compare the recall of attributes when they are common, unique, or absent with a mixed-effects logistic regression that uses each participant's success or failure to recall each attribute at a separate data point. There are 10 attributes in each choice, and a total of 100 participants, generating 1000 observations. For each of these observations, we use the *recall* of the attribute as a dependent variable (*recall* = 1 if the attribute was listed in the recall task by the participant; *recall* = 0 otherwise). We also use dummies for each of the attributes as independent variables, allowing us to have fixed effects on an attribute level. We specify two more independent variables, *unique* and *absent* (*unique* = 1 if the attribute is unique, and *unique* = 0 otherwise; *absent* = 1 if attribute is absent, and *absent* = 0 otherwise), which indicate whether the attribute in consideration was unique or absent in the choice set offered to the participant (common attributes serve as a basis for comparison as the mean recall for common attributes is between that for unique attributes and absent attributes, and they correspond to data points where both *unique* = 0 and *absent* = 0). Finally we allow for random effects on a participant level, generating 100 different groupings on our dataset. This regression controls for attribute-level influences on recall through the fixed-effects terms, and participant-level influences on recall through the random-effects terms. Examining whether the variables *unique* and *absent* have a significant effect on *recall* would tell us whether recall is significantly higher for unique attributes than for common attributes and whether recall is significantly lower for absent attributes than for common attributes, controlling for attribute-specific and participant-specific influences.

Using this approach, we do find that decision makers are significantly less likely to recall an attribute if it is absent from the choice set than if it is common in the choice set ($\beta = -4.41$, $z = -11.38$, $p < .001$). We do not, however, find that decision makers are significantly more likely to recall an attribute if it is unique in the choice set than if it is common in the choice set ($\beta = 0.68$, $z = 1.61$, $p = .11$).

It may be argued that this experiment fails to detect a difference between the recall of unique and common attributes due to power. This point can be addressed by comparing the Bayesian information criterion (BIC) score of the above logistic regression with the score of a simpler regression model with only *absent* as the main independent variable (i.e., a regression that ignores differences between

	Applicant 1
Hard worker	
Lots of experience	
Good recommendations	
Intelligent	X
Creative	
Motivated	
Friendly	X
Go-getter	
Organized	
Good education	

	Applicant 2
Hard worker	
Lots of experience	
Good recommendations	
Intelligent	
Creative	X
Motivated	
Friendly	X
Go-getter	
Organized	
Good education	

	Applicant 1
Hard worker	
Lots of experience	X
Good recommendations	
Intelligent	X
Creative	X
Motivated	
Friendly	X
Go-getter	
Organized	
Good education	

	Applicant 2
Hard worker	X
Lots of experience	
Good recommendations	
Intelligent	
Creative	X
Motivated	
Friendly	X
Go-getter	
Organized	X
Good education	

	Resort 1
Casinos	—
Famous spa	—
Adventure sports	—
Beaches	X
Wildlife excursions	—
Exciting nightlife	—
Good weather	X
Family activities	—
Beautiful scenery	—
Great local cuisine	—

	Resort 2
Casinos	—
Famous spa	—
Adventure sports	X
Beaches	—
Wildlife excursions	—
Exciting nightlife	—
Good weather	X
Family activities	—
Beautiful scenery	—
Great local cuisine	—

Figure 1. Displays used in Experiments 1 and 5 (top panel), in Experiments 3 and 6 (middle panel), and in Experiment 2 (bottom panel).

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common and unique attributes). The BIC score for these models would be calculated using the following formula:

$$\mathrm{BIC} = -2L + k \cdot \ln(n)$$

Here L is the log-likelihood of the model in consideration, k is the number of its parameters, and n is the total number of data points. The BIC score is a useful way to compare model fits controlling for model flexibility, and models with lower BIC scores are those that achieve the best fits with the fewest parameters. Using this approach, we find that the BIC score of the above logistic regression, which has both *unique* and *absent* as independent variables, is 852.92. In contrast the BIC score for a regression with only *absent* as an independent variable is 848.58. These scores show that the best performing model is one that only uses the *absent* variable to predict recall and ignores differences between attributes that are unique and attributes that are common. This further indicates that decision makers are not more likely to recall an attribute if it is unique in the choice set than if it is common in the choice set.

Discussion

This experiment provided strong evidence that decision makers attend to attributes selectively when making their decisions. Particularly, participants were much better at recalling attributes if they were

Table 1. The average recall probabilities of the different attributes when they are unique, common and absent, in Experiment 1

Attribute	Unique	Common	Absent
Hard worker	1.00	1.00	.29
Experience	.90	.80	.16
Recommendations	.84	.70	.03
Intelligent	1.00	.58	.20
Creative	.91	.71	.15
Motivated	.95	.89	.08
Friendly	.95	1.00	.13
Go-getter	.80	1.00	.13
Organized	1.00	1.00	.18
Good education	.95	.91	.16
Average	.91	.84	.15

associated with the available alternatives (i.e., common and unique attributes) than if they were not associated with any of the available alternatives (i.e., absent attributes). Changing the attributes associated with different alternatives changed which of the attributes were most likely to be recalled.

This experiment also provided a test of differences in attribute attention between common and unique attributes. It found that while unique attributes were slightly more likely to be recalled than common attributes, the difference in recall probability was not statistically significant. For this reason, the best performing statistical model in terms of the BIC was a model that lumped common and unique attributes into a single category. Additionally, the difference in the recall probabilities of common versus unique attributes was much smaller than the difference in the recall probabilities of common versus absent and unique versus absent attributes. This implies that even though unique attributes may be slightly more salient, decision makers do not ultimately ignore common attributes in forced binary choice. This indicates that their attention may not be perfectly efficient and also provides evidence against a number of existing theories of decision making (e.g., Bordalo, Gennaioli, & Shleifer, 2013; Houston et al., 1989; Kőszegi & Szeidl, 2013), which predict that attribute attention is a product of the dispersion of the available alternatives on the attributes. According to these theories, common attributes should be attended to as frequently as absent attributes, and both should be attended to much less frequently than unique attributes.

EXPERIMENTS 2 AND 3

The goal of Experiments 2 and 3 is to test the robustness of the results in Experiment 1. Experiment 2 utilizes a different choice domain—choices between vacation resorts rather than potential employees—and additionally modifies the presentation of the choice stimuli, so as to include an explicit symbol to indicate attribute absence (instead of leaving the corresponding table cell blank). Experiment 3 considers settings with a higher number of unique and common attributes and correspondingly smaller number of absent attributes. The use of a separate choice domain and different types of presentation formats is necessary to test whether the results of Experiment 1 are a product of a general decision-making strategy, rather than a strategy applicable only to a small class of choice alternatives presented in a highly specific manner. Likewise the use of settings with a greater number of common and unique attributes and fewer absent attributes is necessary to test whether the results of Experiment 1 hold when decision makers are offered richer choice alternatives, which are associated with multiple attributes.

Method

Participants

One hundred participants were recruited through Amazon Mechanical Turk for Experiment 2 (60% male, $M_{age} = 33.45$ years, $SD = 10.88$) and for Experiment 3 (61% male, $M_{age} = 32.48$ years, $SD = 9.88$) each. All participants were English speakers living in the United States.

Materials and procedure

Experiments 2 and 3 were identical to Experiment 1 in terms of their procedure and implementation. The only differences between these studies and Experiment 1 involved the choice options given to participants (in both studies) as well as the presentation of the choice options (in Experiment 2).

In Experiment 2, participants were asked to make a choice between hypothetical vacation resorts, defined on attributes such as "casinos", "famous spa", "beaches", and so on. This is in contrast to Experiment 1, which involved choices between job applicants. A second difference involved the types of tables used to display the options. These tables did use an "X" to indicate that an attribute was associated with an alternative. However, instead of leaving table cells blank if the attribute was not associated with an alternative, Experiment 2 used a long dash sign, "—", as shown in Figure 1. Again, as in Experiment 1, participants were told that an "X" indicates that a resort has that attribute

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whereas a "—" indicates that a resort does not have that attribute. As in Experiment 1, there were a total of 10 attributes, with one attribute being unique to each alternative, one attribute being common to the two alternatives, and the remaining seven attributes being absent from the alternatives.

Experiment 3 utilized the same attributes and presentation format as those in Experiment 1, but varied the total number of unique, common, and absent attributes in the two choice options. Unlike Experiment 1, Experiment 3 presented choice alternatives with two unique attributes each, two common attributes, and four absent attributes. This is shown in Figure 1. Again, the attributes that were unique, common, or absent in each choice set were counterbalanced. Finally, as above, each participant answered only one question, and the two experiments, including introduction and debriefing, took approximately five minutes.

Results

The results of Experiment 2 were nearly identical to those of Experiment 1, except for the fact that the mild difference between the recall probabilities of unique and common attributes, observed in Experiment 1, reversed. Particularly, participants recalled an average of 80% of the unique attributes, compared to an average of 85% of the common attributes. Additionally, as in Experiment 1, absent attributes were much less likely to be recalled than common and unique attributes, with participants recalling an average of 17% of the absent attributes. The recall probabilities of the 10 attributes when they are unique, absent, and common are presented in Table 2.

As in Experiment 1, we can use a mixed-effects logistic regression to examine the differences in recall probabilities, controlling for attribute-level and participant-level heterogeneity. Using this approach, we do find that decision makers are significantly less likely to recall an attribute if it is absent from the choice set than if it is unique in the choice set ($\beta = -3.42$, $z = -13.30$, $p < .001$). We do not, however, find that decision makers are significantly more likely to recall an attribute if it is common in the choice set than if it is unique in the choice set ($\beta = 0.36$, $z = 1.00$, $p = .32$). As above, a BIC score analysis indicates that the BIC score for this regression (BIC = 946.08) is higher than the BIC score for a similar regression with only absent as the independent variable (BIC = 940.22), further demonstrating that there are no statistically relevant differences between unique and common attributes in terms of their effects on recall.

Experiment 3 also finds similar results. Particularly, participants recalled an average of 73% of the unique attributes, 69% of the common attributes, and 19% of the absent attributes.

With the above-mentioned mixed-effects logistic regression we find that decision makers are significantly less likely to recall an attribute if it is absent from the choice set than if it is common in the choice set ($\beta = -2.54$, $z = -10.97$, $p < .001$). We do not, however, find that decision makers are significantly more likely to recall an attribute if it is unique in the choice set than if it is common in the choice set ($\beta = 0.17$, $z = 0.83$, $p = .41$). This is further reflected in a higher BIC score for this regression (BIC = 915.81) than for a similar regression with only absent as the independent variable (BIC = 908.21). The recall probabilities of the 10 attributes when they are unique, absent, and common are presented in Table 3.

Discussion

Experiments 2 and 3 replicated the result of Experiment 1 using different types of choice alternatives and presentation formats, as well as choice alternatives with a higher number of unique and common attributes and fewer number of absent attributes. Particularly, these studies found that decision makers were much more likely to recall unique and common attributes than absent attributes, indicating that attribute attention is selective. Additionally, there were no statically relevant differences between the recall probabilities of unique and common attributes. This indicates that attribute attention may not be perfectly efficient. These results also contradict the predictions of some existing theories of multi-attribute choice (Bordalo et al., 2013; Houston et al., 1989; Kőszegi & Szeidl, 2013), which suggest that decision makers ignore common attributes relative to unique attributes.

Before proceeding, let us compare the recall probabilities in Experiment 3 with those in Experiment 1, to examine the effect of increasing the number of present or absent attributes, and the changes to stimuli presentation this generates, on participant behaviour. Experiment 3 and Experiment 1 are identical except for the fact that Experiment 3 has twice as many present attributes (and fewer absent attributes). For this reason its display involves more "X"s, and these "X"s and their corresponding present attributes stand out less

Table 2. The average recall probabilities of the different attributes when they are unique, common and absent, in Experiment 2

Attribute	Unique	Common	Absent
Adventure sports	.94	.82	.19
Beautiful scenery	.82	.86	.21
Beaches	.50	.63	.06
Activities for family	.89	.90	.23
Exciting nightlife	.70	.85	.20
Good weather	.94	1.00	.14
Casinos	.82	.92	.20
Great local cuisine	.77	.88	.15
Famous Spa	.74	.90	.15
Wildlife excursions	.85	.78	.19
Average	.80	.85	.17

(see Figure 1). It could be that this standing out (figure/ground contrast) plays a role in directing attention and generating the observed behavioural patterns. We do find that the recall probabilities of absent attributes in Experiment 3 are higher than those in Experiment 1 (19% vs. 15%), but that these differences pale in contrast to the recall probabilities of present attributes, which frequently exceed 70%. This suggests that the total number of present or absent attributes can influence recall probability, but that their effect is minor and cannot account for all of the differences observed in this paper. It could be useful, in future work, to consider a variant of Experiment 3 with no absent attributes whatsoever, to ensure that these patterns persist and that the findings of Experiments 1 and 3 are robust.

EXPERIMENT 4

While the results of Experiments 1–3 are useful for characterizing the nature of attribute attention in preferential choice, they measure attribute attention indirectly. Particularity, the recall of attributes after the decision alternatives have been displayed is used as a proxy for attribute attention during the display of the decision alternatives. In order to more rigorously examine how decision makers allocate attention, it would be useful to observe attention during the decision process itself. This is the goal of Experiment 4, which uses a Mouselab interface (Willemsen & Johnson, 2011) that allows us to observe information acquisition during deliberation.

Method

Participants

One hundred participants were recruited through Amazon Mechanical Turk (61% male, $M_{age} = 31.81$ years, $SD = 9.89$) and performed the experiment online. All participants were English speakers living in the United States.

Materials and procedure

The specific choice alternatives used were identical to those in Experiment 1. Unlike Experiment 1, however, the names of the attributes (e.g., "good education", "intelligent", etc.) were hidden behind grey boxes. Decision makers needed to click on the grey boxes in order to find out which attributes the boxes represented. Clicking on a grey box would open it up, uncovering its corresponding attribute. Clicking on the next grey box would close the first box and open up the second.

Information about whether an attribute behind a grey box was associated with the alternatives was freely available. Thus decision makers could choose whether they wanted to uncover grey boxes corresponding to unique attributes, common attributes, or absent attributes. Examining the number of times that decision makers clicked on the grey boxes in order to uncover the different attributes, and the total amount of time that decision makers spent looking at the attributes in the grey boxes, can quantify attribute attention in the choice task.

An example of the display used in Experiment 4 is shown in Figure 2. The left panel shows the display to participants when none of the boxes have been clicked. The right panel shows the display to participants when one of the boxes is clicked. It is only by clicking that participants are able to determine the specific attribute in a box. As in Experiment 1, attributes associated with different alternatives were indicated by an "X" in their corresponding cell, and participants were told that the presence of this "X" indicated that the candidate possessed the attribute and that the absence of this "X" indicated that the candidate did not possess the attribute. Additionally, choice was made on a separate screen after examination of all of the attributes. Finally, the order that the attributes and alternatives were presented in was randomized, and the attributes that were common, unique, and absent were counterbalanced. Participants were given detailed instructions (including illustrations and examples) regarding this presentation format; however, there were no practice problems. Each participant answered only one question.

Results

We found that participants were much more likely to click the attributes that were associated with the available applicants (that is, unique and common

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Table 3. The average recall probabilities of the different attributes when they are unique, common and absent, in Experiment 3

Attribute	Unique	Common	Absent
Hard worker	.84	.82	.33
Experience	.73	.58	.14
Recommendations	.61	.50	.15
Intelligent	.73	.65	.18
Creative	.74	.87	.11
Motivated	.63	.65	.15
Friendly	.77	.78	.24
Go-getter	.73	.91	.17
Organized	.67	.57	.25
Good education	.81	.60	.19
Average	.73	.69	.19

attributes) compared to the attributes that were not associated with the available applicants (that is, absent attributes). On average, participants clicked unique attributes 1.71 times, common attributes 1.65 times, and absent attributes 0.49 times. We obtained identical results for the total viewing time of each attribute. We found that participants spent more time looking at unique and common attributes than absent attributes. On average, participants spent an average of 3.80 s viewing each unique attribute, an average of 3.30 s viewing each common attribute, and an average of 0.69 s viewing each absent attribute. The average clicking frequencies and viewing times of the 10 attributes when they are unique, absent, and common are presented in Table 4.

A rigorous way to examine attention to attributes when they are common, unique, or absent involves a mixed-effects regression that uses each participant's clicking data or viewing time data for each attribute at a separate data point. For this, we can again use the approach outlined in Experiment 1, which controls for attribute-level influences on recall through fixed-effects terms, and participant-level influences on recall through random effects terms, and specifies *unique* and *absent* as independent variables that indicate whether an attribute is unique or absent for a participant in a particular choice set. With this approach we do find that decision makers are significantly less likely to click on an attribute if it is absent from the choice set than if it is common in the choice set ($\beta = -1.16$, $z = -16.94$, $p < .001$). Likewise we find that decision makers are significantly less likely to spend time viewing an attribute if it is absent from the choice set than if it is common in the choice set ($\beta = -2.64$, $z = -12.59$, $p < .001$). We do not, however, find that decision makers are significantly more likely to click on an attribute if it is unique in the choice set than if it is common in the choice set ($\beta = 0.06$, $z = 0.74$, $p = .46$). Likewise we do not find that decision makers are significantly more likely to spend time viewing on an attribute if it is unique in the choice set than if it is common in the choice set ($\beta = 0.46$, $z = 1.94$, $p = .06$), though note that this difference is only marginally above the threshold used for statistical significance.

As in the previous studies, we can compare the BIC scores of the above regressions with similar scores for a simpler regression model that only permits *absent* as the dependent variable. With regards to clicks, we find that the above regression has a higher BIC score (BIC = 2217.60) than a simpler regression model (BIC = 2211.24), indicating that a simpler model that ignores differences between unique and common attributes performs better than a model that permits these differences. We find similar results for viewing times, with lower BIC scores for the simpler regression (18,232.92 vs. 18,235.95).

It is also possible to examine the order in which participants click on the various attributes. Although

Table 4. The average mouse clicks and viewing times for the different attributes when they are unique, common and absent, in Experiment 4

	Mouse clicks			Viewing times (ms)		
Attribute	Unique	Common	Absent	Unique	Common	Absent
Hard worker	1.95	1.64	0.53	4620.33	3121.00	553.04
Experience	1.60	1.60	0.51	3411.90	2545.10	611.90
Recommendations	1.74	1.78	0.46	3571.95	3059.33	795.94
Intelligent	1.95	1.00	0.47	3166.95	2498.56	764.28
Creative	1.26	2.40	0.56	4273.37	2974.70	748.03
Motivated	2.05	1.40	0.41	4330.30	3008.70	520.67
Friendly	1.52	1.50	0.54	4714.10	2671.60	749.57
Go-getter	1.47	1.64	0.47	2640.84	6312.73	541.77
Organized	1.77	1.89	0.54	3016.86	3166.67	851.46
Good education	1.75	1.64	0.39	4212.35	3623.00	743.93
Average	1.71	1.65	0.49	3795.89	3298.14	688.06

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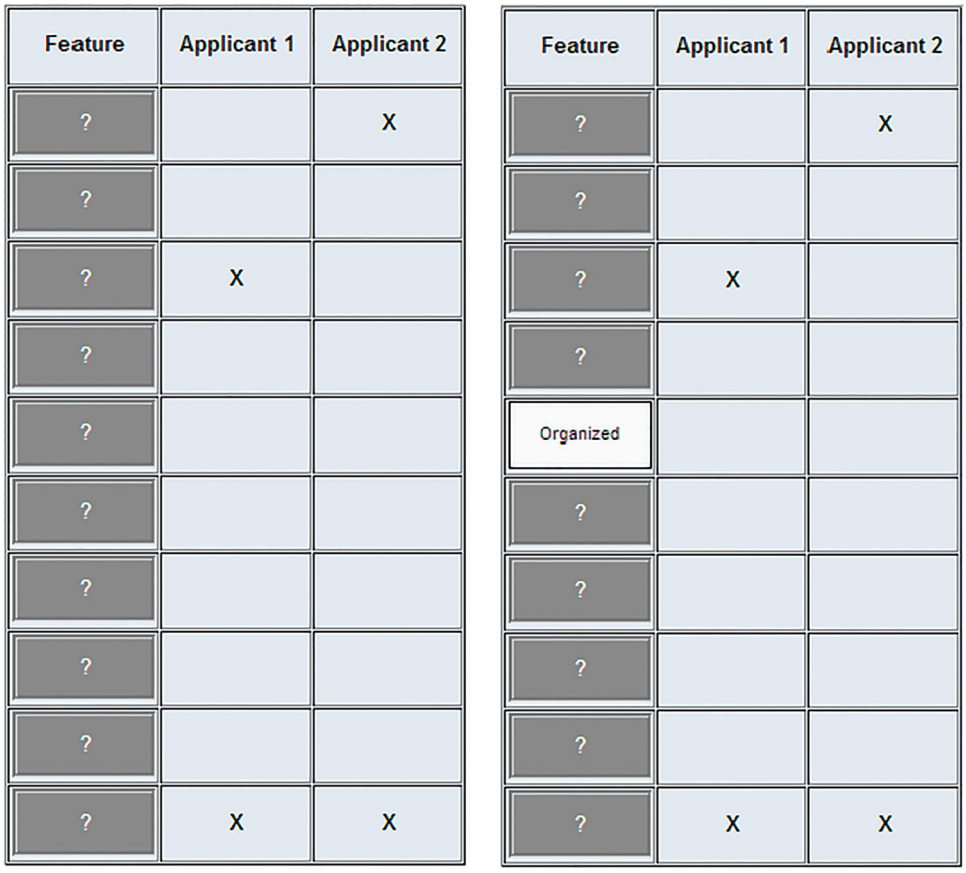

Figure 2. Example of display used in Experiment 4. The left panel shows the display when none of the boxes have been clicked. The right panel shows the display when one of the boxes is clicked.

existing theories about attention to common attributes do not make strong predictions regarding which attributes are attended to first, attentional order has been shown to be a theoretically relevant construct, predicting, for example, findings such as the endowment effect and present bias (Johnson, Häubl, & Keinan, 2007; Weber et al., 2007). For this analysis, we formalize attentional order for unique, common, and absent attributes, using the average rank of these attributes for each participant. For example, for a participant that clicks on the two unique attributes at least once, we can calculate the average ranks of each of this participant's unique attribute clicks in the list of all clicks, and then average these ranks to get a measure of the order in which unique attributes are clicked by this participant. This can be repeated for common and absent attributes, and a comparison can be made between average click orders to determine which attributes this participant is most likely to click on early versus late in the decision. This is similar to the Mouselab analysis in Johnson et al. (2007), and, as with this analysis, and unlike the analyses performed thus far in this paper, it requires participant-level rather than attribute-level comparisons.

Now out of the 100 subjects in this study, only 85 subjects clicked on both unique attributes, and the average rank of these clicks was 4.14 ($SD = 2.82$). Likewise only 87 subjects clicked on the common attribute, and the average rank of these clicks was 3.67 ($SD = 2.77$). Finally, only 28 subjects clicked on all absent attributes, with an average click rank of 5.99 ($SD = 1.72$). These averages indicate that common attributes are likely to be clicked on earlier in the decision, followed by unique attributes, and then by absent attributes. Using a paired t-test to compare click order for the 85 subjects who clicked on both all of the unique attributes and all of the common

attributes, we find that the click order for these two types of attributes is not significantly different ($t = 1.91$, $p = .20$). Repeating this analysis for the 28 subjects that clicked on all absent attributes, all unique attributes, and all common attributes, we again find no difference in click order ($p > .10$ for all comparisons). This could, however, be due to the relatively small sample size for this analysis: If more than 28 participants clicked on the absent attributes at least once, we may have been able to observe statistically relevant differences in click order between absent and present attributes.

Discussion

Experiment 4 examined attribute attention using the Mouselab interface. In this study, information about whether or not an attribute was associated with an alternative was available to the participants. However, participants had to click on the grey boxes that covered the various attributes to determine what the attributes actually were. This study found that decision makers were significantly more likely to click and view the attributes that were associated with the available alternatives (that is, common or unique attributes) than the attributes that were not associated with the available alternatives (that is, absent attributes). There were no statistically relevant differences in clicking frequencies and viewing times between common and unique attributes. This suggests that decision makers are unable to ignore common attributes, which are often non-diagnostic for the purposes of the choice.

It is useful to note that the viewing times measured in this study may be overestimates, as they correspond to the entirety of the time between two clicks. Additionally, they may be noisy and imperfect measures of attribute attention: Decision makers need not be actively viewing and processing the attribute when its box is uncovered. Nonetheless these viewing times serve as a suitable proxy for relative attribute attention for current purposes, as it is unlikely that the extent of this overestimate and noise varies across different types of attributes.

Additionally note that many process-tracing studies using tools like Mouselab examine multiple phases in decision makers' search for information. For example, sometimes decision makers first open all boxes before focusing in on the attributes or cues that are relevant for the decision. The average click counts for the attributes in this study indicate that, on average, there is only one major phase of information acquisition: The average click count for absent attributes is very small, indicating that the typical decision maker does not even open this type of attribute, and subsequently does not display a general orientation phase.

Overall, these results reproduce the findings of Experiments 1–3 using a novel measure of attention and provide further evidence that attention, while being selective, is nonetheless not perfectly efficient. Additionally, these results contradict the predictions of several theories of multi-attribute choice (Bordalo et al., 2013; Houston et al., 1989; Kőszegi & Szeidl, 2013), which propose that common and absent attributes are both ignored during the choice process.

EXPERIMENT 5

Experiments 1–4 utilized attribute recall and mouse tracking. These measures of attribute attention provide strong evidence that decision makers are able to ignore absent attributes but not common attributes when making their decisions: Common and unique attributes are recalled with almost equal probability and are additionally clicked on and viewed with almost equal frequency. Absent attributes, in contrast, are seldom recalled, clicked on, or viewed.

The recall and mouse-tracking measures used in Experiments 1–4 suffer from some important limitations. While they may serve as reasonable proxies of attribute attention, an increased recall or viewing time for an attribute does not indicate that the decision maker is necessarily spending more time thinking about the attribute. Experiment 5 attempts to address this by using a third method. It presents choices similar to those used in Experiments 1, 3, and 4, but varies the number of common versus absent attributes in the choice. Additionally, it measures total decision time instead of attribute recall or click-based information acquisition. If, in addition to ignoring absent attributes, decision makers are able to ignore common attributes, then increasing the number of common attributes in a particular choice should not significantly alter decision time. In contrast, if decision makers attend to and process common attributes, total decision time should increase with the number of common attributes in a choice task. Along with providing an new type of test of decision makers' attention, this design can also be used to verify whether decision makers' observed attentional strategies are in fact detrimental

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for the choice at hand. Short decision times are a characteristic of efficient decision making, and decisions that sample more information than they need to, and subsequently take longer than they need to, are commonly seen as being inefficient.

Method

Participants

Fifty participants (64% male, $M_{age} = 21.32$ years, $SD = 2.35$) performed the experiment in a behavioural laboratory at a British university. Participants were recruited from the university's experimental participant pool. Our use of a laboratory environment in this study (compared to performing the experiment online as in other studies in this paper) was necessitated by the fact that we wished to study decision times, which require additional experimental control.

Materials and procedure

Once again, the decision task asked participants to choose between two job applicants defined on 10 different attributes. The attributes used were identical to those of Experiments 1, 3, and 4. However, unlike these studies, this experiment asked each participant to make 30 different binary forced choices. Each of these binary choices offered participants two applicants, with one unique attribute each. These 30 choices were composed of 10 sets of three choices. The choices within each set were similar in that the two options they offered had the same composition of unique attributes. The only difference between these choices was the number of common versus absent attributes. The first choice in each set did not have any common attributes (with the remaining eight attributes being absent), the second choice had one common attribute (with the remaining seven attributes being absent), and the third choice had two common attributes (with the remaining six attributes being absent). Thus, for example, the first set used in this experiment offered participants three choices between an applicant with "good recommendations" and an applicant who is a "go-getter". In the first of the three choices in this set, the applicants had none of the other eight attributes. Thus the choice was between an applicant who had only good recommendations and an applicant who was only a go-getter. In the second of the three choices, both applicants were also creative. Thus the choice was between an applicant who had good recommendations and was creative, and an applicant who was a go-getter and was creative. In the third of the three choices, the applicants also had had a good education. Thus the choice was between an applicant who had good recommendations, was creative, and had had a good education, and an applicant who was a go-getter, was creative, and had had a good education. Again there were 10 different sets of these three types of choices. The attributes that were unique and common across the choices and across the sets were counterbalanced, and the order in which the choices, choice alternatives, and attributes were presented was randomized.

Note that this experiment did not capture recall or mouse-tracking data. Thus in each of the 30 choices, participants were given the two choice options on the screen (presented as in Figure 1) and were then asked to make their choice on the same screen. This experiment did, however, collect decision time data for each choice.

Results

The primary dependent variable in this experiment is decision time. If decision makers ignore both common and absent attributes, then varying the number of common versus absent attributes within each set should not affect the time that decision makers spend deliberating during the choice. Thus decision times within each set of three choices should be constant.

For choices without common attributes, the average decision time was 6.05 s ($SD = 4.42$). This time increased to 9.33 s ($SD = 4.71$) in choices with a single common attribute, and to 11.24 s ($SD = 4.86$) in choices with two common attributes. Overall, the difference in decision times in the setting without common attributes and the setting with a single common attribute is statistically significant, when assessed using a linear regression with participant-level random effects and set-level fixed effects ($\beta = 3.41$, $z = 4.52$, $p < .001$). The difference in decision times in the setting with a single common attributes and the setting with two common attributes is similarly statistically significant ($\beta = 1.91$, $z = 2.59$, $p < .01$). Figure 3 illustrates these differences. Both these regressions also controlled for the trial number of the problem at hand (*trial number* = 1 for the problem presented first, and *trial number* = 30 for the problem presented last), to make sure that these results were not due to the fact that earlier decisions take longer on average than later decisions.

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These differences can also be examined with a combined regression, whose main independent variable is the total number of common attributes in the choice at hand. As above, this regression would use participant-level random effects and set-level fixed effects. After running this regression we find that the total number of common attributes has a significant positive effect on decision time ($\beta = 2.65$, $z = 6.92$, $p < .001$), indicating that choice sets with multiple common attributes take longer than choice sets with few common attributes. These results do not change if we take a log-transform of the decision time data, or if we exclude decision time outliers.

Discussion

Experiment 5 attempted to test whether decision makers are able to ignore common attributes while deliberating. For this purpose it gave each participant multiple binary forced choices, with each choice varying the number of common versus absent attributes between the two alternatives. If, like absent attributes, common attributes are able to be ignored, then making an absent attribute a common attribute should not affect decision outcomes, such as decision time. On the other hand, if decision makers are more likely to attend to common attributes, then increasing the number of common attributes in a decision should make choices take relatively longer. This study found that the number of common attributes in the decision did have a significant positive effect on decision time, suggesting that common attributes are not ignored during deliberation. This indicates that attribute attention may not be perfectly efficient. It also provides evidence against a number of existing theories of decision making, which predict that attribute attention is a product of the dispersion of the available alternatives on the attributes. According to these theories, decision makers pay as much attention to common attributes as to absent attributes, implying that making absent attributes common should not affect decision outcomes such as decision time.

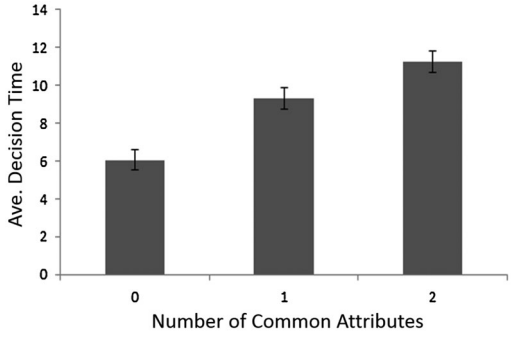

Figure 3. Average (ave.) decision time (in seconds) as a function of the number of common attributes in Experiment 5. Error bars indicate ±1 standard error.

In addition to providing a test of attribute attention, this study also tests whether decision makers' observed attentional strategies can be detrimental to the decision. Both common and absent attributes are non-diagnostic, and thus changing whether an attribute is common or absent should not slow down the decision. By finding that decisions do take longer with more common attributes, Experiment 5 illustrates the pernicious effect of common attributes on important decision outcomes like decision time. Ultimately, the same decision could have been made quicker, if decision makers were able to ignore common attributes in the same way that they ignored absent attributes.

EXPERIMENT 6

The studies thus far have attempted to test for differences in attribute attention across unique, common, and absent attributes. They have involved forced choices, in which common attributes are non-diagnostic, and have found that unique and common attributes are attended to roughly equally, whereas absent attributes are largely ignored.

In Experiment 6 we study both attention in forced choices and attention in free choices, using a design similar to that of Experiments 1–3. In free choices, decision makers have the option to not choose either of the two alternatives, which requires that decision makers compute not only the relative desirability of the choice alternatives, but also the absolute desirability of the alternatives. It may, after all, be better to avoid choosing either of the two alternatives if they are both undesirable. As discussed above, the overall value of a choice alternative is often the sum of the values of all its component attributes—that is, a sum of the values of attributes that are unique to the alternative, as well as attributes that are shared with other alternatives. As a result of this, decision makers need to focus on common attributes in order to make a good decision. Absent attributes are typically irrelevant for evaluating the absolute desirability of an alternative.

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Comparing attention in free choices with attention in forced choices can provide some preliminary insights regarding why decision makers attended to common attributes in our experiments. Free choices are fairly widespread (indeed, most everyday decisions permit the possibility of choice deferral). Both unique and common attributes are diagnostic in these settings, implying that it is often efficient for decision makers to pay attention to common attributes. It may be the case that decision makers fail to modify their attentional strategies appropriately when given forced choices instead of free choices. If this explanation were correct, we would expect the allocation of attention to be similar across both types of choices. Experiment 6 provides a direct test of this prediction.

Method

Participants

One hundred participants (58% male, $M_{age} = 31.11$ years, $SD = 11.35$) recruited from Amazon Mechanical Turk performed the experiment online. All participants were English speakers living in the United States.

Materials and procedure

The choice alternatives and attributes used in this experiment were identical to the alternatives and attributes in Experiment 3, with participants given a choice between two job applicants, each defined on 10 attributes. As in Experiment 3, there were two unique attributes for each applicant, two common attributes, and four absent attributes. Additionally, half the participants were assigned to the forced choice condition and had to choose one of the two applicants. The other half of the participants were assigned to the free choice condition and had the option to choose one of the two applicants, or to not choose either of the two applicants and instead continue the hypothetical job search. Prior to being presented with the choice alternatives, participants in the two conditions were told whether or not they would have the opportunity to defer their decision. As in Experiments 1–3, the presentation of the choice alternatives was followed by a recall task, in which participants had to list as many of the attributes as they could remember. After this task they were taken to the choice screen in which they made a decision between the two applicants (in the forced choice condition) or a decision between the two applicants and the option to choose neither of the applicants (in the free choice condition). Each participant answered only one question.

Results

We begin by examining overall choice and recall patterns across the two conditions. We find that the probability of recalling an attribute in the forced choice condition is 50%, whereas the probability of recalling an attribute in the free choice condition is 51%. This is not a significant difference ($z = 0.56$, $p = .58$), when examined using a mixed-effect logistic regression controlling for attribute-level influences using fixed effects and participant-level influences using random effects. Overall choice is deferred 24% in the free choice condition, implying that decision makers made an active choice 76% of the time in this condition.

Let us now examine the relationship between recall and attribute uniqueness, commonality, and absence in the forced choice condition. We find that the results of this condition are nearly identical to those of Experiment 3, except for the fact that the mild and non-significant difference between the recall probabilities of unique and common attributes is again reversed. Particularly, participants recalled an average of 68% of the unique attributes compared to an average of 72% of the common attributes. Additionally, as in Experiment 3, absent attributes were much less likely to be recalled than common and unique attributes, with participants recalling an average of 16% of the absent attributes. The recall probabilities of the 10 attributes in the forced choice condition, when they are unique, absent, and common, are presented in Table 5.

As in earlier studies, we can use a mixed-effects logistic regression to examine the differences in recall probabilities more rigorously. Using this approach, we find that decision makers are significantly less likely to recall an attribute if it is absent from the choice set than if it is common in the choice set ($\beta = -2.63$, $z = -8.86$, $p < .001$). We do not, however, find that decision makers are significantly more likely to recall an attribute if it is common in the choice set than if it is unique in the choice set ($\beta = 0.34$, $z = 1.09$, $p = .27$). This is also reflected in a higher BIC score for this regression (BIC = 564.71) than for a simpler regression model that ignores the difference between common and unique attributes (BIC = 559.81).

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We obtained a similar set of results in the free choice condition. Particularly, participants recalled an average of 62% of the unique attributes, an average of 74% of the common attributes, and an average of 29% of the absent attributes. Our mixed-effects logistic regression finds that decision makers are significantly less likely to recall an attribute if it is absent from the choice set than if it is unique in the choice set ($\beta = -1.61$, $z = -6.58$, $p < .001$), and additionally significantly more likely to recall an attribute if it is common in the choice set than if it is unique in the choice set ($\beta = 0.69$, $z = 2.36$, $p < .05$). Unlike all the prior studies, this difference between unique and common attributes is reflected in a lower BIC score for this model (BIC = 676.70) than for a simpler regression model that ignores the difference between common and unique attributes (BIC = 677.48), suggesting that common and unique attributes do have divergent effects on recall probabilities. The recall probabilities of the 10 attributes in the free choice condition, when they are unique, absent, and common, are also presented in Table 5.

Thus far, our analysis has examined the two conditions separately and has found some evidence for a higher recall probability of common attributes compared to unique attributes in free choices than in forced choices. We can test this more rigorously by combining the two conditions and applying the above type of mixed-effects logistic regression with an interaction term. A positive significant interaction between the type of attribute (common vs. unique) and the condition (forced vs. free) would indicate that being given free choices instead of forced choices increases the relative attention to common attributes compared to unique attributes. Using this method, we find that there is no significant interaction effect ($\beta = 0.36$, $z = 0.83$, $p = .40$), indicating that relative recall probabilities of common and unique attributes are roughly identical across the two conditions.

Discussion

We find that the patterns in attribute recall probabilities observed earlier in this paper emerge in both forced and free choices in Experiment 6. Particularly, decision makers pay roughly equal attention to common and unique attributes, and moreover pay more attention to these attributes than to absent attributes. These results replicate those of Experiment 3, as the forced choice conditions in Experiment 6 and Experiment 3 are identical. Additionally, these results suggest that decision makers may be using similar attentional strategies in both forced and free choices. Common attributes are diagnostic in free choices, and the fact that decision makers do not appear to significantly change how they allocate their attention across these two settings implies that the attention to common attributes observed in our experiments may be due to an error in selecting the right attentional strategy in forced choice.

GENERAL DISCUSSION

The experiments presented in this paper examine attention to decision attributes in two-alternative forced choice tasks, with binary attributes. Experiments 1–3 and 6 measure attribute attention indirectly by the ability of decision makers to recall the relevant decision attributes after they have been displayed. Experiment 4 measures attribute attention through mouse clicks and viewing times on a Mouselab interface. Experiment 5 measures attribute attention indirectly, using overall decision times. These six experiments find that decision makers are as likely to attend to common attributes as they are to unique attributes. Common attributes are often non-diagnostic; that is, they do not affect the relative desirability of the two alternatives. These experiments also find that attribute attention is selective. Particularly, decision makers are significantly more likely to attend unique or common attributes than absent attributes. Changing the attributes that are associated with the alternatives in the choice set can subsequently alter attribute attention.

These results contradict a number of existing behavioural theories. Some of these theories propose that decision makers completely cancel out common attributes in multi-attribute choice (Houston et al., 1989, 1991). Others propose that decision makers' attention depends on the dispersion of the alternatives on each attribute, with attributes that are present in identical amounts in the two alternatives being given the least amount of attention (Bordalo et al., 2012, 2013; Koszegi & Szeidl, 2013). Yet others suggest that decision makers place less weight on attributes on which alternative differences are very small (Tversky, 1969; also Leland, 1998; Rubinstein, 1988), which can in some settings be seen as a hypothesis regarding attribute attention. The fact that we observe nearly equivalent attention to common and unique attributes in our experiments suggests that these theories provide an incomplete

Table 5. The average recall probabilities of the different attributes when they are unique, common and absent, in the forced and free choice conditions of Experiment 6

	Forced choice			Free choice		
Attribute	Unique	Common	Absent	Unique	Common	Absent
Hard worker	.79	.82	.21	.62	.89	.55
Experience	.42	.71	.39	.67	.70	.32
Recommendations	.73	.60	.08	.65	.56	.33
Intelligent	.73	.85	.06	.90	1.00	.26
Creative	.70	.54	.29	.55	.67	.26
Motivated	.55	1.00	.06	.79	.58	.16
Friendly	.80	.50	.24	.56	.90	.46
Go-getter	.61	.77	.08	.63	.75	.21
Organized	.61	.78	.06	.33	.71	.12
Good education	.88	.67	.14	.48	.64	.22
Average	.68	.72	.16	.62	.74	.29

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account of attribute attention in simple binary-attribute forced choice.

These limitations of existing theories suggest the need to build new models of attribute attention, with increased descriptive power, which are able to explain why decision makers display the types of attentional patterns documented in this paper. Ultimately attribute attention is one of the most important components of the decision process, and it is necessary to rigorously understand the ways in which attribute attention depends on the task at hand, in order to fully characterize preferential decision making.

Cognitive constraints and the structure of the environment

The attentional strategy observed in this paper can be considered to be associative, in that it directs attention towards all attributes that are associated with the alternatives in the choice set and ignores all attributes that are not associated with the alternatives in the choice set (see Bhatia, 2013; Khader, Pachur, & Jost, 2013, for a discussion of this type of strategy). While the associative attentional strategy is not completely efficient when attributes are independent, it may very well be a reasonable way to direct attention given decision makers' cognitive constraints and the structures of the decision environments that they are usually exposed to.

Non-additive utility

Research on multi-attribute preferential choice nearly always considers settings in which decision makers' preferences are additive in attribute values, and this additive structure is generally seen as providing the standard model of multi-attribute choice (see Keeney & Raiffa, 1993). It is this additive structure that makes common attributes unnecessary in two-alternative forced choice, and subsequently justifies the attribute-cancellation assumptions in lay decision rules like Benjamin Franklin's heuristic and in related behavioural theories such as those discussed above (e.g., Bordalo et al., 2012, 2013; Houston et al., 1989, 1991; Koszegi & Szeidl, 2013). Indeed even theories that do not explicitly ignore common attributes still rely on the assumption of additivity. Thus prominent accounts of multi-attribute choice, such as those involving lexicographic decision making (Fishburn, 1974; Gigerenzer, Hoffrage, & Kleinbölting, 1991; Tversky, 1969), the equal weighting of attributes (Dawes, 1979), the tallying of attributes (Alba & Marmorstein, 1987; Russo & Dosher, 1983), weighted additive rules (Keeney & Raiffa, 1993), the sequential sampling of attributes (Bhatia, 2013; Roe et al., 2001; Usher & McClelland, 2004), and neural network-based recurrent activation (Glöckner & Betsch, 2008; Holyoak & Simon, 1999), all assume that the desirability of an alternative is a simple weighted sum of its component attributes.

However, there are settings in which the alternatives offered to participants have non-additive components. This is the case with certain economic bundles, which contain complementary goods such as printers and print cartridges. Here the presence of a print cartridge in a bundle with a printer adds non-linearly to the desirability of that bundle, regardless of whether that print cartridge is common across the bundles in the choice set. Although choices between these types of economic bundles are typically not considered within multi-attribute choice research, they are nonetheless present in many day-

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to-day decision-making environments. It is necessary to attend to common goods in choices between these types of economic bundles, in order to select the bundle with the highest overall desirability. Due to the task-switching costs (Monsell, 2003), it is likely that decision makers could be using the same attentional strategy, the associative attentional strategy, in choices between bundles with non-additive goods, in which attention to common goods is efficient, as they do in choices between alternatives with additive attributes, in which attention to common attributes is inefficient.

Note that it is also possible that participants' evaluations of the stimuli in our experiments are non-additive. For example, it may be the case that the desirability of an applicant who is both motivated and intelligent is more than the sum of the desirabilities of applicants who are only motivated and applicants who are only intelligent. This could be one reason why participants attend to common attributes. However, such an explanation would also predict that participants would attend to absent attributes (as both common and absent attributes are diagnostic when utility is non-additive). The fact that we are seeing absent attributes being ignored implies that this explanation cannot account for all of our results.

Absolute desirability

Preferential choice tasks do not always involve considerations of relative option desirability, as with forced binary choice. Decision makers also sometimes need to evaluate the absolute desirability of the available alternatives. This is the case with free choices in which decision makers can obtain as many of the available alternatives as they would like, as discussed in Experiment 6. It is also the case in contingent valuation tasks, such as those eliciting buying and selling prices or likability ratings. It is in these settings that the associative attentional strategy, which directs attention towards an attribute if and only if it is present in the alternatives, is efficient. More formally, as the absolute desirability of an alternative $\boldsymbol{x}$ is written as $U(x) = \sum_{i \in A_x} V_i$, decision makers need to consider all the attributes in $A_x = \{i \mid x_i = 1\}$, in order to determine $U(\boldsymbol{x})$. Again, given that task switching is effortful (Monsell, 2003), it is probably difficult for decision makers to change attentional strategies between tasks involving evaluations of both absolute and relative desirability (such as free choice tasks) and tasks involving evaluations of only relative desirability (such as forced choice tasks). If the associative attentional strategy is not too detrimental in forced choices, it may be the case that decision makers use this strategy consistently in all value-based decisions.

The results of Experiment 6 provide evidence to support this claim. Experiment 6 finds that decision makers display similar patterns of attention allocation in free and forced choices. More specifically, common attributes are attended to almost as frequently in forced choices, in which these attributes are non-diagnostic, as they are in free choices, in which they are diagnostic. Additionally, absent attributes are ignored in both types of choices. Given these similarities, it is possible that decision makers are using a single attentional strategy, the associative attentional strategy, in both settings. However, these similarities could also be due to similarities in presentation format and other aspects of the experimental design that these conditions have in common.

Real-world environments

There is another reason why decision makers use the observed associative attentional strategy. It may, in fact, be an efficient way of allocating attention in environments that decision makers are exposed to in the real world, as it could be that there are relatively few common attributes in these environments. The intuition for this claim for this adaptive rationality claim (e.g., Gigerenzer & Goldstein, 1996; Payne, Bettman, & Johnson, 1993; see also Anderson, 1990; Oaksford & Chater, 2007) is as follows: The universe of choice alternatives that could be available in any choice task is large and diverse. Subsequently the set of attributes on which these alternatives are defined is also very large. This implies that any two available alternatives, $\boldsymbol{x}$ and $\boldsymbol{y}$, are most likely associated with only a small subset of all possible attributes; that is, $\boldsymbol{x}$ and $\boldsymbol{y}$ are sparse vectors. If the distribution of attributes in these alternatives is independent, then due to their sparseness, these alternatives are unlikely to overlap on any of their attributes. In other words the available choice alternatives for large attribute spaces most probably do not have common attributes. In these settings, the tendency of the associative attentional strategy to direct attention to common attributes is not detrimental, and associative attention is largely efficient.

Consider, for example, picking any two items at random in a grocery store. These stores carry a large range of diverse items, and it is relatively unlikely that two randomly chosen items would have many overlapping attributes. The probability and extent of

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overlap would reduce further as the store gets larger and larger. The same holds for other types of decisions—for example, whether to spend a bonus salary on a new television or on a vacation.

More formally, let us consider a setting in which there are n possible attributes in the attribute space, and choice alternatives $\boldsymbol{x}$ and $\boldsymbol{y}$ are associated with an average of m_x and m_y of these n attributes. We assume that the probability of an alternative being associated with a given attribute is described by a Bernoulli distribution with the probability of success equal to m_x/n for $\boldsymbol{x}$ and m_y/n for $\boldsymbol{y}$. Both attributes and alternatives are assumed to be independent so that the association of one alternative with an attribute does not affect that alternative's association with other attributes, or the association of the other alternative with any of the attributes. Additionally, for simplicity, the association probability of an alternative with an attribute is assumed to be identical for all attributes.

With these assumptions we can write the probability of both the alternatives having a given attribute—that is, the probability that the given attribute is common, as $(m_x \cdot m_y)/n^2$. Correspondingly the probability of this attribute being either absent or unique is $1-(m_x \cdot m_y)/n^2$. From this, we can write the probability of all attributes being absent or unique, and none of the attribute being common, as $[1-(m_x \cdot m_y)/n^2]^n$. This is the probability that a given pair of alternatives do not overlap on any attribute at all. We can show that $[1-(m_x \cdot m_y)/n^2]^n$ is increasing in n, with $[1-(m_x \cdot m_y)/n^2]^n$ approaching 1 as n approaches infinity.[1] Thus, as the number of possible attributes, n, gets larger, the probability that there are no common attributes also gets larger, and for large enough n, it is very likely that there are no common attributes to attend to. This implies that in everyday decision environments, which consist of large attribute spaces, associative attribute attention is almost always efficient.

Of course, there is one important limitation of the above argument: The distribution of attributes across alternatives is not necessarily independent. Sometimes, decision makers have to make choices between two similar choice options. This means that it is not always the case that the probability of there being a common attribute falls to zero in large attribute spaces. Despite this limitation, the above analysis is useful: It provides a formal study of one possible environmental structure and its interaction with a particular decision strategy, and establishes that there are indeed environments where the strategies observed in this paper are beneficial for decision making. Future work should attempt to more rigorously characterize the interplay between environmental structure and the observed attentional strategies, in order to better understand why these strategies are used by decision makers.

Attentional biases

The findings documented in this paper can be seen as illustrating a type of attention bias in preferential choice. These types of biases are well known and are often able to account for deviations from traditional economic rationality. For example, Birnbaum and colleagues (Birnbaum, 2008; Birnbaum & Chavez, 1997) have argued that attention is disproportionately directed towards low gamble outcomes, providing one explanation for violations of expected utility theory, and Bhatia (2014) has shown how these violations can be attributed to randomness in attention allocation. Similarity, Yechiam and Hochman (2013a, 2013b) have shown that disproportional attention towards losses relative to gains provides a powerful psychological explanation for loss aversion. Relatedly, Weber et al. (2007) have noted that decision makers are more likely to focus on immediate outcomes in reward sequences, predicting immediacy biases and other violations of exponential discounting.

Attention has also been used to explain the dependence of choice on the way that preferences are elicited—that is, the response modes in the decision task. Tversky et al.'s classic account of preference reversals in risky choice, for example, assumes that decision makers pay more attention to monetary payoffs in matching tasks than in choice (Tversky, Sattath, & Slovic, 1988). Multi-attribute choice reversals across logically identical task frames have been explained in a similar manner, with acceptance frames guiding attention towards positive attributes and rejection frames guiding attention towards negative attributes (Shafir, 1993).

Similar work has used attention to study the effect of focal alternatives on final choices. For example Houston et al. (1989, 1991) have used Tversky's feature-based attention model of similarity to

[1]The increasingness of $[1-(m_x \cdot m_y)/n^2]^n$ can easily be established by taking the first derivative (with positive n). The limit can be obtained by examining the limit of $\ln\{[1-(m_x \cdot m_y)/n^2]^n\}$ and applying L'Hôpital's Rule.

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account for reversals in choice as the focus of comparison in the choice task is varied. This model can also account for order effects in preferential choice. More recently, the effect of numerical anchors has been explained using attentional biases that favour the anchored response (Chapman & Johnson, 1994; Strack & Mussweiler, 1997). A similar explanation has been used to predict the effects of endowments and other reference points on final choices. According to this account, decision makers are more likely to attend to the attributes of reference points, making them seem more attractive than their competitors (Carmon & Ariely, 2000; Johnson et al., 2007).

It may be the case that existing theories of attentional bias may be able to characterize the types of attentional strategies observed in this paper. Perhaps the theory most relevant to the results of this paper is Bhatia's (2013) associative accumulation model, which attempts to use attribute attention to explain the effects of irrelevant decoy alternatives and salient alternatives such as reference points on choice. This model states that decision makers attend to attributes in proportion to the association of these attributes with available alternatives. Subsequently altering the set of alternatives in a choice task in a logically irrelevant manner (such as by adding dominated decoys) leads to seemingly irrational reversals in choice.

There are, however, some differences between the associative attentional strategies described in Bhatia's (2013) account and the attentional strategy observed in the participants in our experiments. Most notably, Bhatia's (2013) model assumes that the attention towards an attribute has an increasing relationship with the associations of the attribute with the alternatives in the choice set. Thus while decision makers are predicted to ignore absent attributes, they are also predicted to pay more attention to common attributes than to unique attributes. We did not observe this in our experiments. In all of our tasks, we found that decision makers paid the same amount of attention to common attributes as they did to unique attributes.

The difference between our experimental results and Bhatia's (2013) predictions could be due to the nature of the tasks considered in this paper. In order to characterize efficient attention, we examined only two-alternative choices with binary attributes. Bhatia's analysis however pertains to three-alternative choice with continuous attributes. Future work should examine attribute attention in larger choice sets with continuous attributes, so as to build more general theories of attribute attention in preferential choice.

Additional avenues for future work

The discussion in this section has outlined the necessity of developing and testing theories of attribute attention that are able to account for the effects observed in this paper. There are also, however, many ways in which the experimental techniques in this paper can be improved upon, to further validate the observed attentional patterns and to better understand their underlying properties. First, it is necessary to examine additional measures of attention. Those used in this paper—namely recall, mouse tracking, and decision time—are indirect and imperfect proxies of what the decision maker is actually thinking about. For example, while recall probability is positively associated with the depth and extent of cognitive processing, it is also influenced by various attribute-level factors, such as the frequency with which the attribute occurs in the natural environment (though the fixed-effects terms in the logistic regressions performed in this paper do help control for these attribute-level biases). Additionally, in Experiments 1–3 in this paper, decision makers would need to look at the various attributes to see whether they were unique, common, or absent in the alternatives. Merely looking at the attributes could influence recall and subsequently add noise to our recall measure. Likewise, although our mouse clicking and viewing time information in Experiment 4 bypasses many of these problems, it does not, by itself, provide a noiseless account of what the decision maker is thinking about, or even looking: Decision makers often attend to objects other than those that are on the screens in front of them. Lastly, although the overall decision time measure in Experiment 5 does allow us to determine when decision makers are processing additional information in the choice problem, it does not tell us exactly what this information is. We are only able to state that decision makers are attending more to some things in one condition than in another, but not conclusively state that it is the attributes themselves that are getting the increased attention.

There are two ways in which these limitations can be addressed. The first involves better behavioural measures of attention, such as eye tracking (see e.g., Noguchi & Stewart, 2014). Unlike the mouse-tracking tools used in this paper, eye tracking and related

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measures would be able to directly assess what decision makers are looking at. The second involves neural measures of attention and cognitive processing, such as blood-oxygen-level-dependent (BOLD) activation (see Lim, O'Doherty, & Rangel, 2013). Unlike eye tracking, which is only able to capture visual attention, these measures would also be able to determine what decision makers are thinking about. Future work should attempt to examine the phenomena studied in this paper using these two alternative approaches.

Another limitation of the studies in this paper is their one-shot nature. Experiments 1–4 and 6 all involve only one decision problem. Although this is necessary for measures such as recall (in which is it important for participants not to know about the recall test that follows stimuli presentation), it limits the insights of this paper to novel decision settings in which decision makers do not have much experience with the choice problem at hand. These settings are vulnerable to increased error, as well as the effects of curiosity, which could be driving attention towards the common attributes. Future work should thus attempt to replicate the experiments in this paper in repeated-choice settings with feedback. It is possible that after obtaining enough experience with a particular choice problem, decision makers may be able to learn to ignore non-diagnostic common attributes.

A repeated-choice study with feedback is also valuable as it would allow for the experimenter to control the reward structure in the task. This is necessary to ensure additive utility, which is the only setting in which common attributes are non-diagnostic. Currently we cannot rigorously claim that decision makers are aggregating attribute values independently, and subsequently we cannot claim that the observed attentional strategies are inefficient. With a repeated-choice study we could test these claims and subsequently enhance the theoretical implications of our results.

The studies could also be improved by controlling for the manner in which the associations of the attributes with the alternatives are conveyed to participants. Currently the presence of an attribute in an alternative is indicated on an attribute-by-alternative matrix with signs like "X". This is the standard way of presenting this information in multi-attribute and multi-cue decision-making research. It is also closely related to the way in which the presence or absence of features in objects is conveyed in the real world. However, it is possible that this type of stimuli presentation, rather than some innate behavioural tendency, is the reason why decision makers attend to present attributes and ignore absent attributes. To control for this, it would be necessary to counterbalance the use of signs like "X" so that in some conditions they indicate attribute presence but in other conditions they indicate attribute absence, or else use neutral signs (involving other symbols or different colours) for presence and absence. If the observed attribute attention biases continue to emerge in these types of designs then these biases could be seen as being a much more integral and prevalent feature of multi-attribute decision making.

A final limitation of the experiments in this paper involves the fact that the attentional biases that they study do not influence decision makers' choices. This is due to the fact that these biases pertain to decision makers' attention towards irrelevant information—information that should not, in theory, alter the way in which the decision makers evaluate the options. It may, however, be the case that there are some settings in which this type of biased attention can influence the actual decision outcome. For example, some researchers have found that drawing attention towards missing options or missing information can affect choice probabilities (Huber & McCann, 1982; Schulte-Mecklenbeck & Kühberger, 2014). Future work should examine whether it is possible for the attentional strategies documented in this paper to influence decision outcomes in a similar manner.

CONCLUSION

This paper provides an empirical examination of attribute attention. Across six experiments we find that decision makers focus attention on attributes that are unique to each of the alternatives as well as attributes that are common to the two alternatives—that is, attributes that are associated with one or both of the alternatives. Attributes that are not associated with either of the two alternatives are ignored. Although this strategy does direct attention selectively, it is not always efficient. Common attributes are often non-diagnostic for determining which of the available alternatives is most desirable. Our results contradict some existing accounts of attribute attention in preferential choice, while also presenting novel insights about how more powerful descriptive and explanatory theories of attribute attention may be constructed.

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