Short Communication

Attribute preference and selection in multi-attribute decision making: Implications for unconscious and conscious thought

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ABSTRACT

Unconscious thought theory (UTT) states that all information is taken into account and the attributes are weighted optimally resulting in better decisions in complex decision problems during unconscious thought. Very few studies have investigated the actual amount of information processed in the unconscious thought condition. We hypothesized that only a small subset of information might be considered during unconscious thought (like conscious thought). To test this possibility and to explore the way attribute information is selected and combined, we performed computer simulations on the datasets used by previous researchers. The simulations showed that considering a small subset (3–4) of attributes, yields results comparable to previous studies. There is no need to posit infinite capacity in the unconscious thought condition. The results also suggest that weight information is used for attribute selection that could potentially explain the difficulties in replicating the deliberation-without-attention effect.

1. Introduction

Traditionally the benefits of conscious deliberation in making a complex decision have been emphasized over quick unconscious decision making. However, recent studies based on unconscious thought theory (UTT) have suggested that decision makers should leave complex decisions to the unconscious for making better decisions (Dijksterhuis, 2004; Dijksterhuis, Bos, Nordgren, & van Baaren, 2006; Dijksterhuis, Bos, van der Leij, & van Baaren, 2009; Dijksterhuis & Nordgren, 2006). The UTT (Dijksterhuis & Nordgren, 2006) defines unconscious thought as object-relevant or task-relevant cognitive or affective thought processes that occur while attention is directed elsewhere. Dijksterhuis et al. (2006) presented information about four objects described by four (simple decision problem) or 12 attributes (complex decision problem) and asked participants to make the ‘best’ choice followed by either a period of conscious deliberation or a period of unconscious thought. More participants made the best decision in the unconscious thought condition with complex problems (deliberation-without-attention effect). The UTT argues that is due to the optimal weighting of attributes during high capacity unconscious thought, where all the attributes are considered for making a decision in contrast to the limited capacity conscious thought that focuses only on a subset of available information (Dijksterhuis & van Olden, 2006).

The hypothesis that unconscious thought does indeed consider almost all of the information, has not been directly tested till date and has been inferred solely based on better performance in the unconscious thought conditions. Alternatively, it could indeed be possible that unconscious thought (also) focuses on a subset of available information (attributes) while deciding on a complex decision problem. A related suggestion has been made in the attention literature by Myczek and Simons (2008) who suggested that people might employ sub-sampling to judge statistical properties of objects in a display.
Through simulations, Myczek and Simons (2008) argued that the existing evidence for mean judgments (Chong & Treisman, 2005) could be explained by focused attention strategies in which people focus on a small subset of the objects to estimate the mean size. Using this as an analogy, one could argue that sub-sampling could occur in the unconscious thought condition as well.

In a similar vein, Rey, Golstein, and Perruchet (2009) has argued that only a small number of attributes might be considered in unconscious thought. They have argued that the amount of time available for deliberation is critical and might affect the number of attributes used in making a decision. Lower deliberation and attentional allocation (low or high) may determine the attribute selection processes leading to fewer attributes being considered in the unconscious thought condition compared to the conscious thought condition.

In addition to the number of attributes, it is also not clear how information about attributes is combined in arriving at a decision unconsciously. One possible strategy is the weighted additive decision strategy (WADD) in which every attribute is attached a weight (level of importance) and then the weights of the attributes for each choice option is summed up (Newell, Wong, Cheung, & Rakow, 2008). The option that has the largest weight is chosen as the ‘best’. Dijksterhuis and Nordgren (2006) have suggested that WADD is too complex to be performed during unconscious thought and actually used TALLY (best choice is the one with the highest number of positives) to find the best alternative (Dijksterhuis et al., 2006). It should also be noted that efforts to replicate the deliberation-without-attention-effect have failed to find an advantage for unconscious decision making (Acker, 2008; Calvillo & Penaloza, 2009; Newell et al., 2008; Thorsteinson & Withrow, 2009).

In the context of the discrepancies in the empirical findings on unconscious decision making and to determine the decision strategies used in unconscious thought, we decided to perform computer simulations to evaluate the possibility of sub-sampling of attributes in making a complex decision. We propose that the results from the empirical studies on unconscious decision making (Acker, 2008; Dijksterhuis et al., 2006; Newell et al., 2008) does not necessitate that almost all attributes be considered for arriving at the correct choice (which also is a prime assumption in UTT). We hypothesized that considering a subset of attributes might suffice for arriving at the best choice most (around 70–80%) of the time and we wanted to know how much information (number of attributes) is needed for such a performance. This is similar to the suggestions made by Rey et al. (2009) and the simulations would also provide information about the selection of attributes, the number of attributes used to make decisions and the way information about attributes are combined.

To test this hypothesis, we performed computer simulations on the datasets used previously in Experiment 1 of Dijksterhuis et al. (2006), Experiments 1 and 3 of Newell et al. (2008) and Rey et al. (2009). If the simulations produce comparable results to those studies with the selection of a subset of attributes, then it is possible for people to arrive at an optimal decision without considering all of the attributes in a multi-attribute decision problem following unconscious thought. If consideration of all attributes were needed to make an optimal decision, then the simulations would produce results comparable to empirical results only with the selection of almost all of the attributes. The simulations were also expected to shed more light on the decision strategies used in unconscious thought (Dijksterhuis & Nordgren, 2006).

2. Method

The simulations were performed using R (R Development Core Team, 2008). The data sets (see Appendix A for information) are structured in the following manner: “Name of Attribute”, weight, Attribute-value for A, Attribute-value for B, Attribute-value for C, Attribute-value for D, where A–D are the choice options.

The weights of the attributes were obtained separately from a different pool of participants. Given that the attributes are weighted, the weights could guide the initial choice of which attributes are to be considered (probability-based sampling) and at the stage in which the attribute information is combined to make a decision (WADD). In probability-based sampling, we calculated the probability of an attribute being chosen based on the weights (see Tables 1 and 2). Probability of the attributes was computed by using a simple transformation \(\frac{1}{(20 - \text{weight})}\) and then normalized to range from 0 to 1 (\(\text{Highest value of scale} = 20\) in dataset1 and 10 in Dataset 2). We computed the frequency of choice (percentage of trials in which a particular alternative is chosen) in the simulations.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Weight</th>
<th>(N_W = \frac{1}{(20-\text{weight})})</th>
<th>(\text{Prob} = \frac{N_W}{\text{sum}(N_W)})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gas mileage</td>
<td>18.3</td>
<td>0.58824</td>
<td>.274</td>
</tr>
<tr>
<td>Handling</td>
<td>16.5</td>
<td>0.28571</td>
<td>.133</td>
</tr>
<tr>
<td>Environment friendly</td>
<td>15.6</td>
<td>0.22727</td>
<td>.106</td>
</tr>
<tr>
<td>Sound system</td>
<td>14.6</td>
<td>0.18159</td>
<td>.086</td>
</tr>
<tr>
<td>Service</td>
<td>14.3</td>
<td>0.17544</td>
<td>.082</td>
</tr>
<tr>
<td>Ease of shifting gears</td>
<td>12.9</td>
<td>0.14085</td>
<td>.066</td>
</tr>
<tr>
<td>Trunk space</td>
<td>12.3</td>
<td>0.12987</td>
<td>.060</td>
</tr>
<tr>
<td>Legroom</td>
<td>11.8</td>
<td>0.12195</td>
<td>.057</td>
</tr>
<tr>
<td>New</td>
<td>10.2</td>
<td>0.10204</td>
<td>.047</td>
</tr>
<tr>
<td>Available in different colors</td>
<td>6.1</td>
<td>0.07194</td>
<td>.033</td>
</tr>
<tr>
<td>Has sunroof</td>
<td>5.9</td>
<td>0.07092</td>
<td>.033</td>
</tr>
<tr>
<td>Has cupholders</td>
<td>1.6</td>
<td>0.05435</td>
<td>.025</td>
</tr>
</tbody>
</table>

\(\sum \text{Prob} = 1.0\)
In probability-based sampling, weights were used to choose the attributes (after the transformation and normalization) and in random sampling, weights were not used in the sampling process. The rationale for using probability-based sampling is to closely simulate variability in selecting the attributes to be considered in the decision process because of individual differences and bounded rationality. Empirical research has shown that people are not strictly rational (Newell, 2005) and hence one may not always choose the attributes strictly according to its (mean) weight. This idea is captured when attributes are sampled based on a probability that is derived from the mean weight of the attribute. This means a higher weighted attribute has more chances of getting picked than a lower rated attribute but the higher weighted attribute does not get picked always before a lower rated one.

The programs chose \( n \) (1 to maximum) attributes sequentially using two methods: probability-based sampling and random sampling. We used both TALLY (where weights were not considered) and WADD (where weights were considered) with the attributes chosen using probability-based sampling as well as random sampling resulting in four different simulations: (a) probability-based sampling followed by WADD, (b) probability-based sampling followed by TALLY, (c) random sampling followed by WADD, and (d) random sampling followed by TALLY.

When certain subsets of attributes were considered, ties occurred between the choice options and in such scenarios; the corresponding simulated trial was rejected. For each \( n \) (number of attributes ranging from 1 to maximum), 1500 trials were simulated and we computed the percentage of times a specific choice was made across the trials as a function of the number of attributes.

### 2.1. Simulation 1

The first simulation was performed on the dataset used by Dijksterhuis et al. (2006), Newell et al. (2008) and Rey et al. (2009). The dataset (see Appendix A, Dataset 1) comprised of four hypothetical Japanese cars: Hatsdun, Kaiwa, Dasuka and Nabusi with each defined by twelve attributes (like ‘Has cupholders’). Weights of the attributes were not considered in Dijksterhuis et al. (2006) and Newell et al. (2008) (TALLY was used to predict the best car) but Rey et al. (2009) obtained the weights for the attributes that has been used in the current simulations. The attribute value for a given car is 1 (attribute is present) and –1 (attribute is absent). For example, [“New”, 10.2, 1, –1, 1, –1] means that “New” is an attribute with a weight of 10.2 (on a scale of 20) and Hatsdun is new, Kaiwa is not new, Dasuka is new and Nabusi is not new. The program choose \( n \) (=1–12) attributes and the percentage of times each choice was made for different number of attributes was calculated. The probabilities of the attributes (dataset 1) that were used in the simulations (for probability-based sampling) is shown in Table 1.

### 2.2. Simulation 2

The second simulation was performed on the dataset used by Newell et al. (2008) that comprised of four apartments to be rented by students of New South Wales, Australia (see Dataset 2 in Appendix A for attribute information). The apartments A–D were defined by 10 attributes (like ‘Crime rate of area’). For example, [“Security of building”, 8.95, –1, 1, –1, 1] means ‘Security of building’ is an attribute with a weight of 8.95 (on a scale of 10) and Apartment A is not secure, Apartment B is secure, Apartment C is not secure and Apartment D is secure. The percentage of times each choice is made for \( n \) (1–10) attributes was calculated. Table 2 lists the associated probabilities of the attributes used in the second simulation.

### 3. Results

#### 3.1. Simulation 1

The correct choice predicted by both TALLY (with nine positive attributes) and WADD (with 116.4 as the aggregate weight) is Hatsdun. When all the 12 attributes for the four cars were presented in the unconscious thought condition, the

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Weight</th>
<th>( N_W = 1/(10\text{-weight}) )</th>
<th>( \text{Prob} = N_W/\text{Sum}(N_W) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Security of building</td>
<td>8.95</td>
<td>0.9524</td>
<td>.2295</td>
</tr>
<tr>
<td>Rent</td>
<td>8.60</td>
<td>0.7143</td>
<td>.1722</td>
</tr>
<tr>
<td>Crime rate of area</td>
<td>8.36</td>
<td>0.6098</td>
<td>.1470</td>
</tr>
<tr>
<td>Flatmate is friend</td>
<td>7.91</td>
<td>0.4785</td>
<td>.1153</td>
</tr>
<tr>
<td>Size of apartment</td>
<td>7.56</td>
<td>0.4098</td>
<td>.0988</td>
</tr>
<tr>
<td>Kindness of neighbors</td>
<td>5.41</td>
<td>0.2179</td>
<td>.0525</td>
</tr>
<tr>
<td>View</td>
<td>5.18</td>
<td>0.2075</td>
<td>.0500</td>
</tr>
<tr>
<td>Built-in wardrobe</td>
<td>4.70</td>
<td>0.1887</td>
<td>.0455</td>
</tr>
<tr>
<td>Direction</td>
<td>4.61</td>
<td>0.1855</td>
<td>.0447</td>
</tr>
<tr>
<td>Leisure facilities</td>
<td>4.59</td>
<td>0.1848</td>
<td>.0445</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( \Sigma \text{Prob} = 1.0 )</td>
<td></td>
</tr>
</tbody>
</table>
correct choice (Hatsdun) was made 58% of the time in the Dijksterhuis et al. (2006) study, 43% of the time in Newell et al. (2008) study and 63% in Rey et al. (2009).

The simulation results show that with just two attributes, Hatsdun gets selected 49% of the time and with three attributes 57% of the time (Fig. 1d) when random sampling is performed followed by TALLY (Fig. 1d). In probability-based sampling followed by both WADD and TALLY, the correct choice (Hatsdun) gets chosen around 60% of the time with just three or four attributes (Fig. 1a and b). The comparison of results from probability-based sampling and WADD with the previous empirical studies is shown in Table 3 (also see Fig. 1).

3.2. Simulation 2

With the second data set (see Dataset 2 in Appendix A), the correct choice predicted by WADD is Apartment B and correct choice predicted by TALLY is Apartment A (considering all the attributes). When all the 10 attributes for the four apartments were presented in unconscious thought condition in the Newell et al. (2008) study, Apartment B was chosen around 65% of the time and Apartment A was chosen around 17% of the time indicating that WADD is the more probable decision strategy compared to TALLY that people used to make a choice.

With probability-based sampling followed by WADD, the simulation results show that with just three attributes, the results closely match with the results from the Newell et al. (2008) study following unconscious thought (see Table 4 and Fig. 2a).

Interestingly, in probability-based sampling followed by TALLY, a close fit to the data reported by Newell et al. (2008) was also found with around three attributes (see Fig. 2b). It is to be noted that Apartment A is the correct choice according to TALLY only when all the attributes and in the simulations Apartment A is selected more often compared to Apartment B only when almost all (9 out of 10) attributes are considered. Random sampling followed by either WADD or TALLY does not match the results from Newell et al. (2008) and hence we do not consider them any further in our discussion.

Fig. 1. Simulations with Dataset 1. The percentage of times each car is chosen is plotted as function of n (1–12) attributes for (a) probability-based sampling of attributes followed by WADD, (b) probability-based sampling of attributes followed by TALLY, (c) random sampling of attributes followed by WADD, and (d) random sampling of attributes followed by TALLY.

Table 3

<table>
<thead>
<tr>
<th></th>
<th>Experiment 1, Dijksterhuis et al. (2006)</th>
<th>Experiment 3, Newell et al. (2008)</th>
<th>Rey et al. (2009)</th>
<th>Simulation results (three attributes)</th>
<th>Simulation results (four attributes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HATSDUN</td>
<td>58</td>
<td>43</td>
<td>63</td>
<td>56.72</td>
<td>63</td>
</tr>
<tr>
<td>KAIWA</td>
<td>Not specified</td>
<td>27</td>
<td>23</td>
<td>23.43</td>
<td>29.65</td>
</tr>
<tr>
<td>DASUKA</td>
<td>Not specified</td>
<td>27</td>
<td>3</td>
<td>10.39</td>
<td>7.27</td>
</tr>
<tr>
<td>NABUSI</td>
<td>25</td>
<td>3</td>
<td>10</td>
<td>0.24</td>
<td>0.07</td>
</tr>
</tbody>
</table>
4. Discussion

The results of our simulations support our hypothesis that sub-sampling can lead to correct choices and there is no need to posit an infinite capacity for unconscious thought (Dijksterhuis & Nordgren, 2006). This can be seen with the match between simulation results and results from empirical studies (Dijksterhuis et al., 2006; Newell et al., 2008; Rey et al., 2009). The studies on unconscious vs. conscious thought have not estimated directly the number of attributes actually used in making a choice (Acker, 2008; Dijksterhuis et al., 2006; Lassiter, Lindberg, Gonzalez-Vallejo, Bellazza, & Phillips, 2009; Newell et al., 2008; Thorsteinson & Withrow, 2009). The simulation results show that it is less likely that all or most attributes are considered during unconscious thought since with all or most attributes the correct choice gets picked all or most of the time. The actual behavioral performance ranges only between 50% and 70% in most of the studies and around three or four attributes are enough to produce comparable performance. We do not argue that capacity limitations are always present for unconscious processing, in general. However, it appears that when a complex decision making problem is presented and participants are not allowed to consciously deliberate, they may still focus on a small set of attributes to make a choice.

Although from simulation 1 it is not possible to estimate when the weights are used (in the sampling process or in the evaluation process, where WADD is performed), the results of simulation 2 (Fig. 2) indicate probability-based sampling (where weights of the attributes drive the initial choice of attributes) produces results closer to those from human participants (reported by Newell et al., 2008) compared to random sampling. Thus, the weights of the attributes appear to guide the initial choice or selection of attributes.

The simulations also tried to explore the strategies used to combine information from different attributes. Dijksterhuis and Nordgren (2006) had argued against the strict use of WADD in unconscious thought because of the computational

<table>
<thead>
<tr>
<th>Experiment 1, Newell et al. (2008)</th>
<th>Experiment 2, Newell et al. (2008)</th>
<th>Simulation results (3 attributes)</th>
<th>Simulation results (4 attributes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apt. A 17.4</td>
<td>4.3</td>
<td>7.44</td>
<td>10.97</td>
</tr>
<tr>
<td>Apt. B 69.6</td>
<td>65.2</td>
<td>61.79</td>
<td>62.1</td>
</tr>
<tr>
<td>Apt. C 4.3</td>
<td>4.3</td>
<td>3.01</td>
<td>5.21</td>
</tr>
<tr>
<td>Apt. D 13.0</td>
<td>26.1</td>
<td>27.74</td>
<td>21.71</td>
</tr>
</tbody>
</table>

Table 4: Comparison of behavioral results with data set 2 and simulation results from the probability-based sampling followed by WADD condition with three and four attributes. Simulation results indicate the percentage of times each option is chosen.

Fig. 2. Simulations with Dataset 2. The percentage of times each apartment is chosen is plotted as function of \( n \) (1–10) attributes for (a) probability-based sampling of attributes followed by WADD, (b) probability-based sampling of attributes followed by TALLY, (c) random sampling of attributes followed by WADD, and (d) random sampling of attributes followed by TALLY.

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The simulations also tried to explore the strategies used to combine information from different attributes. Dijksterhuis and Nordgren (2006) had argued against the strict use of WADD in unconscious thought because of the computational
complexity of WADD even though the results of unconscious thought processes match well with what WADD would predict. This argument was based on the assumption that information from all attributes was combined in unconscious thought. Our simulation results with sub-sampling make WADD a definite possibility. While WADD might be complex to perform with all the attributes, it can still be computed easily with a small subset of attributes even under the deliberation-without-attention condition.

If a subset of attributes are used, then although one decision strategy predicts a correct choice (as WADD predicts Apartment B in the Newell et al., 2008 study) it could be possible that some other strategy like TALLY is used because both strategies could give the same pattern of results. This can be observed from both simulation 1 (Fig. 1a and b) and simulation 2 (Fig. 2a and b), where both WADD and TALLY followed by probability-based sampling gives almost the same results for 3–4 attributes. Thus, even though people make the choice predicted by WADD in the Newell et al. (2008) study (note that whether people used WADD or TALLY cannot be estimated in Dataset 1 because both strategies predict the same choice: Hatsdun), that might not necessarily mean that people did indeed use WADD (assuming probability-based sub-sampling). It is also possible that other simpler adaptive strategies could be used to make choices with a small set of attributes (Newell, 2005; Rey et al., 2009).

Moreover, if unconscious thought (without deliberate attention) does indeed focus on a subset of attributes (like conscious thought with attention), then this potentially can explain the failures to replicate the advantages of unconscious thought over conscious thought (Acker, 2008; Newell et al., 2008; Thorsteinson & Withrow, 2009). The subset of attributes that drives a decision process might differ for different datasets. The number of attributes selected will depend on the weights of individual attributes (based on the experience of the individual). Pre-existing biases and heuristics will have a larger role to play given that a smaller number of attributes are selected. Using a small sample of relevant (or important) cues/attributes to arrive at a ‘moderately good’ judgment is consistent with the satisficing heuristic (Simon, 1990). Heuristics is commonly portrayed as an alternative to complex algorithms like the WADD. Our idea of sub-sampling of information followed by the use of algorithms like WADD/TALLY lies midway between simple heuristics like Take the Best (Gigerenzer, Todd, & the ABC Research Group, 1999) and complex algorithms which assume that decision makers considers all the information. The results suggest decision makers opt for strategies that reduce processing (Shah & Oppenheimer, 2008) due to cognitive constraints and limited attentional resources. These to some extent may explain differences obtained with different studies studying multi-attribute decision making with unconscious thought.

Rey et al. (2009) describe two opposing views (and predictions made): the powerful unconscious view and the conscious thought view. According to the powerful unconscious view, only a small number of attributes are considered in the ‘conscious thought condition’ and many/all attributes are considered in the ‘unconscious thought condition’ (Dijksterhuis & Nordgren, 2006). In contrast, the conscious attention view assumes that only a few attributes are considered in the ‘unconscious thought condition’ (where the amount of time allocated to processing is less) and many/all attributes are considered in the ‘conscious thought condition’ (where processing time is more).

Rey et al. (2009) found a significant difference in decision making performance only between immediate thought and conscious thought. They argued that this could be due to the fact that with increase in the number of categories (in the conscious thought condition), the difference between the cars (calculated from the mean evaluation score = Mean weight of attribute/Number of attributes sampled) reduces as the number of attributes increase. This line of reasoning was based on the assumption that the sampling process strictly selects the attributes according to a ranked order in terms of weights. However, this might not be the case due to potential individual differences in attribute selection. The simulations in the current study used probability-based sampling and not a direct analysis of the dataset as done in Rey et al. (2009) to account for such individual differences. When probability-based sampling is performed on the attributes a large number of times, the difference between the cars do not reduce as much as indicated in the analysis by Rey et al. (2009). Fig. 3 shows the aggregate mean evaluation score (=(Sum of weights/Number of trials)/Number of attributes) of all the cars as a function of number of attributes sampled (using probability-based sampling). The difference between the best car (Hatsdun) and the second best (Kaiwa) does not change drastically as more number of attributes is considered for both WADD (Fig. 3a) and TALLY (Fig. 3b). Similar to Rey et al. (2009), the difference between Hatsdun and Kaiwa does reduce with increase in the number of attributes. For example, with WADD the difference is negatively correlated, \( r = -0.921, t(1, 10) = -7.456, p = .000021 \).

The current simulations capture the idea of bounded rationality in the sampling process and assume operation of a rational strategy like (WADD or TALLY) after the attributes are sampled. The suggestion of Rey et al. (2009) supposes that a decision maker rationally selects the attributes based on the weights (based on weights) but after the attributes are selected, the decision taken is not purely rational (where the best choice is not selected always if the evaluated values of the choices are close to each other). However, it seems reasonable to assume that attributes might not always be selected in strict rank order and there is also no (simple) algorithmic way that could explain how a decision is arrived at when the differences between the alternatives are close to one another.

Both the powerful unconscious and the conscious attention views treat attention and consciousness almost synonymously but it is quite possible that attention (and hence deliberation) could be manipulated independently of consciousness. Different types of attention or differences in allocation of attentional resources might result in differences in decision making independent of manipulations of consciousness in thought. The amount of deliberation would depend on available attentional resources. Keeping this in mind, we propose a simple framework (see Fig. 4) in which attention/deliberation and consciousness constitute independent dimensions that could be varied in a given task. In this framework, the unconscious thought condition involves less attention and unconscious thinking, the conscious deliberation condition involves more...
attention and conscious thought, and the immediate thought condition may involve conscious thought but with less attention/deliberation. These conditions may also differ in terms of the number of attributes selected. The current simulations indicate that the quality of decisions improve with increase in the number of attributes considered in making a decision. However, it is not clear that just the number of attributes used determines the performance in empirical studies or other factors like memory (and experience) also play a role.

Memory-related processes have been proposed to explain effects associated with unconscious thought (Lassiter et al., 2009; Shanks, 2006). Lassiter et al. (2009) have argued that conscious thought may employ memory-related processes and unconscious thought might employ online computation of choice when the attributes are presented. Our simulations do not directly address differences between conscious and unconscious thought, but do indicate that only a smaller number of attributes be memorized or processed in either mode of thinking. An accurate examination of memory (implicit and

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**Fig. 3.** Aggregate mean evaluation score of the cars as a function of number of attributes using (a) WADD and (b) TALLY.

**Fig. 4.** Schematic of the unified conscious attention view of decision making, where attention/deliberation and consciousness constitute independent dimensions.
explicit) of attribute information would enable us to determine the approximate number of attributes used in making a choice.

Based on the simulation results, we conclude that in a multi-attribute decision problem involving unconscious thought without deliberation, people might consider only a subset of attributes and not all (or even most) of the attributes as suggested by UTT. Our simulations are consistent with the unified conscious attention view of decision making. Further studies and computational models would be needed to understand the selection of attributes and the way they are combined to make choices in complex decision making problem.

Appendix A

A.1. Dataset 1

["Gas Mileage", 18.3, 1, 1, –1, –1],
["Handling", 16.5, 1, –1, 1, –1],
["Environment Friendly", 15.6, 1, –1, –1, –1],
["Sound System", 14.6, –1, 1, 1, –1],
["Service", 14.3, 1, 1, –1, –1],
["Ease of Shifting Gears", 12.9, –1, 1, 1, –1],
["Trunk Space", 12.3, 1, 1, –1, –1],
["Legroom", 11.8, –1, 1, –1, 1],
["New", 10.2, 1, –1, 1, –1],
["Available in different colors", 6.1, 1, 1, –1, 1],
["Has sunroof", 5.9, 1, –1, 1, 1],
["Has cupholders", 1.6, 1, –1, 1, –1].

A.2. Dataset 2

["Security of building", 8.95, –1, 1, –1, 1],
["Rent", 8.6, –1, 1, 1, –1],
["Crime Rate of Area", 8.36, 1, –1, 1, –1],
["Flatmate is friend", 7.91, –1, 1, 1, –1],
["Size of apartment", 7.56, –1, 1, 1, –1],
["Kindness of neighbors", 5.41, 1, –1, –1, –1],
["View", 5.18, 1, 1, 1, –1],
["Built-in wardrobe", 4.7, 1, 1, –1, –1],
["Direction", 4.61, 1, 1, –1, –1],
["Leisure facilities", 4.59, 1, 1, 1, –1].

References


