The Effect of Salience on Valuation:

Addressing the Dual-Causality Problem in Decision Biases

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ABSTRACT

How do individuals evaluate products? Many decades of research have proposed models of how individuals integrate information and what influences evaluations (e.g., Anderson 1971; Wilkie and Pessemeier 1973), one of which is the accessibility-diagnosticity framework (Feldman and Lynch 1988). This memory-based decision-making framework proposes that the accessibility of an input (i.e., likelihood with which it is perceived or recalled) and the diagnosticity of those inputs (i.e., perceived relevance and validity) determine whether or not that input will be used in judgment. However, this framework is relatively silent on the interdependence of these factors: it only suggests inputs accessible in memory are judged for their diagnosticity. We argue those factors are not likely to be independent or merely feed-forward; that is, accessibility can influence diagnosticity, and diagnosticity can influence accessibility. Further, we contend that the framework applies not only to memory-based but also to stimulus-based decision-making. A conjoint task is implemented to demonstrate how accessibility can affect diagnosticity in a stimulus-based decision environment. Results from several product categories show that manipulating the salience of particular attributes (accessibility) can affect their judged part-worths (diagnosticity). Specifically, attributes that are more salient receive higher part-worths, while those that are less salient have relatively lower part-worths. Further, attributes in more salient top and bottom positions of a product profile had consistently higher part-worths than attributes in middle positions.

Keywords: accessibility, diagnosticity, conjoint, memory, attention

How do people integrate information when making decisions? Logic, economic theory, and Bayesian inference all prescribe that potential inputs, whether found in the external environment or retrieved from memory, should be weighted by their information value based on task goals and combined in a way that gives greater importance to inputs with greater informational value (Anderson 1971; Bettman et al. 1998; Birnbaum 2008; Birnbaum and Stegner 1979; Payne, Bettman, and Johnson 1993; Wilkie and Pessemier 1973; Van Osselaer and Janiszewski 2012). That is, the inputs that are used should be diagnostic for choosing the best decision alternative. This process of focusing on information that is relevant and important while ignoring irrelevant information is typically called analytic processing (Hutchinson and Alba 1991; Payne et al. 1993).

Although people are sometimes able to process information analytically, there is much empirical research that shows that important information is often ignored and irrelevant information is often given substantial weight (Klayman and Ha 1987; Lord, Ross, and Lepper 1979; Meehl and Rosen 1955; Tversky and Kahneman 1974). That is, the information that is most accessible at the time a decision is made is not always the most diagnostic information (Feldman and Lynch 1988; Lynch, Marmorstein, and Weigold 1988). The result of this contamination is decisions that are biased (see Alba and Hutchinson 2000; Kahneman and Tversky 1984).

One such model for information use is the accessibility-diagnosticity framework (Feldman and Lynch 1988; Lynch et al. 1988; Lynch 2006), which presents a theory of memory-based decision-making. According to this model, the relative accessibility of a focal input over competing inputs (i.e., based on frequency, recency, time) and the judged diagnosticity of that input (i.e., perceived relevance and validity) determine what inputs people weight heavily or not at all when making decisions.

Initially, the accessibility-diagnosticity model specified a “feed-forward” type of relationship between accessibility into diagnosticity. That is, informational inputs to be used in judgment either are or are not accessible, and accessible inputs may be judged to be more or less diagnostic. But, if the input is not accessible at the time of judgment, it will not be used, regardless of how diagnostic it is. In this way, considerations of the component factors of accessibility and diagnosticity were left as relatively separate (Feldman and Lynch 1988). To illustrate this process, suppose a participant was filling out a political survey and first answered a question about how dishonest politicians are. If the participant then responds to a second question about how dishonest Bob Dole, a politician, is, the answer to the previous question is likely to be accessible. The participant would then need to judge how valid its response is to the Bob Dole scenario (how diagnostic it is; Feldman and Lynch 1988). However, if the first question about politicians preceded the question about Bob Dole by several pages, it may not be accessible, in which case participants may not consider the answer to the first question when answering the question about Bob Dole. In this example, each factor (accessibility and diagnosticity) independently act on information use rather than contaminate one another.

However, we argue two important pieces of the accessibility-diagnosticity framework have been largely ignored in the literature. First, this framework should not be limited to memory-based decisions; it also applies to stimulus-based decision-making (Lynch and Srull 1982). As we argue below, many principles from scene perception (e.g., Antes 1974; Henderson 1992) that mirror memory-based principles also abide by the accessibility-diagnosticity framework. Given the growing exploration into attention-based factors using eye-tracking in consumer behavior (e.g., Atalay et al., 2012; Chandon et al. 2009), expanding the framework to this domain is important and timely.

Second, accessibility can affect diagnosticity (e.g., Menon and Raghubir 2003; Schwarz et al. 1991), and diagnosticity can influence accessibility (e.g., Alba and Hasher 1983). While occasional articles have suggested these interrelationships (e.g., Lynch 2006), there have been no formalizations of this idea or its implications.

This paper makes three contributions: first, it generalizes the accessibility-diagnosticity framework beyond memory-based judgments to a stimulus-based context. Second, it updates the accessibility-diagnosticity framework to include the interactions among accessibility and diagnosticity that were largely ignored in previous work. Third, it demonstrates how stimulus-based features have an impact on product valuation (Meisner et al. 2016). We manipulate accessibility within a stimulus-based conjoint task to demonstrate that 1) accessibility and diagnosticity indeed interact beyond a feed-forward mechanism, and 2) accessibility-diagnosticity is a broader theory than originally conceived. Conjoint serves as a striking test of our theory to demonstrate how a task that is argued not to be influenced by accessibility is, in reality, susceptible to accessibility effects.

ACCESSIBILITY AND DIAGNOSTICITY AS "FEED-FORWARD"

One framework for how individuals use informational inputs is the accessibility-diagnosticity model (Feldman and Lynch 1988). This model dictates that consumer decision-making can rely on two inter-related factors: accessibility of informational inputs, and the perceived diagnosticity, or validity of those inputs. Pre-existing notions of accessibility define it as the readiness with which an input can be applied in a task (Higgins 1989). Notably, what is accessible is only a small subset of what is *available* to individuals given their goals and the cues in the environment (Estes 1955; McGeoch 1930; Tulving and Pearlstone 1966). Only a small portion of what is available may be accessible due to retrieval failure, which is distinct from encoding failures or actual loss of information in memory (e.g., Kahana 2012; Kim 2011; Lewandowsky and Murdock 1989; Mensink and Raaijmakers 1988).

Previously, accessibility and diagnosticity were argued to operate in a feed-forward manner: individuals had some set of accessible information based on recency, frequency, or other factors (Feldman and Lynch 1988). This information is subsequently weighted based on its perceived diagnosticity based on task-specific goals. For example, attribute weighting, a measure of diagnosticity, in some tasks could depend on whether the response modality was consistent with that attribute format (Tversky et al. 1988). Ultimately, in this framework, information that is not accessible (but may be available otherwise) can be diagnostic, but will not be used as an input to judgment unless some cue in the environment helps retrieve it from memory (e.g., Estes 1955).

Another implication of this operationalization of accessibility and diagnosticity is also how it shapes research studying their relative contribution to a phenomenon. Other literature in which accessibility fed into diagnosticity tests accessibility and diagnosticity as separate factors. For example, Herr, Kardes, and Kim (1991) test the model with separate factors in the context of word of mouth communication, and Aaker (2000) explores cross-cultural asymmetries in persuasion effects and argues accessibility is a key process. In the realm of voting surveys regarding presidential elections, Simmons et al. (1993) find that individuals with prior voting attitudes (who had accessible attitudes) were less susceptible to carryover effects based on question responses earlier in the survey, whereas those individuals without prior voting attitudes used accessible, recent responses from earlier in the survey (question order effects). In these cases, accessibility and diagnosticity are treated separately as one or both could independently contribute to a phenomenon.

INTERACTIONS OF ACCESSIBILITY-DIAGNOSTICITY IN MEMORY-BASED AND STIMULUS-BASED JUDGMENTS

Several streams of research have found that accessibility and diagnosticity can affect one another in both memory and stimulus-based decision contexts (see Table 1). By memory-based decision-making, we mean that some amount of information is absent or missing such that it requires retrieval, while for stimulus-based decision-making "all of the relevant information is directly present" (Lynch and Srull 1982, p. 19).

First, accessibility can affect diagnosticity in memory-based decision-making. Most notable is the ease-of-retrieval effect, in which ease of recall can lead people to use cognitive feelings of ease as inputs to judgment instead of number of arguments or argument strength (Menon and Raghubir 2003; Schwarz et al. 1991; Weingarten and Hutchinson 2016), the latter of which may subsequently be perceived to be less diagnostic due to inferences from subjective difficulty (Greifeneder & Bless, 2008; Wänke and Bless 2000). This effect stems from earlier research on the availability heuristic, which argued, without testing the mechanism, that ease of thinking of information could bias judgments (Tversky and Kahneman 1974). Another example of accessibility contaminating diagnosticity is conceptual priming (i.e., through presentation of relevant preceding sentences prior to words) can affect recognition judgments through increased fluency (Whittlesea 1993).

Second, accessibility can influence diagnosticity in stimulus-based decision-making. For example, several streams of literature have suggested the relative fluency with which information is processed may affect judgments (Alter and Oppenheimer 2009; Oppenheimer 2006; Unkelbach 2006). These fluency effects are present in multiple decisions such as consumer evaluation (Labroo, Dhar, and Schwarz 2008), artistic judgments (Reber et al. 2004), categorization (Oppenheimer and Frank 2008), truth and accuracy judgments (Unkelbach 2006, 2007), and many others (see Alter and Oppenheimer 2009). Consistent with the previous paragraph, even fluent stimulus presentation can affect judged stimulus familiarity (Whittlesea, Jacoby, and Girard 1990).

Third, diagnosticity can affect accessibility in memory-based decision-making. One case for this effect is importance effects: past research has found that people tend to remember more important information first (Alba and Hasher 1983; Bargh and Thein 1985). Second, valence of information can bias which pieces of information, especially negative information, are recalled (Lingle and Ostrom 1979). Further, goal-based value effects may promote activation of particular concepts in memory (Fishbach and Ferguson 2007). Moreover, Barsalou (1985) demonstrated that ad hoc categories, which are idiosyncratic groups of items (e.g., “places to look for antique desks,”) tend to affect consistency and reduce exemplar accessibility (i.e., speed of access).

Fourth, diagnosticity can affect accessibility in stimulus-based decision-making. Several examples inside and outside of consumer behavior support this claim. Classic scene-perception results suggest people tend to look at the more important portions of a scene first (Antes 1974; Loftus and Mackworth 1978), and goals or where to look in scenes may similarly change to where people attend (Buswell 1935; Land and Hayhoe 2001; Sullivan et al. 2012; Yarbus 1967). In an advertising example, goals regarding learning or memorization changed to which parts of the advertisement people attended (Pieters and Wedel 2007). Further, reference points may shift to which information people attend and how much time they spend processing that information (Ashby et al. 2015; Willemsen, Bockenholt, and Johnson 2011). Moreover, although there is some controversy over some results in scene perception (Henderson 1992, 2011; Henderson and Hollingworth 1999), it is argued that knowledge of scenes may operate in a top-down fashion and determine for how long people look at regions of scenes that violate expectations (Biederman 1972; Biederman et al. 1982).

Key to these interactions is that several principles that operate within memory-based decision-making have parallels in stimulus-based decision-making. Goal-related effects can change what information is most accessible in memory or what is salient in a scene (Alba and Hasher 1983; Barsalou 1985; Buswell 1935; Yarbus 1967), and fluency effects can shape judgments involving recall of personal examples or in scenarios in which all information is present (Alter and Oppenheimer 2009). These common principles suggest that the interactions and relationships inherent in the accessibility-diagnosticity framework may not be limited to memory-based decision-making.

Therefore, we expand the accessibility-diagnosticity framework, which until now only loosely recognizes that interactions may exist among accessibility and diagnosticity, to incorporate these interactions. We choose to expand it using a stimulus-based context to demonstrate the generalizability of the framework.

MODEL

We propose a model to reflect how individuals use accessible inputs from all those available in the environment, judge the diagnosticity of inputs associated with possible alternatives, and ultimately evaluate an alternative. We use a notation system based on similar systems from prior literature (Hutchinson and Mungale 1997; Tversky and Sattath 1979).

We define $x, y, z \in S$, a set of *available inputs* in the external environment or in memory (e.g., possible stimuli). These inputs are used according to a function $a(x)$: $S \rightarrow [0,1]$, which is an *accessibility* function that maps inputs into the interval from 0 to 1. For example, accessibility might be a probability of activation; however, these values are not assumed to satisfy the requirements of probabilities and might also simple be a "weight" of some sort. An input is *accessible* if and only if $a(x) > 0$, which means that the input is activated in working memory and can be used for current cognitive tasks.

Available inputs are valued based on $b(x)$: $S \rightarrow \Re$, which is the *diagnosticity* function that maps inputs into real numbers, which represents the information value of the input for current cognitive tasks. These inputs are associated with $i, j, k \in R$, a set of *decision alternatives* (e.g., possible responses). S and R are integrated as an *information structure* denoted $[S, R, \boldsymbol{M}]$. $\boldsymbol{M}$ is a matrix in which m_{ix} is 1 if input x is associated with decision alternative i, and 0 otherwise. $I, J, K \subset S$ are the sets of inputs associated with alternatives i, j, and k, respectively. R_x is the set of alternatives that are associated with input x. Thus, $R_x \subset R$.

For valuation, we define $V(i)$: $R \rightarrow \Re$, the *valuation* function that maps alternatives into real numbers. More specifically:

$$V(i) = \sum_{x \in I} w(x) \tag{1}$$

and weighting function $w(x) = a(x)\, b(x)$.

We then define a series of functions in which accessibility and diagnosticity may influence each other. All functions can be conditioned on individual, s, and time, t (e.g., $a_{s,t}$, $b_{s,t}$, $V_{s,t}$, and $w_{s,t}$), θ_{ab} and θ_{ba} (the effect of diagnosticity on accessibility and accessibility on diagnosticity, respectively), weighting parameter α, and an exogenous shock indicated δ_t, which we use to represent any manipulations we implement.

$$a_{s,t}(x) = f_{s,t}(\mathrm{x}, a_{s,t-1}, b_{s,t-1}, \delta_t, \alpha_a, \theta_{ab}) \quad (2a)$$

$$b_{s,t}(x) = g_{s,t}(\mathrm{x}, a_{s,t-1}, b_{s,t-1}, \alpha_b, \theta_{ba}) \quad (2b)$$

$$w_{s,t}(x) = a_{s,t}(x)\, b_{s,t}(x) \quad (2c)$$

Importantly, $a_{s,t}$ and $b_{s,t}$ may be expressed with a number of possible functional forms.

With respect to the functional form of $a_{s,t}$, we argue that it should place some amount of weight on prior accessibility and prior diagnosticity to allow for possible carryover effects between those factors. Further, this accessibility function needs to be increasing in the effect of the manipulation, operating through δ_t, and θ_{ba}, which indicates an impact of diagnosticity akin to importance effects (Alba and Hasher 1983; Loftus and Mackworth 1978; Sullivan et al. 2012). Additionally, this function would ideally be able to represent a type of habituation effect. Therefore, we contend one set of possible forms for $a_{s,t}$ are elaborated on in equations 3a and 3b:

$$a_{s,t}(x) = \alpha_a\, a_{s,t-1}(x) + (1 - \alpha_a)\Delta_{a_{s,t}} \quad (3a)$$

$$\Delta_{a_{s,t}} = \frac{e^{\delta_t + \theta_{ab} b_{s,t-1}}}{k + e^{\delta_t + \theta_{ab} b_{s,t-1}}} \quad (3b)$$

These equations have several important features. First, for high values of constant k, the accessibility function should return a smaller impact of the previous period’s diagnosticity (i.e., how important people decide a piece of information is) and manipulations of accessibility (i.e., through directing attention). Second, for larger values of δ_t and θ_{ab}, we should see a bigger impact of exogenous shocks (e.g., our manipulation of salience, described below) and diagnosticity from a previous period. Third, the values for α_a can weight how much previous salience does or does not determine current salience.

Regarding $b_{s,t}$, we again require a function with a weighting between pre-existing diagnosticity (which might represent prior, enduring, or true beliefs) and the potential impact of accessibility. The impact of this accessibility function should be increasing in θ_{ba}, and should magnify the diagnosticity effect on that part-worth (not reverse it) in line with attention amplification (Blaser, Sperling, and Lu 1999; Reynolds, Pasternak, and Desimone 2000; Windschitl, Kruger, and Simms 2003).

Thus, one set of example functions for $b_{s,t}$ are:

$$b_{s,t}(x) = \alpha_b\, b_{s,t-1}(x) + (1 - \alpha_b)\, \Delta_{b_{s,t}} \tag{4a}$$

$$\Delta_{b_{s,t}} = \theta_{ba}\, a_{s,t-1}(\mathrm{sign}(b_{s,t})) \tag{4b}$$

These forms for $b_{s,t}$ suggest a weighting of previous diagnosticity versus other influence from exogenous shocks and prior-period accessibility. Further, the influence of prior period accessibility is multiplied by whether the diagnosticity of an attribute is positive or negative (i.e., people get disutility from higher values of an attribute) to represent a polarization effect from attention.

Our model is differentiated from the old accessibility-diagnosticity framework via the accessibility function and diagnosticity functions incorporating an element of dual-causality. We test this model using an experimental paradigm described below.

EXPERIMENTAL DESIGN

Experimental Paradigm

We test our model using a conjoint analysis paradigm in which the salience of particular attributes is manipulated across conditions such that some attributes have greater accessibility (i.e., have higher readiness with which they can be used). Conjoint presents a striking test for this theory because prior work suggests that stimulus-based (bottom-up) factors do not predict choice, but instead, valuation and goal-based (top-down) factors drive choice and fixations (Meisner, Musalem, and Huber 2016). According to this model, all weighting should be based solely on b(x), with minimal updating over time (i.e., α_b = 1 in equation 4a).

We employ a two-phase paradigm consisting of a learning phase and a test phase. The instructions for Study 1A and 1B are included in Appendix A, with the complete study setup depicted in Figure 1.

Prior to either phase, participants read a cover story informing them to assume that they are in the market to buy a particular product and then state willingness to pay for various versions of this product. For example, some participants saw information about cars. Participants were given information about four attributes for the car (e.g., MPG, sound system, safety rating, and warranty length), each of which has two levels: a low level and a high level. Participants were then informed about a general price range for the product (e.g., $16,000-$30,000, with an average of $23,000) and that they will make 16 judgments in which they state their maximum willingness to pay for the product. Similar stimuli were used for other products, such as monthly cell phone plans and Disney Vacation packages (see Table 3).

Hereafter we refer to attributes one, two, three, and four based on their position in the product profile: first, second, third, and fourth, respectively. Importantly, the semantic identity of each attribute (e.g., MPG, sound system) was displayed in one of four orders designed from a 4x4 Latin square design (Rosenthal and Rosnow 2008). These orders are a between-subject factor.

In the learning phase, participants were presented four pages with two willingness-to-pay judgments per page; we manipulate accessibility in this phase (Figure 2). This manipulation formed one of two between-subject cells: a Single condition meant to affect the accessibility (and ultimately diagnosticity) of one attribute, and a Multiple condition. In the single condition, within each page only one attribute (the attribute to which attention was to be called) differed between the two products on the page; this attribute was in the fourth (final) position of each product description. Even though the willingness-to-pay judgments were distinct, subjects were expected to realize that the difference between their two judgments should reflect their valuation of the focal attribute. The focal attribute was the same for all four pages of the learning phase. By contrast, attributes one (first in the list), two (second in the list), and three (third in the list) were identical between the two products in the learning phase. In the Multiple condition, within each page two other attributes in addition to the fourth attribute also differed between the two products on the page. This condition was meant to make the fourth attribute not as salient as in the single condition. Importantly, the same eight products were displayed to participants in the learning phase, but they were shown in different orders to construct the salience manipulation; the exact design of products and orders in the learning phase are shown in Table 2A and 2B.

In the test phase (Figure 3), participants saw eight pages with one willingness-to-pay judgment per page, and all subjects complete the same test phase. This setup tests the enduring effects of the attention manipulation. One to three attributes differed from page to page (see Table 2C).

The eight judgments in each phase were used to compute the part-worths of the four attributes for each phase. Thus, the original 16 judgments were used to compute two sets of four measures for each subject. These part-worths represent the diagnosticity of each attribute (i.e., $w_{s,t}(x)$ in equations 1 and 2c). In Study 1A, 1B, and 2 in this paper, we scale these part-worths by the stated average price of the product category (Table 3) and multiply them by 100 to obtain a percentage part-worth metric as our diagnosticity dependent measure.

Experimental Predictions

This paradigm enables us to test our model of accessibility-diagnosticity, as outlined generally in the previous section of this paper and depicted via Figure 4. In this paradigm, each phase of the study can be thought of as a time period t, resulting in 3 time periods with baseline beliefs at t = 0. Baseline accessibility may be defined as a_0, and baseline valuation of these attributes b_0. We posit the following five hypotheses in which we manipulate accessibility through an exogenous shock δ, which we align with equations 3a, 3b, 4a, and 4b:

H1: If accessibility from a time period affects subsequent accessibility in the next time period, we should see a nonzero α_a for $a_{s,t}(x)$.

H2: If accessibility affects diagnosticity, then θ_{ba} should be nonzero for $b_{s,t}(x)$.

H3: If diagnosticity affects subsequent accessibility in the next time period, we should observe a nonzero θ_{ab} for $a_{s,t}(x)$.

H4: If diagnosticity from a first time period influences diagnosticity in a second time period, we should see a nonzero α_b for $b_{s,t}(x)$.

Conversely, if the original model of accessibility-diagnosticity is accurate, we should only see evidence for H1 and H4 because temporary accessibility manipulations may determine carryover effects in accessibility (Feldman and Lynch 1988).

We predict that our manipulation should bolster the part-worth of the fourth attribute in the Single condition over and above that of the Multiple condition in both the learning and test phases. This would be manifest in equation 3b as δ exerting a nonzero influence on accessibility and a nonzero value for θ_{ba} in equation 4b. This attribute should receive higher relative salience, which will have an impact on diagnosticity (through one of a few possible mechanisms discussed below.

Further, our predictions imply a different set of results for the other three attributes. Namely, we argue that by diverting attention away from attributes one, two, and three in the Single condition, those attributes should not have larger part-worths in in the single condition compared to the Multiple condition. This result would be akin to the property in the accessibility-diagnosticity framework in which accessibility of a focal input or inputs (attributes one, two, and three) also declines with the increased accessibility of an alternative input or inputs (attribute four in the Single condition).

Importantly, we assume two facets regarding a) traditional conjoint and b) accessibility. First, in traditional conjoint analysis, accessibility should only play a small role in valuation (α_b = 1), while valuation should reflect true preference weightings and attribute tradeoff preferences (see Green et al. 2001; Meisner, Musalem, and Huber 2016). Therefore, we should not see any accessibility effects on diagnosticity if the traditional conjoint model is correct.

We recognize that we are suggesting stimulus-based features (i.e., position) of the conjoint environment can affect part-worths, which while theoretically consistent with past work (e.g., Atalay et al. 2012), contrasts from Meisner, Musalem, and Huber (2016) by extending what features of stimulus-based salience are tested. Meisner, Musalem, and Huber (2016) employ choice-based conjoint studies in which stimulus-based attention is operationalized based on position effects (left, center, right); any attention effects found from position were not predictive of choice in this task as each position was chosen approximately a third of the time in one study. Our study manipulates salience differently from the Meisner et al. (2016) setup (in addition to using a different measure), which itself does not extensively manipulate salience beyond position.

Further, in studies without eye-tracking, we assume that information is becoming more or less salient but is nonzero (a(x) > 0), but we cannot estimate relative attention effects beyond that of the main effect of the manipulation.

We first present empirical evidence for the efficacy of our manipulation in the experimental paradigm.

STUDY 1A: EFFECTS OF SALIENCE ON PART-WORTHS

In Study 1A, we use three different product replicates to test our theory. Across cars, cell phone plans, and Disney vacation packages, we predict that calling more attention to tradeoffs on a fourth attribute will lead that attribute to have a relatively greater part-worth. If part-worths are unaffected by accessibility and H2 fails, which would correspond to diagnosticity independence (i.e., accessibility not affecting diagnosticity; $\theta_{ba} = 0$ in equation 4b, we should observe a similar pattern of means as that in Figure 5A. In this figure, there are no differences among conditions, and each attribute position has a roughly similar part-worth. However, if H2 holds and θ_{ba} is greater than 0 (Figure 5B), then we should observe an effect of our manipulation on the Single condition's fourth attribute part-worth.

However, we should also not see increases in the part-worths of attributes one, two, and three in the Single condition because attention is not directed to those; if anything, attention is directed away from them. If those attributes' part-worths increase in the Single condition relative to the Multiple condition, then our salience manipulation is merely generally boosting valuation, which is not theory-consistent. Thus, attributes one, two, and three should not have larger part-worths in the Single condition.

Method

Participants from Amazon Mechanical Turk (N = 774) were randomly assigned to one cell in a 4 (Order) x 2 (Condition: Single or Multiple) x 3 (Product: Cars, Cell Phone Plans, or Disney) between-subject design.

Participants completed the basic setup as described in the experimental paradigm section. Participants saw one of cars, cell phone plans, or Disney vacation packages. A summary of the attributes for each product category can be seen in Table 3.

As described in the experimental paradigm section, participants randomly saw one of four fixed orders of attributes based on a 4x4 Latin square design (Rosenthal and Rosnow 2008).

In the Single condition, participants also were instructed to be mindful of how much they valued whatever attribute that would subsequently appear in the fourth position (referred to by name, not position). In the Multiple condition, these instructions merely asked participants to be mindful of tradeoffs across attributes. Full instructions can be found in Appendix A.

Participants completed sixteen willingness-to-pay judgments: eight in learning phase with two per page for four pages, and eight in the test phase with one per page for eight pages. Each judgment was inputted via numerical entry.

Results

Across both learning and test phases, we predicted that increasing the attention paid to the fourth attribute should a) bolster its part-worth, and b) reduce (or at least not increase) the relative part-worths of the other attributes. In order to have a meaningful measure across three product categories, we analyze the combined data across product categories and across attributes in which each product's part-worth is divided by the stated average price in the study (e.g., $23,000 for Cars, $80 for Cell Phone Plans, and $850 for Disney Vacation Packages; see Table 3) then multiplied by 100. This enabled a test of standardized part-worths as percentage changes in the stated average price of the product. In all analyses we include Order to control for the semantic differences across the identity of the fourth attribute for each product category.

The Effect of Accessibility on Diagnosticity (H2). We find evidence in support of our predictions, as shown in Table 4. Consistent with our predicted effect of salience, the attribute in the fourth position in the learning and test phases was higher in the Single condition compared to the Multiple condition. Further, this result was not the case for attributes in the first, second, or third positions. These attributes had directionally larger part-worths in the Multiple condition compared to the Single condition.

Further, the pattern of means reveals a position effect in the average attribute part-worths: the first part-worth is larger than the second and the second is larger than the third. This effect is present in both learning and test phases. Although it was not initially predicted, the position effect is consistent with the proposed accessibility-diagnosticity framework. Even though the attributes are counterbalanced across the different experimental orders, the most salient attribute (i.e., those in the top position) received larger part-worths than those in less salient positions.

Preliminary Statistical Tests. We tested our predictions using a 4 (Repeated Attribute Part-worths) x 2 (Condition: Single or Multiple) x 3 (Product) x 4 (Order) mixed ANOVA separately for the learning phase and the test phase. We first tested whether product category interacted with our manipulation or merely interacted with semantic elements of the design before aggregating over product. In the learning phase, the product category did not interact with our manipulation ($F(2, 750) = 1.02$, $p = .36$) but instead only exerted a main effect ($F(2, 750) = 89.13$, $p < .001$) and interaction with order ($F(6, 750) = 1.96$, $p = .069$), attribute ($F(6, 750) = 4.05$, $p < .001$), and order by condition ($F(6, 750) = 3.33$, $p = .003$) and order by attribute ($F(18, 750) = 27.39$, $p < .001$). The quadruple interaction was nonsignificant ($F(18, 750) = 1.29$, $p = .19$). These interactions mean there may be some differences over various attributes across products but the effect of the manipulation was similar across products and, therefore, were not reason to separate the analysis by product category. Similarly, in the test phase product category did not interact with condition ($F(2, 750) = .61$, $p = .54$), but it did have a main effect ($F(2, 750) = 51.26$, $p < .001$) and interactions with attribute ($F(6, 750) = 6.98$, $p < .001$) and order ($F(6, 750) = 2.37$, $p = .028$). Product category also had triple interactions with condition and attribute ($F(6, 750) = 1.26$, $p = .27$) and attribute and order ($F(18, 750) = 37.55$, $p < .001$), but not with condition and order ($F(6, 750) = .75$, $p = .61$). The quadruple interaction was again nonsignificant ($F(18, 750) = .67$, $p = .85$). We therefore aggregate over product category, adjusted for the stated average price of each product category (Table 3) for the learning phase and test phase.

Statistical Tests for Learning Phase. Consistent with our theory, in the learning phase a 4 (Repeated Attribute Part-worths) x 2 (Condition: Single or Multiple) x 3 (Product) x 4 (Order) mixed ANOVA revealed that attribute (one, two, three, or four) interacted with condition ($F(3, 750) = 17.88$, $p < .001$).

First, in support of H2, we found a boost in the attribute four part-worths in the Single ($M = 6.61$) versus Multiple ($M = 3.94$; $F(1, 750) = 51.54$, $p < .001$) conditions. However, also consistent with our predictions, this relationship was not the case for attribute one ($M_{Single} = 5.43$, $M_{Multiple} = 5.98$, $F(1, 750) = 1.86$, $p = .17$), two ($M_{\text{Single}} = 4.50$, $M_{\text{Multiple}} = 4.81$, $F(1, 750) = .81$, $p = .37$), or three ($M_{Single} = 3.59$, $M_{Multiple} = 4.00$, $F(1, 750) = 1.26$, $p = .26$). For all studies, given our predictions specifying that the manipulation should only boost the fourth attribute part-worth, we contrast the effect of the Single condition on attribute four versus the effects on attributes one, two, and three as an interaction, for which we find evidence in the learning phase ($F(1, 750) = 53.17$, $p < .001$; see Figure 6A). There was also not a main effect of condition ($\text{M}_{Single} = 5.03$ vs. $\text{M}_{Multiple} = 4.68$; $F(1, 750) = 2.62$, $p = .11$), meaning that it was not the case that our manipulation merely increased willingness to pay in the Single condition across the board.

We also observed an effect of attribute position on our results in the learning phase ($F(3, 750) = 23.98$, $p < .001$) that was consistent with top and bottom effects. That is, part-worths were higher for attributes in the first and fourth positions. This result was reflected in a significant contrast between the first ($M = 5.70$) and fourth ($M = 5.28$) positions, and the second ($M = 4.65$) and third ($M = 3.79$) positions ($F(1, 750) = 56.80$, $p < .001$). We observed further evidence consistent with the top position bump: the attribute in the first position had a significant boost over that in the second ($F(1, 750) = 18.18$, $p < .001$) and third ($F(1, 750) = 58.42$, $p < .001$)

positions but not the fourth attribute ($F(1, 750) = 2.44$, $p = .12$). The second attribute had a significant boost in part-worth relative to the third attribute ($F(1, 750) = 13.47$, $p < .001$). Yet, in line with the bottom effect, the fourth attribute (on average, but not necessarily in the Multiple condition; see Figure 6B) had a bigger part-worth than the second ($F(1, 750) = 6.44$, $p = .011$) and third attributes ($F(1, 750) = 37.21$, $p < .001$).

Statistical Tests for Test Phase. The same analysis (a 4 (Repeated Attribute Part-worths) x 2 (Condition: Single or Multiple) x 3 (Product) x 4 (Order) mixed ANOVA) on the test phase yielded another interaction of condition and attribute ($F(3, 750) = 8.17$, $p < .001$; see Figure 6B) without a main effect of condition ($F(1, 750) = 1.07$, $p = .30$).

First, in support of H2 and in line with our predictions, we found a significant contrast between the attribute four part-worths in the Single ($M = 5.57$) compared to Multiple ($M = 3.88$; $F(1, 750) = 18.03$, $p < .001$) conditions. However, consistent with our theory, this relationship was not the case for attribute one ($M_{Single} = 4.46$, $M_{Multiple} = 4.65$, $F(1, 750) = .28$, $p = .59$), two ($M_{Single} = 3.82$, $M_{Multiple} = 4.18$, $F(1, 750) = 1.10$, $p = .29$), or three ($M_{Single} = 2.37$, $M_{Multiple} = 2.75$, $F(1, 750) = 1.29$, $p = .26$). The predicted interaction between attributes 1-3 versus 4 and condition was significant ($F(1, 750) = 24.48$, $p < .001$).

The aforementioned attribute position effects also replicated in the test phase ($F(3, 750) = 29.23$, $p < .001$) that again supported top and bottom effects. The contrast pitting the first ($M = 4.55$) and fourth ($M = 4.73$) positions against the second ($M = 4.00$) and third ($M = 2.56$) positions ($F(1, 750) = 59.95$, $p < .001$) was again significant. The first attribute part-worth was significantly greater than the second ($F(1, 750) = 5.59$, $p = .018$) and third ($F(1, 750) = 63.85$, $p < .001$) but not the fourth attribute part-worths ($F(1, 750) = .54$, $p = .46$). Further, the second attribute had a significant boost in part-worth compared to the third attribute ($F(1, 750) = 32.16$,

$p < .001$), but in line with a bottom effect, the fourth attribute had a bigger part-worth than the second ($F(1, 750) = 8.57$, $p = .004$) and third attributes ($F(1, 750) = 72.59$, $p < .001$).

Discussion

Study 1A demonstrates that increasing the relative salience of particular tradeoffs across attributes had a carryover effect on diagnosticity: part-worths for the fourth attribute were higher for the Single condition relative to the Multiple condition. This effect held across various attributes for multiple products (cars, cell phone plans, vacation packages), which serves as evidence of the effect's generalizability.

Further, attributes in positions one (first) and four (last) had increased part-worths compared to the middle attributes. This relationship is consistent with our theory because attributes in more salient positions (top, bottom) had heightened part-worths (diagnosticity). While the fourth part-worth is boosted in the Single condition, the fact that we see an effect of the manipulation beyond recency (bottom position) is striking. The higher part-worth for the top attribute is also noteworthy as a manipulation-free test of accessibility affecting diagnosticity.

However, two arguments may be levied against Study 1A's results concerning whether the instructions were too heavy-handed, and whether the Multiple condition had higher memory load. First, the instructions asking participants to attend to the attribute of interest might have led to demand effects. Second, the Multiple condition involved three attributes changing simultaneously in the same page in the learning phase, which may have been more difficult to process than the Single condition's learning phase.

We run Study 1B to address both of these concerns. We resolve the demand effect by excising the instructions in the Single condition that cue people into the attribute of interest. We handle the memory-load issue by segmenting the attribute to which attention is called in both the Single and Multiple conditions.

STUDY 1B: REPLICATION

In Study 1B, we replicate Study 1A and address the two methodological concerns from Study 1A. Study 1B also provides participants with a slider scale on which participants can indicate their willingness to pay for ease of use and to restrict people from responding with values that are far from the stated product value range.

Method

Participants (N = 1238) from Amazon Mechanical Turk were randomized into one cell of a 3 (Product: Cars, Cell Phone Plans, or Disney Vacation Packages) x 4 (Order) x 3 (Condition: Single, Multiple_{1B}, or Multiple_{1A}) between-subject design.

Study 1B's Single and Multiple_{1B} conditions had two major changes from the Single and Multiple conditions in Study 1A: the attribute of interest was in the fifth position, and both had a fixed, meaningless attribute in the fourth position (Cars: "Version: 2"; Cell Phone Plans: "Monthly: Yes"; Disney: "Hotels: Yes"). Second, products in the learning phase were presented side by side (as depicted in Figure 2). This manipulation was meant to ease the processing of comparing changes in the fourth attribute in the learning phase to address concerns about memory load. However, we retain referring to the final attribute as the fourth attribute to align the results across studies and conditions.

We also included a third condition (Multiple$_{1A}$) that was a replication of the Multiple$_{1B}$ condition without the fourth, meaningless attribute to test whether memory load accounted for the results. If memory load explains the results, the Single condition should have identical fourth-attribute part-worths as the Multiple$_{1B}$ condition, but not the Multiple$_{1A}$ condition. If memory load does not explain the results, the Multiple$_{1B}$ and Multiple$_{1A}$ conditions should be similar.

Further, instead of typing in willingness to pay judgments, we had participants use a slider bar to indicate their valuation of the product to prevent any experimental errors from typos. Full instructions can be found in Appendix A.

Results

We present the combined results across product category with part-worth adjusted by the mean stated value of the product category in each study.

The Effect of Accessibility on Diagnosticity (H2). Consistent with Study 1A and H2, Table 5, Figures 7A, and Figure 7B depicts a pattern of means in support of our theory. First, the fourth attribute had a larger part-worth in the Single condition compared to the Multiple$_{1B}$ and Multiple$_{1A}$ conditions, which demonstrates the predicted effect of our salience manipulation. Second, also consistent with the proposed impact of our salience manipulation, attributes one, two, and three were smaller in the Single condition compared to the Multiple$_{1B}$ and Multiple$_{1A}$ conditions. The latter two of these conditions were closer to each other than to the Single condition, which contradicts the memory load alternative explanation.

Further, we again observe the attribute position effect reported in Study 1A. The top attribute was as large if not larger than the middle two attributes in learning and test phases. The third attribute was again the smallest part-worth despite the counterbalancing of semantic attributes across experimental orders.

Preliminary Statistical Tests. We again examine the learning and test phases for interactions with product category that might trouble aggregating over product categories, and find that the manipulation's impact was the same across product categories. In the learning phase, there was a main effect of product ($F(2, 1202) = 158.30$, $p < .001$), but it did not interact with condition ($F(4, 1202) = 1.66$, $p = .16$), attribute ($F(6, 1202) = 1.26$, $p = .28$), order ($F(6, 1202) = .49$, $p = .82$). However, it did interact with attribute by order ($F(18, 1202) = 33.05$, $p < .001$) and with condition by order ($F(12, 1202) = .65$, $p = .80$). The quadruple interaction was nonsignificant ($F(36, 1202) = 0.86$, $p = .70$). The test phase again only had a main effect of product ($F(2, 1202) = 162.99$, $p < .001$) and an interaction with attribute and order ($F(18, 1202) = 58.93$, $p < .001$) but not condition ($F(4, 1202) = .92$, $p = .53$). All other interactions with product category were nonsignificant, inclusive of the quadruple interaction ($F(36, 1202) = .93$, $p = .58$). We therefore did not separate our analyses within each product category.

Statistical Tests for Learning Phase. A 3 (Condition) x 4 (Attribute) x 4 (Order) x 3 (Product) mixed ANOVA yielded our predicted interaction in the learning phase among condition and attribute ($F(6, 1202) = 9.24$, $p < .001$; see Figure 7A).

Consistent with our theory (but not a memory load story), we see an increase in the part-worth of the fourth attribute in the Single condition ($M = 5.49$) relative to the Multiple$_{1B}$ (M= 4.50) and Multiple$_{1A}$ conditions ($M = 4.10$; contrast: $F(1, 1202) = 16.56$, $p < .001$). However, also consistent with our predictions about the part-worths of attributes one through three not being higher in the single condition, the single condition had lower attribute part-worths for attribute one ($M_{Single} = 4.23$; $M_{Multiple1B} = 5.05$; $M_{Multiple1A} = 4.76$; contrast: $F(1, 1202) = 4.95$, p =

.026), two (M_{Single} = 3.16; $M_{Multiple1B}$ = 4.74; $M_{Multiple1A}$ = 4.42; contrast: $F(1, 1202) = 24.99$, $p <$ .001), and three (M_{Single} = 1.90; $M_{Multiple1B}$ = 3.03; $M_{Multiple1A}$ = 3.16; contrast: $F(1, 1202) = 21.72$, $p < .001$). Therefore, the learning phase demonstrated results in support of our predictions, and just as in Study 1A, had a significant interaction of the manipulation's effect on attributes one, two, and three, and attribute four ($F(1, 1202) = 50.49$, $p < .001$).

The learning phase in Study 1B's attribute position effects also mirrored the aforementioned top and bottom pattern ($F(3, 1202) = 45.63$, $p < .001$) that found evidence for primacy and recency effects. We again tested the contrast between the first ($M = 4.68$) and fourth ($M = 4.70$) positions, and the second ($M = 4.11$) and third ($M = 2.70$) positions, which was significant ($F(1, 1202) = 79.81$, $p < .001$). In step with primacy, the attribute in the first position had a significant boost over that in the second ($F(1, 1202) = 7.51$, $p = .006$) and third ($F(1, 1202) = 92.82$, $p < .001$) positions (supportive of a top effect), and it was nonsignificantly smaller than the fourth's part-worth ($F(1, 1202) = .01$, $p = .93$). The second attribute had a significant boost in part-worth relative to the third attribute ($F(1, 1202) = 52.03$, $p < .001$), but the fourth attribute had a bigger part-worth than the second ($F(1, 1202) = 7.75$, $p = .006$) and third attributes ($F(1, 1202) = 97.82$, $p < .001$), which supported a bottom effect.

Statistical Tests for Test Phase. The test phase yielded similar theory-consistent results from the condition by attribute interaction ($F(6, 1202) = 2.41$, $p = .026$; see Figure 7B). In directional support of H2, we observe an increase of the part-worth of the fourth attribute in the Single condition relative to the multiple and multiple' conditions (M_{Single} = 4.39; $M_{Multiple1B}$ = 4.05; $M_{Multiple1A}$ = 3.84; contrast $F(1, 1202) = 2.40$, $p = .12$). However, in the learning phase and test phase there was also a main effect of condition ($F(2, 1202) = 4.12$, $p = .017$) such that the Single condition had lower part-worths than other two conditions (Learning phase contrast F(1,

1202) = 12.18, $p < .001$; Test phase contrast $F(1, 1202) = 8.13$, $p = .004$), which is why we do not interpret the nonsignificant contrast on attribute four to be contrary to our predictions.

Further consistent with our theory, we also observe relatively lower part-worths in the Single condition for attribute one ($M_{Single} = 3.43$; $M_{Multiple1B} = 4.15$; $M_{Multiple1A} = 4.39$; contrast $F(1, 1202) = 9.93$, $p = .002$), two ($M_{Single} = 2.98$; $M_{Multiple1B} = 3.48$; $M_{Multiple1A} = 3.49$; contrast $F(1, 1202) = 3.66$, $p = .056$), and three ($M_{Single} = 2.14$; $M_{Multiple1B} = 2.86$; $M_{Multiple1A} = 2.60$; contrast $F(1, 1202) = 6.11$, $p = .014$). The contrast built on the interaction of the effect of the manipulation on attributes one, two, and three, and attribute four was again significant ($F(1, 1202) = 12.16$, $p < .001$).

The test phase in Study 1B's attribute position effects also replicated the study 1A results ($F(3, 1202) = 28.73$, $p < .001$). We again observe that the first ($M = 3.99$) and fourth ($M = 4.10$) attributes had significantly larger part-worths compared to the second ($M = 3.32$) and third ($M = 2.53$) attributes ($F(1, 1202) = 63.36$, $p < .001$). The first attribute part-worth was significantly larger than the second attribute ($F(1, 1202) = 11.94$, $p < .001$) and third attribute ($F(1, 1202) = 53.36$, $p < .001$), which was in favor of a top effect, but it was directionally smaller than the fourth attribute ($F(1, 1202) = .26$, $p = .61$). The second attribute part-worth was also significantly larger than the third attribute part-worth ($F(1, 1202) = 16.83$, $p < .001$). However, the fourth attribute had a bigger part-worth than the second ($F(1, 1202) = 13.98$, $p < .001$) and third attributes ($F(1, 1202) = 70.26$, $p < .001$), which provided evidence for a bottom effect.

A further test controlling for heterogeneity. The analyses reported for Studies 1A and 1B estimate and test aggregate average effects. However, it is likely that individuals differ in their personal part-worths, and this heterogeneity could dilute effects that are present at the individual level or create aggregate effects that are not present at the individual level (e.g., Hutchinson, Kamakura, and Lynch 2000). To address this potential problem we used each individual's part-worths (estimated from Test phase responses) to "backcast" responses during the learning phase. Thus, individual differences in preference are accounted for. If accessibility does not affect diagnosticity, then the estimated coefficients for the test phase part-worths should be the same for each attribute position. If there is an effect of position, then this effect will be revealed in the regression coefficients.[1] However, we predict that the coefficient on the fourth attribute part-worth should be larger in the Single condition than in the Multiple condition because participants in that condition should continue to be influenced by the salience manipulation.

We conduct this analysis separately for Study 1A (Figure 8A) and Study 1B (Figure 8B).

Indeed, in Study 1A, as shown in Figure 8A, we find that the coefficient on attribute four was larger in the Single condition compared to the Multiple condition. Therefore, our manipulation, when controlling for individual heterogeneity, has marked effects on part-worth valuation.

For Study 1B, we again predict that the coefficient on attribute four’s part-worth in our regression will be greater in the Single condition relative to the Multiple_{1B} and Multiple_{1A} conditions. Indeed, as depicted in Figure 8B, that was the case, demonstrating a smaller difference in part-worths between the learning and test phase for the attribute made salient by the manipulation.

Discussion

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[1] Although intuitive, the derivation of this prediction is complex and was confirmed via simulation for this experimental design. Simulation results are available from the authors upon request. This analysis requires regressing willingness to pay from each of the eight learning-phase judgments onto the four part-worths from test phase (sign corrected based on the design matrix for whether the attribute was high or low for each judgment), and also three variables to represent the particular attribute’s semantic identity (e.g., MPG, Safety Rating) part-worths, and a condition-specific intercept based on the sum of the high (+1) or low (-1) attribute design matrix for the product profile (e.g., row 1 from Table 2A would be 4 in the Multiple condition: 1 + 1 + 1 + 1 =4; row 1 from Table 2B would be 0 in the Single condition: 1 + 1 – 1 – 1 = 0).

Study 1B replicates Study 1A using a modified layout. We again find that manipulating the salience of an attribute can affect its part-worth. In particular, increasing the relative salience of an attribute can bolster its part-worth, while attributes that become relatively less salient as a result of our manipulation did not receive this benefit or had lower part-worths. Further, we do not find evidence for the memory-load account of the results from Study 1A: segmenting off the final attribute did not influence its ultimate part-worth.

The attribute position analysis provided supplementary evidence consistent with our theory: attributes in positions first (primacy) and last (recency) positions had bolstered part-worths relative to those in the middle positions. This result is akin to many memory-based effects (Murdock and Anderson 1975; Postman and Philips 1965) that emphasize improved memory performance to items at the beginning and ends of lists.

STUDY 2: ATTRIBUTION

In Study 2, we manipulate the diagnosticity of the salient attribute based on calling into question the nature of order effects to subjects (Greifeneder, Bless, and Pham 2011; Schwarz et al. 1991). Participants either proceeded through the same task for cars as in Study 1A or were interrupted before the learning phase to be warned about being sure they were thinking of stable part-worths that weren't influenced by the order in which they read the attributes. If questioning the diagnosticity behind what is made more accessible conforms to standard attribution manipulations, then we should see accessibility affect diagnosticity (part-worths) when the attribution is absent but not when it is present. This prediction suggests a similar pattern to study 1A and 1B when the attribution is absent (only a boost to the final attribute's part-worth in the

Single condition and relative null effects, if at all, on the other attributes), but a smaller effect on the fourth attribute's part-worth in the Single condition when the attribution is present. This manipulation would be akin to increasing the value of the constant *k* in equation 3b to mitigate our saliency manipulation (or affecting the impact of δ). However, if this interaction is absent, then people may unintentionally use salience as a cue to part-worth valuation. Yet, interpreting null effects is difficult, so that interpretation is less straightforward.

Method

Participants from Amazon Mechanical Turk (N = 369) were randomized into one cell of a 4 (Order) x 2 (Condition: Single or Multiple) x 2 (Attribution: Present or Absent) between-subject design.

The study was akin to Study 1A with one major exception: participants in the Attribution Present condition also saw a screen before the learning phase that asked them to think carefully about their long-run valuation of attributes, and warned them that their immediate reactions would be. Specifically, this text said:

> "When determining your willingness to pay values, please think of how you value each attribute level in the long run—how might you value each attribute beyond the confines of this study?
>
> Do not be mislead by your immediate reactions, as these may sometimes be influenced by unimportant aspects of the task, such as which attributes are first or

last. After reading about each attribute level for each car, please take a moment to pause before stating your willingness to pay."

Results

The Effect of Accessibility on Diagnosticity (H2). Again supporting H2, the pattern of means in Table 6 (and shown collapsing over the attribution conditions in Figure 9A and 9B) reflects the predicted effect of the salience manipulation but not the attribution manipulation. In both attribution-absent and attribution-present conditions, we see a boost in the part-worth of attribute four in the Single condition compared to the Multiple condition. However, the less salient attributes in the Single conditions, attributes 1-3, did not receive this shift. Therefore, we find results directionally in line with our predictions.

Additionally, we observe the position effect in which the top attribute and bottom attribute are larger or similarly sized (with a few exceptions) compared to the second and third attributes in learning and test phases. This result remains consistent with accessibility contaminating diagnosticity despite each attribute's semantic identity (i.e., MPG, warranty) being counterbalanced across the between-subject order manipulation.

Statistical Tests for Learning Phase. In the learning phase, a 4 (Attribute) x 2 (Condition) x 4 (Order) x 2 (Attribution: Yes or No) mixed ANOVA did not find a significant interaction or attribute with condition or attribution ($p > .9$). This is not consistent with our predictions suggesting that the attribution condition could mitigate our salience manipulation. However, we did find directional evidence for our attribution manipulation inasmuch as the gap between the single and multiple conditions was larger on the fourth attribute without an attribution, as shown in Table 6.

Notwithstanding our attribution manipulation, we did find more evidence of the results from Study 1A and 1B, as depicted in Figure 9A.

Consistent with our predictions, we observe a significant condition by attribute interaction ($F(3, 353) = 4.19$, $p = .006$). In support of H2, the fourth attribute the Single condition had a larger part-worth ($M = 4.03$) than in the Multiple condition ($M = 2.67$; $F(1, 353) = 16.47$, $p < .001$). Yet, this was not the case for attributes one ($M_{Single} = 3.42$, $M_{Multiple} = 3.66$; $F(1, 353) = .35$, $p = .55$), two ($M_{Single} = 2.97$ vs. $M_{Multiple} = 2.91$; $F(1, 353) = .03$, $p = .87$), or three ($M_{Single} = 1.66$ vs $M_{Multiple} = 1.58$; $F(1, 353) = .05$, $p = .82$). This interaction was reflected in a significant contrast interacting attributes 1-3 versus 4 and condition ($F(1, 353) = 12.41$, $p < .001$).

Study 2's attribute position effects in the learning phase also provided consistent evidence for boosts to top and bottom positions ($F(3, 353) = 23.40$, $p < .001$). This result emerged in a significant contrast between the first ($M = 3.54$) and fourth ($M = 3.35$) positions, and the second ($M = 2.94$) and third ($M = 1.62$) positions ($F(1, 353) = 39.34$, $p < .001$). In line with heightened diagnosticity to the top attribute, the first attribute part-worth was again larger than the second's part-worth ($F(1, 353) = 5.06$, $p = .025$) and the third's part-worth ($F(1, 353) = 43.93$, $p < .001$), yet it had only a small jump over the fourth attribute's part-worth ($F(1, 353) = .46$, $p = .50$). The second attribute's part-worth was larger than the third's part-worth ($F(1, 353) = 32.26$, $p < .001$), but the fourth attribute's part-worth was directionally larger than the second's part-worth ($F(1, 353) = 2.95$, $p = .087$). Finally, the fourth attribute's part-worth was significantly larger than the third attribute's part-worth ($F(1, 353) = 55.72$, $p < .001$).

Statistical Tests for Test Phase. In the test phase, a similar pattern emerged as in the learning phase from a 4 (Attribute) x 2 (Condition) x 4 (Order) x 2 (Attribution: Yes or No) mixed ANOVA. While the aforementioned triple interaction among condition, attribute, and attribution was not significant ($p > .9$), the gap on the part-worth for attribute four between the Single and Multiple conditions was larger in the no attribution conditions ($M_{Single} = 3.44$ vs. $M_{Multiple} = 2.31$) compared to the attribution conditions ($M_{Single} = 2.95$ vs. $M_{Multiple} = 2.32$).

However, consistent with H2, our prior studies and the learning phase of this study, the fourth attribute the Single condition again had a larger part-worth ($M = 3.19$) than in the Multiple condition ($M = 2.32$; $F(1, 353) = 7.08$, $p = .008$). Yet, this was not the case for attributes one ($M_{Single} = 2.71$, $M_{Multiple} = 2.43$; $F(1, 353) = .73$, $p = .39$), two ($M_{Single} = 2.44$, $M_{Multiple} = 2.34$; $F(1, 353) = .08$, $p = .78$), or three ($M_{Single} = 1.29$, $M_{Multiple} = 1.73$; $F(1, 353) = 1.66$, $p = .20$). The interaction between condition and attribute was again significant ($F(3, 353) = 2.48$, $p = .061$; Figure 9B), which was also reflected in the contrast interaction between attributes 1-3 and four, and condition when collapsing over the attribution (present, absent) conditions similarly being significant ($F(1, 353) = 5.51$, $p = .019$). Therefore, although the attribution manipulation did not consistently reduce the size of the effect, we replicate our prior results again.

Study 2's attribute position effects in the test phase again favored top and bottom attributes in the variation among attributes from its omnibus main effect from the aforementioned ANOVA ($F(3, 353) = 9.71$, $p < .001$). We again drew a contrast comparing the first ($M = 2.57$) and fourth ($M = 2.76$) positions against the second ($M = 2.39$) and third ($M = 1.51$) attributes, which was again significant ($F(1, 353) = 16.57$, $p < .001$). Consistent with a top effect, first attribute was only directionally larger than the second attribute part-worth ($F(1, 353) = .61$, $p = .44$), but it was significantly larger than the third attribute part-worth ($F(1, 353) = 18.99$, $p < .001$). It was nonsignificantly lower than the fourth attribute's part-worth, however ($F(1, 353) = .69$, $p = .41$). The second attribute was also larger than the third ($F(1, 353) = 12.22$,

$p < .001$), and the fourth attribute was larger than the third ($F(1, 353) = 26.05$, $p < .001$). However, the fourth attribute's part-worth was only directionally (but nonsignificantly) larger than the second's part-worth ($F(1, 353) = 2.23$, $p = .14$).

Discussion

Study 2 demonstrates (albeit weak) preliminary evidence that a combination of encouraging increased processing depth and attribution of immediate reactions to the order of attributes on the page somewhat reduces the effect of increased salience. By questioning the diagnosticity created by accessibility, we find directional but nonsignificant evidence of attenuation by which attributes with greater salience no longer receive as much of a boost through salience.

However, given that there was still a boost in the attribute part-worth when salience was increased, it is possible that people have a difficult time naturally overriding the effect. There were still attribute position effects in the attribution conditions despite explicit warning to be cognizant of attribute position, which suggests people may under-adjust bias.

STUDY 3: TRAINING

In Study 3, we address whether people can overcome the effect of accessibility influencing diagnosticity by becoming acclimated to the decision environment through training. We duplicated the first 16 judgments from the study into a second set of 16 judgments in two additional test phases. Each test phase (test phase II, test phase III) had eight judgments (one judgment per page) in one common order for participants, and these phases followed the initial learning and test phases found in the previous study.

If participants are able to overcome the effect through training, the relative size of the effect of accessibility (from the Single versus Multiple manipulation) should decline between the learning phase attribute part-worths and test phase III's attribute part-worths. We quantify this effect by comparing the fourth attribute value against the average of the first, second, and third attributes. This value should be higher for the Single condition relative to the Multiple condition because the former increases the fourth attribute valuation compared to the other attributes.

We also handle a potential confound from the previous studies. In those studies, the learning and test phases always had the same eight products. In this study, we developed a new set of designs for a Single and Multiple condition using the products from the test phase, and a new test phase using the products from the learning phase. This counterbalancing ensures our results are not particular to what products (of the 16 possible combinations of four attributes with two levels each) are present in the learning phase.

Method

Participants from Amazon Mechanical Turk (N = 823) were randomized into one cell of a 4 (Order) x 2 (Condition: Single or Multiple) x 2 (Learning Stimuli: Original or Test) between-subject design.

The study used the same layout as Study 1B without the dummy attribute from the Single and Multiple_{1B} conditions for the cars product category.

Participants randomly received either the same design matrix as the previous studies (Learning Stimuli: Original condition), or a different design matrix in which the Single and

Multiple conditions were constructed using the products from the Test phase (Learning Stimuli: Test condition). This counterbalancing of what products were in learning and test phase reduces the likelihood that our results are a design confound.

Participants, in addition to making the initial set of 16 judgments from the previous studies, also completed two test phases: test phase II, which duplicated the judgments from the learning phase, and test phase III, which duplicated the judgments from the test phase. These phases had one judgment per page for eight pages each for the eight products.

Results

For simplicity, we compute one dependent measure to illustrate the size of the effect for each phase (learning, test I, test II, and test III) of the study. This dependent measure examines the percentage-size of each attribute valuation and subtracts the mean of attributes one, two, and three from attribute four. This dependent measure depicts the size of the effect of accessibility on diagnosticity because the relative boost to attribute four is contrasted against attributes one, two, and three, which should yield a larger effect in the Single condition (in which attribute four has a boost in valuation from the learning phase design) compared to the Multiple condition.

As shown in Figure 10A, consistent with training reducing the effect of accessibility from the learning phase, the size of the effect declines from the learning phase to test phase III. In the learning phase, the effect is much stronger in the Single condition compared to the Multiple condition. This effect declines for test phase I and test phase II, and is almost attenuated between the Single and Multiple conditions for test phase III (see Table 7). Additionally, the difference between the size of the effect in Single and Multiple appears larger in the learning phase compared to when the same eight products appear in test phase II. The same pattern holds true for test phase I and test phase III.

A 4 (Order) x 2 (Condition) x 2 (Learning Stimuli) x 4 (Phase) ANOVA yielded the critical phase (learning, test I, test II, or test III) by condition (Single or Multiple) interaction of interest ($F(3, 807) = 12.99$, $p < .001$), in addition to a main effect of condition ($M_{Single} = 1.36$, $M_{Multiple} = 0.44$; $F(1, 807) = 18.44$, $p < .001$). Importantly as well, the size of the Single versus Multiple manipulation is different between the learning phase and its duplication, test phase II ($F(1, 807) = 11.53$, $p < .001$), and between test phase I and its duplication, test phase III ($F(1, 807) = 8.70$, $p = .003$). Therefore, we find evidence that additional judgments in this task are associated with overcoming the nature of the accessibility manipulation.

Further, the nature of which products were used in the learning or test phase (I) did not meaningfully interact with condition ($F(1, 807) = .01$, $p = .907$), and did not exert a main effect either ($F(1, 807) = .00$, $p = .982$). We therefore do not find evidence for any confounds from the specific products used in our design matrix for the learning phase.

Replication with Third Attribute (Study 3B)

We also replicate Study 3 in a context in which we switch the design matrix for the third and fourth attribute. In this replication, instead of calling attention to the fourth attribute in the learning phase Single condition by having only the fourth attribute change within each page of two products, we direct people to the third attribute by making it the only one to change within a page in the Single condition. We therefore compute the size of the effect of accessibility onto diagnosticity based on subtracting the mean (percentage-adjusted) valuation from attributes one, two, and four from attribute three. 298 participants from Amazon Mechanical Turk completed this study for the cars product category.

The results, as depicted in Figure 10B (means in Table 7), replicate our pattern from Study 3: the size of the effect between Single and Multiple conditions declines from learning phase through test phase III. This result emerges through a marginal main effect of condition (M_{Single} = 0.96; $M_{Multiple}$ = 0.38; $F(1, 290) = 3.71$, $p = .055$) that is qualified by the key phase (learning, test I, test II, test III) x condition interaction ($F(3, 290) = 6.64$, $p < .001$). Further, the difference in the size of the effect in the Single and Multiple conditions is greater between the learning phase and when the same products appear in test phase II ($F(1, 290) = 8.58$, $p = .004$); the same is true for test phase I and test phase III ($F(1, 290) = 8.96$, $p = .003$). These results demonstrate the robustness of our effect across attribute positions (third instead of fourth).

Discussion

Study 3 demonstrates that training can help attenuate the effect of accessibility on diagnosticity. In two additional test phases, participants exhibited smaller effects of accessibility compared to the earlier learning phase and test phase. Therefore, experience with the stimulus-based environment can help overcome the impact of the Single versus Multiple manipulation.

These results also rule out a demand explanation of our effect. According to a demand explanation, participants infer that the experiment wants them to value the fourth (or in the case of Study 3B, third) attribute in the Single condition, which leads participants to overvalue it. However, this explanation is inconsistent with a decline in the size of the effect of accessibility because the demand explanation would suggest participants would continue to overvalue the fourth attribute in the Single condition.

GENERAL DISCUSSION

How do individuals scan the environment for product information to make decisions? Recent research into consumer behavior has seen an explosion in the number of papers examining how attentional processes contribute to an understanding of product consideration and choice (Atalay et al. 2012; Chandon et al. 2009; Townsend and Kahn 2014).

Several decades of research into consumer decision-making have tried to answer how consumers integrate informational inputs to make judgments (Anderson 1970; Birnbaum 2008; Lynch 1985; Priester et al. 2004; Wilkie and Pessemier 1973). While normatively there should be some proper weighting of crucial attributes with systematic processing, people instead typically employ decisions rules that shift which attributes receive attention (Bettman et al. 1998; Payne et al. 1993). These rules lead to bias and shifts from perfect rationality (Tversky and Kahneman 1974).

In the face of less well-defined preferences, one framework to explain what inputs people use in judgments is the accessibility-diagnosticity framework (Feldman and Lynch 1988; Lynch et al. 1988). According to this framework, relatively accessible inputs in memory (based on recency and frequency) may become evaluated based on their diagnosticity (i.e., perceived validity) before ultimately being employed in judgment. However, this framework assumes a feed-forward progression of accessible inputs into diagnosticity without further interaction among the factors.

Whereas the previous framework suggests accessibility merely feeds into diagnosticity, principles of memory and attention suggest that accessibility and diagnosticity should interact to affect one another. The manner by which they affect one another may tap into multiple different mechanisms. For example, subjective ease during recall may itself become diagnostic (Alter and Oppenheimer 2009; Lynch 2006) or affect diagnosticity of arguments (Wänke and Bless 2000). Further, the relative importance of information may bias what is recalled (Alba and Hasher 1983) or to what elements of scenes people attend (Sullivan et al. 2012).

Three studies provide evidence of how accessibility (relative discriminability or salience of one attribute) may affect diagnosticity (attribute part-worths) in a stimulus-based environment. Specifically, we employ a conjoint task to test how accessibility may affect diagnosticity. While attributes with greater salience subsequently had greater part-worths, other attributes which had attention called away from them in that process had directionally lower part-worths. Beyond effects of our manipulation, attributes in prominent, top or bottom positions also had relatively higher part-worths than those attributes listed in the middle of the product description.

These results also suggest a corollary to prior findings on conjoint analysis, which argue that conjoint analysis reflects stable, top-down preferences (Meisner et al. 2016). To the contrary, we demonstrate stimulus-based manipulations can shift around attribute part-worths. However, we note that several differences exist between the studies in Meisner et al. (2016) and our work. First, they use more attributes with a greater number of levels. Second, they use a choice-based conjoint setup (Green et al. 2001), whereas we use a design closer to rating-based conjoint (Elrod et al. 1992). Third, whereas our manipulation is on the attribute part-worth level, they focus on position of three options and the relative choice share and number of fixations on of the central option as a test of stimulus-based, bottom-up contributions.

Implications for Theory

This work makes two major contributions to the theory of decision-making and information integration. First, it serves as a corrective to the previous instantiation of accessibility-diagnosticity (Feldman and Lynch 1988) by carving out the interactions among those two factors. Additionally, we expand the framework to stimulus-based decision-making. While all information is present in a stimulus-based decision environment, not all information is equally salient (Biederman et al. 1982; Henderson 2007; Itti and Koch 2001; Loftus and Mackworth 1978). Because humans have limited attentional capacity (Kahneman 1973; Lavie 2005; Shiffrin and Schneider 1977) or may not be motivated to process all of the information present (Hutchinson and Alba 1991), only select details may be integrated into the decision-making process.

Second, this theoretical advancement posits a different route by which papers may assess whether accessibility or diagnosticity account for their results. While past research has tried to isolate accessibility or diagnosticity as drivers of effects (Aaker 2000; Herr et al. 1991), our results suggest that studies need additional tests of how those factors may interact before assuming one factor alone accounts for the results. Further, it is not sufficient to argue merely that accessibility governs diagnosticity or vice-versa. Given the vast set of mechanisms by which accessibility and diagnosticity interact, it is necessary to test how certain types of accessibility (e.g., frequency, recency; chronic, temporary) influence diagnosticity.

Third, we push back on typical assumptions about conjoint analysis regarding the stability of what it's measuring (Meisner et al. 2016). While conjoint research attempts to reflect underlying preferences and valuation (Green et al. 2001; Wilkie and Pessmeier 1973), we also contend that some forms of conjoint may be susceptible to bottom-up factors. For example, even in the absence of our manipulation, we consistently find a primacy effect by which attributes listed first receive directionally higher part-worths than attributes in the middle of the list. Therefore, it should not be taken for granted that conjoint is reflecting the truth.

Boundary Conditions and Future Research

While we attempt to pose a general theory of information use, we recognize there are several boundary conditions to address that are also arable for future research.

First, our studies implement a type of rating-based conjoint that is less popular compared to more recent choice-based conjoint tasks (Elrod et al. 1992; Iyengar and Jedidi 2012; Meisner et al. 2016). These choice-based conjoint tasks might enable further tests of how our manipulation may influence what choice strategies people pursue (Bettman et al. 1998). The present salience manipulation may facilitate the use of compensatory or non-compensatory strategies, which may be better explored in a choice environment. Yet, we argue our context is still demonstrative of how the stated raw dollar part-worth of an attribute can change based on its position and salience.

Second, while this paper addresses the two factors from the original framework, it does not explicitly comment on the debate regarding constructed preferences (Bettman et al. 1998; Feldman and Lynch 1988). While the results suggest that temporarily salient information can affect preferences, which supports the constructionist view, we do not expand as deeply on that point as other pieces of the framework. Recent years have occasionally revisited whether preferences are stable, constructed, dual-faceted, or even inherent (Cohen and Reed 2006; Priester et al. 2004; Simonson 2008; Wilson et al. 2000), and whether chronically or temporarily accessible information is more likely to shape judgments (e.g., Schimmack and Oisho 2005). However, it is relatively less known how the strategies people employ may be more or less correlated with more stable versus more constructed preferences (for exceptions, see Amir and Levav 2008). Future work may wish to categorize what types of attentional patterns or information-search strategies are related to promoting more enduring versus more labile preferences through what becomes accessible, diagnostic, or the intersection of the two.

Third, other research should test how other dimensions of accessibility (i.e., principles of scene perception and memory retrievability) contaminate diagnosticity. While we highlight several dimensions of primacy, recency, fluency, and salience, there are other “flavors” of accessibility. For example, how does visual clutter affect diagnosticity? There are a rich set of mechanisms to explore to cohere the framework and unite many previously-separate research areas.

Ultimately, this research proposes an updated view of how individuals integrate information to make decisions by reconsidering a widely-regarded framework (Feldman and Lynch 1988; Lynch et al. 1988).

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Table 1
PRINCIPLES OF ACCESSIBILITY-DIAGNOSTICITY

Principle	Stimulus-based	Example	Memory-based	Example
Accessibility Alone				
Coarse/Fine	Scene perception from coarse to fine; Bruner coarse-to-fine viewings of pictures	Enns and MacDonald (2013); Schyns and Oliva (1994); Bruner and Potter (1964)	Natural categories, prototypicality	Rosch & Mervis (1975)
Overload	Visual crowding, information overload	Treisman and Gelade (1980); Louviere et al. (2008)	Interference effects; list-length effects	Murdock & Anderson (1975)
Similarity		Tversky (1977)	Typicality effects on recall	
Recency	Order effects		Decay of info over time	Higgins, Bargh, and Lombardi (1985)
Context/Congruence	Violations of knowledge/expectations during scene viewing	Biederman (1972); Biederman et al. (1982)	Temporal Context Model; context-dependent learning; superior recall for chess masters only with realistic boards; better recall of novel info; better recall of higher family resemblance	Kahana (2012); Mercurio and Forehand (2011); Chase and Simon (1973); Rosch and Mervis (1975); Estes (1955); McGeoch (1932)
Diagnosticity Alone				
Task-related goals	Choice models (EBA); conjoint task structure	Tversky (1972)	Information integration theory	Anderson (1971)
Similarity	Representativeness of feelings dictate use in judgment	Tversky (1977); Greifeneder, Bless, and Pham (2011)		
Accessibility → Diagnosticity				
Context/Congruence	Familiarity improves navigation; cue-dependent learning	Park et al. (1989); Shimp, Stuart, and Engle (1991)	Interpret categories or stories based on context	Roth and Shoben (1983)
Fluency	Fluently presented text has a wide range of behavioral effects	Alter and Oppenheimer (2009); Labroo, Dhar, and Schwarz (2008); Unkelbach (2006, 2007); Whittlesea (1993); Kelley and Lindsay (1993)	Priming of similar concepts to be retrieved; ease-of-retrieval	Whittlesea (1993); Schwarz et al. (1991)
Diagnosticity →				

Accessibility				
Importance	Scene Perception: examine more "informative" regions first	Antes (1974); Buswell (1935)	Important details recalled earlier & more frequently	See Alba and Hasher (1983)
Valence	Attention disruption by negative information; higher weight to negative info	MacLeod (1991); Birnbaum (1974)	Improved recall for negative information	Impression formation (Anderson 1971; Lingle and Ostrom 1979)
Inhibition of Competition	Screening of irrelevant stimuli; inhibition of return	Treisman and Gelade (1980)	Inhibition of other unrelated concepts from priming; negative effect compared to novel info	Brenner (1971); Detterman (1975)
Typicality	Look at unexpected or interesting areas	Loftus and Mackworth (1978)	Every category finding ever; recall of story happens according to typicality; recall of minority vs. majority	Bower et al. (1979); Mandler (1978); Bargh and Thein (1985); Hutchinson et al. (1994)
Goal Effects	Attention focused to particular areas of the scene based on goals; task goals change local/global switches and what's seen	Hayhoe and Ballard (2005); Land and Hayhoe (2001); Sullivan et al. (2012); Yarbus (1967)	Related means more accessible based on goal activation; use of goals for category recall	Shah and Kruglanski (2003); Barsalou (1985)
Congruence	Task response mode: choice versus rating changing focus of attribute weights	Tversky, Sattath, and Slovic (1988)		

Table 2A

DESIGN MATRIX FOR LEARNING PHASE OF MULTIPLE CONDITION

Page	Product	Attribute 1	Attribute 2	Attribute 3	Attribute 4
1	1	+1	+1	+1	+1
1	2	-1	-1	+1	-1
2	3	-1	+1	-1	-1
2	4	-1	-1	+1	+1
3	5	+1	-1	-1	-1
3	6	-1	+1	-1	+1
4	7	+1	-1	-1	+1
4	8	+1	+1	+1	-1

Table 2B

DESIGN MATRIX FOR LEARNING PHASE OF SINGLE CONDITION

Page	Product	Attribute 1	Attribute 2	Attribute 3	Attribute 4
1	4	-1	-1	+1	+1
1	2	-1	-1	+1	-1
2	3	-1	+1	-1	-1
2	6	-1	+1	-1	+1
3	5	+1	-1	-1	-1
3	7	+1	-1	-1	+1
4	1	+1	+1	+1	+1
4	8	+1	+1	+1	-1

Table 2C

DESIGN MATRIX FOR TEST PHASE FOR BOTH CONDITIONS

Page	Product	Attribute 1	Attribute 2	Attribute 3	Attribute 4
1	9	+1	-1	+1	-1
2	10	-1	+1	+1	+1
3	11	+1	+1	-1	-1
4	12	+1	+1	-1	+1
5	13	-1	-1	-1	-1
6	14	+1	-1	+1	+1
7	15	-1	-1	-1	+1
8	16	-1	+1	+1	-1

Table 3
ATTRIBUTES USED FOR EACH PRODUCT IN STUDY 1A, 1B, AND 2

Product	**Attribute**	**Low Level**	**High Level**
Cars	MPG	28	33
Cars	Sound System	Basic – 3 speakers, 1 subwoofer	Advanced – 9 speakers, 2 subwoofers
Cars	Safety Rating	3.5 Stars	4.5 Stars
Cars	Warranty	1 year	4 years
Cell Phone Plans	Monthly Data	1 GB	3 GB
Cell Phone Plans	Texts	100	Unlimited
Cell Phone Plans	Minutes	150	Unlimited
Cell Phone Plans	3-way calling	Unavailable	Available
Disney Vacations	Visit Length	3 days	5 days
Disney Vacations	Number of Disney Dinners	0	2
Disney Vacations	Hotel quality	2.5 stars	4 stars
Disney Vacations	Number of lines skipped per day	2	3
	Average Price	Low Price	High Price
Cars	$23,000	$16,000	$30,000
Cell Phone Plans	$80	$30	$130
Disney Vacations	$850	$600	$1100

Table 4
MEANS (STANDARD ERRORS) FOR STUDY 1A

	Learning Phase		Test Phase	
Attribute	**Single**	**Multiple**	**Single**	**Multiple**
1	5.43 (0.27)	5.98 (0.29)	4.46 (0.23)	4.65 (0.25)
2	4.5 (0.24)	4.81 (0.26)	3.82 (0.23)	4.18 (0.25)
3	3.59 (0.24)	4 (0.27)	2.37 (0.23)	2.75 (0.25)
4	6.61 (0.25)	3.94 (0.27)	5.57 (0.27)	3.88 (0.29)

Table 5
MEANS (STANDARD ERRORS) FOR STUDY 1B

	Learning Phase			Test Phase		
Attribute	**Single**	**Multiple**	**Multiple$_{1A}$**	**Single**	**Multiple**	**Multiple$_{1A}$**
1	4.23 (0.21)	5.05 (0.30)	4.76 (0.30)	3.43 (0.19)	4.15 (0.27)	4.39 (0.27)
2	3.16 (0.20)	4.74 (0.28)	4.42 (0.29)	2.98 (0.19)	3.48 (0.27)	3.49 (0.27)
3	1.9 (0.18)	3.03 (0.26)	3.16 (0.26)	2.14 (0.17)	2.86 (0.24)	2.6 (0.24)
4	5.49 (0.21)	4.5 (0.29)	4.1 (0.29)	4.39 (0.20)	4.05 (0.28)	3.84 (0.28)

Table 6
MEANS (STANDARD ERRORS) FOR STUDY 2

Attribute	**Attribution Absent**		**Attribution Present**	
	Learning Phase			
	Single	Multiple	Single	Multiple
1	3.11 (0.41)	3.44 (0.47)	3.72 (0.39)	3.88 (0.38)
2	2.90 (0.38)	2.96 (0.44)	3.04 (0.36)	2.85 (0.36)
3	1.83 (0.38)	1.63 (0.43)	1.50 (0.36)	1.52 (0.35)
4	4.20 (0.33)	2.70 (0.38)	3.87 (0.32)	2.64 (0.31)
	Test Phase			
	Single	Multiple	Single	Multiple
1	2.45 (0.33)	2.21 (0.38)	2.98 (0.31)	2.66 (0.30)
2	2.55 (0.36)	2.19 (0.42)	2.33 (0.35)	2.48 (0.34)
3	1.42 (0.34)	1.71 (0.39)	1.16 (0.32)	1.75 (0.32)
4	3.44 (0.33)	2.31 (0.38)	2.95 (0.31)	2.32 (0.31)

Table 7
MEANS (STANDARD ERRORS) FOR STUDY 3 AND 3B FOR SIZE OF EFFECT

Phase	Single	Multiple
	Study 3	
Learning	2.49 (0.18)	0.70 (0.18)
Test I	1.26 (0.19)	0.37 (0.19)
Test II	1.09 (0.19)	0.28 (0.19)
Test III	0.60 (0.18)	0.39 (0.19)
	Study 3B	
Learning	2.18 (0.34)	0.39 (0.34)
Test I	1.39 (0.28)	0.56 (0.28)
Test II	0.32 (0.30)	0.10 (0.30)
Test III	-.03 (0.26)	0.46 (0.27)

Figure 1
OUTLINE OF EXPERIMENTAL TASK

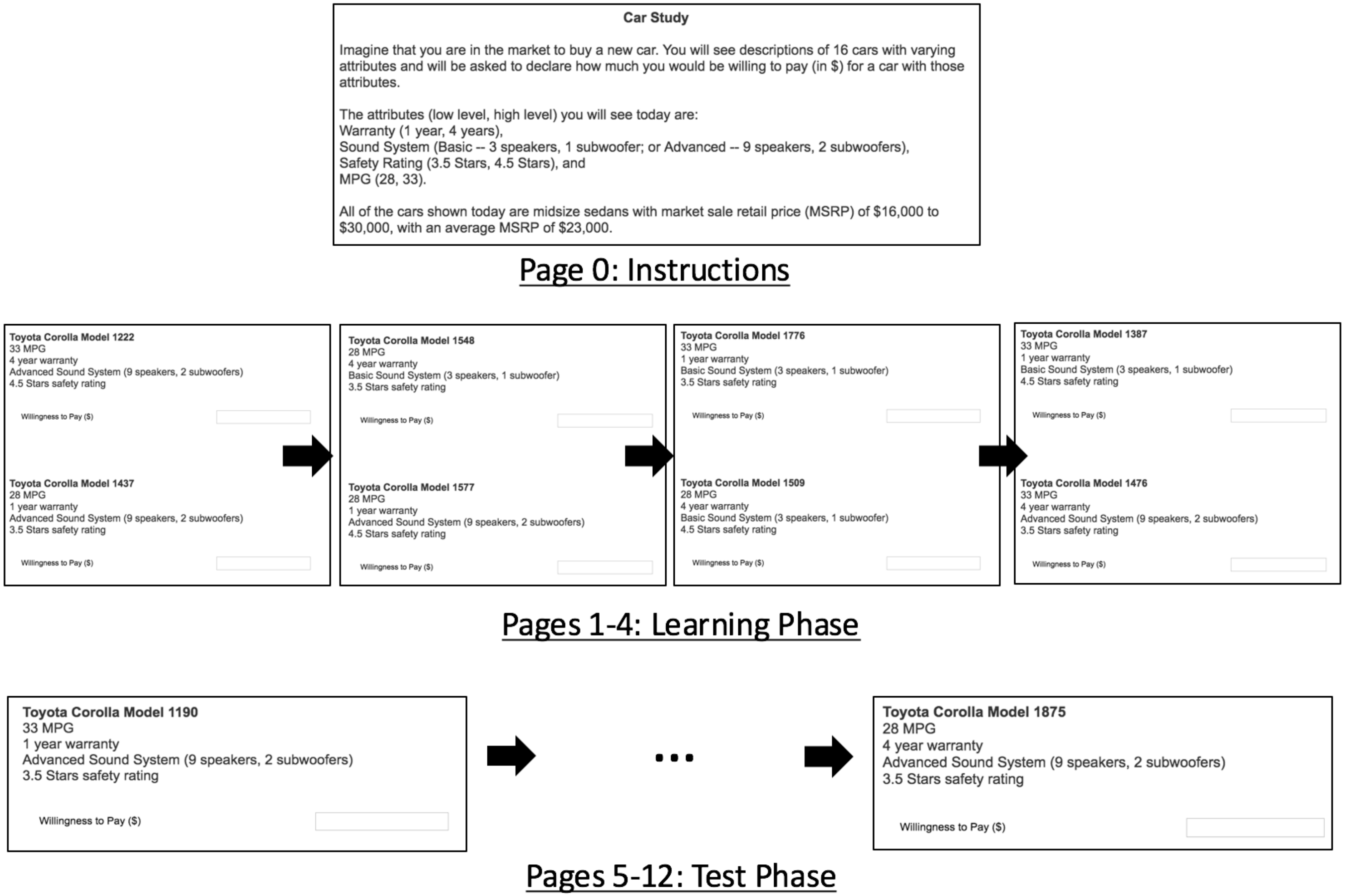
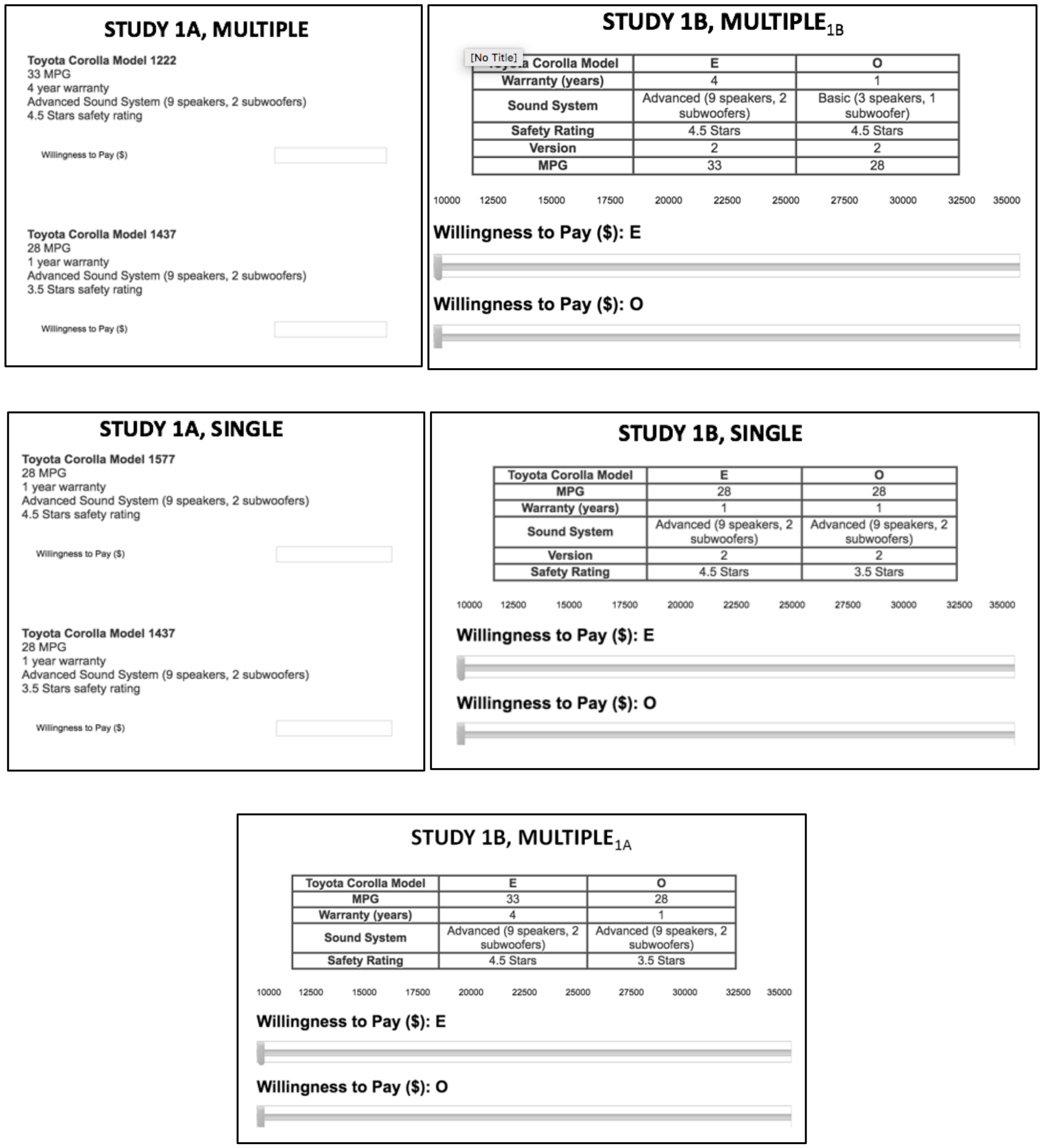


Figure 2

FIRST PAGE OF LEARNING PHASE IN EACH CONDITION



STUDY 1A, MULTIPLE

Toyota Corolla Model 1222
33 MPG
4 year warranty
Advanced Sound System (9 speakers, 2 subwoofers)
4.5 Stars safety rating

Willingness to Pay ($)

Toyota Corolla Model 1437
28 MPG
1 year warranty
Advanced Sound System (9 speakers, 2 subwoofers)
3.5 Stars safety rating

Willingness to Pay ($)

STUDY 1B, MULTIPLE$_{1B}$

[No Title] a Corolla Model	E	O
Warranty (years)	4	1
Sound System	Advanced (9 speakers, 2 subwoofers)	Basic (3 speakers, 1 subwoofer)
Safety Rating	4.5 Stars	4.5 Stars
Version	2	2
MPG	33	28

10000 12500 15000 17500 20000 22500 25000 27500 30000 32500 35000

Willingness to Pay ($): E

Willingness to Pay ($): O

STUDY 1A, SINGLE

Toyota Corolla Model 1577
28 MPG
1 year warranty
Advanced Sound System (9 speakers, 2 subwoofers)
4.5 Stars safety rating

Willingness to Pay ($)

Toyota Corolla Model 1437
28 MPG
1 year warranty
Advanced Sound System (9 speakers, 2 subwoofers)
3.5 Stars safety rating

Willingness to Pay ($)

STUDY 1B, SINGLE

Toyota Corolla Model	E	O
MPG	28	28
Warranty (years)	1	1
Sound System	Advanced (9 speakers, 2 subwoofers)	Advanced (9 speakers, 2 subwoofers)
Version	2	2
Safety Rating	4.5 Stars	3.5 Stars

10000 12500 15000 17500 20000 22500 25000 27500 30000 32500 35000

Willingness to Pay ($): E

Willingness to Pay ($): O

STUDY 1B, MULTIPLE$_{1A}$

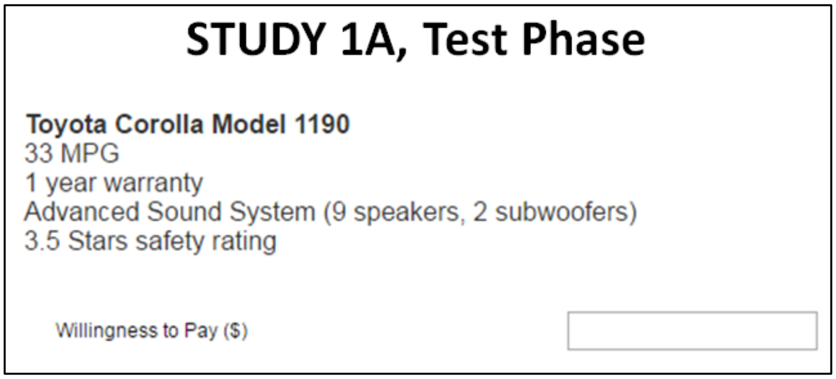
Toyota Corolla Model	E	O
MPG	33	28
Warranty (years)	4	1
Sound System	Advanced (9 speakers, 2 subwoofers)	Advanced (9 speakers, 2 subwoofers)
Safety Rating	4.5 Stars	3.5 Stars

10000 12500 15000 17500 20000 22500 25000 27500 30000 32500 35000

Willingness to Pay ($): E

Willingness to Pay ($): O

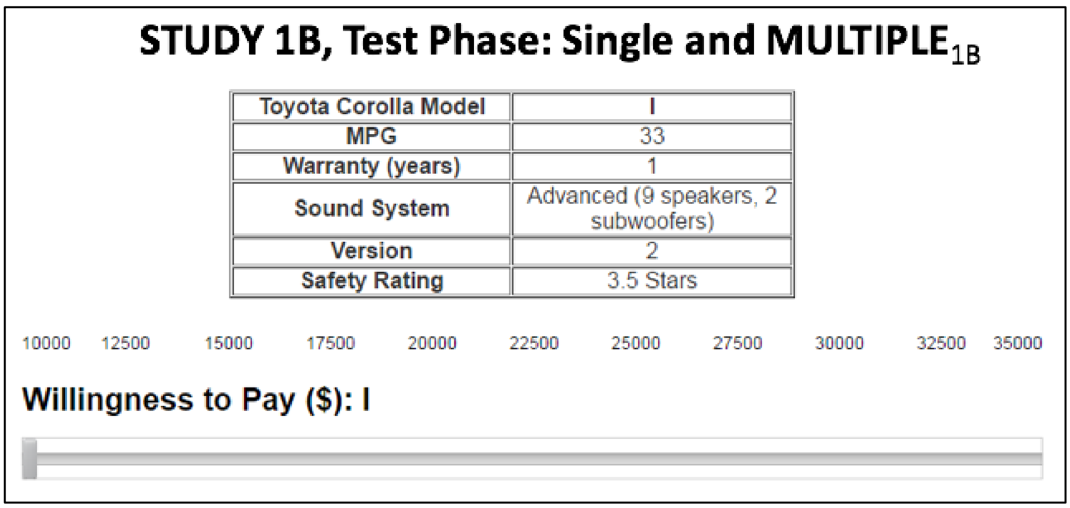
Figure 3
FIRST PAGE OF TEST PHASE IN EACH CONDITION



STUDY 1A, Test Phase

Toyota Corolla Model 1190
33 MPG
1 year warranty
Advanced Sound System (9 speakers, 2 subwoofers)
3.5 Stars safety rating

Willingness to Pay ($)

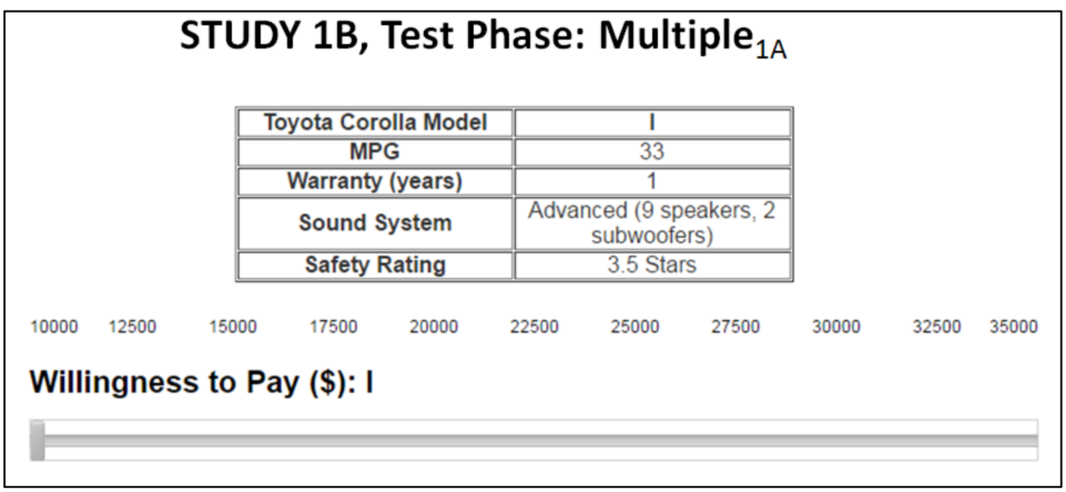


STUDY 1B, Test Phase: Single and MULTIPLE$_{1B}$

Toyota Corolla Model	I
MPG	33
Warranty (years)	1
Sound System	Advanced (9 speakers, 2 subwoofers)
Version	2
Safety Rating	3.5 Stars

10000 12500 15000 17500 20000 22500 25000 27500 30000 32500 35000

Willingness to Pay ($): I



STUDY 1B, Test Phase: Multiple$_{1A}$

Toyota Corolla Model	I
MPG	33
Warranty (years)	1
Sound System	Advanced (9 speakers, 2 subwoofers)
Safety Rating	3.5 Stars

10000 12500 15000 17500 20000 22500 25000 27500 30000 32500 35000

Willingness to Pay ($): I

Figure 4
CURRENT PARADIGM FOR UPDATED ACCESSIBILITY-DIAGNOSTICITY FRAMEWORK

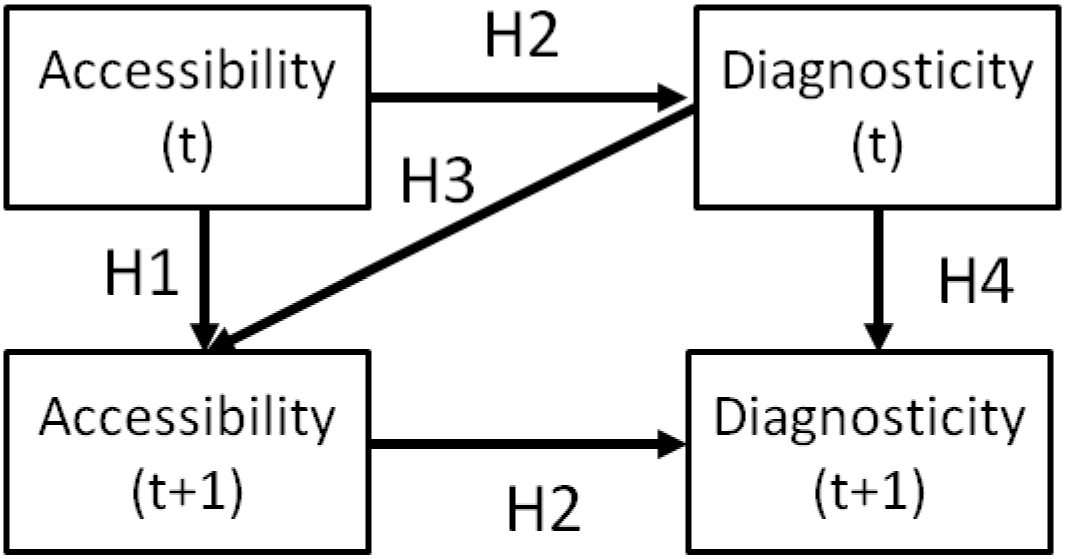
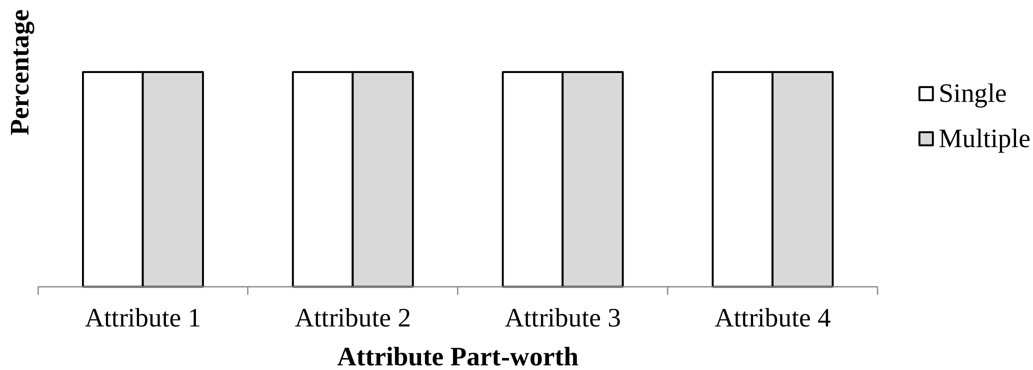


Figure 5
HYPOTHETICAL RESULTS GIVEN $\theta_{ba} = 0$ (DIAGNOSTICITY INDEPENDENCE: 5A) AND $\theta_{ba} > 0$ (5B)

5A



5B

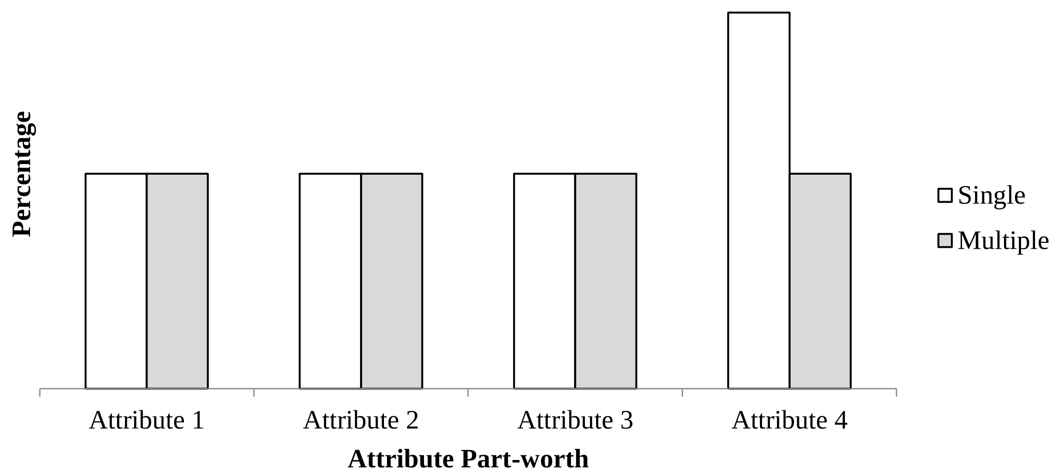


Figure 6
LARGER PART-WORTH (%) WEIGHTS ON ATTRIBUTE FOUR IN LEARNING (6A) AND TEST (6B) PHASES IN STUDY 1A

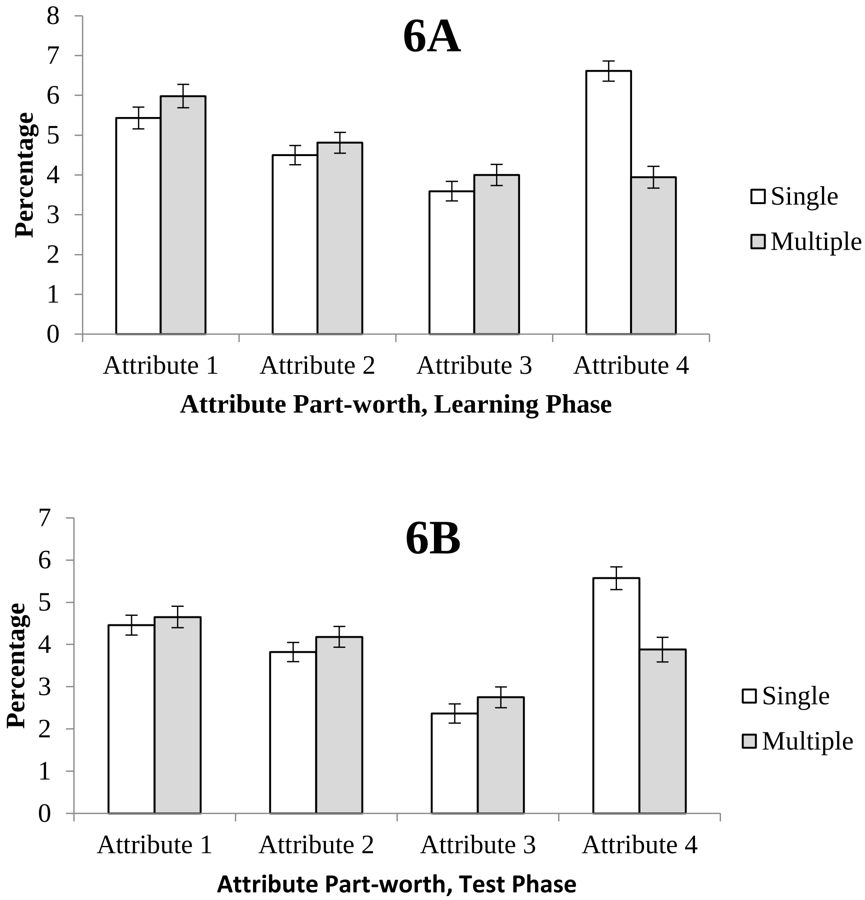
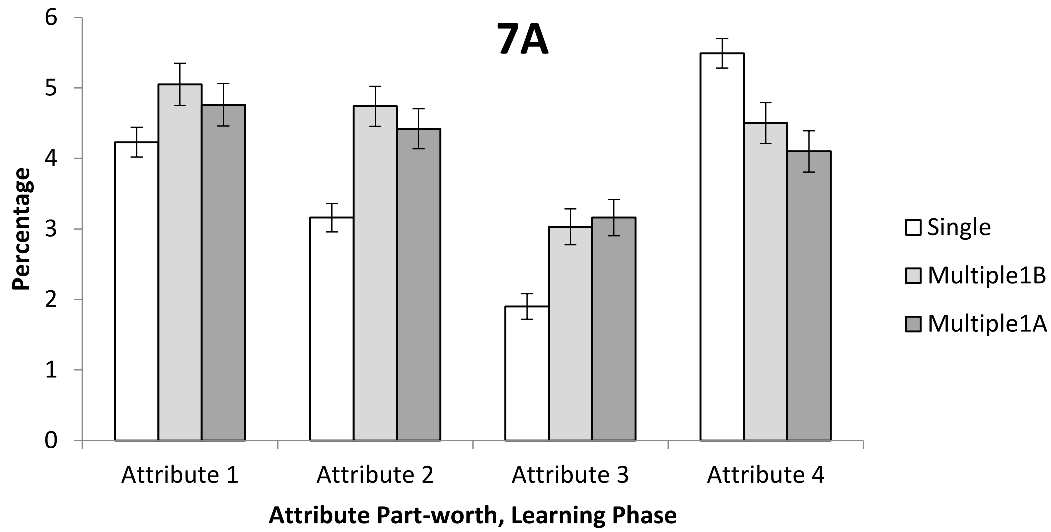


Figure 7
LARGER PART-WORTH (%) WEIGHTS ON ATTRIBUTE FOUR IN LEARNING (7A) AND TEST (7B) PHASES IN STUDY 1B



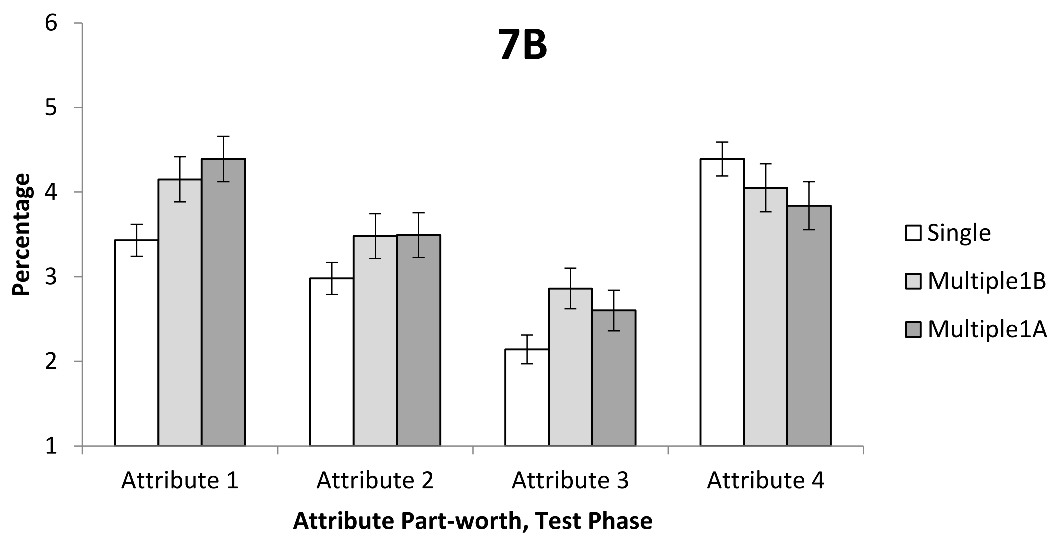
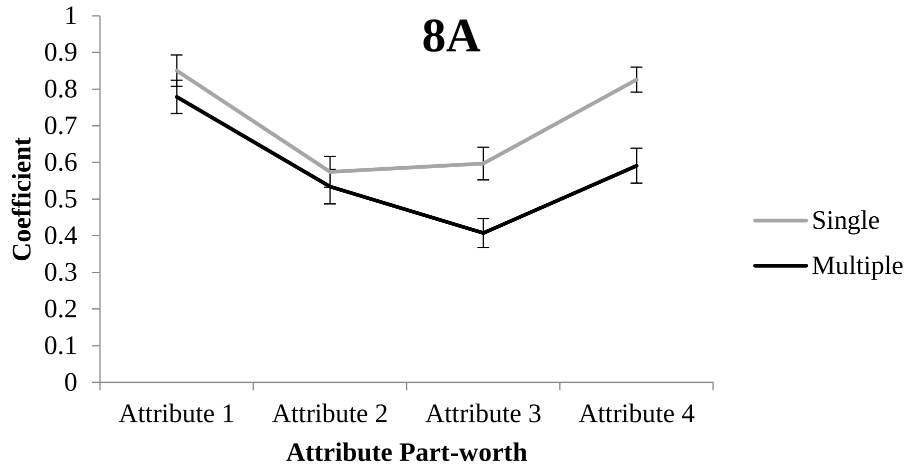


Figure 8
LARGER BETA COEFFICIENT ON ATTRIBUTE FOUR IN STUDY 1A (8A) AND STUDY 1B (8B)



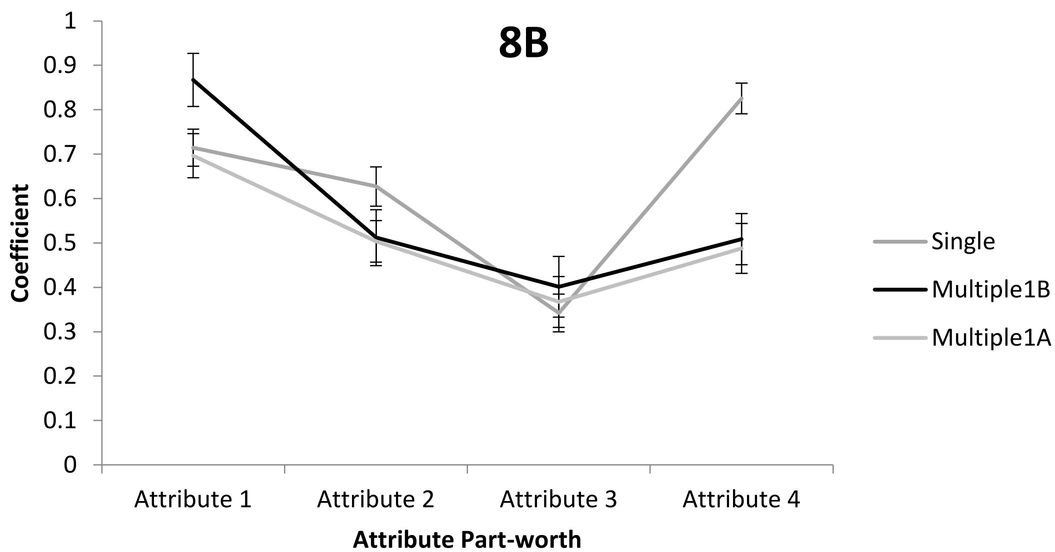
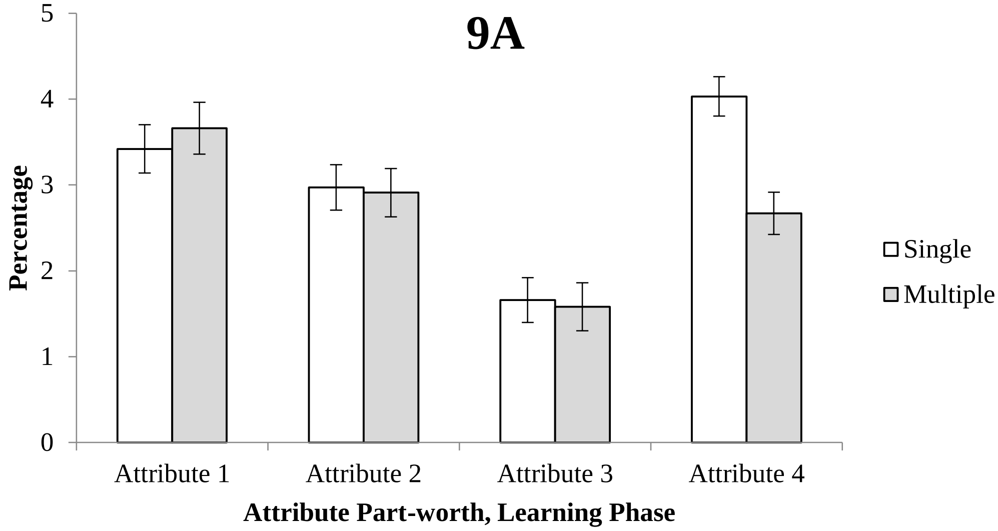


Figure 9
LARGER PART-WORTH (%) WEIGHTS ON ATTRIBUTE FOUR IN LEARNING (9A) AND TEST (9B) PHASES IN STUDY 2



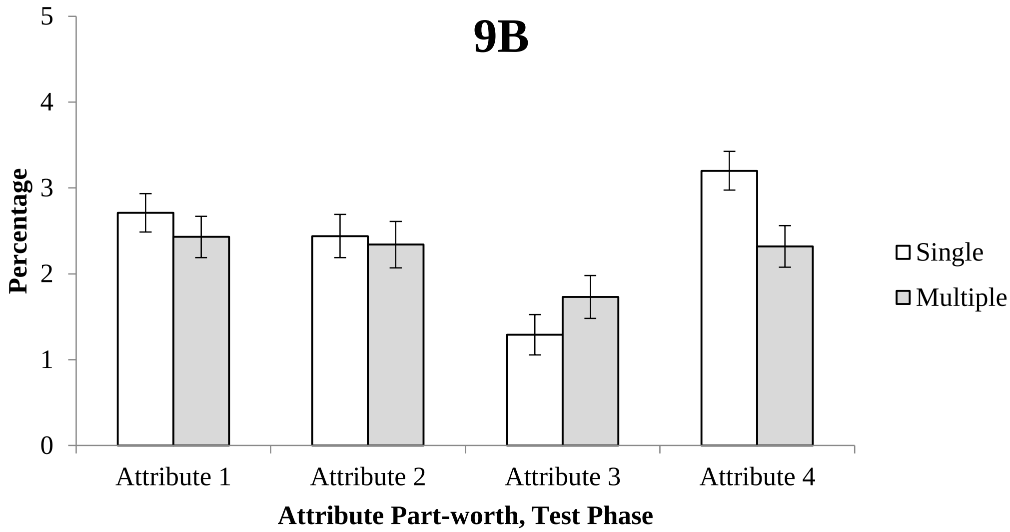
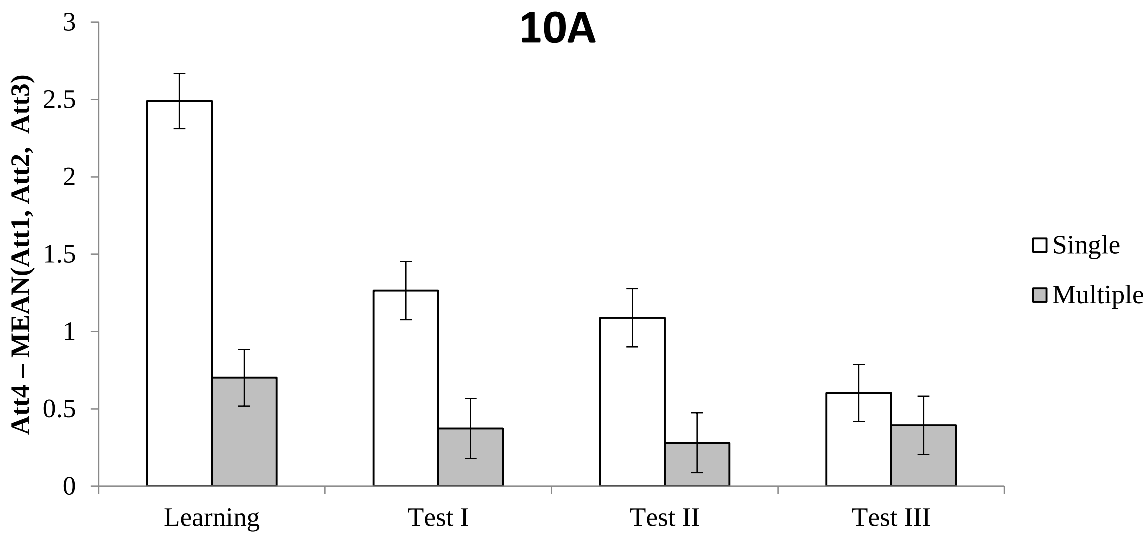
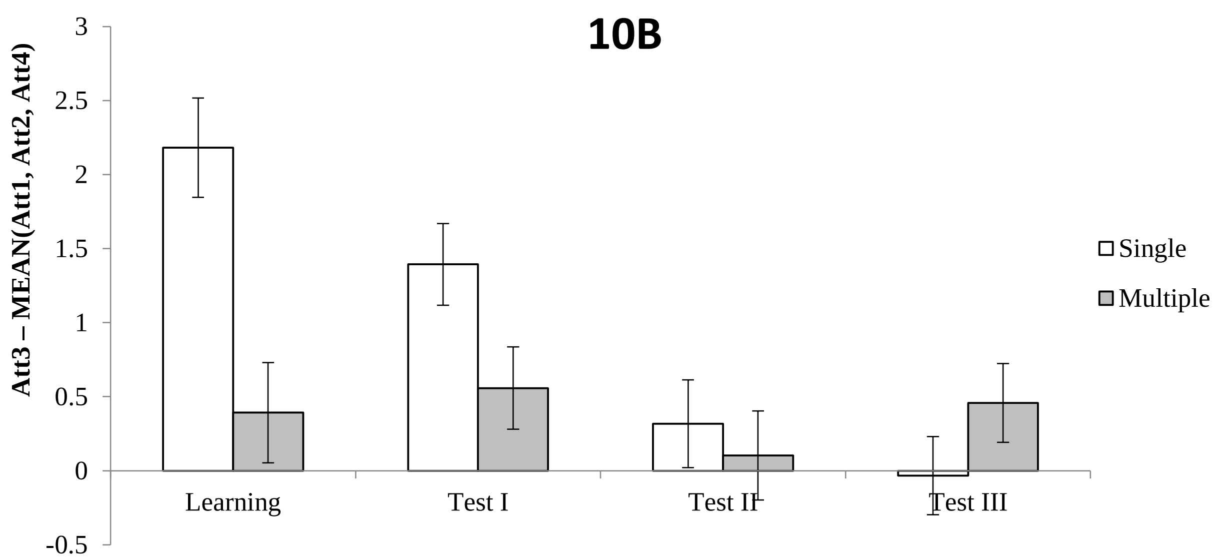


Figure 10
DECLINE IN SIZE OF EFFECT OVER TASK WHEN CALLING ATTENTION TO THE FOURTH ATTRIBUTE (10A) OR THE THIRD ATTRIBUTE (10B) IN STUDY 3





APPENDIX A: STUDY INSTRUCTIONS

STUDY 1A (CARS)

Car Study

Imagine that you are in the market to buy a new car. You will see descriptions of 16 cars with varying attributes and will be asked to declare how much you would be willing to pay (in $) for a car with those attributes.

The attributes (low level, high level) you will see today are:
Warranty (1 year, 4 years),
Sound System (Basic – 3 speakers, 1 subwoofer; or Advanced – 9 speakers, 2 subwoofers),
Safety Rating (3.5 Stars, 4.5 Stars), and
MPG (28, 33).

All of the cars shown today are midsize sedans with market sale retail price (MSRP) of $16,000 to $30,000, with an average MSRP of $23,000.

Please take your time and be sure to think carefully about each judgment you make in this task and to list valid willingness to pay (WTP) numbers. Note that, obtaining more than a 10% discount off the MSRP is very rare and, in addition to buying a car for yourself, you might be willing to buy a car you do not like and then sell it. **<u>Thus, your WTP amount should reflect the MAXIMUM amount you would be willing to pay for the car, and you might either keep it for yourself or sell it for profit</u>**.

[Multiple Condition: We are especially interested in how people determine their valuations **<u>across attributes</u>**. While providing willingness to pay numbers, please be mindful of the tradeoffs across **<u>all of the attributes</u>**. Sometimes multiple attributes will change within or across pages, and it is important for you to figure out how much you value the improvements from **<u>low</u>** to **<u>high levels</u>** for **<u>each attribute</u>**.]

[Single Condition, MPG: We are especially interested in how people determine their valuation of **<u>MPG</u>**. While providing willingness to pay numbers, please be mindful of the values for **<u>MPG</u>**. Sometimes the value of **<u>MPG</u>** will change within or across pages, and it is important to figure out how much you value the improvement from **<u>28 MPG</u>** to **<u>33 MPG</u>** for **<u>MPG</u>**.]

Please click “Next” to begin.

STUDY 1B INSTRUCTIONS (CARS)

Car Study

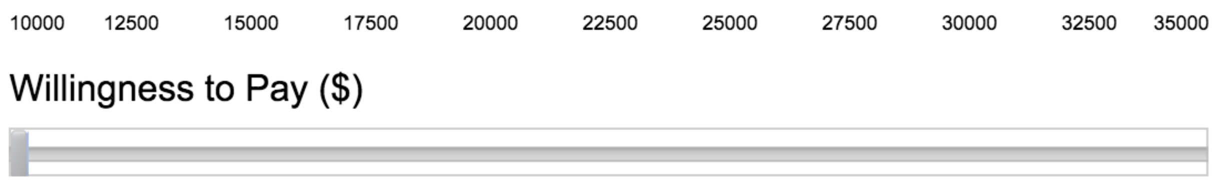
Imagine that you are in the market to buy a new car. You will see descriptions of 16 cars with varying attributes and will be asked to declare how much you would be willing to pay (in $) for a car with each of those attributes.

The attributes (low level, high level) you will see today are:
Warranty (1 year, 4 years),
Sound System (Basic – 3 speakers, 1 subwoofer; or Advanced – 9 speakers, 2 subwoofers),
Safety Rating (3.5 Stars, 4.5 Stars), and
MPG (28, 33).

Please click “Next” to continue.
==Next page==
You will be indicating your willingness to pay (WTP) for each of these products on the scale below. That is, you will be rating the maximum price you would pay. For example, suppose you wanted to buy a laptop with 15” display and a light weight, and the maximum price you would pay is $1,000. In this task, you would indicate $1,000 as your willingness to pay.

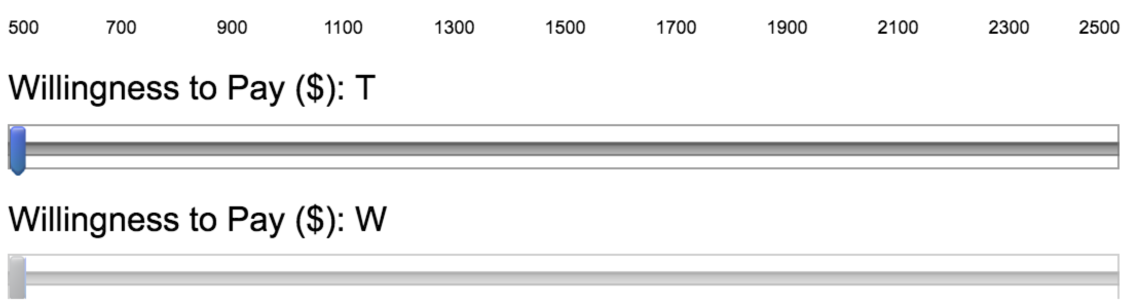
On each page you will be asked to indicate your willingness to pay (WTP) for two products.

Please click “Next” to continue.



==Next page==
An example set of judgments is shown below for two laptops. Please indicate your willingness to pay (WTP) for each of the below laptops.

Laptop Model	T	W
Processor Speed	1.9 GHz	3.2 GHz
Hard Drive Space	320 GB	500 GB
Screen Size	12"	15"



==Next page==
All of the cars shown today are midsize sedans with market sale retail price (MSRP) of **$16,000** to **$30,000**, with an average MSRP of **$23,000**.

Note that, obtaining more than a 10% discount off the MSRP is very rare and, in addition to buying a car for yourself, you might be willing to buy a car you do not like and then sell it. **Thus, your WTP amount should reflect the MAXIMUM amount you would be willing to pay for the car, and you might either keep it for yourself or sell it for profit**.

Please click "Next" to begin.