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The implications of Willingness to Pay of Respondents Ignoring Specific Attributes

By

David A Hensher, John Rose & William H Greene*

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*William H. Greene, Department of Economics, Stern School of Business, New York University, New York USA
wgreene@stern.nyu.edu

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ABSTRACT: Individuals processing the information in a stated choice experiment are typically assumed to evaluate each and every attribute offered within and between alternatives, and to choose their most preferred alternative. However, it has always been thought that some attributes are ignored in this process for many reasons, including a coping strategy to handle one's perception of the complexity of the choice task. Nonetheless, analysts typically proceed to estimate discrete choice models *as if* all attributes have influenced the outcome *to some degree*. The cognitive processes used to evaluate trade-offs are complex with boundaries often placed on the task to assist the respondent. These boundaries can include prioritising attributes and ignoring specific attributes. In this paper we investigate the implications of bounding the information processing task by attribute elimination through ignoring one or more attributes. Using a sample of car commuters in Sydney we estimate mixed logit models that assume all attributes are candidate contributors, and models that assume certain attributes are ignored, the latter based on supplementary information provided by respondents. We compare the value of travel time savings under the alternative attribute processing regimes. Assuming that all attributes are not ignored and duly processed, leads to estimates of parameters which produce significantly different willingness to pay (WTP) to that obtained when the exclusion rule is invoked.

KEY WORDS: ***Stated choice designs, relevance, complexity, information processing, willingness to pay***

AUTHORS: David A Hensher, John Rose & William Greene

CONTACT: Institute of Transport and Logistics Studies (Sydney)
The Australian Key Centre in Transport Management, (C37)
The University of Sydney NSW 2006 Australia

Telephone: +61 9351 0071
Facsimile: +61 9351 0088
E-mail: itsinfo@its.usyd.edu.au
Internet: http://www.its.usyd.edu.au

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1. Introduction

Stated choice (SC) methods are used extensively in many application contexts to reveal the willingness to pay for specific attributes. Within the SC setting, sampled individuals typically assess a number of alternatives defined by a set of attributes, each of which is offered as a level drawn from a pre-specified set of levels and range of levels. They are asked to choose the most preferred alternative (which may also include the option to choose none of the offered alternatives). This assessment is repeated a number of times up to the total number of choice sets being offered. The data are then subject to econometric modelling techniques such as multinomial logit (MNL) and mixed logit.

Stated Choice experiments typically are based on a pre-specified design plan with respect to the number of attributes (including their levels and range), the number of alternatives in a choice set and the number of choice sets to be assessed. While some studies allow for variation in some of these design dimensions, it is common for all sampled individuals to be given the exact same design. While this is not necessarily a failing of a study, it does raise questions about the influence that the SC design has on the behavioural outputs of discrete choice models such as willingness to pay (WTP) measures. With no variation in the dimensionality of the design, it is not possible to assess what influence the design *per se* has on WTP. Does the design impact in some systematic or non-systematic way on the parameters associated with each attribute and hence WTP? Is the impact stronger with respect to the mean or the variance associated with estimated parameters and the random component of each alternative's utility expression? A number of these questions have been investigated in Malhotra (1982), Swait and Adamowicz (2001a,b), White et al. (1998), Louviere *et al*. (2002), Hensher (in press, 2004) and DeShazo and Fermo (2004) with supporting evidence of design bias, although none of the studies investigated the implications on estimation of attribute marginal (dis)utilities, and hence WTP, of attribute inclusion or exclusion.

In the typical stated choice study (see Hensher in press, 2004) it is assumed that all presented attributes are attended to in the assessment of the alternatives. However, it is quite possible that individuals assess choice situations in many different ways, through a variety of information processing (IP) strategies that might include one or more of the following: (i) ignoring[1] specific attributes as a coping strategy in order to deal with the perceived 'complexity' of a SC experiment, (ii) deciding that the benefits of evaluating a specific attribute are not greater than the costs of evaluating it, and (iii) not attending to an attribute because it is truly not relevant in influencing the choice made. It is reasonable to propose that there exist a number of attribute processing styles invoked by different individuals in evaluating SC settings, including the strategy of ignoring or not attending to certain attributes (for whatever reason). Failure to account for such an attribute processing strategy is tantamount to assuming that all designs are comprehensible, all design attributes are relevant (to some degree) and/or the design has accommodated the relevant amount of complexity necessary to make the choice experiment meaningful. It is also important to recognise that complexity is not strictly defined by the quantity of information to process, with more information suggesting greater complexity. Designs with a small number of attributes and alternatives may, for some individuals, be 'complex' if an individual expects more information that they know is relevant in making such a choice in a real market setting.

[1] The word 'ignored' and the phrase 'not attending to' are treated herein as interchangeable.

In this paper we investigate the implications of an individual bounding the information processing task by attribute elimination through ignoring or not attending to them. In particular, we investigate the influence on WTP of an individual stating, after completion of the SC experiment, that they ignored one or more attributes, *for whatever reason*. While we would like to assume that the attributes were ignored because they were not behaviourally relevant, we acknowledge that such attributes may be ignored for a host of other reasons (e.g., task simplification). While one might debate the merits of alternative questions asked outside of the choice experiment to elicit the way that attributes are treated in a pre-choice behavioural processing strategy, this is left to ongoing research. Herein we are limited to one specific elicitation question as an example of how one might identify attribute preservation in the choice outcome.[2]

Using a sample of car commuters in Sydney, we estimate two mixed logit models; one that treats all attributes as candidate contributors, and one which explicitly recognises that subsets of attributes for each individual are ignored or not attended to in their choices (based on supplementary information provided by respondents). We compare the value of travel time savings (VTTS) under these two information (or pre-choice behaviour) processing regimes to demonstrate that we get significantly different mean valuations of travel time savings. The final section proposes some directions for ongoing research as well as highlighting the implications of the findings on the application of behavioural outputs from stated choice designs.

2. Attribute Processing Strategies

Some researchers (e.g., Heiner 1983, Swait and Adamowicz 2001a) suggest that an increase in choice set 'complexity' will compromise choice consistency, preventing the variation in choice responses from being explained by the underlying preference function. This is particularly problematic when the preference function assumes unlimited human capacity to process information of varying degrees of magnitude and quality in a costless and optimal (minimum effort) manner to arrive at a utility-maximising choice. Heiner argues that increasing choice 'complexity' would widen the gap between an individual's cognitive ability and the cognitive demands of the decision; which would lead to a restriction of the range of decisions considered. While this may satisfy a particular cognitive ability and produce greater predictability in the outcomes, they are not welfare maximising. What we see is an increase in unobserved influences on outcomes.

In reality individuals adopt a range of bounded rationality conditions as coping strategies to handle their perceptions of the 'complexity' of the choice task (e.g., DeShazo and Fermo 2004) The cognitive processes used to evaluate trade-offs are complex with boundaries often placed on the task to assist the respondent. This can include ignoring subsets of attributes, aggregating attributes (where feasible such as components of travel time), imposing thresholds on attribute levels, and conditioning one attribute on the level of other attributes. Given these strategies, analysts nonetheless

[2] Hopefully, this paper will encourage researchers to focus on the choice process that precedes the selection of a choice outcome in stated choice experiments. See DeShazo and Fermo (2004) and Hensher et al. (2004) for more details.

generally proceed to estimate discrete choice models as if all attributes have influenced the outcome *to some degree*.

In previous papers, Hensher (in press, 2004) and others (e.g., Swait and Adamowicz 2001a,b), have investigated the complexity of the choice task, identified in terms of the number of attributes, the number of choice sets, the number of levels of the attributes and the ranges of the attributes. Arentze *et al.* (2003) scrutinised the influence of task complexity in terms of the number of attributes, alternatives and choice sets presented, as well as the influence of presentation format (surveys with or without pictorial material) including the effects of considering a less literate population. They found that both the presentation method and the literacy level had no significant impacts, while task complexity had a significant effect on data quality.

Task 'complexity' can be represented by these 'raw' dimensions as well as by a range of representations broadly referred to as information load (a source of cognitive burden). The focus on choice 'complexity' is only interesting when viewed more broadly under what we call the information processing strategy (IPS) of a decision maker. It is important to consider that decision makers may differ in their information processing capacities as well as receptiveness to complex information. These differences will likely result in different levels of attention, interest or excitement to varying tasks and lead some decision makers to prefer 'less complex stimuli', whilst other decision makers may prefer more 'complex stimuli' (Berlyne 1960). Individual's use a range of IPS's according to their capability to process, which is linked to cognitive capability, commitment to effort etc. The variability in processing is often defined by constructs such as habit formation (e.g., Aarts and Dijksterhuis 2000, Aarts *et al*. 1997) and variety seeking (e.g., Khan 1995), both of which suggest mechanisms used to satisfy the individual's commitment of effort and cognitive abilities. If we knew what role these constructs played in behavioural response then we could design an SC experiment tailored to a specific IPS.[3]

Our challenge becomes the inverse – to have a sufficiently wide ranging set of SC experiments that enable us to reveal the IPS of each decision maker. This setting enables us to investigate the use of attribute elimination (or ignoring an attribute) as a coping strategy or as a genuine process of assessing alternatives and making a choice; and its implications on the value of travel time savings. Importantly, if an individual chooses not to attend to a particular attribute in the setting of a stated choice experiment, it does not mean in general that the attribute's actual marginal disutility is zero. Rather, within the SC context being assessed, the benefits of a full consideration of the specific attribute are perceived as less than the costs of consideration. The presence of SC design confoundment in the way that information is processed is very real, and is the essential challenge in our continuing effort to improve the value of the stated choice paradigm as a source of information on preference revelation, and hence choice behaviour and willingness to pay for specific attributes.[4]

[3] Such a SC experiment has some similarities to an adaptive choice experiment in which alternative behavioural choice response segments are identified as a way of recognising decision rules such as 'hard-core loyal', 'brand-type', IIA-type and product or service form. This was considered by Kamakura et al. (1996) as a finite mixture of nested logits (brand and product), latent class (for hard-core) and multinomial logit (IIA) models.

[4] DeShazo and Fermo (2001, 2004) and Hensher (2004, 2004a) are examples of recent efforts to address this issue.

3. The Design Plan

The data are drawn from a larger study reported in Hensher (in press, 2004) in which 16 stated choice sub-designs (Table 1) have been developed, embedded in one overall design, with each sub-design being used in surveying a sample of car commuter trips in Sydney in 2002. Each commuter evaluated one sub-design; however, across the full set of stated choice experiments, the designs differed in terms of the number, range and levels of attributes, the number of alternatives and the number of choice sets. The combination of the dimensions of each design is often seen as the source of design 'complexity' (Dellaert *et al*. 1999) and it is within this setting that we have varied the number of attributes that each respondent is asked to evaluate. The overall sample was built up by an inbuilt random number generator that selected one of the sub-designs each time a respondent is interviewed.

Table 1: The Sub-Designs of the Overall Design

Number of choice sets	Number of alternatives	Number of attributes	Number of levels of attributes	Range of attribute levels
15	3	4	3	Base
12	3	4	4	Wider than base
15	2	5	2	Wider than base
9	2	5	4	Base
6	2	3	3	Wider than base
15	2	3	4	Narrower than base
6	3	6	2	Narrower than base
9	4	3	4	Wider than base
15	4	6	4	Base
6	4	6	3	Wider than base
6	3	5	4	Narrower than base
9	4	4	2	Narrower than base
12	3	6	2	Base
12	2	3	3	Narrower than base
9	2	4	2	Base
12	4	5	3	Narrower than base

The candidate attributes have been selected based on earlier studies (see Hensher 2004, Ohler *et al*. 2000). They are: free flow time (FFT), slowed down time (SDT), stop/start time (SST), trip time variability (TTV), toll cost (TLC), and running cost (RC) (based on c/litre, litres/100km). Given that the 'number of attributes' dimension has four levels, we have selected the following combinations of the six attributes, noting that the aggregated attributes are combinations of existing attributes:

- *designs with three attributes:* total time (free flow + slowed down + stop/start time), trip time variability, total costs (toll + running cost)
- *designs with four attributes:* free flow time, congestion time (slowed down + stop/start), trip time variability, total costs
- *designs with five attributes:* free flow time, slowed down time, stop/start time, trip time variability, total costs
- *designs with six attributes:* free flow time, slowed down time, stop/start time, trip time variability, toll cost, running cost

The specific SC design is three unlabelled alternatives that have attribute levels that pivot off the levels associated with a current car-commuting trip. The designs are computer-generated. They aim at minimising the correlations between attributes and maximising the amount of information captured by each choice set. We maximised the determinant of the covariance matrix, which is itself a function of the estimated attribute parameters (within the experimental design literature this is known as D-optimality). The design developed herein takes into account the expected signs of the parameters (e.g., negative for the time and cost attributes). We found that in so doing, the search eliminates dominant alternatives. Carlsson and Martinsson (2003) have recently shown, using Monte-Carlo simulation, that D-optimal designs, like orthogonal designs, produce unbiased parameter estimates but that the former have lower mean square errors[5]. The method used finds the D-optimality plan very quickly. An example of two of the designs is given in Appendix A.

The design dimensions are translated into SC screens as illustrated in Figure 1. Each respondent was introduced to the SC screens with the following statement:

> "For the following questions, we would like you to imagine that you are making a trip just like the recent one that you have described: same purpose, same vehicle, same passengers, same weather, and same time. But we are going to give you a choice of different roads to travel on, in addition to your usual route. On the next screen, please check the information we have recorded for your recent trip. If something is incorrect, please go back and amend."

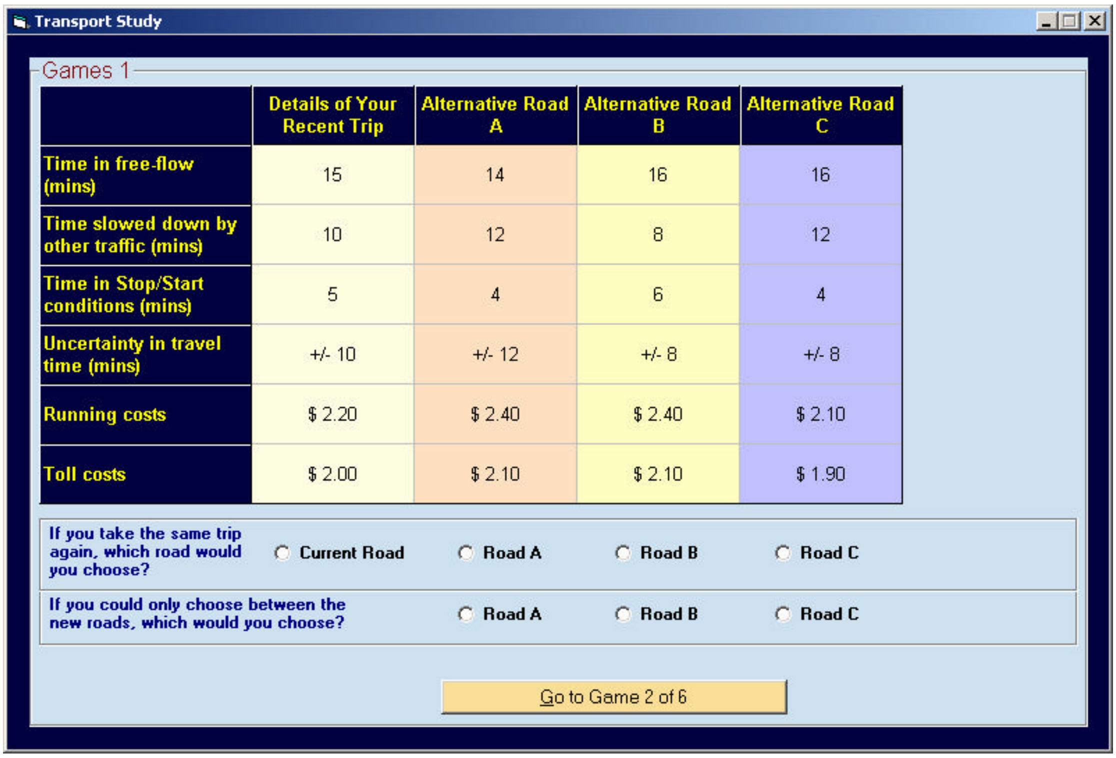

Figure 1: Example of a stated choice screen

[5] However, one can never be totally sure that the design *per se* introduces biases, but then one cannot be sure in the context of RP data that bias is not induced by the quality of the respondent's information, especially on non-chosen alternatives.

4. Mixed Logit Specification and Results[6]

We assume that a sampled individual q (q=1,…,Q) faces a choice among J alternatives in each of T choice situations. Individual q is assumed to consider the full set of offered alternatives in choice situation t and to choose the alternative with the highest utility. The utility associated with each alternative j as evaluated by each individual q in choice situation t, is represented in a discrete choice model by a random utility expression of the general form in (1).

$$U_{jtq} = \sum_{k=1}^{K} \beta_{qk} x_{jtqk} + \varepsilon_{jtq}$$
$$U_{jtq} = \boldsymbol{\beta}_q' \mathbf{x}_{jtq} + \varepsilon_{jtq} \tag{1}$$

where $\mathbf{x}_{jtq}$ is the full vector of explanatory variables, including attributes of the alternatives, socio-economic characteristics of the individual and descriptors of the decision context and choice task itself in choice situation t. The components β_q and ε_{jtq} are not observed by the analyst and are treated as stochastic influences.

Individual heterogeneity is introduced into the utility function through β_q. Thus,

$$\beta_q = \beta + \Delta\mathbf{z}_q + \eta_q, \tag{2}$$

or $\beta_{qk} = \beta_k + \delta_k'\mathbf{z}_q + \eta_{qk}$ where β_{qk} is the random coefficient whose distribution over individuals depends in general on underlying parameters, $\mathbf{z}_q$ is observed data and η_q denotes a vector of K random components in the set of utility functions in addition to the J random elements in ε_{jtq}. Since β_q may contain alternative specific constants, η_{qk} may also vary across choices and, in addition, may thus induce correlation across choices. The terms $\beta + \Delta\mathbf{z}_q$ accommodate heterogeneity in the mean of the distribution of the random parameters.

The *mixed logit* class of models assumes a general distribution for β_{qk} and an IID extreme value type 1 distribution for ε_{jtq}. For example, β_{qk} can take on different distributional forms such as normal, lognormal, uniform or triangular. For *a given value* of β_q, the *conditional* probability for choice j in choice situation t is multinomial logit, since the remaining error term is IID extreme value:

$$L_{jtq}(\beta_q|\mathbf{X}_{tq},\mathbf{z}_q,\eta_q) = \exp(\beta_q'\mathbf{x}_{jtq}) / \Sigma_j \exp(\beta_q'\mathbf{x}_{jtq}). \tag{3}$$

The given value of β_q will also be conditioned on whether an individual attends to a specific attribute in their pre-choice behavioural processing strategy. Certain elements of $\boldsymbol{\beta}_q$ are known to equal zero when the corresponding attribute is ignored.

In the current study we condition each parameter on whether a respondent included or excluded an attribute in their attribute processing strategy. The probabilities are constructed in such a way that for those individuals, the actual elements of β_q that enter the likelihood function are set to zero (as are their derivatives as part of the optimization

[6] Mixed Logit has been well documented in many sources (see Hensher and Greene (2003) and Train (2003)), and is summarised as appropriate herein.

process). Intuitively, the overall model that we fit to accommodate this aspect of the choice process takes into account that the actual choice model is different (by virtue of the zeros in b_q) for these individuals.

Five hundred and fourteen face to face CAPI surveys were undertaken in the Sydney metropolitan area in 2002. Five hundred and two of the 514 surveys were useable. With a varying number of choice sets per sub-design the total number of observations used in model estimation was 4,593. Full details of the sampling and response rates are given in Hensher (in press). Two specifications of mixed logit models are estimated: model 1 (ML1) assumed that all attributes were treated as if they were processed for inclusion (i.e., were attended to), and model 2 (ML2) in which attributes reported by a respondent as ignored (i.e., not attended to) in the pre-choice response process were excluded for that respondent in the estimation of the parameter attached to that specific attribute, be it a fixed or a random parameter.

The contrast between ML1 and ML2 is in respect to those attributes that were specified in the SC design that were preserved by model assumption or excluded by respondent ruling. In the current paper we have eliminated the sub-sample that traded-off total time with total cost and uncertainty because it is not of sufficient interest in the comparison between the two models in terms of willingness to pay.[7] This reduced the estimated sample size to 3,411 observations.[8]

The incidence of attributes or attribute combinations not attended to is summarised in Table 2.[9] The combinations reported in Table 2 are an exhaustive set of the non-zero combinations.[10] The uncertainty of travel time was ignored by a substantial proportion of the sample (e.g., 37.4 percent and 31.5 percent of the individuals facing sub-designs with six and five attributes respectively). This high percentage of respondents not attending to the 'uncertainty of time' attribute might be due to the difficulty of processing this concept compared to other attributes. In contrast, other mixtures of attributes exhibiting attribute exclusion varied from a high of 12.32 percent for the pair – *slowed down time and stop start time* within the six attribute sub-design to a low of

[7] These sub-designs had total time and total cost and uncertainty of time. With uncertainty eliminated in most cases, the remaining observations tended to preserve the remaining two attributes.

[8] All attributes for each individual that were ignored or not attended to were not included in ML2 for that individual. The full sample was preserved, however, unlike some studies where we have seen entire observations incorrectly removed.

[9] A referee had thought that we had designed the experiments by introducing an inclusion-exclusion rule on each attribute. However, this was a rule that was invoked by respondents after completed the stated choice experiments, with additional survey questions used to elicit this response for each attribute faced in their sub-design.

[10] A referee stated that he does not have much trust in respondents having to articulate how they reached a decision and indicated 'that's why stated choice methods were developed in the first place'. While it is true that we promote SC methods to give us greater confidence in the revelation of respondent preferences, SC designs implicitly assume that all attributes are processed as if they are relevant to varying degrees. The mere presence of the attribute then contributes to the estimation of the mean and standard deviation parameters of the attribute. One interpretation of what is happening, process-wise is offered by DeShazo and Fermo (2004) who describe this as the *passive bounded rationality* model wherein individual's attend to all information in the choice set. Contrasting this is the *rationally-adaptive* model that assumes individuals recognise that their limited cognition has positive opportunity costs. As DeShazo and Fermo (2004) state: "Individuals will therefore allocate their attention across alternative-attribute information within a choice set in a rationally-adaptive manner by seeking to minimise the cost and maximise the benefit of information evaluation" (page 3).

0.49 percent for mixtures on three to five attributes also within the six attribute sub-design.[11]

The mixed logit models in Table 3 are estimated with a constrained triangular distribution for the random parameters that ensures a non-negative willingness to pay for travel time savings over the entire range of the distribution. For the triangular distribution, the density function looks like a tent: a peak in the centre and dropping off linearly on both sides of the centre.[12] Both models specified the travel time component parameters as random with all the cost parameters as point estimates. The valuation of travel time savings is defined by the random parameter for travel time divided by the fixed parameter estimate for travel cost.[13]

The overall goodness of fit of the two models is impressive. All parameters are statistically significant and of the expected sign, except for uncertainty in travel time which was removed from the final models. To establish whether the inclusion or exclusion of an attribute in the processing of the choice sets was systematically linked to heterogeneity across commuters, we specified the mean and standard deviation of each random parameter as a function of a dummy variable representing inclusion/exclusion. We were unable to find any statistically significant relationship on all candidate attributes. The VTTS are reported in Table 4 for both models.

Table 2: Profile of Mixtures of Attributes Not Attended to by a Respondent

	Percentage Not Attended To
Individuals facing six attributes before exclusion	
(Free flow time, slowed down time, stop start time, uncertainty with run cost, toll cost):	
Uncertainty of time (in presence/absence of other attributes)	37.4
Slowed down time, stop start time	12.32
Slowed down time	9.08
Free flow time, slowed down time, stop start time	6.38
Slowed down time, toll cost	2.52
Slowed down time, stop start time, run cost	0.98
Free flow time, slowed down time, stop start time, run cost	0.49
Free flow time, slowed down time, stop start time, toll cost	0.49
Slowed down time, stop start time, toll cost	0.49
Free flow time, slowed down time, stop start time, run cost, toll cost	0.49
Individuals facing five attributes before exclusion	
(Free flow time, slowed down time, stop start time, uncertainty with total cost):	
Uncertainty of time (in presence/absence of other attributes)	31.5
Slowed down time, stop start time	7.93
Slowed down time	7.12

[11] A referee stated that the percentages are larger for individuals facing a smaller number of attributes. A closer examination suggests that in general this is not correct and only applies to two combinations. The comparisons are not strictly valid without adding up the total percentage of attributes excluded. We acknowledge that the profile displayed in Table 2 raises many issue as to why specific attributes are being ignored in the presence of other attributes, with explanations that may have nothing to do with the number of attributes but everything to do with the relevancy of attributes not available in the SC design (the over-simplicity proposition) and the levels of other SC attributes. This is an area for further research.

[12] Let c be the centre and s the spread. The density starts at c-s, rises linearly to c, and then drops linearly to c+s. It is zero below c-s and above c+s. The mean and mode are c. The standard deviation is the spread divided by $\sqrt{6}$; hence the spread is the standard deviation times $\sqrt{6}$. The height of the tent at c is 1/s (such that each side of the tent has area $s\times(1/s)\times(1/2)=1/2$, and both sides have area $1/2+1/2=1$, as required for a density). The slope is $1/s^2$.

[13] This ratio gives the value of travel time savings in $/minute which is then converted to an hourly value.

Free flow time, slowed down time, stop start time	4.77
Individuals facing four attributes before exclusion	
(Free flow time, slowed down time plus stop start time, total cost, uncertainty):	
Uncertainty of time (in presence/absence of other attributes)	27.6
Free flow time, slowed down time plus stop start time	8.65
Slowed down time plus stop start time	8.48
Free flow time	3.78
Free flow time, slowed down time plus stop start time, total cost	1.62
Free flow time, total cost	1.45
Slowed down time plus stop start time, total cost	1.45

The evidence suggests that when we do not condition parameter estimation on the attribute processing strategy of the respondent, we get a significantly higher estimate of the mean value of travel time savings, on average of the order of 18-62 percent depending on the specific attribute. Based on a single study, we cannot conclude that the VTTS will always be in the upwards direction, although it is statistically different under the two specifications (see Table 5).[14]

Table 3: Mixed Logit Choice Models with alternative information processing conditions
(3,411 observations) Time is in minutes, cost is in dollars. (500 Halton draws)

Attribute	Alternatives	ML1	ML2
Free flow time	2-4, 6-8, 10-12, 14-16, 18-20	-0.1516 (-17.49)	-0.1521 (-17.01)
Slowed time	3,4, 7,8, 11,12,15,16,19,20	-0.1166 (-11.66)	-0.1098 (-11.04)
Stop/start time	3,4, 7,8, 11,12,15,16,19,20	-0.1504 (-13.90)	-0.1451 (-13.54)
Slowed/stop/start time	2, 6,10,14,18	-0.1632 (-17.11)	-0.1355 (-15.03)
Cost attributes:			
Running cost	4,8,12,16,20	-0.8484 (-7.74)	-1.0021 (-7.2)
Toll cost	4,8,12,16,20	-1.6939 (-24.21)	-2.3183 (-24.25)
Total cost	1-3,5-7,9-11,13-15,17-19	-0.9775 (-14.56)	-1.3358 (-15.65)
*Spread of random parameter distribution:**			
Free flow time	2-4, 6-8, 10-12, 14-16, 18-20	0.1516 (17.49)	0.1521 (17.01)
Slowed time	3,4, 7,8, 11,12,15,16,19,20	0.1166 (11.66)	0.1098 (11.04)
Stop/start time	3,4, 7,8, 11,12,15,16,19,20	0.1504 (13.90)	0.1451 (13.54)
Slowed/stop/start time	2, 6,10,14,18	0.1632 (17.11)	0.1355 (15.03)
Pseudo-R^2		0.590	0.593
Log-Likelihood		-3783.9	-3758.9

* Constrained by the triangular distribution to equal the mean.

Table 4: Mean values of travel time savings inclusive and exclusive of individuals who ignored specific attributes
time = random parameter, cost = fixed parameter

Attribute	ML1	ML2
Free flow time	10.71	9.09
Slowed time	8.25	6.58
Stop/start time	10.61	8.69
Slowed/stop/start time	11.96	8.12

Table 5: Ratio of non-ignored to ignored mean VTTS

Attribute	Ratio NI/I
Free flow time	1.18
Slowed time	1.25
Stop/start time	1.22
Slowed/stop/start time	1.62

Note: for all times, running cost is the cost parameter.

[14] Recent studies by Rose et al. (2004) and DeShazo and Fermo (2004) in different contexts, found that the estimates marginal willingness to pay was higher at the mean when attributes not attended to were either ignored or conditioned on this information.

5. Conclusions and Future Directions

The empirical evidence supports a growing view that recognition of varying information processing strategies in respect to how specific attributes are processed, in terms of exclusion and inclusion, is of sufficient importance to take seriously in future stated choice studies and all studies that have as their objective the estimation of willingness to pay. When we compare the value of travel time savings distributions before and after accounting for the attribute processing strategy of each individual, we find sizeable differences in the mean.

Although we cannot suggest whether the exclusion of an attribute is due to some underlying behavioural rationale for the attribute's role, or simply a coping strategy in processing the amount of information presented in the stated choice experiment, the growing body of research in economics and psychology of ways in which individual's process information, suggests that in the future we must take more serious the *process stage* leading to a study of choice outcomes. The findings herein also apply to data from real markets. Recent research by DeShazo and Fermo (2004) supports this conclusion.

It is unlikely, however, that there exists a preferred SC design, given the large number of attribute (and more broadly, information) processing strategies adopted by a sampled population within a specific choice context.[15] Rather, what this study suggests is that, regardless of the SC design selected, there is behavioural appeal in accounting for the process adopted by each and every sampled individual in the way they treat each attribute in arriving at their preferred alternative. Accounting for relevancy and cognitive burden is essential if we are to accommodate individual heterogeneity in the processing of choice experiments. The fact that this has been ignored in the majority of previous stated choice experiments must be a concern. Importantly, if we want to compare the empirical findings of same-context studies (e.g., urban commuting travel) that use different SC designs, we must account for the influence of different design dimensions and processing rules.

The ongoing research challenge is best stated as follows: What matters is not whether different designs require different attribute (and information) processing strategies, but whether the stated choice design *per se* contributes to different behavioural responses and associated attribute valuations. Importantly, the processing strategy should be built into the estimation of choice data from stated choice studies.

Given the importance of 'process', we need to place a greater emphasis on establishing better ways of measuring the processes used by individuals in evaluating the information in a SC experiment, leading to a choice outcome. One appealing avenue is that developed by Jacoby (1991) who developed an experimental procedure known as the process-dissociation procedure[16]. This experimental paradigm has been extensively used to investigate the relative influences of conscious and unconscious processes in memory performance. This method subsequently discouraged researchers from equating processes to tasks (e.g., implicit vs explicit memory tests), and instead encouraged researchers to employ a strategy that would enable them to estimate the relative

[15] This is demonstrated in Hensher (2004a) by the range of influences on the propensity to ignore attributes.

[16] We thank our colleague Tony Bertoia for directing us to this literature and helping to draft the ideas in the conclusions.

contributions of conscious and unconscious processes on the performance of a single task, and also to show (in Jacoby *et al*. 1994) dissociations of the effects of attributes on these estimates.

This is achieved by comparing the performance on two tasks within an experimental memory procedure – an inclusion and exclusion test. An inclusion test involves a word stem completion task, involving instructing participants to use the stem as a cue to recall an old word, or if they are unable to do so, to complete the stem with the first word that comes to mind. An exclusion test involves the same word completion task, but with instructions to use the stem as a cue to recall an old word but not to use recalled words to complete the stem. In other words, participants are instructed to exclude old words and to complete stems only with unrecalled words. Researchers can use these two tasks to estimate the relative contributions of recollection and automatic influences in memory (see Jacoby 1998).

More recently, Aarts and Dijksterhuis (2000) have adapted the process dissociation procedure in an investigation of habitual travel mode choice behaviour. Habits may be defined as person-related, stable factors which affect the decision-making process on a recurrent basis (Aarts *et al*. 1997). Once habits toward a particular behaviour are formed, individuals will engage in minimal information processing each time they encounter comparable situations.

Aarts and Dijksterhuis (2000) adapted the process dissociation procedure by asking subjects to respond to questions regarding which type of travel mode they would use for given trips. In some experimental conditions, they asked subjects to suppress their habitual transport mode choice in response to a travel goal. Their hypothesis was that the suppression of this automatic, habitual response would be difficult and resource-consuming (i.e., requiring attentional control). Thus, habitual responses would lead to errors, and such errors would be most likely in conditions of reduced mental capacity. Aarts and Dijksterhuis (2000) claim that their results support the notion that habits are represented in a manner similar to other frequently-consulted and automatically activated mental knowledge structures such as stereotypes and attitudes.

The key issue arising from this evidence is whether we can infer something about the mental knowledge structure of habits and apply it to the issue of what attributes and concepts are personally relevant to an individual undertaking a stated choice experiment. In order to answer this question, we need to ensure that the mechanism underlying habits is similar to that which may be involved in the activation of personally-relevant concepts in a decision-making paradigm such as the stated choice paradigm.

According to Aarts and Dijksterhuis (2000), the underlying mechanism for habits is similar to that of other knowledge structures such as stereotypes and attitudes. Indeed, they suggest that this is explained by the underlying associative links that are common to both. This is no surprise considering the burgeoning literature on the measurement of implicit stereotypes and attitudes. A particularly common instrument used in this literature is known as the Implicit Association Test (https://**implicit**.harvard.edu/**implicit**/). This instrument has been applied to a number of different fields, but not yet, as far as we are aware, to the area of choice-making in stated choice experiments.

The IAT measures implicit attitudes by pairing two concepts (e.g., *young* and *good*, or *elderly* and *good*). By investigating how quickly people respond to the pairing when presented briefly on a computer screen, one can estimate how strongly associated the two concepts are. For example, if *elderly* and *good* are not strongly associated, it should be harder to respond quickly when they are paired.

The importance of this research is that it is aimed at understanding the differences between what people say they think and what they really think. In other words, it is aimed at understanding conscious-unconscious divergences. The two main reasons for these divergences are that individuals might not be *willing* to share their private attitudes, but just as important is the likelihood that individuals may not always be *aware* of their own attitudes, beliefs and preferences. For these reasons, it seems important that an investigation of the personal relevancy of alternatives, attributes and attribute levels in stated choice experiments involve an understanding of the role of unconscious preferences. This is particularly relevant given that the only way personal relevancy is measured in the literature involves asking participants to explicitly state which attributes they have ignored, as was the process herein. Ongoing research should take these suggestions on board and establish the extent to which the simply conscious statements used herein to classify attribute inclusion/exclusion have proxy merit under other tests.

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Appendix A

Examples of Design Tables (Two of 16 such designs in this study).

Scenarios	Alternative 1				Alternative 2				Alternative 3			
	Free Flow time	Stop/Start-Slowed down time	Uncertainty of travel time	Total Cost	Free Flow time	Stop/Start-Slowed down time	Uncertainty of travel time	Total Cost	Free Flow time	Stop/Start-Slowed down time	Uncertainty of travel time	Total Cost
1	3	3	3	2	1	0	0	3	2	2	1	3
2	3	3	1	1	0	2	2	2	1	0	3	3
3	3	2	1	3	1	3	0	2	0	1	3	3
4	1	0	2	3	2	2	0	1	3	1	1	2
5	3	2	1	0	1	3	0	1	2	0	2	3
6	0	1	0	0	1	0	2	2	2	3	3	1
7	3	0	0	0	0	2	1	1	2	3	2	0
8	3	1	2	3	0	3	0	3	1	2	3	2
9	3	0	2	1	0	2	3	3	2	3	1	0
10	3	1	0	0	2	2	2	3	0	0	1	2
11	2	1	3	1	1	3	1	0	0	2	0	2
12	1	1	1	2	2	3	0	1	0	0	3	3
1	0	2	0	3	1	3	3	2	3	1	1	3
2	2	0	3	2	0	3	2	0	1	2	1	1
3	3	2	3	1	2	0	1	0	0	1	2	2
4	0	0	1	1	1	1	2	0	3	3	0	0
5	3	3	2	0	1	1	1	1	2	2	3	0
6	0	3	3	0	3	0	0	2	2	1	2	1
7	0	0	0	1	3	2	3	0	2	1	2	3
8	3	2	2	0	2	0	0	2	1	1	3	1
9	0	1	3	2	1	2	2	1	2	3	1	0
10	2	1	0	2	0	3	2	1	1	0	1	3
11	2	0	2	2	1	3	3	3	3	1	0	3
12	1	2	0	0	0	1	1	2	3	0	3	1

Block	Scenarios	Alternative 1			Alternative 2			Alternative 3			Alternative 4		
		Total time	Uncertainty of travel time	Total cost	Total time	Uncertainty of travel time	Total cost	Total time	Uncertainty of travel time	Total cost	Total time	Uncertainty of travel time	Total cost
1	1	2	1	2	3	2	1	0	0	3	1	3	0
1	2	0	0	1	3	2	2	1	3	0	2	1	0
1	3	2	0	0	3	3	1	0	1	2	1	2	1
1	4	2	2	0	0	1	3	3	0	1	1	3	2
1	5	2	1	1	0	0	2	3	3	0	1	2	0
1	6	1	0	2	0	2	0	2	3	3	3	1	1
1	7	0	0	1	3	2	0	2	3	0	1	1	0
1	8	3	2	3	2	0	3	1	3	1	0	1	2
1	9	0	0	3	2	2	2	1	1	1	3	3	2
2	1	2	3	1	1	0	3	3	1	0	0	2	2
2	2	3	2	3	2	1	3	0	3	3	1	0	2
2	3	2	0	1	3	3	0	0	2	0	1	1	2
2	4	0	1	3	1	2	1	2	3	0	3	0	2
2	5	1	0	3	2	3	1	3	1	2	0	2	3
2	6	0	3	1	3	0	0	2	1	3	1	2	2
2	7	1	0	3	2	2	2	3	3	0	0	1	1
2	8	1	1	3	3	0	3	0	3	2	2	2	1
2	9	0	3	0	3	2	1	2	0	2	1	1	3