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Respondents' ignoring of attribute information in a choice modelling survey

William Henry Kaye-Blake, Walt L. Abell and Eva Zellman†

One debate in economics centres on consumers' decision-making strategies and whether they should be explicitly considered. The default assumption for choice modelling has been that all the attributes presented to respondents somehow influence their choices. More recently, choice modelling research has begun examining how respondents use information. This article presents research that focused on which pieces of information respondents used in responding to a choice modelling survey. The use of information by respondents was captured in the course of the administration of a computer-aided survey, so the research did not rely on posterior self-reporting. Access to the information was captured for each attribute of every alternative, which allowed flexibility in assessing use of information. Three mixed logit models are presented, based on three different assumptions about information use. The results suggest that accounting for respondents' information use affects modelling results, but the impact on estimates of willingness to pay may be relatively small.

Key words: choice modelling, computer-aided, information, potatoes, New Zealand.

1. Introduction

Economists have for decades debated whether it is important to consider consumers' decision-making strategies explicitly. One view is represented by Friedman's (1953) focus on the outcome of models, rather than their descriptive accuracy. The opposite perspective is provided by Simon (1955) and, more recently, Rabin (2002) and Bettman *et al*. (1998), that the outcome of decisions is a function of the process of individuals' decision-making behaviours. Research using choice modelling surveys has tended to rely on a non-behavioural interpretation of respondents' choices (McFadden 2001), using models based on complete integration of full information. The default assumption for choice modelling has been that everything counts: all the attributes presented to respondents in the choice set somehow influence their choices (Hensher *et al*. 2005b). Recent choice modelling research, by contrast, has begun examining the information processing strategies that respondents use when answering surveys (Hensher *et al*. 2005b; Louviere *et al*. 2005). This research follows prior work in economics, marketing, and psychology, investigating the decision processes that people use in considering choice tasks

† William Henry Kaye-Blake (email: kayeblaw@lincoln.ac.nz) and Eva Zellman are at the Agribusiness and Economics Research Unit, Lincoln University, Lincoln, New Zealand. Walt L. Abell is at the Applied Computing Group, Lincoln University, Lincoln, New Zealand.

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(e.g. Bettman and Kakkar 1977; Jacoby *et al.* 1977; Simon 1983; Harte and Koele 2001).

This article builds on prior literature focused on how respondents attend to and process information presented to them in choice surveys (Hensher *et al.* 2005b, 2007; Hensher 2006). It proceeds by first reviewing this work, its methods and its findings. It then presents a computerised surveying method that was used to capture data on the information that respondents viewed as they answered a choice modelling survey. Contrary to prior choice modelling research, the method used did not rely on the respondents' self-reported behaviour, and captured information use for each question rather than the survey as a whole. This additional data was used to estimate three mixed logit models, based on assuming full information, actual information or average information. The results of incorporating this additional data are presented and discussed. The conclusion considers the lessons from this research and some potential future work.

2. Attention to attributes in choice modelling

Choice modelling surveying is based on Lancaster's (1966) theory of consumer behaviour, according to which consumers choose those goods whose vectors of attributes result in the maximum utility, depending on the weight that they put on the individual attributes. For choice modelling, respondents are presented with sets of alternative products or policies, which are described by their component attributes. Respondents are assumed to compare the levels of these different attributes and select the alternative with the highest 'score' or utility (McFadden 2001).

Researchers have tended to assume that respondents consider all the attributes presented to them. In the data analysis, all the attributes presented affect all the alternatives. However, respondents' use of survey information and their decision-making protocols have begun attracting more attention in choice modelling research (Ben-Akiva *et al.* 2001; Bolduc and McFadden 2001; McFadden 2001). There are several ways in which respondent behaviour may deviate from the assumption of full integration of all available information. Respondents may not consider all the attributes in a survey (Rose *et al.* 2005), may use the attributes to define minimum levels of acceptability (Swait 2001; Cantillo and de Dios Ortuzar 2006; Cantillo *et al.* 2006), may employ cognitive short-cuts to limit task complexity (Gabaix and Laibson 2000; Yamamoto *et al.* 2002) and may combine attributes in non-linear ways (Sethi and King 1999; Gilbride and Allenby 2004). Consumer research suggests that consumers may use different strategies to reach their decisions, and that the choice of strategies is a function of the choice environment (e.g. Bettman and Kakkar 1977; Jacoby *et al.* 1977; Earl 1986; Bettman *et al.* 1998).

Consumers in markets or respondents to surveys may make decisions subject to the constraints of time and cognitive abilities (Louviere *et al.* 2005).

First, the opportunity cost of the time to consider attributes should be taken into account, so that attributes whose value is below a certain threshold may not be fully considered. Second, given the cognitive difficulties of processing and integrating the information (Simon 1955), integrating information about an attribute with little utility may not be worth the cognitive cost (Louviere *et al.* 2005). A related topic is the impact of learning about the choice task on respondents' behaviour; respondents may improve their decision-making abilities as they progress through a choice survey. Hanley *et al.* (2002) found little evidence for learning effects when comparing two choice surveys of different sizes. By contrast, Caussade *et al.* (2005) found learning effects that reduced the error variance as more choice questions were presented, up to the 9th or 10th question, whereas Rose *et al.* (2009) found that the number of choice questions affected some groups of respondents but not others. Thus, the effort and ability to process information may be a factor affecting choice survey results.

Some choice modelling researchers have begun to collect information from respondents about their use of attribute information and found that incorporating this information affects modelling results. Swait (2001) examined the use of thresholds in a survey on rental car preferences. Respondents indicated which attribute levels were unacceptable, and these were modelled as thresholds. These thresholds were included in a standard model to create a penalised utility function: individuals could make choices that violated their stated 'requirements' but at a cost. Swait (2001) reported that the 'addition of the penalties to the utility functions is *extremely* powerful' [emphasis in original]. Further modelling work with thresholds has demonstrated that inertia, minimum perceptible changes and non-compensatory decision-making can all be analysed with a threshold model (Cantillo and de Dios Ortuzar 2006; Cantillo *et al.* 2006). Furthermore, analysis of synthetic data showed that ignoring thresholds in datasets that contained them led to significant errors (Cantillo *et al.* 2006).

Respondents' use of attribute information was further examined in a choice modelling survey (Hensher *et al.* 2005b). Respondents were asked, after completing the choice experiment, whether they had ignored one or more of the attributes. Conditioning the estimates of value of travel time savings on whether respondents had attended to specific attributes led to lower estimates for the time savings.

This research has been extended. For example, Hensher (2006) specifically examined the dimensions of the choice model survey analysed in Hensher *et al.* (2005b) to determine which elements were affecting respondents' attention to information. Ordered logit modelling that estimated the impact of design dimensionality on the number of attributes ignored suggested that fewer levels with greater differences led to more attribute processing. The specific type of information processing strategy employed was considered in further research by Hensher *et al.* (2007), who found that including different processing strategies affected willingness-to-pay estimates from the modelling.

The above research on decision and information processing strategies indicated the importance of considering these elements in analysing choice modelling survey data. However, they relied on self-reports by respondents of how they behaved during the survey. For example, Swait (2001) relied on respondents indicating which attribute levels were unacceptable (Gilbride and Allenby 2004). The dataset for several articles (Hensher and Rose 2005; Hensher *et al.* 2005b, 2007; Hensher 2006) hinged on what respondents reported about their behaviours after they had completed the choice exercise. Furthermore, these self-reports were used to model how respondents had assessed all the choice questions, which assumed that respondents approached every question exactly the same way. Harte and Koele (2001) reviewed research suggesting that self-reports may be accurate depictions of respondents' behaviour, but also suggested that multiple methods should be used to capture data on behaviour.

One tool for collecting information on respondents' decision processes is the information display board (e.g. Bettman and Kakkar 1977; Jacoby *et al.* 1977; Lehmann and Moore 1980). The information display board is matrix of information on the choice alternatives and their attributes, and it can be used to investigate the depth, pattern and variability of search (Harte and Koele 2001). This research tool produces consistent and valid findings relative to actual consumer search behaviour (Lehmann and Moore 1980). However, Van Ittersum *et al.* (2007) suggested that information display boards and attribute-based choice surveys, such as choice modelling, measure different dimensions of choice. The former measure the relevance of attributes or their importance to individuals by recording the relative importance of attributes, whereas the latter measure the determinance of attributes, or its importance in determining choices. They further found a lack of convergent validity across methods that reveal different dimensions of choice.

3. Method

To test the impacts of respondents' use of attribute information, a choice modelling survey was designed and conducted. The method is described in several parts. The first part describes the survey instrument, a computerised information display board (Harte and Koele 2001, p. 37) that required respondents to collect information actively before making their choices. The second part discusses the content of the survey. The third part presents the method used to analyse the data from the survey: mixed logit models with and without data on respondents' information use.

3.1 Survey design

There were two aspects to designing the survey instrument. The first aspect was appropriate design of the choice sets, and the second was design of the computer software for surveying, which allowed the capture of data on respondents' use of information. These two aspects are discussed below.

Statistically appropriate design of choice sets has been extensively studied. Working from a base of fractional factorial experiments for agricultural research (e.g. Yates 1937), choice modellers concentrated on balance and orthogonality of attributes and their levels in order to isolate the main effects of the attributes (Louviere *et al*. 2000). It was later found that the statistical efficiency of choice sets also depends on the utility weights of the attributes (Kanninen 2002), so more recent choice models have incorporated prior estimates of betas into their designs. The present research used the procedure described in Zwerina *et al*. (2005) to create *D*-efficient choice sets in SAS; the SAS procedure was found in prior research to yield a highly efficient design (Street *et al*. 2005). Table 1 provides the attributes, their levels and the Bayesian priors used to generate the choices sets. The SAS procedure generates an output file containing combinations of attributes that describe a predetermined number of choice alternatives. These alternatives can then be used to create sets of alternatives for the choice questions in a choice modelling survey. In the present work, the SAS output file became an input file for the computer software used in the actual surveying.

Purpose-built software was developed to administer the survey. It used HTML, JavaScript and PHP to generate the screens and record the responses. A Web server running Microsoft IIS was used to store the data. The configuration file contained all the data to define the choices sets, including the row and column labels, the levels of each attribute and the number of cases to use in each set. The data file was based on the SAS output from the *D*-efficiency design procedure and additional information for coding the attributes and levels. Using the information in these two files, the display generator created information display boards, which were Web pages presenting the choice sets in the Web browser (see Figure 1). The initial view of a choice set was a table with column headers (potatoes A, B and C) and row headers (the choice attributes), but with all the attribute information covered by blue 'cards' or boxes. Respondents used the computer mouse to click on a blue card to reveal the level of the attribute hidden 'underneath'. They could click on as many attributes they wanted and the information would remain revealed or 'open' once its card had been clicked. As the respondent clicked on different cards in the set, the order and timing of each click was recorded. The participants then had to select one of the potatoes by clicking on an

Table 1 Attributes and levels for survey

Attribute	Level	Bayesian prior
Texture	Waxy, floury	0
Price	\$1.00, \$1.50, \$2.00, \$2.50	−0.5
Colour	Pink, yellow, white	1
Production	Conventional, GM, organic	−1
Nutrition	Ordinary, low-GI, high-omega3	1
Country of origin	New Zealand, Australia, China	−1

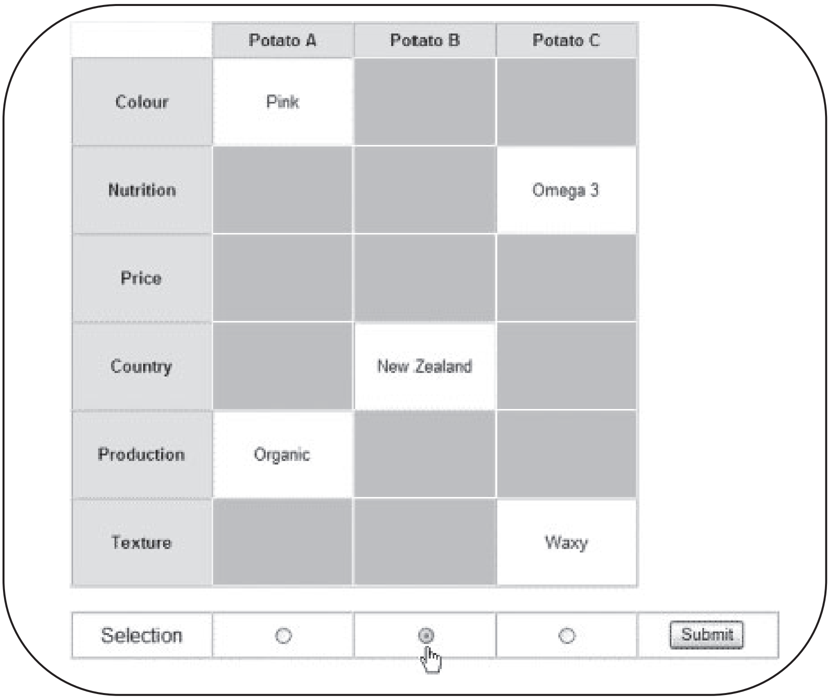

Figure 1 Choice set display in web browser.

option button at the bottom of the column for the potato they wanted to choose, and then click on 'Submit' to move on to the next choice set. The choice sets were designed to allow participants to skip questions. When the respondent made a final selection, the data was sent to the data recorder which stored it on the server and called the display generator to present the next page of choices.

The order in which attributes were presented to respondents was randomly determined, but the order, once determined, was constant for each respondent. The order in which choice sets were presented was not randomised; the ability to randomise choice sets was not included in the development of the software. Attributes were presented as text rather than graphics.

3.2 Survey content

The survey contained four sections: initial questions, choice questions, follow-up questions and demographic questions. The survey centred on attitudes and choices around potatoes, a commonly consumed food. Initially, respondents were asked to rank in order of importance six different potato attributes: texture, price, colour, production practices, nutrition and country of origin. The same attributes were used to describe potatoes for the choice questions. Each respondent was presented with 10 choice sets containing 3 potatoes each. In the follow-up question section, the participants were asked a number of questions about their beliefs and attitudes. The last section asked demographic questions including gender, age, income and educational attainment.

The attributes were selected to provide a range of different hypothetical potatoes to respondents. The list of attributes and their levels is presented in Table 1. Several attributes, such as flesh colour and nutritional enhancements, are the subject of current food research. Potato texture was divided into the common descriptions 'waxy' and 'floury', but the impacts on consumption were *a priori* unknown. The impact of country of origin was tested by including three different sources for the potatoes: New Zealand, Australia and China. Production practices were expected to affect respondents' choices. As some respondents could have strong opinions about whether potatoes were grown organically or were genetically modified, there was also potential for non-compensatory decision strategies based on minimal information.

The survey also included supplemental information. The computerised survey instrument contained several screens with instructions on how to complete the survey. Participants were also provided with a reference sheet that indicated the attributes used to describe the potatoes and the range of potential levels of the attributes. They could refer to this reference sheet at will.

3.3 Analytical method

Choice modelling data analysis has been well explained and developed in number of publications (Louviere *et al.* 2000; McFadden 2001; Train 2003; Hensher *et al.* 2005a). A respondent is assumed to choose alternative a_i because it offers the greatest utility, U, so that $a_i \succ a_j$ for all $j \neq i$ as a result of the perception that $U(a_i) > U(a_j)$. McFadden (1974) showed this choice can be modelled probabilistically with a conditional or multinomial logit (MNL). Assuming that the error terms follow a type I extreme value distribution, the MNL probability of choosing a_i is (Maddala 1983):

$$\Pr(a_i) = \exp(V_i)/\Sigma\exp(V_j) \tag{1}$$

where V is a function of the observed attributes and their estimated utility weights.

The MNL equation can be used to estimate population-level parameters that indicate the average utility weight for the attributes. The mixed logit (ML) relaxes MNL assumptions regarding taste homogeneity (Revelt and Train 1998; Hensher *et al.* 2005a) by assuming that parameters can be drawn from a distribution across the population of respondents. A further benefit of the ML model is that it can be used to estimate panel data (Revelt and Train 1998; Bhat 2003; Hensher *et al.* 2005a). There are two formulations for the mixed logit: the random parameters specification and the error components specification (Hensher and Greene 2003; Hess *et al.* 2004). In the first, the taste parameters are decomposed into their means and distributions; in the second, the unobserved portion of utility is divided into a type I extreme value distribution that allows the logit specification and a separate error distribution that is estimated as part of the observed utility. Hess *et al.* (2004) noted that 'the two approaches … can be combined straightforwardly, allowing for the joint modelling of random taste heterogeneity and inter-alternative correlation' (p. 7). This combined approach was used for the present research.

As a result, the probability of choosing a_i is a function of the fixed and random taste parameters and the estimated error component. This equation can be estimated via simulation. The model is solved by taking draws from the parameter distribution and then calculating the expected probability over those draws:

$$P_{ni} = \int L_{ni}(\beta)f(\beta)d\beta \tag{2}$$

where n indexes the respondents, i indexes the alternatives, $L_{ni}(\beta)$ is the MNL probability evaluated at the utility weights β and $f(\beta)$ is a density function (Train 2003, p. 139). A common choice of parameter distribution is the Normal distribution, although other distributions are also used. Methods for drawing from the distribution for the parameter have been explored in the literature, and a commonly supported method is a Halton draw (Train 2003; Hensher *et al.* 2005a). To solve the model, an iterative process searches over all the parameters to be estimated for the maximum likelihood.

The models in this research were solved with NLogit 4 and some results were verified with Microsoft Excel. Importantly, NLogit 4 allows the researcher to indicate whether a specific attribute in the choice set was ignored (John Rose, pers. comm., 2007). If a respondent does not attend to an attribute in making a decision, that attribute can be coded as –888. This code signals NLogit to apply a zero weight to the β for the attribute, because it had no impact on the utility of the alternative for the respondent. The estimated parameters and covariance matrices from the models were used to estimate willingness to pay using the method described in Hensher and Greene (2003, p. 163). Cholesky decompositions and simulations with 1000 draws were performed with R 2.8.0. Willingness to pay was calculated as the negative of the ratio of a given parameter and the parameter for price (Hensher *et al.* 2005a):

$$-\frac{\beta}{\beta_{\text{price}}}. \tag{3}$$

4. Results

The survey was administered to a convenience sample of university students and staff. Participants were recruited outside the campus library by students, who approached every third passer-by with a flyer and a request to participate in a survey and software trial. Individuals contacted were told that the purpose of the study was to trial software for consumer surveys and that the trial involved purchase decisions regarding potatoes. An inducement of a chance to win a $100 book voucher was offered. These individuals were directed to a library study room, which was equipped with networked computers loaded with the survey. There were 557 flyers handed out, which resulted in 92 people participating in the survey. The data for five participants were incomplete or poorly recorded as the result of a technical flaw, so their responses were excluded. The remaining respondents answered all choice questions presented; no one skipped some questions but answered others. The final dataset included responses from 87 participants. All the participants worked through the survey at their own pace using the instructions provided on the screen, but an administrator was always available to answer any questions.

Forty-seven per cent of the participants were females and 53 per cent were males. The median category age range was 31–35 years, and 69 per cent of the participants earned less than $15 000/year. Over 60 per cent of the participants had either an undergraduate or postgraduate degree or diploma.

4.1 Information obtained by respondents

The survey instrument recorded whether respondents clicked on the attribute cards to reveal the information underneath. It was thus possible to determine which attribute information respondents accessed as they considered the choice questions. Over the whole dataset, 78 per cent of all the cards were opened, so that just over one-fifth of the available information was not accessed. The first level of aggregation is to recall that each potato was a bundle of six attributes. The data revealed that 55.6 per cent of the potatoes had all six cards opened. For the remaining 44.4 per cent, respondents left at least one card unopened. For only those potatoes that were chosen by respondents, 59.4 per cent had all their cards opened, whereas for potatoes not chosen 53.6 per cent had all cards opened. The difference between chosen and non-chosen potatoes is significant ($\chi^2 = 11.6$, df = 1, $P < 0.01$). Respondents thus accessed more information about the potatoes that they selected than about ones not selected.

The next level of aggregation is the choice set, each with three potatoes or 18 attributes total. For the choice sets, 52 per cent had all the cards opened. Nearly one-half of the choice questions thus had at least one piece of information hidden when respondents made their selections. Finally, each respondent was shown 10 choice sets, or 180 attributes in total; 43.7 per cent of the participants opened all the cards in all choice sets. That is, more than one-half of respondents ignored some information in the course of the survey while they made their choices.

Figure 2 includes two graphs. One indicates the average time in seconds to answer each question. The other graphs the average number of cards left

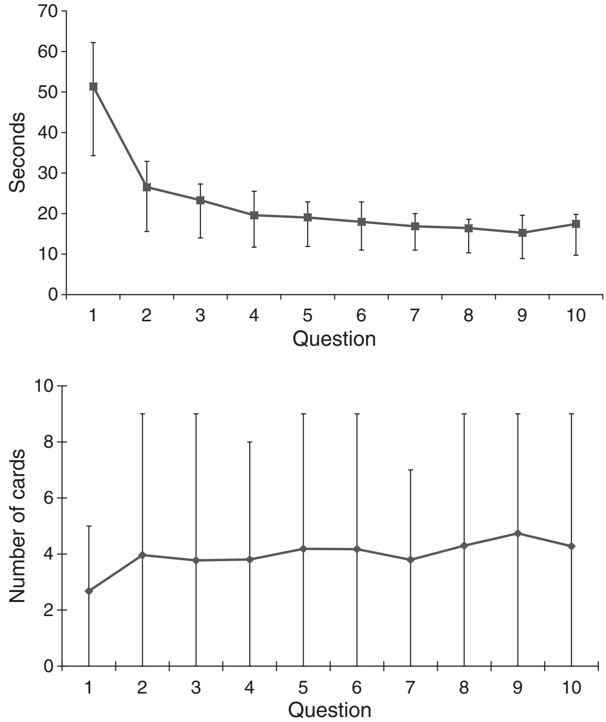

Figure 2 Seconds to answer and cards left unopened per question.

unopened per choice set (18 cards per choice set). In the first choice set, the participants opened more cards than in any of the other choice sets and used more time. For both graphs, error bars indicate the range of the middle 50 per cent of respondents, i.e. the top and bottom 25 per cent are excluded. As respondents moved through the survey, they took less time to answer the questions, but the number of unopened cards stayed around four cards per choice set. This result suggests there may have been some learning about the choice task as respondents progressed through the survey. For the last question, the time to answer increased; the survey instrument indicated the number of the choice question as 'question X out of 10,' so that respondents could have been aware when they reached the final choice question.

The use of information across the attributes was also examined, and the results are presented in Table 2. The percentage of attribute cards that were not opened varied across the attributes, with flesh colour being the most ignored and price the least ignored. The importance of the price attribute replicates prior results using information display boards (Jacoby *et al.* 1977). The counts of cards opened and unopened for the attributes were compared with a chi-square statistic. Respondents opened similar amounts of texture and colour cards, and similar amounts of production and nutrition cards. Amounts of cards opened for other attributes were significantly different

Table 2 Use of information by attribute

	Unopened	Opened	Percentage unopened (%)	Group*
Texture	770	1840	29.5	A
Price	368	2242	14.1	B
Colour	815	1795	31.2	A
Production method	451	2159	17.3	C
Nutrition	434	2176	16.6	C
Country of origin	614	1996	23.5	D

*The number of unopened attributes is statistically similar within groups and statistically different between groups. Groups were determined by chi-square tests, and are significant at the 0.01 level.

from these pairs and from each other. This is shown in Table 2 by a letter indicating which attributes grouped together.

The dataset was analysed to determine whether any group of respondents was more likely to leave cards unopened. For each of the demographic characteristics, those who opened all the cards and those who left any cards unopened were crosstabulated and differences were tested with a chi-square statistic. No significant differences were found for the demographics collected: gender, age, income and education.

4.2 Comparison of choice models

Three ML models were estimated. The first model was solved as a standard mixed logit, with all the attributes in the survey entering into all the utility functions of all respondents. The second model used the coding described above to capture whether a respondent ignored attribute information. If a blue card was not clicked, that attribute was coded as –888. The third model replaced the attributes not viewed with the average value of the attribute. This substitution recognised the fact that participants were provided with an information sheet and descriptions of the attributes. They thus had information about the expected range of each attribute and its potential level, even if they did not click on a specific blue card.

The models were estimated as panel models, and simulations were done with 1000 Halton draws. First, several ‘full-information’ models were estimated to determine which parameters could be assumed fixed and which had significant heterogeneity and should be estimated as random parameters. The two alternative models were then estimated using the same specifications, but on the altered datasets. Table 3 presents the results of the modelling, including estimated parameters, derived SD, and associated *t*-ratios. Also in Table 3 are model fit statistics: the log-likelihood, the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) (Kennedy 2003; Hensher *et al*. 2005a).

The estimated betas for model 1, the full information model, indicated that potatoes were more likely to be chosen if they were organically grown,

Table 3 Model results

Attribute	Full information model		Accessed information model		Average information model	
	Beta (*t*-ratio)	Derived SD (*t*-ratio)	Beta (*t*-ratio)	Derived SD (*t*-ratio)	Beta (*t*-ratio)	Derived SD (*t*-ratio)
Random parameters						
Floury	−0.351 (−2.09)*	0.934 (5.77)**	−0.751 (−3.15)**	1.36 (5.48)**	−0.545 (−2.13)*	1.53 (6.31)**
Organic	0.327 (1.61)	1.02 (4.87)**	0.513 (2.03)*	1.31 (4.57)**	0.428 (1.85)	1.36 (5.03)**
GM	−2.39 (−6.56)**	2.12 (5.07)**	−3.42 (−6.94)**	2.81 (4.85)**	−3.48 (−7.70)**	2.79 (4.62)**
Omega-3	0.806 (2.45)*	1.22 (5.24)**	1.07 (3.21)**	1.67 (6.03)**	1.32 (3.99)**	1.42 (5.31)**
Low GI	0.268 (0.850)	0.794 (3.52)**	0.342 (1.29)	0.925 (3.12)**	0.442 (1.70)	1.05 (3.78)**
Australian	−0.522 (−2.21)*	0.595 (1.81)	−0.841 (−3.45)**	0.755 (2.28)*	−1.00 (−3.83)**	0.944 (2.67)**
Chinese	−1.37 (−4.23)**	1.20 (3.47)**	−2.29 (−5.94)**	1.59 (3.71)**	−2.27 (−6.72)**	1.42 (3.20)**
Fixed parameters						
Price	−1.33 (−8.19)**		−1.82 (−10.5)**		−1.87 (−10.9)**	
Pink	0.151 (0.583)		0.0281 (0.125)		0.0800 (0.373)	
Yellow	0.141 (0.449)		0.319 (1.13)		0.347 (1.32)	
Inter-alternative error components						
Sigma_AltA	0.276 (0.736)		0.330 (1.00)		0.385 (1.28)	
Sigma_AltB	0.326 (0.878)		0.261 (0.711)		0.343 (1.16)	
LL_0	−955.8		−955.8		−955.8	
LL_{model}	−763.4		−719.7		−693.1	
AIC	1565		1477		1424	
BIC	1655		1568		1515	

Statistical significances: $^*P = 0.05$, $^{**}P = 0.01$.

nutritionally enhanced, yellow or grown in New Zealand. They were less likely to be chosen if they were floury, genetically modified, higher in price, or pink, or came from overseas. The random parameters also indicated significant consumer heterogeneity. The parameters that were allowed to vary all had highly significant SD, and many of these deviations were larger than the estimated beta. Thus, for example, although waxy potatoes were, on average, preferred, a significant portion of the respondents preferred floury potatoes.

The results for model 2 suggested that factoring the use of information into the analysis improved the results. Including the indications of whether information was accessed improved the log-likelihood, the AIC, and the BIC. The parameter for the organic attribute went from non-significant in the full information model to significant, the distribution for the parameter for Australian became less significant, and the parameter for pink potatoes changed from negative to positive (although neither estimate was significant).

The results for model 3 are different again. The signs on the parameters and the significances are all similar to model 1, with minor exceptions. The three goodness-of-fit statistics all indicate that this model has the best fit of the models presented here.

All three models also included terms estimating the error from inter-alternative correlation. These terms were non-significant in all three models, suggesting that the variation in responses is sufficiently captured by the random taste parameters.

The willingness to pay for attributes, presented in Table 4, provides another comparison of the three models. The table provides the willingness to pay and the percentage difference between the base model and the two models that incorporated respondents' use of information. Some of the values were nearly identical (leaving aside the price attribute, which is identical by construction). For example, the price across the three models for the attribute for GM was within a few percentage points. On the contrary, the prices for the

Table 4 Willingness-to-pay figures

Attribute	A Full information model (*t*-ratio)	B Accessed information model (*t*-ratio)	C Average information model (*t*-ratio)	Difference, Cols A and B (%)	Difference, Cols A and C (%)
Floury	−0.263 (−0.349)	−0.404 (−0.512)	−0.271 (−0.309)	53.6	3.04
Organic	0.254 (0.318)	0.273 (0.343)	0.273 (0.355)	7.48	7.48
GM	−1.77 (−1.07)	−1.88 (−1.11)	−1.92 (−1.24)	6.26	8.12
Omega-3	0.610 (0.625)	0.594 (0.627)	0.672 (0.833)	−2.62	10.2
Low GI	0.189 (0.301)	0.200 (0.355)	0.207 (0.344)	5.82	9.52
Australian	−0.376 (−0.668)	−0.458 (−0.908)	−0.525 (−0.907)	21.8	39.6
Chinese	−1.04 (−1.06)	−1.26 (−1.32)	−1.22 (−1.46)	20.9	17.3
Price	−1.00	−1.00	−1.00	0.00	0.00
Pink	−0.130 (−0.611)	0.0160 (0.130)	0.0407 (0.344)	−112	−131
Yellow	0.0918 (0.398)	0.175 (1.16)	0.177 (1.25)	90.2	92.4

different colours of potatoes were very different across the three models, with estimates of the price of pink potatoes ranging from positive to negative.

5. Discussion

The most basic finding of this research is that respondents did not access all the information available to them. This was true although the opportunity cost of accessing information was trivial: it required a fraction of a second and the click of a mouse. What is unknown is respondents' expectation regarding the cognitive costs of incorporating any new information into their decisions.[1] The finding that some information was not accessed when respondents had to seek it suggests that the choice modelling research may need to give further consideration the use of information.

The second finding is that accounting for respondents' use of information makes a difference to the estimates from a choice survey. The model fit statistics and the comparison of willingness to pay suggest that accounting for respondents' use of information makes a difference to the results of a choice modelling survey and results in better-fitting models. These results raise the question of whether the better accuracy is worthwhile. First, it is important to note that none of willingness-to-pay figures was significant; the variance of the estimated parameters and the distributions of the random parameters created large variances in the simulated willingness to pay and low *t*-ratios. The sources of heterogeneity and variability in the sample overwhelm any impact from the use of information.

Second, an indication of the importance of information use is apparent in Table 5, which compares the willingness to pay from the accessed and average information models, the number of cards unopened, and the differences between the full information and the other two models. Pearson's correlation coefficients were calculated for three pairs of columns for the two alternative models (the price attribute was excluded because its willingness to pay is unity by construction). The correlations indicate that use of information was highly correlated with the importance of attributes, given by the willingness to pay, and with the error associated with ignoring information use. Respondents tended to look for information concerning important attributes. In addition, the impact of ignoring information use was largest on attributes with low values. The weakest correlation was between columns B and E in Table 5. This correlation compared the prices from the average information model and the difference between those prices and the full information model results. This result suggests that more work is needed to understand how respondents are thinking about the attributes whose information they do not access. Overall, these results suggest congruence of the relevance and determinance of attributes, contrary to the findings in Van Ittersum *et al.* (2007).

[1] We thank an anonymous reviewer for this insight.

Table 5 Comparison of information use and modelling results

	A Price from accessed information model*	B Price from average information model*	C Unopened cards	D Difference, full and accessed information models (%)*	E Difference, full and average information models (%)*
Texture	0.404	0.271	770	53.6	3.04
Colour	0.0955	0.109	815	101	112
Production method	1.08	1.10	451	6.87	7.80
Nutrition	0.397	0.440	434	4.22	9.84
Country of origin	0.859	0.873	614	21.4	28.5
Pearson's correlations					
Cols A and C					−0.622
Cols A and D					−0.737
Cols C and D					0.919
Cols B and C					−0.691
Cols B and E					−0.517
Cols C and E					0.607

*The average of absolute values for each attribute. For the raw figures, see Table 4.

The results indicate that attention to information may affect respondents' decisions, and ignoring how respondents use information can bias the results of a choice modelling survey. However, this bias tends to have smaller impacts on the important attributes. In addition, information use is but one source of variability in the data, and may be less important than other sources. As a result, the impacts on willingness to pay found here are smaller and less conclusive than were found by Hensher *et al.* (2005b), whose modelling was based on a larger sample and posterior self-reports of attention to survey information.

6. Conclusion

The method used in this research expanded on work investigating respondents' use of information (Hensher and Rose 2005; Hensher *et al.* 2005b, 2007; Hensher 2006) in two ways. First, the use of information by respondents was captured in the course of survey administration using a computerised information display board, so it did not rely on their posterior self-reporting. The use of self-reports may suffer from a problem highlighted by the results in Swait (2001), that the attributes may function as thresholds or kinks in the utility functions without being ignored altogether. Second, access to the information was captured for each attribute of every alternative, which allowed more flexibility in assessing use of information. As the analysis showed, respondents accessed more information about the potatoes chosen than about those not chosen.

Of the three models estimated – full information, accessed information and average information – the best-fitting model was based on (i) the observation that respondents did not view all information and (ii) the assumption that they took the unseen attribute to be the average level for that attribute. Respondents seemed to look for more information for the attributes they considered important, and the more information they accessed, the better the full information model. This result may suggest a rational approach to information search. However, the willingness to pay estimated from the three models, while different, were not significantly different from each other because of the multiple sources of variance.

This research could be strengthened in several ways. First, all the data were captured in the course of a computerised survey that required respondents to click on boxes to obtain information. The comparison with a full-information choice survey is thus not exact, because the decision environment is different (Bettman and Kakkar 1977). Another approach would be to compare two treatments, one in which all information was fully presented and a second treatment like the one used here. A second consideration is that the present research was conducted in a controlled situation. The survey tool has proved robust for this work, and could therefore be used on a much larger sample with fewer researchers, such as for a large class held in a computer laboratory. A larger sample would allow information processing to be investigated for subsamples, which could provide greater detail on the impact of the use of information. The survey tool could also be used for Web-based surveying. A third area for future research concerns the impacts of presentation on results. In the present research, the order of attributes was randomised to reduce the impact of attribute placement on search for information, but the order of choice questions was not varied. The amount of information used declined as respondents worked through the survey, so that information use again interacted with choice set design. Further work would be needed to assess the impact of randomisation and information use on model results.

One implication of these findings – that respondents do not necessarily use all available information and that this behaviour affects parameter estimates – is that information use could be better controlled in choice survey research. One approach is outlined here: recording the information that respondents access through mouse-clicks. The same type of information could be recorded by other means, such as eye movement recording. These methods require certain resources, and are not as easily deployed as paper surveys. For paper surveys, an approach similar to 'cheap talk' (Lusk 2003) could be tested. Cheap talk is a technique that reminds respondents of their budget constraints in order to elicit more realistic willingness-to-pay estimates. Similarly, respondents could be reminded to consider all the attributes and reflect on the trade-offs that each set of choices represents. Finally, there may be scope for work on respondents' expectations regarding the information contained in surveys, and observing the results of surprises or challenges to those expectations.

This research does suggest, however, that respondent use of information contained in surveys may significantly affect the data collected. Assuming that respondents use all the information provided may lead to inaccurate results.

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