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A question of taste: recognising the role of latent preferences and attitudes in analysing food choices

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Abstract

There has long been substantial interest in understanding consumer food choices, where a key complexity in this context is the potentially large amount of heterogeneity in tastes across individual consumers, as well as the role of underlying attitudes towards food and cooking. The present paper underlines that both tastes and attitudes are unobserved, and makes the case for a latent variable treatment of these components. Using empirical data collected in Northern Ireland as part of a wider study to elicit intra-household trade-offs between home-cooked meal options, we show how these latent sensitivities and attitudes drive both the choice behaviour as well as the answers to supplementary questions. We find significant heterogeneity across respondents in these underlying factors and show how incorporating them in our models leads to important insights into preferences.

Keywords: food preferences; latent variables; stated choice; taste heterogeneity

1 Introduction

There has long been interest in better understanding consumers' food choices, with a focus on people's motivations, preferences and habits. Recently, particular emphasis has been put on eating habits within an obesity risk context.

Food choices are complex as well as frequent. In a recent study, Wansink and Sobal (2007) estimated that a person can make over 200 food and beverage related decisions every day. Asp

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(1999) in turn discusses in detail some of the factors which affect consumers when they are deciding what to eat, particularly cultural, psychological and lifestyle factors as well as food trends to name but a few. Work by Lennernäs et al. (1997) has highlighted the role of quality/freshness, price, taste, as well as family preferences and trying to eat healthily, while Drewnowski and Darmon (2005) consider the effects of taste, convenience and economic constraints on food choices. Lennernäs et al. (1997) also found that respondents in different socio-economic categories select different factors as contributing a large portion of influence on their food choices. The extent of heterogeneity in preferences is also highlighted in other work. For example, Logue and Smith (1986) indicate that women have higher preferences for low-calorie foods than men and Rappoport et al. (1993) found that insofar as the *health* value of food was concerned, men had a much simpler cognitive structure than women. Consumer information and market research companies are continually developing classification systems which aim to identify different consumer segments and consequently try to predict consumer behaviour (Asp, 1999). These systems make use of important lifestyle factors to describe how consumers make food decisions. With the exception of examples such as above, most food studies focus on a limited socio-geographic based population (Glanz et al., 1998; Jaeger and Meiselman, 2004; Marshall and Bell, 2004).

A large body of work has looked at respondent reported measures of importance of key attributes. For example, Glanz et al. (1998) examine the self-reported importance of taste, nutrition, cost, convenience, and weight control on personal dietary choices and whether these factors vary across demographic groups, are associated with lifestyle choices related to health, and actually predict eating behaviour. They found that the importance placed on taste, nutrition, cost, convenience, and weight control helped predict types of food consumed. A share of studies which have investigated adult preferences for a variety of foods have involved the respondent rating individual food items on either a nine, five or four point scale, wherein the studies reported the mean rating for each food item (see, for example Bell and Marshall, 2003, Drewnowski and Hann, 1999, Jaeger and Meiselman, 2004 and Rappoport et al., 1993).

Whilst simple rating methods can provide rich information about specific food preferences, they do not examine food preference *patterns* which would help elicit more general food preferences. For example, a person's preference for one type of food could be a predictive indicator of that person's preference for another type of food (Logue and Smith, 1986). Across a number of fields, mathematical structures belonging to the family of random utility models have established themselves as the preferred method for the study of choice behaviour at the disaggregate level (Train, 2009). These models quantify the relative importance of the different attributes describing each alternative and are used across fields as diverse as transport, marketing and health economics. This study adds to a growing literature that has used these models to examine food choices and preferences for food attributes (see, for example Campbell and Doherty, 2013, Carlsson et al., 2007, Hu et al., 2004, Jaeger and Rose, 2008, Jaeger et al., 2008, Lusk and Briggeman, 2009, Ortega et al., 2011 and Rigby et al., 2009). More specifically, this paper contributes to the literature where these models have been used to investigate the link between food choice, diet and health (e.g., Balcombe et al., 2010; Gracia et al., 2009; Mueller Loose et al., 2013).

The present paper illustrates how advanced choice models can be used to obtain a better understanding of consumer food choices. In particular, we recognise, in line with previous work, that there exist significant differences in preferences across individual consumers. We hypothesise that while some of these differences can be linked to socio-demographic characteristics, others cannot. The standard modelling approach for such "unexplained" differences would be a model allowing for random taste heterogeneity. Any information about sensitivities[1] and differences in sensitivities would be inferred solely on the basis of the choices made by respondents. We use a more refined approach that allows us to make use of the supplementary information provided by respondents in ranking questions and attitudinal questions within a hybrid choice model making use of latent variables (e.g., Ben-Akiva et al., 2002a,b; Bolduc et al., 2005). This gives us a better understanding of what drives food choices, and the differences in these drivers across the population.

The remainder of this paper is organised as follows. Section 2 presents an overview of the empirical data and methods used in this study. This is followed in Section 3 by a discussion of the results for both the base models and the latent variable models. Finally, a concluding discussion is presented in Section 4.

[1] We have chosen to use the term 'sensitivities' here, as we felt it more appropriate in this specific context, as the more commonly used term 'preferences' can be seen to relate to alternatives, not just attributes.

2 Material and methods

2.1 Survey work

Data were collected as part of a wider study to elicit intra-household trade-offs between home-cooked meal options. The respondents used for the survey formed a random sample of Northern Ireland households, and face-to-face interviews were used for preference elicitation.

Table 1 shows the socio-demographic characteristics of the respondents. Just over a third of the respondents were aged between 35 and 50, with the rest split evenly above and below these ages. The average income per week was £211, with 48% of the respondents in full-time employment. 10% had at least a degree level education.

2.1.1 Stated choice component

In the stated choice component of the survey, respondents were presented with the choice between three different meal options representing a typical evening meal that they would share with their partner at home. After a qualitative stage, including consultation with experts and assisted interviews with respondents, we conducted a pilot study. Following this, we were able to select the following attributes to describe the meal options: calories, cooking time, food type and cost. Taste was not included as a direct variable in the choice tasks as it would be subject to *interpretation* by the respondent. Instead, "food type" was used as a proxy for taste. Three levels were used for each attribute, where the specific combinations presented in a given choice scenario were obtained from a D-efficient experimental design with Bayesian priors (Bliemer and Rose, 2010; Rose and Bliemer, 2009), produced using NGene (ChoiceMetrics, 2012). A D-efficient design was chosen so as to minimise the asymptotic variance covariance matrix. The final design contained 24 rows which were divided into 3 blocks of 8 choices, where each respondent was asked to complete 8 choice tasks. To ensure that any heterogeneity retrieved in both the parameter estimates as well as the variances of the error terms is not simply an artefact of the design of choice set scenarios (Arentze et al., 2003), we used orthogonal blocking, and randomly assigned people to blocks.

Table 2 shows the three levels used for the different attributes, where "Cost" represented the total cost for all of the ingredients needed to produce a typical evening meal, which would feed both the respondent and his or her partner. To allow respondents to better relate to the attribute

Tab. 1: Socio-demographic characteristics

Age		Female		Male		Total	
18-24		32	11%	27	9%	59	10%
25-34		71	24%	66	23%	137	23%
35-50		100	34%	100	34%	200	34%
51-59		35	12%	40	14%	75	13%
60-64		22	8%	20	7%	42	7%
65-75		32	11%	35	12%	67	11%
75+		0	0%	4	1%	4	1%
Income							
Per week	Per Year	Female		Male		Total	
Less than £150	Less than £7,800	142	49%	91	31%	233	40%
£150 - £299	£7,800 - £15,599	98	34%	121	41%	219	38%
£300 - £449	£15,600 - £23,399	41	14%	59	20%	100	17%
£450 - £599	£23,400 - £31,199	8	3%	15	5%	23	4%
£600+	£31,200+	3	1%	6	2%	9	2%
Employment		Female		Male		Total	
In full-time employment		109	37%	174	60%	283	48%
In part-time employment		68	23%	18	6%	86	15%
Self-employed		7	2%	11	4%	18	3%
Unemployed		36	12%	30	10%	66	11%
Retired		48	16%	50	17%	98	17%
Student/Otherwise not working		24	8%	9	3%	33	6%
Education		Female		Male		Total	
No qualifications		52	18%	46	16%	98	17%
CSE/GCSE/O Levels		148	51%	141	48%	289	49%
A Level/Baccalaureate		46	16%	36	12%	82	14%
Vocational Qualification		18	6%	38	13%	56	10%
Degree		25	9%	25	9%	50	9%
Postgraduate Degree		3	1%	6	2%	9	2%
Total		292	100%	292	100%	584	100%

levels for calories, cooking time and food type, they were provided with illustrative reference cards that showed what type of meal could be expected for given attribute combinations. We chose cost levels of £5, £10 and £15 pounds after conducting a pilot study; the large cost differences were found to be needed as respondents were reacting very strongly to the different levels of the other attributes, causing the cost attribute to become insignificant when smaller price differences were used.

In each choice task, respondents were asked to choose their most preferred option for a typical evening meal that they would share together with their partner at home, and which would be

Tab. 2: Attribute levels

Attribute	Levels
Calories *(per portion)*	Less than 400 calories
	Between 400 and 600 calories
	Over 600 calories
Cooking Time	Less than 30 minutes
	Between 31 and 60 minutes
	Over 60 minutes
Food Type *(proxy for taste)*	Asian
	Italian
	Local
Cost	£5
	£10
	£15

cooked at home. An example choice scenario is shown in Figure 1. We decided against explicitly including a “no choice” option, but if a respondent could not decide, then this was recorded as a “Don’t know” by the interviewer[2]. For the present study, we made use of responses from 584 individuals, giving $4,672$ observations in total.

2.1.2 Supplementary questions

In addition to completing the choice tasks, respondents were also asked to state their most preferred and least preferred level of each of the three non-cost attributes. A summary of the information obtained in this manner is shown in Figure 2, where the first two columns in each subfigure show the responses to the questions eliciting the respondent’s *most* preferred options, for females and males respectively, and the last two columns in each subfigure show the responses to the questions eliciting the respondent’s *least* preferred options, for females and males respectively.

The results from this exercise are in line with expectations and the prior literature. We can see that for calories, 49% of the interviewed women prefer the medium calories range, with a total of 80% preferring fewer than 600 calories in their meal. Whilst this preference pattern is also shown by male respondents, the level of uncertainty (“Don’t know”) is increased, especially for the least

[2] We acknowledge this potential limitation within the data (Olsen and Swait, 1997), but this approach was taken as the sample size was quite small and we did not want to reduce the data further by encouraging “Don’t know” responses. However, although respondents were not told upfront that they could state “Don’t know”, if they did so, it was recorded. Further, if the respondent stated “Don’t know” at any point in the questionnaire and it was recorded down then they would know that it was safe to say “Don’t know”, meaning that only the first instance of “Don’t know” could be subject to any bias.

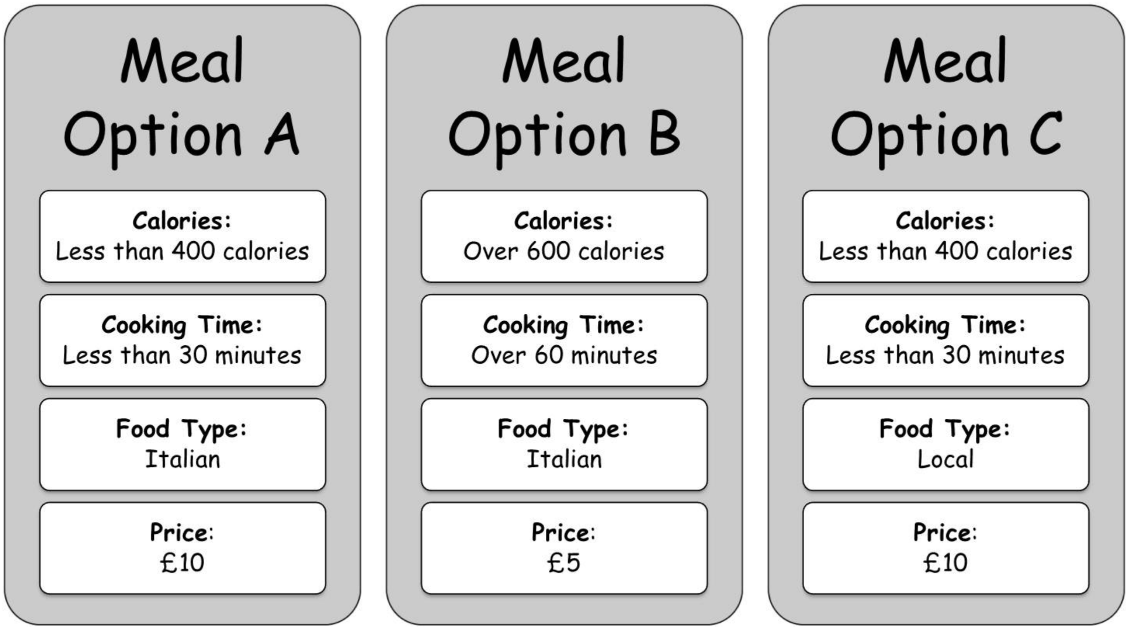
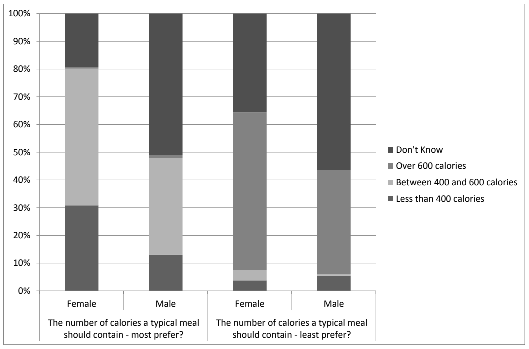


Fig. 1: Example choice task

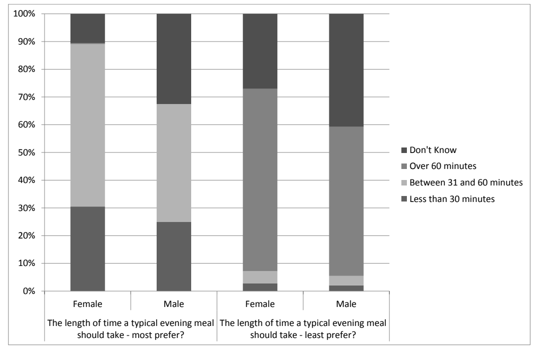
preferred calorie level. With regards to cooking time, medium cooking time is again the most preferred, while high cooking time is generally the least preferred. Overall, the question which encountered the fewest "Don't know" responses was that which asked respondents for their most preferred food types. Local food was the most popular choice; this is in line with findings by McIlveen and Chestnutt (1999), where they conclude that greater product awareness needs to be instigated by retailers in Northern Ireland in order to inform consumers of the larger range of food products available to them and consequently encourage greater uptake. McIlveen and Chestnutt (1999) found that the Italian food sector represented a growth area, whereas Indian and other newly developing food sectors were not yet evident in Northern Ireland. Note that this relates to cooking meals at home rather than eating out, where there is an abundance of international restaurants available.

As a final component, respondents were also presented with three questions relating to attitudes towards cooking. In particular, respondents were asked to indicate their level of agreement (on a five-point Likert scale) with three statements, namely:

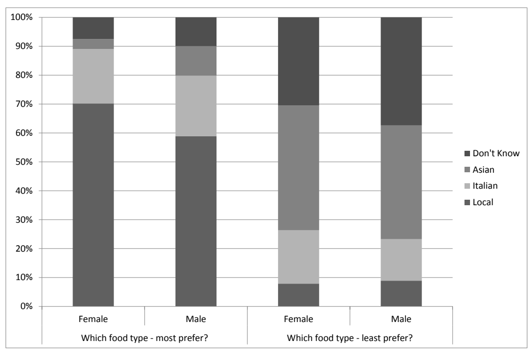
- *"Cooking is not much fun"*;
- *"Compared with other daily decisions, my food choices are not very important"*; and



(a) Calories



(b) Cooking Time



(c) Food Type

Fig. 2: Attribute importance rankings

- *"I enjoy cooking for others and myself"*.

Figure 3 shows a summary of the responses to the three attitudinal questions, highlighting a more positive attitude towards cooking for female respondents, along with a higher prevalence of "Don't know" responses for male respondents.

The inclusion of these statements was driven in part by the success achieved in Bell and Marshall (2003) and Marshall and Bell (2004) at being able to classify differences in food choices and food choice patterns by using a measure of food involvement, namely the "Food Involvement Scale" (FIS). Bell and Marshall (2003) define food involvement as 'the level of importance of food in a person's life'. They also assume that as a result of this, the level of food involvement will vary across individuals. Bell and Marshall (2003) and Laaksonen (1994, pg. 8-9) suggest that food involvement is a mediating variable, acting between stimulus objects and response, depending on

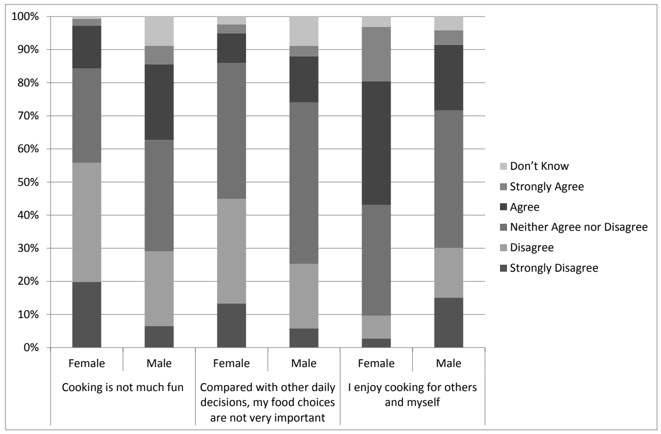


Fig. 3: Answers to attitudinal questions relating to cooking

both the characteristics of the stimulus object and those of the consumer.

2.2 Base model specification

As a first step, we estimate simple Multinomial Logit (MNL) models on our data, where we use the panel specification of the sandwich estimator to recognise the repeated choice nature of the data in the computation of standard errors (cf. Daly and Hess, 2011). All models reported in this paper were coded in Ox 6.2 (Doornik, 2007). For the MNL model, we used maximum likelihood estimation, while maximum simulated likelihood estimation was used for the hybrid models, with simultaneous estimation of all model components.

Two different specifications are used. In the first model, the deterministic component of utility[3] for respondent n and alternative i in choice task t (out of 8) is written as:

[3] In the MNL specification, the random component of the utility function follows a type I extreme value distribution.

$$
\begin{aligned}
V_{int} =& \beta_{\text{LowCal}}\text{LowCal}_{int} + \beta_{\text{HighCal}}\text{HighCal}_{int}+ \\
& \beta_{\text{LowTime}}\text{LowTime}_{int} + \beta_{\text{HighTime}}\text{HighTime}_{int}+ \\
& \beta_{\text{Asian}}\text{Asian}_{int} + \beta_{\text{Italian}}\text{Italian}_{int}+ \\
& \beta_{\text{Cost}}\text{Cost}_{int} \qquad \forall 1 \leq i \leq 3 \qquad (1) \\
V_{4nt} =& \delta_{\text{DK}}\text{DK}_{4nt}, \qquad (2)
\end{aligned}
$$

where, as an example, LowCal_{int} is set to 1 if alternative i has the low calories level (and is set to 0 if alternative i has a calories level other than low), and where β_{LowCal} is the associated marginal utility coefficient, which is to be estimated. Equation 1 shows the utility individual n will receive if they select any of the first three alternatives, whereas Equation 2 shows the utility individual n will receive through the selection of the "Don't know" option (displayed as alternative 4, in this case)[4]. Other than cost, the attributes were entered as dummy variables in order to allow us to capture any non-linear preference structure for these attributes, where the middle level was used as the base (i.e. sensitivity fixed to zero).

The specification thus far has assumed that the sensitivities to the different attribute levels (i.e. the preferences) are constant across individuals in our sample. To address this shortcoming, we make use of a revised specification that allows for differences in sensitivities for the three non-cost attributes by age group as well as by gender. For each level (other than middle), we thus estimate a base coefficient, along with offsets for male respondents, respondents under the age of 35 and respondents over the age of 50, using the middle age group as the base. This specification is shown in Equation 3, where, for example, $\Delta_{\text{Italian;Male}}$ shows the shift in the utility for Italian food for a male respondent aged 35-49 years relative to a female respondent aged 35-49 years.

$$
\begin{aligned}
V_{int} =& \beta_{\text{LowCal;Base}}\text{LowCal}_{int} + \Delta_{\text{LowCal;Male}}\text{LowCal}_{int} \\
& +\Delta_{\text{LowCal;Under 35}}\text{LowCal}_{int} + \Delta_{\text{LowCal;Over 50}}\text{LowCal}_{int}
\end{aligned}
$$

[4] We previously tested for left-to-right bias by estimating alternative specific constants for $i-1$ of the hypothetical choices and found none, so we decided to use an alternative specific constant for the "Don't know" choices.

$$
\begin{aligned}
&+\beta_{\text{HighCal;Base}}\text{HighCal}_{int}+\Delta_{\text{HighCal;Male}}\text{HighCal}_{int}\\
&+\Delta_{\text{HighCal;Under 35}}\text{HighCal}_{int}+\Delta_{\text{HighCal;Over 50}}\text{HighCal}_{int}\\
&+\beta_{\text{LowTime;Base}}\text{LowTime}_{int}+\Delta_{\text{LowTime;Male}}\text{LowTime}_{int}\\
&+\Delta_{\text{LowTime;Under 35}}\text{LowTime}_{int}+\Delta_{\text{LowTime;Over 50}}\text{LowTime}_{int}\\
&+\beta_{\text{HighTime;Base}}\text{HighTime}_{int}+\Delta_{\text{HighTime;Male}}\text{HighTime}_{int}\\
&+\Delta_{\text{HighTime;Under 35}}\text{HighTime}_{int}+\Delta_{\text{HighTime;Over 50}}\text{HighTime}_{int}\\
&+\beta_{\text{Asian;Base}}\text{Asian}_{int}+\Delta_{\text{Asian;Male}}\text{Asian}_{int}\\
&+\Delta_{\text{Asian;Under 35}}\text{Asian}_{int}+\Delta_{\text{Asian;Over 50}}\text{Asian}_{int}\\
&+\beta_{\text{Italian;Base}}\text{Italian}_{int}+\Delta_{\text{Italian;Male}}\text{Italian}_{int}\\
&+\Delta_{\text{Italian;Under 35}}\text{Italian}_{int}+\Delta_{\text{Italian;Over 50}}\text{Italian}_{int}\\
&+\beta_{\text{Cost}}\text{Cost}_{int} \qquad\qquad \forall 1\leq i\leq 3
\end{aligned}
\tag{3}
$$

2.3 Integrated Choice and Latent Variable (ICLV) model specification

The base model with deterministic heterogeneity allows for variations in sensitivities as a function of age and gender. However, it is easily conceivable that additional differences exist which cannot entirely be linked to socio-demographic characteristics. Rather than relying on a simple random coefficients specification, we propose to make use of the additional information collected from respondents in terms of attribute rankings as well as attitudinal questions. Specifically, we hypothesise that these additional data can serve as proxies for the underlying differences in sensitivities. However, it is important to recognise that answers to attribute ranking questions and attitudinal questions do not provide us with a direct error-free measure of the actual underlying sensitivities. Indeed, they are merely a function of these sensitivities. Similarly, these data points are likely to be correlated with other unobserved effects, and their incorporation as explanatory variables in our choice models would thus put us at risk of endogeneity bias.

To allow us to use the additional data while not exposing ourselves to the risk of measurement error and endogeneity bias, we make use of a hybrid model specification in which the answers to ranking questions and attitudinal questions are treated as dependent rather than explanatory variables. A number of latent variables are then used to create a link between a given respondent's choices and his/her answers to these additional questions. Within such an Integrated Choice and Latent Variable (ICLV) model, the responses to the subjective questions are modelled jointly with the actual choice processes, all the while maintaining the assumption that *both* processes are at least in part influenced by the latent attitudes. This approach integrates choice models with latent variable models resulting in an improvement in the understanding of preferences and allow us to make use of additional data sources. The theoretical developments of such hybrid choice models centre on the work of Ben-Akiva et al. (2002a,b) and Bolduc et al. (2005), with numerous applications, for example Abou-Zeid et al. (2010), Alvarez-Daziano and Bolduc (2009), Daly et al. (2012a), Fosgerau and Bjørner (2006), Hess and Beharry-Borg (2012), Johansson et al. (2006) and Yáñez et al. (2010).

Our work makes use of seven latent variables:

- two latent variables linked to the underlying sensitivities to the low and high levels for calories, α_{LowCal} and α_{HighCal};
- two latent variables linked to the underlying sensitivities to the low and high levels for cooking time, α_{LowTime} and α_{HighTime};
- two latent variables linked to the underlying sensitivities to Italian and Asian food, α_{Italian} and α_{Asian}; and
- one latent variable linked to general attitudes towards food, hereafter known as the *'cooking'* attitude, α_{Cooking}.

We use a linear in attributes specification for the deterministic part, and write:

$$\begin{aligned} &\alpha_{k,n} = \gamma_{\alpha_k} z_n + \eta_{k,n}, \\ &\qquad k = \text{LowCal, HighCal, LowTime, HighTime, Italian, Asian, Cooking} \end{aligned} \tag{4}$$

where $\gamma_{\alpha_k} z_n$ represents the deterministic part of $\alpha_{k,n}$, with, z_n being a vector of socio-demographic variables, γ_{α_k} being a vector of estimated parameters and $\eta_{k,n}$ being a random disturbance, which follows a standard Normal distribution across respondents.

Hereafter, α_n represents the vector of latent attitudes for respondent n. These latent variables are now used as explanatory variables in the utility function, which is rewritten as:

$$V_{int} = f(\beta, x_{int}, \delta, \alpha_n, \tau) \quad (5)$$

where τ is a vector of parameters that explain the impact of the vector of latent variables α_n on the utility of alternative i, possibly in interaction with the attributes x_{int} and the parameters β.

At the same time, we use the latent variables to explain the responses to the ranking questions and the attitudinal questions. In particular, the first two latent variables, α_{LowCal} and α_{HighCal}, are used to explain the ranking of the three different calorie levels, the following two latent variables, α_{LowTime} and α_{HighTime}, are used for the ranking of the three different time levels, and the fifth and sixth latent variables, α_{Italian} and α_{Asian}, are used to explain the ranking of the three different food types. Finally, the seventh latent variable, α_{Cooking}, is used to explain the answers to the three attitudinal questions about cooking.

For each of the three non-cost attributes, respondents were asked to state their most preferred and least preferred level (i.e. *best* and *worst* level respectively). We represent the underlying sensitivities to the different levels in a utility framework, where, for the example of the calories attribute, we have that:

- the utility for *low* calories is given by the latent variable for the underlying sensitivity to low calories, i.e. α_{LowCal}, plus a parameter $\mu_{R,\text{LowCal}}$; where $\mu_{R,\text{LowCal}}$ captures the mean ranking in the sample;
- the utility for *high* calories is given by the latent variable for the underlying sensitivity to high calories, i.e. α_{HighCal}, plus a parameter $\mu_{R,\text{HighCal}}$; where $\mu_{R,\text{HighCal}}$ captures the mean ranking in the sample; and
- the utility for *medium* calories is set to zero.

For the response to the *worst* attribute level, the sign of the utilities was reversed[5]. Respondents

[5] Clearly, the actual latent variable used in the two specifications needs to be the same here, so the only assumption relates to using the same μ_R terms in the best and worst (with sign change) specifications. We found no significant asymmetry in these terms, hence our decision. The same does not apply for the "Don't know" term where separate constants were used.

were also allowed to opt out of each ranking question, by giving a "Don't know" response to either their best or worst preferred level. The utilities for such responses are given by constants, where separate constants are used for the best and worst rankings, given the differential rates of "Don't know".

The actual probabilities for the observed responses to the best and worst ranking questions are now given by:

$$P_{\text{cal-best,n}} = \frac{\mathbb{I}^B_{\text{LC,n}} e^{\mu_{R,\text{LowCal}}+\alpha_{\text{LowCal},n}} + \mathbb{I}^B_{\text{MC,n}} + \mathbb{I}^B_{\text{HC,n}} e^{\mu_{R,\text{HighCal}}+\alpha_{\text{HighCal},n}} + \mathbb{I}^B_{\text{DK BC,n}} e^{\delta_{R,\text{DK BestCal}}}}{e^{\mu_{R,\text{LowCal}}+\alpha_{\text{LowCal},n}} + 1 + e^{\mu_{R,\text{HighCal}}+\alpha_{\text{HighCal},n}} + e^{\delta_{R,\text{DK BestCal}}}} \tag{6}$$

$$P_{\text{cal-worst,n}} = \frac{\mathbb{I}^W_{\text{LC,n}} e^{-\mu_{R,\text{LowCal}}-\alpha_{\text{LowCal},n}} + \mathbb{I}^W_{\text{MC,n}} + \mathbb{I}^W_{\text{HC,n}} e^{-\mu_{R,\text{HighCal}}-\alpha_{\text{HighCal},n}} + \mathbb{I}^W_{\text{DK WC,n}} e^{\delta_{R,\text{DK WorstCal}}}}{e^{-\mu_{R,\text{LowCal}}-\alpha_{\text{LowCal},n}} + 1 + e^{-\mu_{R,\text{HighCal}}-\alpha_{\text{HighCal},n}} + e^{\delta_{R,\text{DK WorstCal}}}} \tag{7}$$

where:

- $\mathbb{I}^B_{\text{LC,n}}$ is an indicator variable, equal to 1 if respondent n choose 'Low' as his/her most preferred calorie level and 0 otherwise;
- $\mathbb{I}^B_{\text{MC,n}}$ is an indicator variable, equal to 1 if respondent n choose 'Medium' as his/her most preferred calorie level and 0 otherwise;
- $\mathbb{I}^B_{\text{HC,n}}$ is an indicator variable, equal to 1 if respondent n choose 'High' as his/her most preferred calorie level and 0 otherwise; and
- $\mathbb{I}^B_{\text{DK BC,n}}$ is an indicator variable, equal to 1 if respondent n did not know his/her most preferred calorie level and 0 otherwise.

Equivalently $\mathbb{I}^W$ is an indicator variable for the least favourite rankings. The parameters $\delta_{R,\text{DK BestCal}}$ and $\delta_{R,\text{DK WorstCal}}$ give the utility for the "Don't know" choices.

A corresponding specification was used for the ranking questions for time and food type. From this, we then obtain:

$$L\left(R_n \mid \alpha_{*,n}\right) = P_{\text{cal-best,n}} P_{\text{cal-worst,n}} P_{\text{time-best,n}} P_{\text{time-worst,n}} P_{\text{type-best,n}} P_{\text{type-worst,n}}, \tag{8}$$

which gives the probability of observing the specific responses given by respondent n to the ranking questions as a product of logit probabilities which is conditional on the first six latent variables, where $\alpha_{*,n} = \langle \alpha_{LowCal,n}, \alpha_{HighCal,n}, \alpha_{LowTime,n}, \alpha_{HighTime,n}, \alpha_{Italian,n}, \alpha_{Asian,n} \rangle$.

The specification used for the cooking indicators is somewhat different. In line with Daly et al. (2012a), we treat the responses to these three attitudinal questions using an ordered logit model specification (see also Bierlaire, 2008). The probability of observing a given value s for the k^{th} indicator (with $k = 1, 2, 3$) for respondent n, with $s = 1, \ldots, 5$, where $s = 1$ indicates a strong agreement with the statement and $s = 5$ indicates a strong disagreement, is now given by:

$$P\left(I_{k,n} \mid \alpha_{\text{Cooking},n}\right) = \frac{e^{\psi_{k,s} - \zeta_{I_k} \alpha_{\text{Cooking},n}}}{1 + e^{\psi_{k,s} - \zeta_{I_k} \alpha_{\text{Cooking},n}}} - \frac{e^{\psi_{k,s-1} - \zeta_{I_k} \alpha_{\text{Cooking},n}}}{1 + e^{\psi_{k,s-1} - \zeta_{I_k} \alpha_{\text{Cooking},n}}} \tag{9}$$

where the estimated effect of the latent variable $\alpha_{\text{Cooking},n}$ on this indicator is given by ζ_{I_k}, and the probability of the actual observed response is then given by:

$$L\left(I_{k,n} \mid \alpha_{\text{Cooking},n}\right) = \sum_{s=1}^{S} \mathbb{I}_{\mathrm{s}}^{k,n} \left[\frac{e^{\psi_{k,s} - \zeta_{I_k} \alpha_{\text{Cooking},n}}}{1 + e^{\psi_{k,s} - \zeta_{I_k} \alpha_{\text{Cooking},n}}} - \frac{e^{\psi_{k,s-1} - \zeta_{I_k} \alpha_{\text{Cooking},n}}}{1 + e^{\psi_{k,s-1} - \zeta_{I_k} \alpha_{\text{Cooking},n}}} \right] \tag{10}$$

where $\mathbb{I}_1^{k,n} = 1$ if respondent n gives level 1 as the answer to the k^{th} attitudinal question, and zero otherwise. For normalisation, we set $\psi_{k,0} = -\infty$ and $\psi_{k,5} = +\infty$ and estimate the four intermediate thresholds, where $\psi_{k,s} \geq \psi_{k,s-1}$. Finally, we set $L\left(I_n \mid \alpha_{\text{Cooking},n}\right) = \prod_{k=1}^{3} L\left(I_{k,n} \mid \alpha_{\text{Cooking},n}\right)$.

Our joint model now has three components in the likelihood function; a choice model, a measurement model for the ranking questions, and a measurement model for the three attitudinal questions. These are driven by structural equations for utilities and latent variables, respectively. The likelihood for the observed sequence of choices for respondent n is given by $L\left(y_n \mid \beta, \delta, \tau, \alpha_n\right)$, which is a product of logit probabilities, and a function of the parameters of the base choice model (grouped together into β), the τ parameters and the vector of seven latent variables α. The likelihood for the measurement model for the ranking question is given by $L\left(R_n \mid \mu_R, \delta, \alpha_{*,n}\right)$ which is a function of the first six latent variables as well as a set of constants and the mean ranking parameters. Finally, the likelihood for the measurement model for the attitudinal questions is given by $L\left(I_n \mid \zeta_I, \psi, \alpha_{\text{Cooking},n}\right)$, which is a function of the ζ terms, the threshold parameters ψ, and the seventh latent variable.

In combination, the log-likelihood function is thus given by:

$$LL\left(\beta, \gamma, \tau, \zeta_I, \psi, \mu_R, \delta\right) = \sum_{n=1}^{N} \ln \int_{\eta} L\left(y_n \mid \cdot\right) L\left(I_n \mid \cdot\right) L\left(R_n \mid \cdot\right) g\left(\eta\right) \mathrm{d}\eta \tag{11}$$

Equation 11 is dependent on the latent variables, which is shown by the integration over η, the random component of α, and the fact that the log-likelihood is a function of γ, which drives the deterministic part of α. Hence, in addition to the parameters estimated for the standard model, the estimation of this model entails the estimation of the vector of τ terms, the parameters of the various measurement equations, and the socio-demographic interaction terms γ. As previously mentioned, maximum simulated likelihood estimation was used for this model in the absence of a closed form solution for the log-likelihood function in Equation 11.

The entire structure of the model is represented graphically in Figure 4. At the top of the graph, we have the indicators, I_k; "Calorie Ranking", "Time Ranking", "Food Type Ranking" and "Cooking Attitudes" (for which we have three indicator functions). These indicators are explained using the seven latent variables, which in turn are a function of socio-demographic variables (in addition to having a random component). The latent variables are then at the same time interacted with the coefficients of the choice model (β), which are possibly also interacted with socio-demographic indicators, and which, in interaction with the attribute levels, explain the choices observed in the data.

Before proceeding with the discussion of results, it should of course be acknowledged that the use of ICLV leads to increased estimation cost and the need for datasets to contain additional indicators, but this is commonly the case. Additionally, there is the added demand for the analyst to specify structural equations for the latent variables and to make decisions relating to functional form, including for the measurement model. However, when done in a competent manner, the advantages can be very substantial, where, as explained previously, as key advantage of ICLV over more standard models (e.g. mixed logit and latent class) is its ability to use additional data to explain the heterogeneity across decision makers, and to provide further insights.

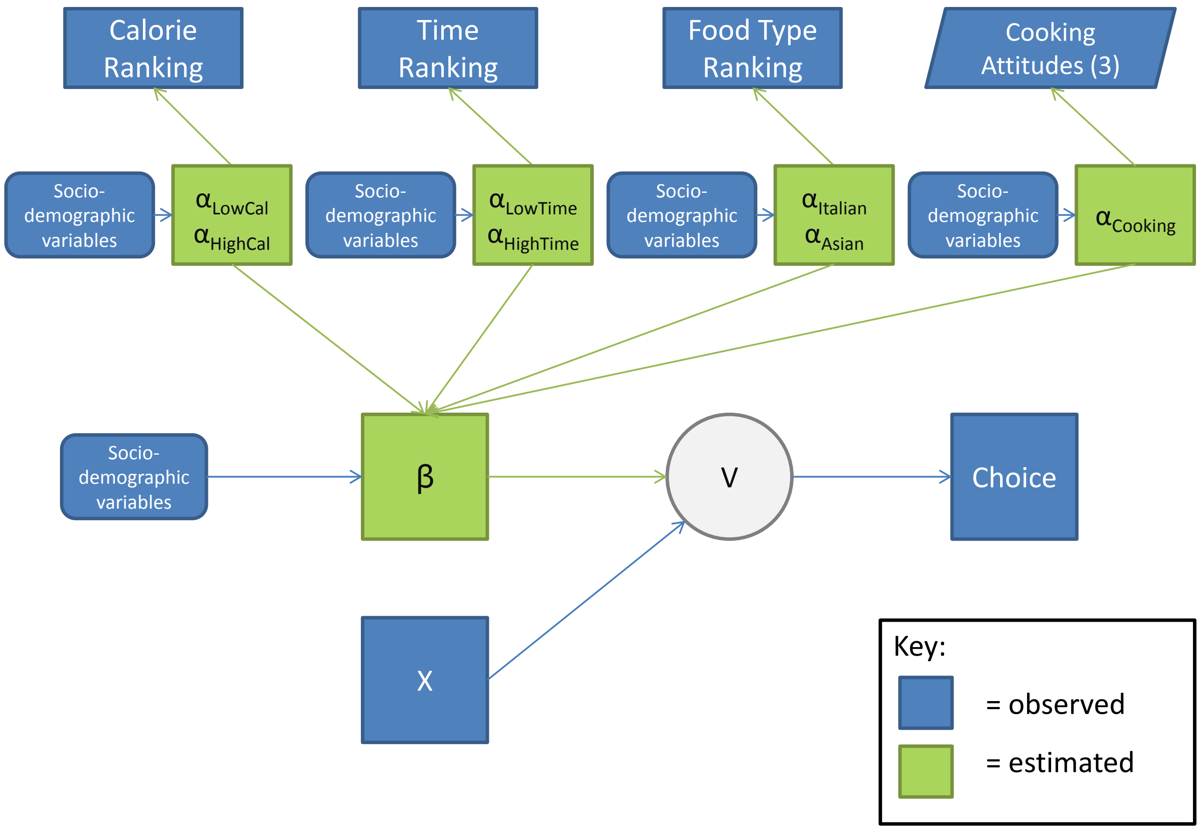


Fig. 4: ICLV model outline

3 Results

3.1 Base model results

The results for the two base models are summarised in Table 3. Looking first at the model without socio-demographic interactions, we can see that the coefficients for low calories (β_{LowCal}) is positive and significant while the coefficient for high time (β_{HighTime}) is negative and significant. This indicates that low levels of calories are preferred to medium levels of calories, while medium time is preferred to high time. The signs for the coefficients for high calories (β_{HighCal}) and low time (β_{LowTime}) are not in line with this, but the coefficients are not statistically significant, making the sign irrelevant and showing that there is no difference from the sensitivity for the medium level in these cases; at the aggregate level, the respondents are not distinguishing between high calories and the base level medium calories, or between low time and the base level of medium

Tab. 3: Base MNL model and MNL with age and gender effects

	Base MNL		MNL with age and gender	
	est.	rob. t-rat.	est.	rob. t-rat.
$\beta_{\text{LowCal;Base}}$	0.2468	4.74	0.5050	4.97
$\Delta_{\text{LowCal;Male}}$	-	-	-0.1970	-2.00
$\Delta_{\text{LowCal;Under 35}}$	-	-	-0.3231	-2.66
$\Delta_{\text{LowCal;Over 50}}$	-	-	-0.1652	-1.36
$\beta_{\text{HighCal;Base}}$	0.0341	0.69	0.0341	0.35
$\Delta_{\text{HighCal;Male}}$	-	-	0.0310	0.33
$\Delta_{\text{HighCal;Under 35}}$	-	-	0.1261	1.08
$\Delta_{\text{HighCal;Over 50}}$	-	-	-0.1826	-1.56
$\beta_{\text{LowTime;Base}}$	-0.0142	-0.34	0.1048	1.22
$\Delta_{\text{LowTime;Male}}$	-	-	-0.0061	-0.07
$\Delta_{\text{LowTime;Under 35}}$	-	-	-0.1402	-1.28
$\Delta_{\text{LowTime;Over 50}}$	-	-	-0.2086	-2.00
$\beta_{\text{HighTime;Base}}$	-0.2197	-6.52	-0.1220	-1.57
$\Delta_{\text{HighTime;Male}}$	-	-	-0.0319	-0.45
$\Delta_{\text{HighTime;Under 35}}$	-	-	-0.2219	-2.42
$\Delta_{\text{HighTime;Over 50}}$	-	-	-0.0182	-0.21
$\beta_{\text{Italian;Base}}$	-0.0599	-1.20	0.1852	2.00
$\Delta_{\text{Italian;Male}}$	-	-	-0.0357	-0.37
$\Delta_{\text{Italian;Under 35}}$	-	-	-0.2900	-2.57
$\Delta_{\text{Italian;Over 50}}$	-	-	-0.4213	-3.34
$\beta_{\text{Asian;Base}}$	-0.3275	-6.65	-0.0888	-0.95
$\Delta_{\text{Asian;Male}}$	-	-	0.0247	0.26
$\Delta_{\text{Asian;Under 35}}$	-	-	-0.5272	-4.62
$\Delta_{\text{Asian;Over 50}}$	-	-	-0.2605	-2.12
β_{Cost}	-0.0493	-7.92	-0.0504	-8.07
δ_{DK}	-3.8274	-20.87	-3.8540	-20.97
$\mathcal{LL}$	-5,192.85		-5,141.8	

time. We can also see that, as expected, the coefficients for Italian (β_{Italian}) and Asian (β_{Asian}) food are negative, meaning that respondents prefer the base of Local food to these alternatives, albeit that the difference with Italian food is not statistically significant. The cost coefficient (β_{Cost}) has the expected negative estimate, while the strong negative estimate for the constant for the "Don't know" alternative (δ_{DK}) reflects the low rate of respondents indicating indecision between alternatives.

Turning to the model incorporating socio-demographic interactions, using a likelihood ratio test, we obtain an improvement in log-likelihood by 51.85 units over the base model at the cost of 18 additional parameters - this is highly significant giving a likelihood-ratio test value of 103.7

compared to a χ^2_{18} critical value of 34.81 at the 99% level. While we note a significant negative shift in preferences towards low calories for males, we do not find significant differences between males and females for any of the other attributes, a finding which is contrary to much of the food preference literature. On the other hand, we observe a number of significant age interactions. Notably, we observe a lower preference for low calorie levels for respondents under the age of 35, along with reduced preferences (or increased dislike) of high time as well as Italian and Asian food. For respondents over 50 years of age, we note a significant negative shift in preferences for low time, as well as once again Italian and Asian food.

3.2 Integrated Choice and Latent Variable (ICLV) model results

The specification for our latent variable model made use of the base specification from the MNL model without socio-demographic interactions, given that these are now dealt with in the latent variable specification.

In the choice model, the first six latent variables were interacted with the associated parameter, e.g. the latent variable for low calories was interacted with the β parameter for low calories. The latent variable for general cooking attitude was interacted with all non-cost coefficients in the choice model, with the exception of high time where no meaningful effect was retrieved. With this in mind, we have that the utilities for the first three alternatives are now given as:

$$\begin{aligned}
V_{int} = {} & \beta_{\text{LowCal}}\text{LowCal}_{int} + \tau_{\alpha_{\text{LowCal}},\beta_{\text{LowCal}}}\alpha_{\text{LowCal},n} + \tau_{\alpha_{\text{Cooking}},\beta_{\text{LowCal}}}\alpha_{\text{Cooking},n} \\
& + \beta_{\text{HighCal}}\text{HighCal}_{int} + \tau_{\alpha_{\text{HighCal}},\beta_{\text{HighCal}}}\alpha_{\text{HighCal},n} + \tau_{\alpha_{\text{Cooking}},\beta_{\text{HighCal}}}\alpha_{\text{Cooking},n} \\
& + \beta_{\text{LowTime}}\text{LowTime}_{int} + \tau_{\alpha_{\text{LowTime}},\beta_{\text{LowTime}}}\alpha_{\text{LowTime},n} + \tau_{\alpha_{\text{Cooking}},\beta_{\text{LowTime}}}\alpha_{\text{Cooking},n} \\
& + \beta_{\text{HighTime}}\text{HighTime}_{int} + \tau_{\alpha_{\text{HighTime}},\beta_{\text{HighTime}}}\alpha_{\text{HighTime},n} \\
& + \beta_{\text{Italian}}\text{Italian}_{int} + \tau_{\alpha_{\text{Italian}},\beta_{\text{Italian}}}\alpha_{\text{Italian},n} + \tau_{\alpha_{\text{Cooking}},\beta_{\text{Italian}}}\alpha_{\text{Cooking},n} \\
& + \beta_{\text{Asian}}\text{Asian}_{int} + \tau_{\alpha_{\text{Asian}},\beta_{\text{Asian}}}\alpha_{\text{Asian},n} + \tau_{\alpha_{\text{Cooking}},\beta_{\text{Asian}}}\alpha_{\text{Cooking},n} \\
& + \beta_{\text{Cost}}\text{Cost}_{int} \qquad (12)
\end{aligned}$$

while the utility for alternative 4 remains the same as in the MNL models.

Tab. 4: Estimation results for choice model component

	est.	rob. t-rat.
β_{LowCal}	0.4103	4.57
β_{HighCal}	-0.2388	-2.79
β_{LowTime}	0.0258	0.42
β_{HighTime}	-0.2444	-6.38
β_{Italian}	0.0444	0.55
β_{Asian}	-0.3197	-3.19
β_{Cost}	-0.0532	-7.55
δ_{DK}	-3.9231	-20.61
$\tau_{\alpha_{\text{LowCal}},\beta_{\text{LowCal}}}$	0.6740	7.50
$\tau_{\alpha_{\text{HighCal}},\beta_{\text{HighCal}}}$	0.3783	2.78
$\tau_{\alpha_{\text{LowTime}},\beta_{\text{LowTime}}}$	0.6065	7.78
$\tau_{\alpha_{\text{HighTime}},\beta_{\text{HighTime}}}$	0.0303	0.75
$\tau_{\alpha_{\text{Italian}},\beta_{\text{Italian}}}$	0.3187	5.53
$\tau_{\alpha_{\text{Asian}},\beta_{\text{Asian}}}$	0.6476	6.80
$\tau_{\alpha_{\text{Cooking}},\beta_{\text{LowCal}}}$	-0.2089	-3.04
$\tau_{\alpha_{\text{Cooking}},\beta_{\text{HighCal}}}$	0.0779	1.21
$\tau_{\alpha_{\text{Cooking}},\beta_{\text{LowTime}}}$	-0.0519	-1.17
$\tau_{\alpha_{\text{Cooking}},\beta_{\text{Italian}}}$	-0.0707	-1.21
$\tau_{\alpha_{\text{Cooking}},\beta_{\text{Asian}}}$	-0.0080	-0.12
Choice component $\mathcal{LL}$	-5,044.01	
Overall $\mathcal{LL}$	-10,666.60	

The specification of the measurement equations is as discussed in Section 2.3. The means of the latent variables were set to zero, and an extensive amount of testing was conducted to establish significant socio-demographic interactions, focussing on age and gender, where only the most significant interactions were retained, as discussed later in this section.

The estimation results for the choice model component, as outlined in Equation 12 above, are shown in Table 4. The overall fit for the hybrid model, also shown in Table 4, cannot be directly compared to that for the MNL model as it jointly models the choices and responses to attitudinal and ranking questions (c.f. Equation 11). However, it is possible to factor out the component of the log-likelihood relating to the choice model, conditional on the other components. This gives us a log-likelihood of $-5,044.01$, which shows that the model offers a better statistical fit for the choice data compared to the two base models, but no formal statistical tests are conducted, given the conditioning on other model components. Extensive discussions on this issue are given in Vij and Walker (forthcoming).

Tab. 5: Estimation results for structural equation model for latent attitudes

Latent variable	Estimated parameter	est.	rob. t-rat.
α_{LowCal}	$\gamma_{\text{LowCal}_{<35}}$	-0.2594	-1.95
α_{HighCal}	$\gamma_{\text{HighCal}_{\text{Male}}}$	0.5171	2.08
	$\gamma_{\text{HighCal}_{<35}}$	0.5011	3.03
α_{LowTime}	$\gamma_{\text{LowTime}_{50+}}$	-0.2595	-1.85
α_{HighTime}	$\gamma_{\text{HighTime}_{\text{Male}}}$	0.5171	2.56
α_{Italian}	$\gamma_{\text{Italian}_{\text{Male}}}$	0.3186	1.76
	$\gamma_{\text{Italian}_{<35}}$	-0.5442	-2.54
	$\gamma_{\text{Italian}_{50+}}$	-0.9269	-4.24
α_{Asian}	$\gamma_{\text{Asian}_{\text{Male}}}$	0.2087	1.39
	$\gamma_{\text{Asian}_{<35}}$	-0.5072	-2.99
	$\gamma_{\text{Asian}_{50+}}$	-0.3310	-1.86
α_{Cooking}	$\gamma_{\text{Cooking}_{\text{Male}}}$	0.6713	5.98
	$\gamma_{\text{Cooking}_{<35}}$	0.5018	3.67
	$\gamma_{\text{Cooking}_{50+}}$	0.2534	1.80

We first observe that β_{HighCal} has changed in sign and has also become significant compared with the base model. This is in line with the preferences found above in Figure 2. Two additional parameters, namely β_{LowTime} and β_{Italian}, also undergo sign changes, but the coefficients remain insignificant. For the first six latent variable effects, we can see that, in line with expectations, a higher value for the underlying attribute sensitivity leads to a more positive parameter in the choice model, albeit that this is not statistically significant for high time. For the final latent variable, i.e. the general cooking attitude, only one effect is significant, indicating that a higher value for the latent attitude equates to a less positive value for the associated low calorie coefficient. As we will see later, this latent variable in fact equates to an *anti-cooking* attitude, meaning that respondents who have a more positive attitude towards cooking also prefer cooking lower calorie meals.

As a next step, we look at the structural equations for the seven latent variables, as outlined above in Equation 4, with estimates summarised in Table 5. These results show that male respondents have a more positive value for the latent variables for high calories, high time and Italian and Asian food types. The result for high time may seem counter-intuitive, but a possible explanation could be that whilst they would prefer to have meals that take longer to cook, they do not necessarily want to be responsible for creating the meal. We also see that male respondents have a more positive value for the general latent cooking attitude, where it is important to remember that this is in fact an *anti-cooking* attitude, which explains the sign. The same applies for the low and high

Tab. 6: Estimation results for measurement models for rankings of attributes; Calories, Cooking Time and Food Type

		est.	rob. t-rat.
Calories: α_{LowCal} and α_{HighCal}			
	$\mu_{R,\text{LowCal}}$	-0.7629	-5.54
	$\mu_{R,\text{HighCal}}$	-4.0481	-15.30
	$\delta_{R,\text{DK Most Cal}}$	-0.1595	-1.65
	$\delta_{R,\text{DK Least Cal}}$	3.5868	17.00
Cooking Time: α_{LowTime} and α_{HighTime}			
	$\mu_{R,\text{LowTime}}$	-0.5965	-4.73
	$\mu_{R,\text{HighTime}}$	-4.2649	-16.80
	$\delta_{R,\text{DK Most Time}}$	-0.7959	-7.30
	$\delta_{R,\text{DK Least Time}}$	3.3050	14.61
Food Type: α_{Italian} and α_{Asian}			
	$\mu_{R,\text{Italian}}$	-0.9207	-4.91
	$\mu_{R,\text{Asian}}$	-2.1267	-10.59
	$\delta_{R,\text{DK Most Type}}$	-1.9328	-12.79
	$\delta_{R,\text{DK Least Type}}$	2.0953	13.74

age groups. In addition, being under the age of 35 has a negative effect on the latent variable for low calories, as well as for Italian and Asian food types, but a positive affect on the latent variable for high calories. Lastly, respondents aged over 50 have a less positive value for the latent variable for low time, as well as non-local food.

As discussed in Section 2.3, the measurement component explains the observed attribute rankings (c.f. Equations 6 and 7) in addition to the answers for the cooking attitudinal questions (c.f. Equation 9). The results for the measurement model for attribute rankings are summarised in Table 6, whereas the results for the three attitudinal questions are shown in Table 7. We will discuss each of these in turn below.

Concerning Table 6, the negative signs for the six mean ranking parameters are a reflection of the fact that, across attributes, the middle level tended to be ranked highest by respondents. The signs for the "Don't know" constants reflect the low rates for choosing "Don't know" in response to the *best* level question, and the high rate for choosing it in response to the *worst* level question. This is an indication that respondents find it harder to evaluate their least preferred option and as a result, are more inclined to state "Don't know".

We finally turn to the results for the measurement model for the three attitudinal questions, which are shown in Table 7. We can see that the thresholds are all increasing in magnitude, as

Tab. 7: Estimation results for measurement model for latent attitude to Cooking, α_{Cooking}

		est.	rob. t-rat.
Cooking is not much fun			
	$\zeta_{\text{Cooking 1}}$	3.1146	7.13
	Threshold 1: $\psi_{1,1}$	-2.2387	-4.84
	Threshold 2: $\psi_{1,2}$	1.3287	2.88
	Threshold 3: $\psi_{1,3}$	4.7295	7.00
	Threshold 4: $\psi_{1,4}$	8.3355	8.82
Compared with other daily decisions, my food choices are not very important			
	$\zeta_{\text{Cooking 2}}$	1.6174	8.51
	Threshold 1: $\psi_{2,1}$	-2.1674	-8.41
	Threshold 2: $\psi_{2,2}$	0.2199	0.88
	Threshold 3: $\psi_{2,3}$	3.4837	9.70
	Threshold 4: $\psi_{2,4}$	5.6278	12.32
I enjoy cooking for others and myself			
	$\zeta_{\text{Cooking 3}}$	-2.8201	-8.87
	Threshold 1: $\psi_{3,1}$	-6.2423	-9.38
	Threshold 2: $\psi_{3,2}$	-4.6090	-8.10
	Threshold 3: $\psi_{3,3}$	-0.8788	-2.21
	Threshold 4: $\psi_{3,4}$	2.6166	5.76

is required by the model. Additionally, we see positive estimates for the effect in the first two equations, and a negative effect in the third model. This means that a more positive value for the seventh latent variable leads to stronger agreement with the statements that *"Cooking is not much fun"* and *"Compared with other daily decisions, my food choices are not very important"*, but increased disagreement with the statement that *"I enjoy cooking for others and myself"*. This is in line with an interpretation of this latent variable as an *anti-cooking* attitude, which explains the role of this latent variable in the choice model as well as the signs of the socio-demographic interactions in its structural equation.

3.3 WTP / Marginal Rates of Substitution

As a final step, we turn our attention to implied willingness to pay (WTP) patterns and other marginal rates of substitution.

We first look at the WTP patterns from our base MNL model without socio-demographic interactions, shown in Table 8(a). The context of the survey was a study of home-cooked meal options, namely respondents' preferences for a typical evening meal that they would share with

Tab. 8: Willingness to pay (WTP) measures

(a) Base MNL model:

	WTP
LowCal	5.00
HighCal	0.69
LowTime	-0.29
HighTime	-4.45
Italian	-1.21
Asian	-6.64

(b) MNL with age and gender effects:

	Percentiles								
	5	10	25	50	75	90	95	Mean	SD
LowCal	-0.30	-0.30	2.83	3.61	6.74	10.01	10.01	4.85	3.25
HighCal	-2.94	-2.94	-2.33	1.29	3.18	3.79	3.79	0.66	2.50
LowTime	-2.18	-2.18	-2.06	-0.70	1.96	2.08	2.08	-0.25	1.73
HighTime	-7.45	-7.45	-6.82	-3.42	-2.78	-2.42	-2.42	-4.33	2.01
Italian	-5.39	-5.39	-4.68	-2.08	2.97	3.67	3.67	-1.30	3.52
Asian	-12.22	-12.22	-11.73	-6.44	-1.76	-1.27	-1.27	-6.69	4.32

(c) ICLV Model:

	Percentiles								
	5	10	25	50	75	90	95	Mean	SD
LowCal	-17.96	-13.05	-4.77	4.30	13.47	21.64	26.53	4.31	13.52
HighCal	-13.48	-10.67	-5.91	-0.61	4.70	9.48	12.33	-0.60	7.84
LowTime	-20.03	-15.82	-8.82	-1.03	6.75	13.73	17.90	-1.04	11.53
HighTime	-5.41	-5.20	-4.84	-4.45	-4.05	-3.69	-3.48	-4.45	0.59
Italian	-12.71	-10.34	-6.36	-1.90	2.59	6.67	9.05	-1.87	6.62
Asian	-28.77	-24.23	-16.64	-8.20	0.24	7.84	12.41	-8.20	12.51

their partner at home. Consequently, the *cost* element of this represented the total cost for all of the ingredients needed to produce this evening meal which would feed them both. We can thus interpret the willingness to pay (WTP) measures as the extra cost that the respondent would be willing to pay for the evening meal to be shifted away from the middle (base) level (or have to obtain in price reductions to accept such a change). In these results, negative WTP measures reflect the fact that some attribute levels are undesirable when compared to the middle level. For the base model, we note a positive WTP for moving from middle calorie to low calorie meals, while cost reductions are required at the aggregate level to accept a move to high time or Asian food. The remaining WTP measures relate to parameters that were not statistically significant.

Table 8(b) and Table 8(c) show the corresponding results for the MNL model with gender and age interactions as well as for the ICLV model. In both cases, we now have variation across respondents, where the variation in the MNL model is purely deterministic, as a result of incorporating socio-demographics in the model, while the variation in the ICLV models is driven by both the socio-demographic and random components in the structural equations for the latent variables. In both models, we summarise the heterogeneity by presenting the values for a number of points on the sample level distribution, in the form of percentiles. While the signs and size of the mean WTP measures remain in line with the simple MNL results, most WTP measures now show tails of opposite signs - for example, in Table 8(b) we see that the proportion of people who would have a negative WTP for moving from middle calorie to low calorie meals contains between 10-25% of the sample. This reflects the high degree of heterogeneity in the data, where, for the ICLV model, it is also important to acknowledge the potential impact of the Normal distribution on results. We see that the tails from the distributions in the ICLV model are very long and suggest some very high WTP measures for a small share of respondents. It is important to recognise that the Normal distribution is unbounded and this clearly plays a role in these tails. Of further key importance is the strong retrieved impact that the latent attitudes have on sensitivities, with several of the estimated τ parameters exceeding the associated coefficient in absolute value, leading to the resulting high level of heterogeneity. It is worth mentioning in this context that we found no evidence of fully lexicographic behaviour in the data.

For other marginal rates of substitution, we focus on a shift from medium calories to low calories, and in particular respondents' willingness to accept a move to high time (from medium

Tab. 9: Marginal rates of substitution (MRS)

(a) Base MNL model:

	MRS
Move to Low Cal and accept High Time	1.12
Move to Low Cal and accept Asian	0.75

(b) MNL with age and gender effects:

	MRS: Percentiles								
	5	10	25	50	75	90	95	Mean	SD
Move to Low Cal and accept High Time	-0.04	-0.04	0.53	0.83	2.42	4.14	4.14	1.65	1.40
Move to Low Cal and accept Asian	-0.03	-0.03	0.30	0.44	4.80	5.68	5.68	2.07	2.32

(c) ICLV Model:

	MRS: Percentiles						
	5	10	25	50	75	90	95
Move to Low Cal and accept High Time	-4.12	-2.97	-1.08	0.97	3.05	4.94	6.09
Move to Low Cal and accept Asian	-5.55	-2.64	-0.73	0.16	1.10	3.03	6.04

time) or Asian food (from local food) in return for such a change. For the simple MNL model, Table 9(a) shows that the desire to shift to low calories is stronger than the desire to avoid a shift from medium time to high time, but is not as strong as the desire to avoid a shift from local food to Asian food. For the model with socio-demographic interactions (cf. Table 9(b)), we see strong heterogeneity, where sign changes are a result of some segments disliking low calories or having a positive preference for High Time or Asian food. While the mean is greater than 1 for both marginal rates of substitution, the medians are both lower than 1. This implies that while some respondents have a very strong preference for a move to low calories, the relative preference for avoiding a move to high time or Asian food is stronger for over fifty percent of respondents. This is also reflected in the results for the ICLV model (cf. Table 9(c)), where the use of the Normal distribution implies that means and standard deviations for the marginal rates of substitution cannot be calculated (c.f. Daly et al., 2012b). The use of the Normal distribution is in this case an inherent component of the ICLV structure. Nevertheless, while moments cannot be calculated, we can of course still report medians and other percentiles, as we do.

4 Discussion

In this paper, we have highlighted the potential benefit of using advanced choice models for studying consumers' food choices. In particular, we have considered the impact that attitudes and underlying preferences can have on the decision making process through the use of a latent variable approach. We started with a simple MNL model which revealed that most of the estimates were in line with expectation, and those that were not were found not to be significant. We also estimated a MNL model with variation in sensitivities by age and gender, producing interesting findings, not least in part due to the significant preference differences found between the age groups used.

As a next step, we illustrated how further differences can be accommodated in a latent variable based hybrid model structure which allows us to make use of additional subjective data on attribute rankings and attitudinal questions. Crucially, this model allows us to use such data without risk of measurement error or endogeneity bias. We formulated a model with seven latent variables and showed how this model provides us with important further insights into behaviour. The latent variables are used to explain both differences in sensitivities in the choice model as well as the responses to attribute ranking questions and attitudinal questions. In this context, a number of interesting socio-demographic interactions were also retrieved.

Some potential limitations in this study must be acknowledged. Firstly, our dataset may have been subject to some endogeneity issues between cost and quality, that has been previously found in other food studies (Richards and Padilla, 2009)[6]. In addition, at an earlier stage of this work, feedback from our survey interviewers indicated that people were associating low cooking time with low quality food, whereas people were associating a lengthy cooking time with high inconvenience, which may help to explain the counter-intuitive finding of the preferred cooking time being between 31 and 60 minutes. Further, a recent paper by Grisolía et al. (2012) mentions an important element in general food choices; the issue of experienced utility vs. expected utility. This could also be an important confounder in our survey, where the types of foods that the respondents had bought and cooked at home previously could have had a bearing on their current food preferences. Finally, the use of the MNL model without socio-demographic variables inside the ICLV model is a simplification. We took this decision primarily with a view to avoiding using the same limited set of socio-demographic variables in two components of the model (utility specification and structural equations for the latent variable) where we were concerned with confounding.

The ICLV model has the key advantage of being a very flexible model, allowing the use of a wide set of different indicators. Future work could make use of other factors such as those related to health risk aversion and weight control problems, which unfortunately were not included in the present survey[7]. We believe that there is wide scope for ICLV applications in a food choices context. Indeed, it is well known that preferences vary extensively across consumers and it is conceivable that a large extent of such heterogeneity relates to underlying convictions, preferences and attitudes. Examples for future areas of application include a focus on topics such as health and diet, ethical food sources, organic food, as well as locally sourced food. A further key advantage of the model is in forecasting. Indeed, once the latent variables have been *calibrated* with the help of the measurement model, this component of the model becomes redundant in forecasting, meaning that indicators are no longer needed, and only choices are predicted. With a sufficiently detailed specification for the structural equations, this would also allow forecasting under hypothetical changes to the make-up

[6] We thank an anonymous referee for conveying this to us.

[7] We are grateful to an anonymous referee for having pointed out these and many other things to us.

of the population of consumers, for example in relation to age and income.

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