The advantages of preference-based segmentation: An investigation of online grocery retailing

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Abstract Most companies aim to identify different groups of attractive customers in order to offer them appropriate products and/or services. To do this, companies need market segmentation. There is, however, a problem with the standard methods employed in market segmentation. The static inductive approach to market segmentation commonly employed by companies does little to identify buying intentions across demographic variables. A more dynamic and deductive approach to developing market segmentation is through analysis of consumer preference structures — an approach which is glaringly absent from most marketing texts, not least because of the difficulty of developing practical approaches which can generate effective marketing strategies. The purpose of this paper is to highlight and demonstrate a preference-based approach to market segmentation, using shoppers' experience of online grocery retail brands in the UK. The paper first demonstrates how using choice-based conjoint analysis could help achieve this objective more effectively than other more traditional conjoint methods. While conjoint analysis is not new, the ability to segment based on markedly different preference structures is a recent development and comprises a powerful, but underutilised segmentation approach. A web-based methodology is then applied to build up a picture of consumers' conscious and unconscious prioritisation of a large number of choice criteria. The paper calculates consumer utility values for both offline and online shoppers in the UK and develops a preference-based segmentation approach, which is compared with a traditional demographic segmentation approach using the same data. From this analysis, the advantages of a preference-based approach to segmentation are extracted. The paper closes with recommendations for market research practitioners.

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INTRODUCTION

Practitioners are constantly attempting to identify the most profitable market(s) in which they can compete. With which customers do companies want and with whom can they have relationships? To do this, companies need to employ some form of market segmentation. According to Zeithaml and Bitner,[1] market segmentation is the second foundation block of relationship marketing.

There is, however, a problem with the standard methods employed in market segmentation. Companies usually identify segments based on demographic data, and within these demographic segments, marketers may refine the offerings, for example, based on lifestyle or usage. Marketing textbooks highlight four types of segmentation: demographic, geographic, psychographic and behavioural.[2,3] It is often assumed that there is somehow a relationship between, say, demographic variables and customer behaviour; that in some way, demographics have a causal relationship with purchasing intentions. This is a static inductive approach to market segmentation that does little to identify buying intentions across demographic variables. This method cannot identify the strength of interrelationships between demographic variables and buyer intentions. These preset demographic lines of segmentation do not allow computation of utility values, the key drivers of economic buyer behaviour. The association of certain demographics with buyer behaviours is also no claim to actual current or future causality.[4]

A more dynamic and deductive approach to developing market segmentation is through the analysis of consumer preference structures — an approach which is glaringly absent from most conventional marketing texts, not least because of the difficulty of developing practical approaches which can generate effective marketing strategies. The purpose of this paper is to highlight and demonstrate a preference-based approach to market segmentation.

CHOICE-BASED CONJOINT ANALYSIS: AN INCREASED REALISM

Taking the example of online grocery shopping, consumers rarely have the opportunity of buying from what they would consider precisely the best, or the ideal, retail proposition. Consumers are therefore forced to make trade-offs as they decide from which online retail offerings to choose to purchase. The assumption is that each online offering possesses, or is defined by, a set of attributes such as delivery time, ordering time, number of items below quality, and so on. Each of these attributes will be operationalised (unconsciously and consciously) into expected service performance. These prioritised attributes become the customer's expectation preference structure (or pre-purchase preference structure), which is the main causal factor in the final buying decision.

Consider a supermarket website that offers a free delivery service and delivers groceries within six hours of receipt of an order, but where there are usually a few substitutes per shopping basket. Consider another supermarket website where the shopper has to pay for their delivery, which takes 48 hours to deliver groceries to the home, but that at the same time guarantees that there will be no substitutes. Shoppers will have to make trade-offs as to which online proposition they will prefer. Their choice will be a function of their pre-purchase preference structure.

The approach in this paper is to analyse the trade-offs that consumers make for each level of each service attribute. To achieve this, a conjoint analysis technique is used to determine the importance of each attribute and the utility value for each level of each attribute.[5] While conjoint analysis is not new, the ability to segment based on markedly different preference structures is a recent development and a powerful, but underutilised segmentation approach.

The first issue to consider was which conjoint method should be used as the basis of calculating utility values — for use in developing preference structures, as well as in later segmentation. Three conjoint methods were considered, namely traditional conjoint analysis, adaptive conjoint analysis and choice-based conjoint analysis.[6] Traditional conjoint analysis uses pair-wise comparisons of individual stimuli. An example would be to ask respondents if they would prefer shopping online for 15 minutes but have their groceries delivered in 24 hours or be able to shop in 45 minutes but have their groceries delivered within two hours. In this example, two profiles (ie two online offerings) are being compared, with the respondent rating their preference for one profile over another. The major criticism of a pair-wise approach is that it lacks realism because a profile does not contain all the attributes. In reality shoppers make their trade-offs by simultaneously comparing and weighting in their mind the relative importance of a set of attributes, not just two attributes at a time. Consequently, traditional conjoint analysis may not be an accurate reflection of the actual selection process.

In the initial investigations, the importance of accurately modelling the actual selection process was highlighted. For example, a focus group study was reviewed, for Virgin Wines (UK), where two bottles of champagne were tested by participants. The brand of each bottle was hidden. Participants were asked to express their preferences based on a tasting test of each bottle of champagne. At the end of the session, each participant could take home one of the bottles of champagne. The labels were uncovered at this point. The marketer responsible for running this focus group was surprised as participants left with the most expensive bottle of champagne (a well-known brand) while during the trial session the participants mostly expressed their preference for the other bottle. This example illustrates that purchase decisions are made based on a combination of attributes rather than one attribute at a time — taste in this case.
The additional realism offered by choice-based conjoint was therefore considered.[7] Choice-based conjoint is more representative of the actual process of selecting a supermarket online offering from a set of competing online offerings.

Moreover choice-based conjoint provides an option of not choosing any of the available stimuli by including a 'no choice' option in the choice set.[8] This again increases realism as shoppers always have the choice of visiting a website and exiting without having made any purchase. This kind of realism is not possible with traditional conjoint analysis methods.

In addition, choice-based conjoint analysis uniquely allows for the calculation of interaction terms. This means that certain combinations of levels of attributes count for more than just their sum. For example, one scenario (a supermarket online offering) could have no items below quality, while another scenario could advertise that they never substitute any products (where the shopper always gets what they have ordered). However, if one supermarket were to combine these two levels, its market share would rise dramatically if the level 'no items below quality' and the level 'no substitutes' are interacting, as the whole would be greater that the sum of each. In the Virgin Wine example, the interaction effect occurs between price and brand. By not taking into consideration the interaction effects between levels, predictions on

Table 1: A comparison of alternative conjoint methodologies

Characteristic	Traditional conjoint	Adaptive conjoint	Choice-based conjoint
Market simulation	No	Limited	Yes
Latent class identification	No	No	Yes
Permit study of all interactions	No	No	Yes
Choice tasks	Choice tasks are less realistic	Choice tasks are less realistic	Increased realism in the choice tasks
Level of analysis	Individual	Individual	Aggregate + individual
Model form	Additive	Additive	Additive + interaction effects
Option of not choosing any of the stimuli presented	No	No	Yes
Heterogeneous attributes across product designs	No	No	Yes
Maximum number of attributes	9	30	10

preferences could be less accurate given that interactions exist.

The other conjoint method considered was adaptive conjoint. The major limitation of adaptive conjoint is that it cannot provide analysis of interaction terms.

The above illustrations demonstrate the need to compare and contrast alternative conjoint methodologies. The practical need for this exercise has arisen because of significant recent statistical developments which deliver a range of important market research benefits. Discussions with a number of market research departments in high-profile global companies revealed that these benefits have not been recognised, and many companies were unaware of the possibilities of conjoint-based market research in general. Even if companies do use some form of conjoint analysis, few, if any, are aware of these recent developments.

The most common form of conjoint methodology is adaptive conjoint, which has widespread commercial use. For example, it is the statistical engine used by some major companies in the automotive and pharmaceutical industries. Adaptive conjoint was developed in the 1980s to accommodate a larger number of attributes than was possible with traditional pairwise conjoint. Pairwise conjoint was the original conjoint methodology developed in the 1970s.

Choice-based conjoint was developed in the late 1990s and represents the latest conjoint methodology. It was developed to overcome a number of serious limitations in adaptive conjoint. Choice-based approach presents the stimuli (specific set of levels of an attribute) in a unique form: in sets (scenarios) rather than one by one. In addition and most importantly, it includes interaction effects. Finally, choice-based allows an estimation of the data at both an aggregate and at an individual level.

The main differences between the different types of conjoint are summarised in Table 1.

ADDITIVE VERSUS INTERACTIVE MODELS OF CONJOINT ANALYSIS

In an additive conjoint model, the respondent simply adds up the values for each attribute to get the total value for a combination of attributes. For example, assume that a specific car has two attributes — the Corsa model, with flame red as the colour. The preference value given for the model is 4 and for the colour the preference value is 3. Using the additive model, the total value would simply be 7. Adding the interaction effects to the additive form allows for certain combinations of levels to be more or less than just their sum. For example if one considers a respondent who strongly prefers a certain brand (Vauxhall Corsa) but only with a certain colour (flame red). Flame red has a low value (3) except when combined with another specific level (Corsa). In this case, the whole is greater than the sum of its parts. In summary, the combination of flame red with a Corsa model results in greater preference for that individual than the main effect utilities would suggest. An interaction term can capture and reflect such synergy. Interaction terms can also reflect differences in price sensitivity for different brands. Adding interactive terms results in a significant improvement in the overall fit of a marketing model

In addition, the less the attributes are tangible (for example, as when aesthetic or emotional reactions play a large role) the more interaction effects will play a role in explaining choice predictions more accurately.

Another example when interaction effects can occur many times is between price and a brand name that is less tangible but does carry specific perceptions. A joint effect table, as opposed to a main effect table, will provide information for pairs of attributes rather than attributes considered one at a time. As a result, it is useful to compare the average of a joint effect table with the main effects for brand and price to evaluate the differences. The implication is that where intangible service dimensions comprise a significant number of attributes in a study, then investigation of the interactions becomes imperative.

There are consequences if an adaptive conjoint methodology is used when interactions exist as the customer choice predictions will be less accurate.

Choice-based conjoint allows the respondent to choose from a full set of alternative stimuli, choice sets or scenarios. It is much more representative of the actual decision-making process when making the final decision to purchase a product from a set of competing products.

With choice-based conjoint, the respondent has the option of making no choice from among alternative choice sets. Providing a no-choice option is important as it allows the respondent to 'walk away' if all the options displayed in a choice task are unattractive. It adds realism, ie it more accurately represents the actual purchase decision-making process.

LATENT CLASS SEGMENTATION

Latent class is a method of dividing the market under investigation into segments with similar preferences. Latent class simultaneously estimates utilities for each segment and the probability that each respondent belongs to each segment. The relative share of preference of each class is estimated.

Latent class is important because it answers some critical marketing questions. For example, where to position the product or service to gain maximum market advantage; which utility-defined segments offer the greatest potential growth; which channels to market the product in; and what should be the communication strategy for each segment? Understanding latent classes also has resource and business process implications. For example, are existing processes and resources focused upon creating best-in-class performances on key preferences that matter to the customer? Latent class segmentation also provides each respondent's probability of belonging to a specific class. In some situations, this insight can have one-to-one selling implications.

But latent class segmentation also represents a powerful new lens through which to view the marketplace because it is closer to the primary factors that *cause* a certain buying choice to be made, namely the comparative utility values of offerings as perceived by the customer. How does this differ from classic forms of segmentation? Segmentation on demographic, geographic and psychographic dimensions is based on the assumption that tastes and buying behaviours are similar within these segments. In effect, these classic segmentation dimensions are proxies for underlying preference structures, and at least two marketing problems arise as a result. First, there is no guarantee that a particular preference structure is contained solely within the classic segment. Indeed, it is highly likely that a unique preference structure will cross the boundaries of a number of classic segmentation types for many products and services. The consequences of centring the marketing message, product positioning and marketing channel on some understanding limited to a rigid classical segment is that it may suboptimise the realisable market. This is a difference of market scope between the two segmentation methods. The implication for the market segmentation process is that preference structure segmentation should precede demographic segmentation.

The second marketing problem arises because classic segmentation tells the marketer nothing about which product characteristics drive the purchasing decision. Consequently, it becomes a matter of subjective judgment as to which product or service characteristics to base the marketing communication or sales orientation on for a particular classic segment. Developing latent class insights into a number of unique preference structures brings the marketer closer to underlying needs of the customer. This is a difference of market type between the two segmentation methods.

It is quite possible that by limiting a segmentation study to classic forms, the marketer may weaken the company's performance by making both marketing scope and marketing type errors. In an age where increased sensitivity in differentiation is often the key to sustainable competitive advantage, segmentation by preference structure becomes an approach that marketers can ill afford to overlook.

DESIGNING CHOICE-BASED CONJOINT ANALYSIS FOR THE ONLINE GROCERY MARKET

One can see the strengths of choice-based conjoint analysis by using it to examine a complex emerging area of preference structure segmentation: competitive online propositions within the UK grocery market, a fast-growing channel to market where the leading retailer already generates annual sales revenues of £1bn.

Calibrating the conjoint analysis in this case required undertaking qualitative interviews with shoppers to identify which online store choice attributes were important to them. Twenty in-home 45-minute qualitative interviews were conducted with a random sample of shoppers from an independent (UK) school chosen as representative of the research population. Initial attributes were defined at this stage.

Following a pilot study, the choice-based conjoint study used respondents drawn from the parents of pupils of four independent schools, located in Surrey and south-west London. This population was chosen to ensure that income profiles and cultural preferences could be similar for participating parents. Their income

Table 2: Attributes and level of attributes used for the main survey

Attributes	Level 1	Level 2	Level 3
1. Special offer section	Has a special offer section	No new special offer section	
2. New product section	Has a new products section	No new products section	
3. Helpline number	Helpline number	No helpline number	
4. Delivery time	Delivered in six hours	Delivered in 24 hours	Delivered in 48 hours
5. Delivery cost	No delivery cost	£5 delivery cost	
6. Delivery time reliability	Delivery at agreed time	Delivery an hour early or late	
7. Quality	No items below quality	Five items below quality	
8. Ordering time	20 minutes to place order	35 minutes to place order	One hour to place order
9. Substitutes	No substitutes	Five substitutes	
10. Discount on internet prices	0% discount on internet prices	10% discount on internet prices	

profiles would suggest that they buy a higher proportion of high-margin products and services. The respondents were mainly women from 27 to 50 years old and comprised a mixture of working and non-working mothers who had between 1–3 children.

Following the pilot, a number of modifications were carried out to increase the internal consistency of the questionnaire and its structure. For reasons of efficiency and to generate a higher response rate, it was decided to carry out the main survey via the internet using Sawtooth software. Random sampling was not used, as each family in the population (defined as the four schools chosen for study) was accessible and had an equal probability of being selected. Conjoint designs are generally more robust than other multivariate techniques in terms of sample size effects on validity.[9]

Ten attributes were finally selected to include in the choice-based survey, based on the theoretical background and findings of the primary qualitative investigation. Each attribute was further divided into two or three levels better to reflect the choices that might be available to shoppers (Table 2).

The survey was in two parts. The first section sought information on underlying demographics and loyalty behaviours (value of residential property, dual or single income, and how many times online shopping was undertaken annually etc). The second section comprised 14 onscreen choice tasks to provide realistic buying contexts from which respondents could choose.

In total, the main survey achieved 258 completed responses. The total number of received questionnaires was much higher but some questionnaires were considered as incomplete if one screen or one question was not completed. The useable response rate was 12.7 per cent.
The useable response rate could have been higher by reducing the number of choice tasks. The choice tasks represented 14 screens and the majority of respondents stopped at 10 screens. These responses were considered to be unusable. Twelve per cent of returned questionnaires were rejected for this reason. The gross response rate was in the order of 25 per cent. Using a priori estimates of standard errors for attribute levels with 258 respondents and total choice tasks of 3,096, shows that the efficiency of any attributes level ranges from 0.9991 to 0.9998. This test of design efficiency shows that the realised useable response rate poses limited scope for design threats to validity. Hair *et al.*[10] suggest that design validity problems only begin to emerge at a response level of less than 130 for designs with average number of choice tasks, attributes and levels.

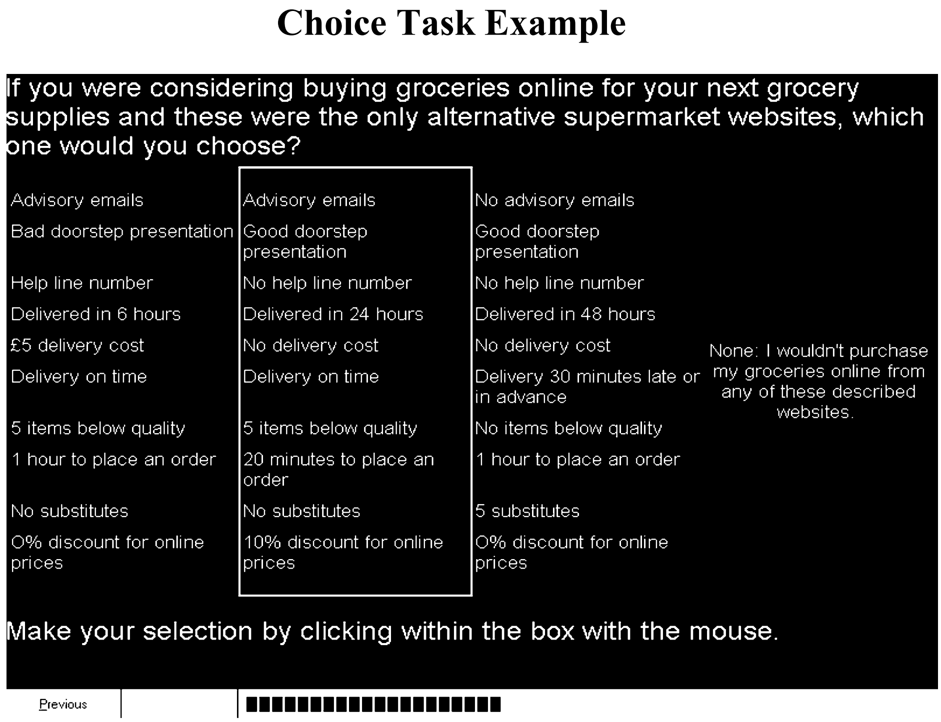

Figure 1: Choice task example

For validation purposes, two fixed holdout tasks were included.[11] They were the only two choice tasks constant across all respondents as the other tasks were randomised. There was a 99 per cent fit between the holdout samples and the main survey data. Figure 1 shows an example of one of the 12 choice task screens.

SHOPPERS' PREFERENCES TOWARDS ONLINE GROCERY BRANDS IN THE UK

Logit analysis was used to calculate the consumer utility values and provide the relative importance of levels of attributes. Hair, Anderson, Tatham and Black[12] define a utility as:

> '… a subjective preference judgment by an individual representing the holistic value or worth of a specific object. In conjoint analysis, utility is assumed to be formed by the combination of part-worth estimates for any specified set of levels with the use of an additive model, perhaps in conjunction with interaction effects.'

From this definition, it is understood that utility measures a level of desirability for a certain attribute level. Consequently the higher the utility, the more desirable the attribute level is. Utility values for the selected levels of attributes are shown in Table 3. The table estimates the utilities for online grocery shoppers by brand in the UK.

Table 3 displays shoppers' preferences towards online grocery main competitive brands in the UK. Wilson-Jeanselme and Reynolds[13] noted that Tesco.com's online market share currently represents 45 per cent of the UK online grocery market. For this particular sample (high net worth families drawn from independent schools in Surrey), 50.39 per cent of respondents were currently shopping online with

Table 3: Utility values for three main online grocery brands

Levels	Utility values **Tesco** (31 respondents)	**Sainsbury's** (29 respondents)	**Ocado** (39 respondents)
Has a special offer section	0.11	0.10	0.11
Has a new product section	0.01	0.00	0.00
Help line number	0.06	0.10	0.04
Delivered in six hours	0.32	0.19	0.30
Delivered in 24 hours	0.10	0.18	–
No delivery cost	0.22	0.26	0.06
Delivery at agreed time	0.29	0.29	0.38
No items below quality	0.47	0.50	0.58
20 minutes to place an order	0.57	0.34	0.72
35 minutes to place an order	0.02	0.08	–
No substitutes	0.31	0.18	0.12
10% discount on internet prices	0.23	0.30	0.24

Tesco.com for groceries. Sainsburys.co.uk was identified as the closest competitor of Tesco.com followed by Ocado.co.uk. Asda and M&S are insignificant in terms of the research population. This paper has therefore focused on shoppers' preferences for these three brands only, as they represent the leading online grocery retailers in the UK.

The study then examined how these utility values split out into latent classes.

AN EXAMPLE OF LATENT CLASS SEGMENTATION

This section will provide the results of the latent class analysis of the online grocery shoppers.

Five latent classes were identified as shown in Table 4. The table has been profiled from the utility values for each level for each respondent. There is a 96 per cent probability that each respondent has been correctly identified to their particular latent class. What can be interpreted from this table? The first thing to note is that each class is identified by a preference for an outstanding attribute or from a combination of two leading attributes. As expected, the latent class analysis results in minimal overlap in the preference structures. The second thing to note is the share of preference of each class. This is illustrated in Figure 2.

If each latent class preference structure is weighted by its share of preference, an enhanced picture of the relative importance of each attribute is achieved (Table 5).

There is some adjustment of priority of each attribute within each latent class. Overall ordering time and quality would have the biggest single impact on share of preference. Understanding these weighted preference structures could guide a number of marketing decisions, such as creating a communication message that targets a certain class of online shopper, or emphasising the importance of certain internal competencies to increase market share.

The study then looked at the how different the preference structure results would look in comparison with a segmentation carried out on the same data, but using a classic segmentation variable.

EVALUATING THE MARKET SCOPE ERROR BETWEEN CLASSIC AND PREFERENCE SEGMENTATION

This paper previously suggested that there may be a market scope error in

Table 4: The five preference structures revealed by latent class analysis

	Speed	Reliability	Speed/Quality	Price	Quality
Special offers	3	6	4	8	1
New products	2	2	3	3	5
Help line	0	9	2	3	3
Delivery time	29	3	20	3	6
Delivery cost	1	5	15	15	9
Delivery reliability	7	45	4	5	7
Quality	5	11	21	11	43
Ordering time	43	11	14	18	10
No substitutes	5	4	15	9	12
Discount	5	5	4	25	3
Share of preference	18.6	18.6	23.3	22.5	17.1

Table 5: Latent class attribute utility values weighted by share of preference percentages

	Speed	Reliability	Speed/Quality	Price	Quality	Total
Special offers	0.558	1.116	0.932	1.800	0.171	4.577
New products	0.372	0.372	0.699	0.675	0.855	2.973
Helpline	0	1.674	0.466	0.675	0.513	3.328
Delivery time	5.394	0.558	4.660	0.675	1.026	12.313
Delivery cost	0.186	0.930	3.495	3.375	1.539	9.525
Delivery reliability	1.302	8.370	0.932	1.125	1.197	12.926
Quality	0.930	2.046	4.893	2.475	7.353	17.697
Ordering time	7.998	2.046	3.262	4.050	1.710	19.066
No substitutes	0.930	0.744	3.495	2.025	2.052	9.246
Discount	0.930	0.930	0.932	5.625	0.513	8.930
Share of preference	18.6	18.6	23.3	22.5	17.1	100.0

using classic versus preference segmentation. To test this hypothesis the study will use brand as the classic segmentation (ie Tesco, Sainsbury's and Ocado) and compare the online shoppers' brand count proportions with the share of preference proportions as calculated in a simulation. The simulation will use the preference structures as provided by the utility values in Table 3. For example, the Tesco scenario will have 20 minutes to place an order set at the highest performance, because this utility value is highest for Tesco as compared with Sainsbury's and Ocado etc.

The shares of preferences calculated by the simulation are shown in Table 6.

The shares of preference were converted into counts (129 respondents) and compared with the brand count proportions. The result is shown in Table 7.

The hypothesis for differences in count proportions was tested for significance using chi-square as shown below:

H_1: The count proportions between brand and preference segmentation are equal.

H_2: The count proportions between brand and preference segmentation are not equal.
$\alpha = 0.05$
Decision rule: If $p \geq \alpha$ then fail to reject H_1

$\chi^2 = 39.63 > \chi^2_{\text{crit}} = 3.84$ therefore we fail to accept the null hypothesis and conclude that there is a significant difference between the brand count proportions and the share of preference proportions as calculated in the simulation.

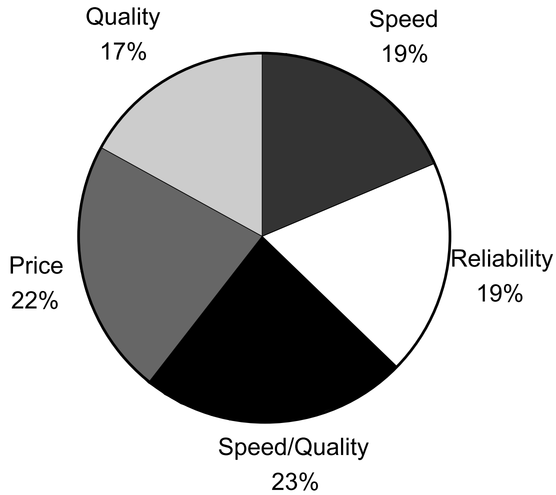

Figure 2: Five latent class preference structures within online shoppers

What does this difference mean? Part of the difference would be accounted for in the lack of sensitivity in converting utility values in Table 3 back into count proportions. It is unlikely that this would account for such a large observed χ^2. Most of the difference would be accounted for by the market scope error between a classic segmentation (which frequently relies on count proportions) and segmentation using a combination of utility values and simulation or latent class analysis.

This difference means that a preference-based segmentation of online shoppers shows that the high net worth respondents in this limited sample conform in substantially greater numbers to the Ocado type than is indicated by simple count proportions of where they currently shop.

What are the implications of the market scope error in this example? One clear implication within this sample is that there is a substantial latent competitive threat to Tesco's and Sainsbury's market share (as measured by simply counting which websites shoppers currently use). If all other factors remain equal, this market scope error would suggest that Ocado will increase its market share over time.

It would not have been possible to identify this potential shift in market share using classic market segmentation methods.

CONCLUSION

This paper recommends a segmentation of consumers based on understanding their preferences as opposed to more traditional segmentation methods. This study also stressed the importance of looking at different combinations of attributes, as this would greatly improve online retailers' share of preference as opposed to only looking at the relative importance of each attribute. Market simulation could additionally be used to conduct 'what-if' scenarios to investigate issues such as retailers' website design, positioning and pricing strategy.

By understanding the customers' preference structures, the gap between what they expect and what they experience can be narrowed. In addition, other performance gaps will also be reduced if the internal logistics,

Table 6: Product shares of preference

	Shares	SE
Tesco	12.13	2.28
Sainsbury's	7.90	2.01
Ocado	79.97	2.86

Table 7: Brand and preference segmentation

Brand	Brand segmentation	Preference segmentation
Tesco	31	16
Sainsbury's	29	10
Ocado	39	103

communication and other resources of the business focus more carefully on these preferences. The overall effect will be a more focused business where there are fewer marketing weaknesses for the competition to exploit.

Finally the study has demonstrated the superiority of a preference-based segmentation approach in identifying the actual market scope of different product and service offerings.

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