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Market segmentation under the choice modelling framework

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A thesis submitted under a joint degree program (cotutelle) at the School of Business and Economics, Universidad del Desarrollo, Chile in fulfilment of the requirements for the degree of Doctor in Business Economics and the Department of Marketing, Macquarie University, Australia in fulfilment of the requirements for the degree of Doctor of Philosophy (PhD)

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Statement of Originality Authorship

I hereby declare that this thesis has not previously been submitted for a degree or diploma in any university or other institution of higher learning. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

I also declare that this thesis is an original research written by me, and the contributions made by my co-authors have been properly recognized in the section “Authorship Contributions Statement”.

The primary data collected for the third paper of this thesis adheres to ethical policies and received approval from the Macquarie University Ethics Committee.

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Authorship Contribution Statement

While I am the principal author of the thesis, the contributions of my supervisors and co-authors in each research study are outlined below.

RESEARCH STUDY 1: Preference heterogeneity and market segmentation: An assessment of the mixed logit and latent class models.

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Name of corresponding author: Nelyda Campos Requena

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Author contributions:

Nelyda Campos Requena – 70% (conceptualization, methodology, formal analysis, writing-original draft)

Felipe Vásquez Lavín – 10% (conceptualization, writing-review & editing, supervision, funding acquisition)

Francisco Fernández – 5% (formal analysis, investigation)

Manuel Barrientos – 5% (investigation, data curation)

Stefan Gelcich – 5% (investigation, funding acquisition, project administration)

Roberto D. Ponce Oliva. – 5% (Validation, funding acquisition, project administration)

Data: The data used in this research study was not collected by me. The data were collected in 2016, prior to this thesis, as part of a project funded by the ANID PIA/BASAL FB0002, with Dr Felipe Vásquez Lavín as a researcher.

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Nelyda Campos Requena – 80% (conceptualization, data collection, methodology, formal analysis, writing-original draft)

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This thesis is being submitted to Macquarie University and Universidad del Desarrollo in accordance with the Cotutelle agreement dated August 2019.

To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

(Signed) ______________________ Date: ____August 2021______

Candidate's statement about the impact of COVID-19 changes on the thesis

Dear Examiner,

Many of our HDR candidates have had to make changes to their research due to the impact of COVID-19. Below you will find a statement from the candidature, approved by their Supervisory Panel, that indicates how their original research plan has been affected by COVID-19 restrictions. Relevant ongoing restrictions in place caused by COVID-19 will also be detailed by the candidate.

Candidate's Statement:

The original research study 3 attempted to collect data to unravel attribute non-attendance (ANA) for market segmentation prediction using eye-tracking technology. Thus, the study aimed to combine inferred ANA with visual ANA as a more effective method to separate the motives behind this type of consumer behaviour—a representation of true preferences or a coping mechanism to reduce complex tasks.

Restrictions to collect data in a laboratory due to the COVID-19 situation led us to modify the aim of this chapter of the thesis. However, I kept the assessment of ANA and market segmentation. Instead of combining inferred ANA with visual ANA, I included stated ANA. The research was adjusted to avoid human contact during the data collection. For this reason, an online survey was developed to recover information about consumer behaviour as a second-best option to assess ANA behaviour.

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AIC	Akaike information criterion
ANA	attribute non-attendance
BIC	Bayesian information criterion
CAIC	consistent Akaike information criterion
CBC	choice-based conjoint
CV	coefficient of variation
DCE	discrete choice experiment
EAA	endogenous attribute attendance model
ECLC	equality constrained latent class model
ISP	individual-specific posterior distribution
LCM	latent class model
LC-MMNL	latent class mixed multinomial logit model
LC-RPL	latent class random parameter model
MEAA	mixed endogenous attribute attendance model
MLM	mixed logit model
OA	Ocean acidification
RMSE	root mean square error
RPM	random parameter model
T&I	text and images
TO	text only
WTP	willingness to pay

Abstract

This thesis examines market segmentation from an economic perspective by drawing on the choice modelling framework. The market segmentation literature focuses on providing information to marketers about customers, especially about their wants, needs and preferences regarding different products or services. A challenge confronting marketing researchers is to improve the estimation of market segments. The latent class model (LCM) has been extensively used to capture consumers' heterogeneity and identify market segments. However, some questions remain unanswered. How reliable and effective is the LCM in capturing customer heterogeneity, especially unobserved heterogeneity? How are estimation results affected if customers do not consider all information provided in the choice tasks; that is, when attribute non-attendance (ANA) occurs? To answer these questions, this thesis assessed the LCM in two ways. First, it was compared with an alternative model—the mixed logit model (MLM)—and the role of individual-specific posterior distributions (ISPs) was evaluated to account for unobserved heterogeneity and identify market segments. Second, the thesis assessed the role of ANA in modelling and identifying market segments.

This thesis consists of three studies. The first study identifies market segments by examining customer heterogeneity from the ISP in the MLM and the LCM. When using the ISP in the LCM as the basis for segmentation, there is an explicit recognition that class membership is probabilistic. The identified market

segments are compared in terms of the number of customers in each segment and their characteristics. The results suggest differences in both customer number and characteristics.

The second study performs a Monte Carlo simulation to determine the impact of consumer heterogeneity on the accuracy of the LCM and the MLM in identifying market segments. The design comprises four experiments with two levels of heterogeneity (low and high) and the presence or absence of small (niche) segments. The results showed that the accuracy of the models is contingent on the level of heterogeneity of individuals. Specifically, when heterogeneity is low, segments estimated by the LCM are more precise; however, when heterogeneity is high, the MLM outperforms the LCM. The results also suggest that using ISPs as the basis for segmentation in the LCM makes it possible to identify market segments more accurately when heterogeneity is high. In the presence of niche segments, there was no evidence of one model outperforming the other.

The third study accounts for ANA in identifying market segments using an LCM. Images were added to text, allowing consumers to visualise attribute levels. This was used to reduce ANA as a coping mechanism for complex tasks, thereby better capturing genuine consumer preferences. The results showed that inferred ANA combined with stated ANA in the LCM improves model performance. Moreover, using images to present attribute levels improves model performance when ANA is accounted for in the estimation.

Chapter 1:

INTRODUCTION

1.1 Introduction

This thesis studies market segmentation through the lens of economic theory using the choice modelling framework. The market segmentation literature focuses on two questions faced by marketers to guide them in tailoring strategies to meet customer needs: “Who are my customers?” and “What products or services do they want and need?” (Dillon & Mukherjee, 2006, p. 523). A challenge confronting marketing scholars is how to improve the estimation of market segmentation (Ding et al., 2020). The latent class model (LCM) has been extensively used since the works of Gupta and Chintagunta (1994) and Kamakura and Russell (1989) to capture consumer heterogeneity and identify market segments. However, some questions remain unanswered: How reliable and effective is the LCM in capturing customer heterogeneity, especially unobserved heterogeneity? How are results affected if customers do not consider all information provided in the choice tasks; that is, when attribute non-attendance (ANA) occurs? To answer these questions, this thesis assesses the LCM in two ways. First, this model is compared with an alternative model (mixed logit), evaluating the role of individual-specific posterior distributions (ISPs) to account for unobserved heterogeneity and also to estimate market segments. Second, the thesis assesses the role of ANA in the modelling and identification of market segments.

The following section provides the principal motivation for incorporating these elements into the study of market segmentation. The aims and objectives of the study are then presented, followed by the contribution of this thesis to the literature. Finally, the chapter concludes by outlining the rest of the document.

1.2 Motivation

This subsection begins with a general description of the theoretical framework, which is then used to motivate the principal focus of the thesis.

1.2.1 General theoretical framework

The concept of market segmentation appears for the first time during the 1950s in the seminal work of Smith (1956). The author acknowledges the existence of several homogeneous subgroups within a heterogeneous market. These subgroups include consumers with similar needs and preferences. Since then, market segmentation has become one of the most important tools for marketers to design customised strategies, such as pricing, product design, advertising and distribution.

Initially, observable variables, such as sociodemographics or frequency of use of the product, were used to inform market segmentation. Although this type of segmentation is relatively easy to implement, it proved to be an overly general way of grouping consumers, leaving out some critical factors. For instance, it did not include unobserved variables, such as perceptions, preferences, values, tastes, among others, that largely explain consumers' motivations. Technical difficulties in measuring and applying these types of variables led to the emergence of new methods and techniques (Wedel & Kamakura, 2000).

Over the past decades, the choice modelling or discrete choice experiments (DCEs)[1] has dominated this debate, especially by considering not just observable but also unobserved heterogeneity. This framework, which can be used to explain consumer choice behaviour, is supported by the traditional random utility model. Here, individuals face a hypothetical market with several alternatives of a product (or service). These are usually two or three alternatives that differ in the level of product attributes plus an opt-out option, and consumers are asked to choose their preferred alternative. The chosen alternative offers them the highest utility level. However, this utility is a latent construct, unobserved by the researcher. Instead, the researcher only observes preference indicators through the chosen alternative and its attributes (Louviere & Woodworth, 1983; Louviere, Flynn, & Carson, 2010; McFadden, 1974; Train, 2009; Walker & Ben-Akiva, 2002). Thus, the decision problem faced by an individual $n = 1, \dots, N$ is selecting the preferred alternative among $j = 1, \dots, J$ alternatives in choice situations $t = 1, \dots, T$. The chosen alternative provides the highest utility level, given by $U_{njt} = V(x_{njt}; \beta) + \varepsilon_{njt}$. This utility has a systematic or deterministic component $V(.)$, where x_{njt} represents a vector of observable attributes of the product (Lancaster, 1966) and β is the corresponding vector of parameters.

[1] This is also known as choice-based conjoint (CBC). Nevertheless, Louviere et al. (2010) state that discrete choice and conjoint analysis are founded on different backgrounds, so theoretically they are different. The conjoint measurement theory supports the conjoint analysis, which is considered a mathematical approach with no economic support. Instead, DCE has its roots in the random utility theory.

U_{njt} also includes an unobserved or stochastic component given by ε_{njt}. By modelling this utility function by assuming some distribution of the random disturbances ε_{njt} and defining how to treat the vector of β's, researchers are able to predict consumers' decisions by using classical or Bayesian techniques. This thesis focuses on classical estimation.

Nowadays, different disciplines use this framework to understand and model consumer behaviour and to learn about how consumers make choices. These disciplines include transportation, health economics and environmental economics, among others. For marketing, DCE has become a valuable tool since the work of Louviere and Woodworth (1983).

Methodological extensions to this original framework were made by Walker and Ben-Akiva (2002). These extensions mean that choice behaviour can be understood more realistically by including additional elements, such as latent classes or flexible disturbances, to allow for random parameters. Figure 1.1 reproduces the generalised random utility model proposed by Walker and Ben-Akiva (2002) where observable variables are in rectangles, unobservable variables in ovals, solid arrows show causal relationships and dashed arrows show measurement relationships. The central part of the figure, highlighted in bold, shows the basic discrete choice model, which is mainly specified as a multinomial logit model. This framework is extended and enhanced by the additional elements of the figure. For marketing, the LCM extension provides a solid theoretical foundation to understand consumers' choice behaviour and to accommodate preference heterogeneity among consumers (through classes or segments). However, the potential for using flexible disturbances to allow random parameters has been less exploited for segmentation purposes. Thus, this thesis explores both extensions by analysing the suitability of the LCM compared with the random parameter model for segmenting a market.

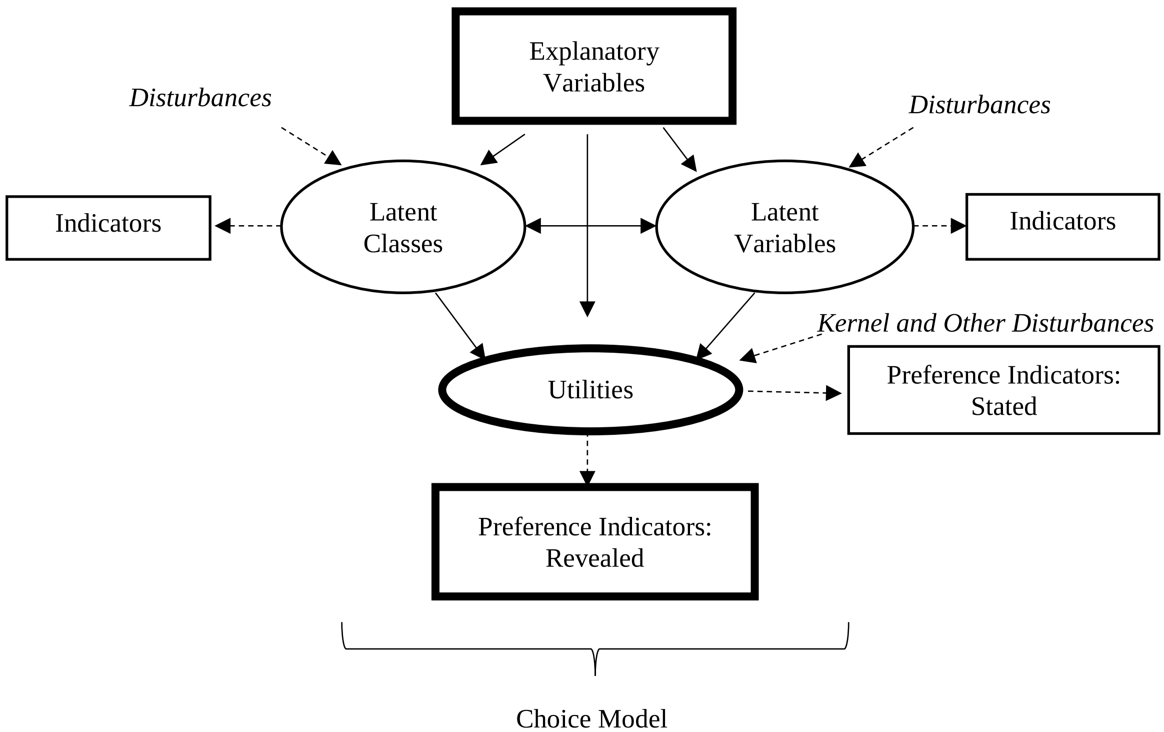

Figure 1.1 Generalised random utility model extracted from Walker and Ben-Akiva (2002)

Moreover, the consumer optimisation problem described in this choice modelling framework assumes rational consumers, with preferences satisfying the properties of completeness, transitivity and continuity (Mas-Colell, Whinston, & Green, 1995). It is assumed that consumers make trade-offs between all attributes presented in the alternatives that they compare during a choice situation. This is known as fully compensatory behaviour (Hensher, 2014). However, several studies challenge this assumption, suggesting that consumers use different information processing strategies, especially attribute processing strategies. Consequently, DCEs should also consider these strategies (Hensher, Rose, & Greene, 2005; Lew & Whitehead, 2020; Puckett & Hensher, 2008). Attribute processing strategies such as ANA have gained attention from researchers, who recognise different strategies followed by consumers when they scrutinise attribute information (Lew & Whitehead, 2020). In particular, ANA behaviour challenges the assumption that consumers make trade-offs between all the attributes of a product, acknowledging that they ignore some of these during choice tasks (DeShazo & Fermo, 2004; Puckett & Hensher, 2008). Two reasons may explain this ANA behaviour. First, consumers may ignore some attributes as a coping strategy to simplify complex tasks. Second, this behaviour may show a genuine preference when attributes are irrelevant for consumers (Hensher et al., 2005). Given that it is imperative to accommodate this ANA behaviour in the modelling process to resemble consumer behaviour more closely, the traditional LCM can be used for this task. Despite the current literature offering different methods of accommodating ANA, more research is needed (Elshiewy, Guhl, & Boztuğ, 2017; Lew & Whitehead, 2020). This thesis explores some elements that can improve the LCM when it accounts for ANA. These elements include the role of images to reduce complexity of the tasks and the use of self-reported ANA to improve the latent class estimation.

This study uses this extended framework to investigate market segmentation based on consumer preferences, especially to overcome some of the criticisms of segmentation. These criticisms include overly focusing on identifying consumers instead of recognising the most important product attributes for consumers or learning more about their behaviour (Yankelovich & Meer, 2006). In particular, this thesis examines consumer preferences focusing on two aspects that may affect accurate market segmentation: assessing which model better allows to capture consumers' heterogeneity and analysing the role of ANA behaviour to uncover segmentation. Both aspects are described in more detail next.

1.2.2 Modelling unobserved heterogeneity to uncover market segments

The choice modelling framework provides two of the most popular models to capture both deterministic and random heterogeneity across individuals. First, there is the random parameter model or RPM (also known as the mixed logit model or MLM), under which the consumer parameters β's follow a continuous distribution. This model can be considered an extreme case of segmentation, where each individual represents one individual segment. Second, the LCM (also known as the finite mixture model), has a discrete distribution of the β's. Under this last model, a specific number of classes represents a definite number of segments (Hess, 2014; Wedel & Kamakura, 2000).

The LCM has been extensively used for market segmentation since the work of Kamakura and Russell (1989) and Gupta and Chintagunta (1994). In contrast, the MLM has been mainly used for welfare analysis (e.g. willingness to pay measures), with just a few cases using it for segmentation (e.g. Crabbe, Jones, & Vandebroek, 2013; Scarpa & Del Giudice, 2004). Although there is still no definitive evidence on which model best represents the real world (Wedel & Kamakura, 2000), the predominance of the LCM over the MLM to perform segmentation is evident.

The primary advantage of the LCM is allowing the estimation and uncovering of classes in a one-stage procedure. Previously, it was common for two stages to be used, with researchers estimating a model at an individual level in the first stage, followed by cluster analysis in the second stage. The extensive use of this last approach is in rating-based conjoint studies (DeSarbo, Ramaswamy, & Cohen, 1995). In addition, unlike the MLM, the LCM does not require assuming a specific continuous distribution for the models' parameters. This model also does not require simulations to be estimated, making it more approachable. However, despite these advantages, some methodological and theoretical issues arise. First, some authors question the very existence of limited segments in a market and, therefore, the consistency of the coefficients estimated under a discrete distribution (Allenby & Rossi, 1998). Second, the actual number of classes is unknown to the researcher. Although there are different information criteria to help in this decision (Andrews & Currim, 2003), it still remains uncertain whether the chosen number of classes represents the true patterns of heterogeneity. Third, during the estimation of the LCM, the number of parameters to be estimated increases exponentially with the number of classes requiring large samples. Moreover, there is a high possibility that the likelihood function achieves a local instead of a global maximum, leading the researchers to repeat the estimation with different starting values to ensure a global maximum (Elshiewy et al., 2017). These disadvantages drive researchers to search for alternative methods to better approximate consumers' behaviour.

The use of the MLM can overcome some of the LCM's disadvantages, making it a potential alternative model to uncover market segments. First, the MLM is highly flexible and can approximate random taste variation (Train, 2009). Second, although it requires simulation methods, computational advances mean it is possible to estimate these models without significant problems nowadays. Third, the model estimates not only the mean but also the standard deviation for each parameter. The statistical significance of the standard deviations provides additional information related to the preference heterogeneity (Hensher & Greene, 2003; Train, 2009). Fourth, by using Bayes' rule, it is possible to recover the ISPs based on the consumers' choices (Hensher & Greene, 2003). These ISPs indicate the distribution of tastes towards the attributes of a product for each individual (Train, 1998), which can be a relevant source of information to identify market segments. Despite these advantages, one of the principal issues associated with using the MLM is related to the distribution chosen by the researcher. Because this is a continuous model, the efficiency of all estimates depends on the choice of the correct random parameters' functional form, which is unknown by the researcher.

Thus, considering the advantages and disadvantages of both models, how reliable and effective is the traditional LCM in capturing consumer heterogeneity and uncovering market segments compared with an alternative model, such as the MLM? This question motivates the first two studies of this thesis to assess the closeness of the predictions from both approaches. For this aim, the ISPs serve as a basis for segmentation in the MLM; however, this base for segmentation is also used for the LCM as an alternative approach to identify the segments. The results from these estimations can be used to evaluate the usefulness of these ISPs, particularly for LCM, since by using them, it is possible to acknowledge the probabilistic nature of individuals' class membership. Finally, the thesis describes the conditions under which each model is more accurate to predict the correct segments in a market.

1.2.3 Analysing the effects of ANA on market segmentation

The second aspect of consumer behaviour included in the market segmentation analysis in this thesis is the potential role of ANA behaviour. There is consensus in the literature that most consumers ignore one or more attributes during a choice task. This is known as ANA (Hensher et al., 2005). Not accounting for ANA during estimation reduces the model's efficiency by providing biased estimates and affecting behavioural outputs (Hensher, 2014; Scarpa, Gilbride, Campbell, & Hensher, 2009).

Generally, ANA can be captured by either asking respondents directly (stated ANA) or by retrieving it analytically from the modelling (inferred ANA). For both cases, there are several alternative approaches to its operationalisation. But how is this connected to market segmentation? Until now, LCM has provided a means of accommodating ANA analytically by restricting the classes to represent different ANA patterns[2] (Campbell, Hensher, & Scarpa, 2011; Caputo, Van Loo, Scarpa, Nayga, & Verbeke, 2018; Hensher & Greene, 2010; Hole, 2011; Scarpa et al., 2009). However, there is no clarity on the number and type of ANA patterns that should be included in the modelling, with these decisions being left up to each researcher. This thesis explores a strategy to define which ANA patterns to include in the LCM by exploiting self-reported ANA. Most previous studies use either stated ANA or inferred ANA, but a complementarity between both has been explored to a lesser extent. Thus, this thesis evaluates the model performance when inferred ANA is combined with stated ANA in an LCM context. The focus is to assess whether the model's performance is improved and how this ANA accommodation affects market segments.

Another issue related to ANA is the reasons behind this behaviour. A few studies have attempted to identify whether ANA is a coping mechanism for complex tasks or whether it represents genuine preferences towards attributes

[2] ANA patterns refer to different combinations of attributes ignored or attended by consumers.

that are not relevant for consumers (Alemu, Morkbak, Olsen, & Jensen, 2013; Heidenreich, Watson, Ryan, & Phimister, 2018). While the work of Alemu et al. (2013) directly asks respondents their reasons for not attending to certain attributes, the study of Heidenreich et al. (2018) infers these motives by assuming that familiarity with the product simplifies choices. But what happens if the DCE uses images to simplify choice decisions? Does that allow the ANA behaviour to be better explored because of preferences? This thesis provides additional evidence on this topic by evaluating whether the presentation format of the choice tasks (images vs texts) can bring the ANA closer through preferences by reducing task complexity.

1.3 Research aims and objectives

This thesis assesses the reliability and effectiveness of the LCM to uncover market segments. Throughout this document, different strategies seek to answer the following questions: Is traditional LCM an accurate method of identifying consumer heterogeneity and consumer behaviour? Which elements allow market segments to be uncovered more accurately?

To answer these questions, the analysis relies on two important sources of information, which have been somewhat underrated in the market segmentation literature: ISP as an element to better understand consumers' heterogeneity and ANA behaviour during choice tasks.

Specifically, the objectives of this thesis are to:

1. evaluate the consistency between the MLM and LCM in identifying market segments by considering ISPs as the basis for segmentation;
2. assess the accuracy of the MLM and LCM in predicting market segments under two levels of heterogeneity and the presence of small (niche) segments;
3. analyse the relevance of ISPs in identifying market segments in the LCM;
4. assess the role of attribute images in identifying market segments in the LCM accounting for ANA; and
5. evaluate inferred ANA combined with stated ANA as a strategy to accommodate ANA in an LCM.

1.4 Contribution

This thesis contributes to the literature in different ways. First, LCMs are one of the most popular post-hoc segmentation techniques[3] available for both researchers and practitioners. However, this thesis provides evidence that it is not always the most accurate technique to follow. In particular, the results showed that the level of heterogeneity among consumers concerning their preferences is crucial to uncover market segments. Although traditional LCM is very precise when consumer heterogeneity is low, this is not the case when heterogeneity is

[3] The literature recognises two types of methods used in segmentation. In the first, known as the a priori approach, the researcher defines the segments before any data collection. In the second, known as the post-hoc approach, the segments arise from the data analysis (Wedel & Kamakura, 2000). The latter relies on a modelling approach instead of subjective criteria to identify the segments.

high. Instead, this thesis suggests taking advantage of ISPs, either from the LCM or the MLM, as a basis for segmentation. For both models, the findings demonstrated that using ISPs to segment the market outperforms the traditional LCM when there is high heterogeneity. This result is relevant from an academic and practical perspective. Academically, it provides additional evidence of the significant role played by ISPs in consumer behaviour analysis. In terms of practice, it assists in performing more effective segmentation. Thus, when there are signs of high levels of heterogeneity in tastes, using ISPs as a basis for segmentation is recommended, either in LCM or MLM, instead of traditional LCM.

Second, the thesis adds new evidence to the current literature comparing these two models. Several studies have compared the MLM and LCM concerning model fit or behavioural outputs (e.g. willingness to pay), with mixed results about which one is more appropriate (e.g. Greene & Hensher, 2003, 2013; Keane & Wasi, 2013). This thesis provides additional evidence about comparing both models, but in terms of market segmentation predictions. While some studies compare both models according to their segmentation predictions (Asioli, Berget, & Næs, 2018; Crabbe et al., 2013), this thesis includes the use of ISPs in this endeavour. Based on the findings, it is possible to state that using ISPs for segmentation improves latent class accuracy to uncover segments when preference heterogeneity is high.

Third, this thesis discusses the role of consumers' ANA behaviour over market segmentation. By considering LCM to accommodate ANA, the evidence found in this thesis indicates that including attribute levels in images during a choice experiment improves the market segmentation model performance. This finding confirms the use of images in reducing choice task complexity, which may lead to a closer representation of ANA reflecting preferences (attributes considered unimportant for the consumer).

Finally, several studies use either a stated or an inferred ANA approach while a couple compare the two approaches (Caputo et al., 2018; Kragt, 2013; Scarpa, Zanoli, Bruschi, & Naspetti, 2013; Weller, Oehlmann, Mariel, & Meyerhoff, 2014). This thesis proposes that combining stated and inferred ANA in the LCM is more effective in identifying market segments than using only an inferred ANA approach.

For marketers, these findings can address one of the challenges described by Sozuer, Carpenter, Kopalle, McAlister and Lehmann (2020) related to personalised marketing. Marketers require precise data about individual preferences towards the attributes of the offered products to customise strategies. With these findings, it is shown that using LCM for segmentation, improved by ISPs under specific circumstances, and adequately accounting for ANA may help to gather more precise information about the segments in the market to customise marketing strategies.

1.5 Outline of the thesis

Apart from this introductory chapter, this thesis consists of four additional chapters. Chapters 2 to 4 present three research studies, while Chapter 5 provides the conclusions.

Chapter 2 is an empirical study comparing two of the most commonly used models to capture unobserved heterogeneity in consumers' preferences: the MLM and the LCM. The principal research question addressed in this chapter is: Do MLMs and LCMs provide similar results in terms of market segmentation? Most previous studies have compared both models in terms of model fit and some behavioural outputs, but there is scarce evidence about market segmentation. Unlike the studies of Crabbe et al. (2013) and Asioli et al. (2018), which also identify market segments through both models, this study exploits the ISPs from both models to uncover the groups of consumers with similar preference patterns. This strategy not only provides a basis for segmentation for the MLM but also for the LCM. For this last model, it recognises the probabilistic membership of each individual in the estimated classes. The ISPs produce richer information at the individual level, identifying differences and similarities in tastes among consumers, thereby revealing the part of the distribution in which each consumer lies (Train, 2009). The comparison of both models considers the number of segments predicted and the characteristics of the consumers in each group. The empirical study uses data from a discrete choice experiment (DCE) applied to a random sample of 1,257 individuals, seeking to analyse how consumers respond to changes in specific attributes of mussels affected by ocean acidification. The results show that both models predict different segments, both in number and in characteristics.

Chapter 3 goes beyond the results found in the previous research study. In particular, considering that both models predict different segments, the research questions addressed in this study are: Which model better predicts market segments? Are the classes suggested by the LCM a reliable predictor of market segments compared with those derived from using the ISPs as a basis for segmentation? Some studies show the advantages of using ISPs in a different context. For instance, Revelt and Train (2000) show that predictions based on the ISPs from the MLM are more accurate than those based on the population distribution. Likewise, Sarrias and Daziano (2018) extend this work for the case of the LCM with similar conclusions. Both articles conclude that ISPs allow more reliable predictions. Thus, this chapter proposes a Monte Carlo study to evaluate market segment predictions from both models by exploiting the ISPs. The main findings indicate that the classes predicted from the traditional LCM are closer to the true segments only when the preference heterogeneity among consumers is low. In the presence of a high heterogeneity, the MLM outperforms the LCM. Nevertheless, when the ISPs are used as the basis for segmentation in LCM, this model improves its predictability of segments under high preference heterogeneity.

Chapter 4 focuses on the role of consumers' attendance towards the attributes of a product during a choice decision and how this may affect market segmentation predictions. Following the work of Hensher et al. (2005), there is consensus that most consumers ignore one or more attributes during a choice task. Thus, this chapter assesses how an LCM is affected when it accommodates ANA behaviour. There are two aspects considered in the analysis. First, it is investigated whether the presentation format (images vs texts) of the attributes influences the model performance when an LCM accommodates ANA. To evaluate the role of images, the choice experiment includes visual aids as a mechanism to reduce the complexity of the choice tasks and adequately identify ANA as a reflection of preferences (when attributes are ignored because they are not relevant for the consumer). Second, the research study compares the analytical approach to accommodate ANA (inferred ANA) using a combination of stated ANA and inferred ANA. The findings suggest that using images to represent the attributes and accommodating ANA through an analytical method, combined with self-reported information about ANA, enhances the model's performance in identifying market segments.

Chapter 5 ends the thesis by providing general conclusions about the research as well as directions for further research.

Chapter 2:

Research Study 1. Preference Heterogeneity and Market Segmentation: An Assessment of the Mixed Logit and Latent Class Models

Abstract

This study explores consumers' heterogeneity represented by individual-specific posterior distribution (ISP) derived from the estimation of both the mixed logit model (MLM) and the latent class model (LCM) to identify market segments. The study uses data from a choice experiment evaluating the relevance of mussels' attributes affected by ocean acidification caused by carbon emissions, on people's preferences. To define the segments, the study considers both the signs and the intensity of these individual distributions from the estimations, to later use them in cluster analysis. A comparison between the MLM and LCM is made in terms of their predicted market segments, evaluating the individual characteristics of each segment and the level of consistency of the individual assigned to each one. The results show that the segments predicted by the MLM and the LCM are different, both in terms of the number of segments and the characteristics of each segment.

Keywords: individual-specific posterior distributions; market segmentation; mussels; ocean acidification; preference heterogeneity

2.1 Introduction

This study categorises consumers' heterogeneity into different patterns based on the signs and intensity (i.e. like or dislike dimension) of individual-specific posterior distributions (ISPs) derived from the mixed logit model (MLM) and the latent class model (LCM). The ISPs provide information regarding the distribution of individuals tastes toward product attributes (Train, 1998). This information at the individual level allows us to divide consumers into homogeneous groups based on their preferences for these attributes. For instance, a higher negative coefficient denotes a stronger intensity in the dislike dimension, whereas a higher positive value implies greater intensity in the like dimension. These different patterns (groups) are known as *market segments* and this study evaluates whether these models (MLM and LCM) provide similar segmentation predictions.

Preference heterogeneity plays a vital role in modern econometric analysis of discrete choice models (Bhat, 2005; Train, 2009).[4] From a policy perspective, preference heterogeneity is critical for designing interventions that target groups with different preferences and behavioural patterns. For instance, it allows us to identify the winners and losers of an environmental program or different groups for a new health program, among other possible applications. Similarly, for marketing purposes, the ability to recognise market segments and capture differences in individuals' tastes is useful for defining the various attributes of a product that appeal to the preferences of different types of consumers (Allenby & Rossi, 1998; Kamakura, Kim, & Lee, 1996; J. Kim, Allenby, & Rossi, 2002). In this case, marketers have richer information to target specific consumers' needs

[4] Discrete choice models have been widely used in the fields of marketing (Kumar, Sunder, & Leone, 2014; Wu, Sun, Grewal, & Li, 2019), transportation (Bhat, 2018; van der Waerden & van der Waerden, 2018; Vij & Krueger, 2017), health economics (Hansen et al., 2019; Hole, 2008; Zhou & Bridges, 2019; Zhu, Li, Zhang, Li, & Cai, 2019) and environmental economics (English et al., 2018; Ponce Oliva et al., 2019; von Haefen & Domanski, 2018; Xu & Shan, 2018).

through advertising or the design of new products, thereby increasing the effectiveness of these marketing strategies.

In a discrete choice model application, individuals must choose one alternative among the several options available for the same product (such as recreational opportunities, health treatments, cereals, yoghurt), in which a mixture of attributes differing in their levels characterises these alternatives.

A discrete choice model captures consumers' heterogeneity, either by including sociodemographic variables into the statistical behavioural model (observed heterogeneity) or into the definition of the error structure (unobserved heterogeneity) (Sarrias & Daziano, 2018; Train, 2009). There are two main approaches to econometrically address this heterogeneity: the mixed logit model or MLM (also known as the random parameter model) and the latent class model or LCM. The MLM uses a parametric continuous distribution function for the parameters of the model, representing the distribution of taste in the sample, while the LCM uses a semi-parametric discrete distribution (DeSarbo et al., 1995; Greene & Hensher, 2003; Kamakura & Russell, 1989; Sarrias & Daziano, 2018; Train, 2009).

Over the last decades, the LCM has gained popularity in preference-based segmentation over other classical clustering techniques, especially for capturing unobserved heterogeneity (DeSarbo et al., 1995; Kamakura & Russell, 1989; Vriens, Wedel, & Wilms, 1996). However, some authors have introduced the MLM to uncover market segments by using the ISP estimates in a cluster analysis or by defining the segments based on preference structure patterns (Asioli et al., 2018; Crabbe et al., 2013; Scarpa & Del Giudice, 2004).

There are several studies comparing MLM and LCM in terms of goodness of fit (log-likelihood value, Akaike information criterion and Bayesian information criterion), behavioural outputs (willingness to pay, elasticities, predicted choice probabilities for alternatives and significance and signs of estimated parameters) or both (Boxall & Adamowicz, 2002; Greene & Hensher, 2003, 2013; Keane & Wasi, 2013; Shen, 2009). However, very few studies compare both models in terms of segmentation predictions, especially using ISPs as the basis for segmentation (Asioli et al., 2018; Crabbe et al., 2013). This is unfortunate, especially if both models differ in terms of preference structure and individuals' characteristics assigned to each segment, with consequences for customised marketing strategies.

Considering that some evaluations of random parameter estimations show that these models perform poorly in terms of aggregate prediction (Bujosa, Riera, & Hicks, 2010; Klaiber & von Haefen, 2019; von Haefen & Domanski, 2018) and conclude that one should discriminate between competing models using out-of-sample criteria, this study does not intend to contribute to the literature on model selection between discrete (LCM) and continuous (MLM) models. Instead, the primary aim of this study is to analyse the differences in market segmentation derived from these two models. Previous approaches that use either in-samples or out-samples to evaluate the performance of these models do not answer the main question guiding this study: Are the market segments derived from MLM and LCM similar? Such segmentation is only possible if it exploits the heterogeneity implicit in the MLM and LCM that allows the estimation of the ISPs. Therefore, the contribution of this study is complementary to previous analyses focused on goodness of fit and prediction. Finally, this research does not intend to recognise which model identifies the true heterogeneity of preferences since this question would require a different approach and cannot be based on a single sample.

Therefore, the contribution of this study to the literature lies in comparing market segment predictions of both the MLM and LCM using the ISPs in both models as a basis for segmentation. To the best of our knowledge, no empirical studies have evaluated whether these two models provide similar results in terms of predicting market segmentation, with both based on ISPs. Nevertheless, some evidence exists for the potential use of ISPs for behavioural predictions in the LCM and MLM (Revelt & Train, 2000; Sarrias & Daziano, 2018). Thus, the study exploits this information for market segmentation and compares the segments predicted from the different models. The closest study to the present one is that of Asioli et al. (2018), who compare market segments from an MLM using their ISPs in cluster analysis with the classes obtained from an LCM estimation. A potential problem arises from using classes from the LCM estimation as market segments: this approach does not consider that membership in each class is probabilistic. Thus, our study considers this fact by obtaining the ISPs from both the MLM and the LCM to use in cluster analysis. This procedure acknowledges that each individual has a certain probability of belonging to each class.

This procedure follows a two-step approach. In the first step, the MLM and LCM estimations provide the ISPs for both models. In the second step, the ISPs serve as the basis for segmentation. At this last stage, two strategies can be followed. First, the segmentation can emerge from a simple binary categorisation of the results among those who like or dislike an attribute (positive or negative sign for ISPs), following Scarpa and Del Giudice (2004). This approach provides all possible combinations of positive and negative coefficients, in which different segments are associated exclusively with the variation in sign patterns. Despite the ease of implementing and profiling the identified segments, this option ignores the intensity of the like–dislike dimension (i.e. some people may strongly like or dislike an attribute). The second strategy exploits both the sign and the intensity of the ISPs through cluster analysis. In this study, the reported results come from the second strategy.[5] To identify the different groups of intensity (market segments), the hierarchical cluster analysis classifies individuals according to groups that are close to each other in the parameter space. Importantly, this strategy may result in the number of segments differing from the number of classes obtained from the original LCM estimation.

[5] This paper does not use the first strategy to compare both models because, even though for the MLM it predicts eight segments, in the LCM, the ISP estimates are all positive values, leading to just one segment with all individuals showing a positive preference for all three attributes (more details are in Appendix A.4).

To compare the segmentation from both the MLM and the LCM, the methodological proposal includes evaluating the similarity of individuals assigned to each segment in two ways. First, in terms of the number of individuals in the segment (market shares) and second, in terms of the characteristics of the individuals in the group (i.e. whether the individuals grouped in one segment under MLM are the same individuals grouped in an equivalent segment under LCM or whether they share the same characteristics). The latter comparison is relevant because the market shares could be alike, yet the groups may not contain the same individuals.

The empirical analysis uses data on people's preferences for mussels' attributes affected by ocean acidification (OA) resulting from carbon emissions. Ocean acidification affects marine shelled molluscs by producing changes in their mortality rates, calcification and growth rates (Gazeau et al., 2013). This also affects market attributes, such as shell appearance, meat colour and nutritional composition. These changes may affect the industry negatively if consumers react to these changes by reducing demand. Hence, properly identifying market segments may help to increase the effectiveness of market adaptation strategies. Thus, this article also contributes to the limited literature on the impact of OA on market attributes (Gasbarro, Rizzi, & Frey, 2016).

2.2 Consumers' heterogeneity in discrete choice models

The MLM and LCM share the same decision problem; that is, an individual $n = 1, \ldots, N$ selecting among $j = 1, \ldots, J$ alternatives in choice situations $t = 1, \ldots, T$. The utility level obtained by individual n when they choose alternative *j* in the choice occasion t is given by $U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt}$, where β_n is the vector of parameters associated with each of the x_{njt} observed alternative attributes and ε_{njt}~ i.i.d. extreme value type I. Notice that subscript *n* means that the coefficient varies across individuals. In each choice situation, individual n chooses the alternative that provides the highest utility (McFadden, 1974; Train, 2009). The MLM and LCM differ in the way they treat β_n .

2.2.1 Mixed logit model

This model considers that β_n follows a continuous distribution. The most common distribution is the multivariate normal, $\beta_n \sim MVN(b, \mathrm{W})$, where b is the vector of means and W is the covariance matrix that must be estimated. If $y_{njt} = 1$ denotes when individual n chooses j in choice situation t, then the unconditional probability of the individual's sequence of choices is given by Equation (1), where θ represents the vector of parameters at the population level. This equation does not have a closed-form solution. The parameters can be estimated by maximising its simulated log-likelihood function (Train, 2009).

$$\mathrm{P}_n(\theta) = \int \left\{ \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{\exp(\beta_n' \mathrm{x}_{njt})}{\sum_{\mathrm{i}}^{J} \exp(\beta_n' \mathrm{x}_{nit})} \right)^{y_{njt}} \right\} f(\beta_n) d\beta_n \qquad (1)$$

To consider the sociodemographic variables and more sophisticated correlation patterns, $\beta_n \sim f(\beta|\mathrm{b}, \mathrm{W})$ can be re-written as $\beta_n = b + \delta z_n + L\eta_n$, where δ is the matrix of parameters associated with the z_n individual-specific covariates (such as age, household size, etc.), $\eta_n \sim N(0, I)$ and L is the lower-triangular Cholesky factor of W such that $LL' = Var(\beta_n) = W$.

2.2.2 Latent class model

The LCM assumes preferences distributed semi-parametrically with a discrete number of potential groups (Boxall & Adamowicz, 2002; Kamakura & Russell, 1989; Shen, 2009). Discrete observed measures characterise these groups, such as attitudinal scales, perceptions or socio-economic characteristics (Boxall & Adamowicz, 2002; Sarrias & Daziano, 2018). The LCM can be considered less flexible than the MLM because the parameters are fixed within each segment (Sarrias & Daziano, 2018; Shen, 2009). However, its advantage is that it does not require defining a distribution of the parameters across individuals (Greene & Hensher, 2003). The researcher must select the optimal number of segments using statistical criteria such as the Akaike information criterion (AIC), Bayesian information criterion (BIC) or consistent AIC (CAIC) (Andrews & Currim, 2003; Boxall & Adamowicz, 2002).

The parameters within each class are fixed, but they differ across classes. Therefore, $\beta_n = \beta_s$ with probability w_{ns}, for $s = 1, \ldots, S$, where S is the total of classes, $\sum_s w_{ns} = 1$ and $w_{ns} > 0$. Given S, the semi-parametric multinomial logit formulation for w_{ns} (Greene & Hensher, 2003; Sarrias & Daziano, 2018; Shen, 2009) is:

$$w_{ns}(\gamma) = \frac{\exp(h_n \gamma_s)}{\sum_{s=1}^{S} \exp(h_n \gamma_s)}, \gamma_1 = 0, \tag{2}$$

where h_n represents a vector of sociodemographic variables determining assignment to segments and γ_s represents the parameters describing the stochastic assignment to each segment s. The unconditional probability of the individual's sequence of choices is given in Equation (3) and the estimation can be performed by using the standard maximum likelihood estimator; however, if the number of segments chosen is large, the iterative expectation–maximisation algorithm (EM) is more suitable (Sarrias & Daziano, 2018).

$$P_n(\theta) = \sum_{s=1}^{S} w_{ns} \left[\prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{\exp(\beta_s' x_{njt})}{\sum_i^J \exp(\beta_s' x_{nit})} \right)^{y_{njt}} \right], \tag{3}$$

where θ is the vector of parameters γ and β at the population level.

2.2.3 Individual-specific posterior distributions

To obtain the conditional estimates for each individual in the sample, also known as ISPs, Train (2009) suggests using Bayes' theorem:

$$f(\beta_n | y_n, x_n, \theta) = \frac{P(y_n | x_n, \beta) f(\beta | \theta)}{P(y_n | x_n, \theta)}, \tag{4}$$

where $f(\beta_n | y_n, x_n, \theta)$ is the conditional distribution of the individual parameters β_n, while $f(\beta | \theta)$ is the unconditional distribution. From Equation (4), the conditional mean of β_n is:

$$\bar{\beta}_n = \int \beta \frac{\mathrm{P}(\mathrm{y}_n|\mathrm{x}_n,\beta) f(\beta|\theta)}{\mathrm{P}(\mathrm{y}_n|\mathrm{x}_n,\theta)}\, d\beta. \tag{5}$$

Equation (5) can be approximated using simulation techniques for the MLM (Revelt & Train, 2000):

$$\widehat{\bar{\beta}_n} = \hat{E}(\beta_n|y_n,x_n) = \frac{\frac{1}{R}\sum_{r=1}^{R}\beta_n^{[r]}\prod_{t=1}^{T}\prod_{j=1}^{J}\left(\frac{\exp\left(\beta_n^{[r]}\mathrm{x}_{njt}\right)}{\sum_{\mathrm{j}}^{J}\exp\left(\beta_n^{[r]}\mathrm{x}_{njt}\right)}\right)^{y_{njt}}}{\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T}\prod_{j=1}^{J}\left(\frac{\exp\left(\beta_n^{[r]}\mathrm{x}_{njt}\right)}{\sum_{j}^{J}\exp\left(\beta_n^{[r]}\mathrm{x}_{njt}\right)}\right)^{y_{njt}}}, \tag{6}$$

where $\beta_n^{[r]}$ is the r-th draw for individual n from the posterior population distribution of β.

For the LCM, Equation (5) is approximated using the posterior class membership probability (Kamakura & Russell, 1989; Sarrias & Daziano, 2017):

$$\widehat{\bar{\beta}_n} = \hat{E}(\beta_n|y_n,x_n) = \frac{\sum_{s=1}^{S}\hat{\beta}_s\,\widehat{w}_{ns}\prod_{t=1}^{T}\prod_{j=1}^{J}\left(\frac{\exp\left(\hat{\beta}_s'\mathrm{x}_{njt}\right)}{\sum_{i}^{J}\exp\left(\hat{\beta}_s'\mathrm{x}_{nit}\right)}\right)^{y_{njt}}}{\sum_{s=1}^{S}\widehat{w}_{ns}\prod_{t=1}^{T}\prod_{j=1}^{J}\left(\frac{\exp\left(\hat{\beta}_s'\mathrm{x}_{njt}\right)}{\sum_{i}^{J}\exp\left(\hat{\beta}_s'\mathrm{x}_{nit}\right)}\right)^{y_{njt}}} \tag{7}$$

2.2.4 Segmentation approach

The segmentation for both MLM and LCM uses the expected value of β's conditional on y_n and vector x_n (ISPs) in a hierarchical cluster analysis (Everitt et al., 2011; Hennig, Meila, Murtagh, & Rocci, 2015; Morey, Thacher, & Breffle, 2006; Zimek & Vreeken, 2015), allowing us to consider both the signs and intensity of the coefficients in the segmentation process. Clustering algorithms measure the degree of similarity or dissimilarity between observations (Aldrich, Grimsrud, Thacher, & Kotchen, 2007), and in particular, hierarchical cluster analysis is an appropriate technique for continuous data such as ISPs (Everitt et al., 2011).

There are two types of hierarchical clustering: (i) agglomerative or bottom-up methods, which proceed by a series of successive fusions of the *n* individuals into groups and (ii) divisive or top-down methods, which assign all the observations to a single cluster and then divide this single cluster into two diverse groups. Computationally, it is more difficult to find optimal splits (divisive method) than to find optimal merges (agglomerative clustering) (Hennig et al., 2015; Roux, 2018). Thus, this study uses agglomerative clustering, which is also the most widely used of the hierarchical methods (Everitt et al., 2011; Hennig et al., 2015). Within this method, a classification tree that shows the variability of data (dendrogram) represents the visual result of these algorithms.

To calculate proximity coefficients, the Euclidean distance[6] between the mean of the ISPs is used. The process starts with a dissimilarity matrix of $n \, x \, n$ order containing the distance measures between each pair of individuals in the sample. From this matrix, the pair of observations with a lower distance is merged, generating a cluster. Thus, by applying the complete method (or furthest neighbour), *n* observations are iteratively merged into a single cluster through a process of *n-1* steps. At each step, two clusters are merged (forming a new

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[6] The Euclidean distance is the most commonly used dissimilarity measure. It is calculated as $d_{il} = [\sum_{k=1}^{A}(x_{ik} - x_{lk})^2]^{1/2}$, where x_{ik} and x_{lk} are, respectively, the k^{th} attribute value of the *A*-dimensional observations for individuals i and l and where d_{il} can be interpreted as physical distances between two *A*-dimensional points $x_i' = (x_{i1}, \ldots x_{iA})$ and $x_l' = (x_{j1}, \ldots x_{jA})$ in the Euclidean space (Everitt et al., 2011).

dissimilarity matrix) and this process is repeated until all the objects belong to the same and only one cluster. The selection of which two clusters to merge at each step is based on the maximum distance between a pair of individuals in different clusters ($D(X,Y) = \max_{x \in X, y \in Y} d(x,y)$, where $d(x,y)$ is the distance between elements $x \in X$ and $y \in Y$, where X and Y are two clusters). For this purpose, this study uses the *hclust* function of the *stat* package of R (Team, 2013).

The dendrogram is then used to estimate the number of clusters. To partition the dendrogram, the decrease in the dissimilarity index (*height*) is used. That is, starting from the top of the dendrogram (the highest level of height) and examining the delta of the heights suggests a division into *n* clusters when the decrease of the level of dissimilarity passing from an *n-1* cluster to *n* clusters is greater than passing from *n* to *n+1* clusters (Husson, Lê, & Pagès, 2017). Other authors have used similar approaches (Alvarez et al., 2018; Alvarez, Paas, Descheemaeker, Tittonell, & Groot, 2014) to capture farm diversity in Zambia's Eastern Province; nevertheless, some degree of researcher decision is needed in the final choice of the partition (Alvarez et al., 2014; Everitt et al., 2011; Hennig et al., 2015).

Finally, to compare the segmentation predictions from the MLM and LCM, each segment is characterised according to sociodemographic (age, educational level, etc.) and attitudinal (level of trust in institutions, risk aversion, etc.) characteristics. Two parametric tests, t-mean and Pearson chi-squared tests, help to compare them; thus, the comparison will indicate whether individuals assigned to each segment are, on average, similar.

2.3 Data and field methods

The analysis involves consumer preferences to changes in attributes of some mussels affected by OA to determine market segmentation. The data come from a discrete choice survey applied to a random sample of 1,257 individuals living in the two largest cities of Chile (Santiago and Concepción). Every individual faced six choice sets with three alternatives each, two of them involving purchase options of mussels with different attribute levels and a non-purchase alternative, producing 22,626 viable observations. The Ngene software generated a D-efficient optimal design of the experiment.[7]

The survey questionnaire had four sections. The first section provided general information about the characteristics of the mussels. The second explained the relationship between mussel production and the environmental consequences of OA, including some questions to evaluate respondents' trust in public institutions related to food safety and other attitudinal and personal characteristics. In the third section, the choice experiment was applied. The survey ended by collecting respondents' sociodemographic characteristics (i.e. age, educational attainment, household size, etc.).

[7] An extensive explanation of the experimental design is in Ponce Oliva et al. (2019).

To simplify the segment definition, the study focused on four attributes of the eight included in the survey: shell appearance, meat colour, nutritional composition and price. The first three attributes have two levels, while price has six levels. Table 2.1 summarises the attributes and their respective levels. The first three attributes directly related to the mussels are considered the most relevant from the perspective of OA. Ocean acidification affects shell appearance by making them discoloured, the nutritional composition will be lower than without acidification and meat colour will become whiter (San Martin et al., 2019).

Table 2.1 Attributes and levels of mussels

Attributes	**Levels**
Shell appearance	No acidification (shinny)/Acidified (discoloured)
Nutritional composition	High / Low
Meat colour	Yellow/White
Price (250 grams)	Six prices per product assortment ranging from US$1.20 – US$5.00

Estimations and posterior analyses were carried out using R software, specifically the *gmnl* package (Sarrias & Daziano, 2017) and Stata software.

2.4 Results

The experiment was applied to individuals aged 18 years and above, with an average of 45 years and an average household size of four people. Nearly 38% of the individuals had post-secondary education. To understand people's attitudes toward health risks (in this case, the study took advantage of the previous event of eating seafood contaminated from red tide), they answered a question about their seafood purchasing decisions under an adverse event such as red tide. About 23% of the individuals claimed they avoided all types of seafood products (these individuals were categorised with the variable *risk aversion*), while 7% avoided shellfish but continued to consume fish (named *only fish consumption*). The remaining individuals claimed they continued to consume sea products but from extraction areas unaffected by red tide. Related to their knowledge about the origin of the product they buy, the variable *origin of the product* indicates that only 15% of the sample knew the region from where the product was extracted. To evaluate individuals' trust in public institutions related to food safety, the question of whether they would consume seafood if an institution certified the product quality showed 67% indicating that they would continue to consume sea products if the institution certified them. Finally, the respondents were asked if they were members of environmental groups, with 2% meeting this criterion. More details about the sample characteristics are provided in Appendix A.1, Table A.1.

In the MLM estimation, a normal distribution for the random coefficients was selected.[8] For the LCM, the definitive number of classes emerged by comparing the AIC and BIC values of several models. The final decision led to

[8] The log-normal distribution was also evaluated, but the model with a normal distribution presented a better fit (lowest BIC).

four classes[9] based on the lowest BIC (Nylund, Asparouhov, & Muthen, 2007)[10]. In general, for both models, the estimated coefficients had the signs expected to reflect that individuals preferred mussels without signs of acidification. The statistical significance of the standard deviation for the random parameters showed strong heterogeneity. As this study focuses on market segmentation based on the ISPs, the econometric results from both the MLM and LCM estimations are in Table A.2.1 in Appendix A.2.

2.4.1 Individual-specific posterior distributions from the mixed logit model and the latent class model

The first part of this subsection describes the ISPs retrieved from both the MLM and the LCM. Understanding the information provided by this data is essential for the market segmentation performed later.

The analysis of the ISPs from the MLM shows that 78.6% of individuals had a positive preference (sign) for shell appearance, meaning that the respondents preferred mussels with no signs of acidification. For the other attributes, 59.1% of individuals preferred yellow-coloured meat, while 68.2% showed a preference for high nutritional levels. In the case of LCM, 100% of the sample had a positive sign for the three attributes, but this varied in intensity (Figure 2.1).

[9] It is relevant to clarify that the analysis does not consider the classes obtained from the LCM estimation as the market segments. Instead, the ISPs from the LCM estimation were used to perform a cluster analysis to define the final market segments of this model.
[10] See Table A.2.2 in Appendix A.2.

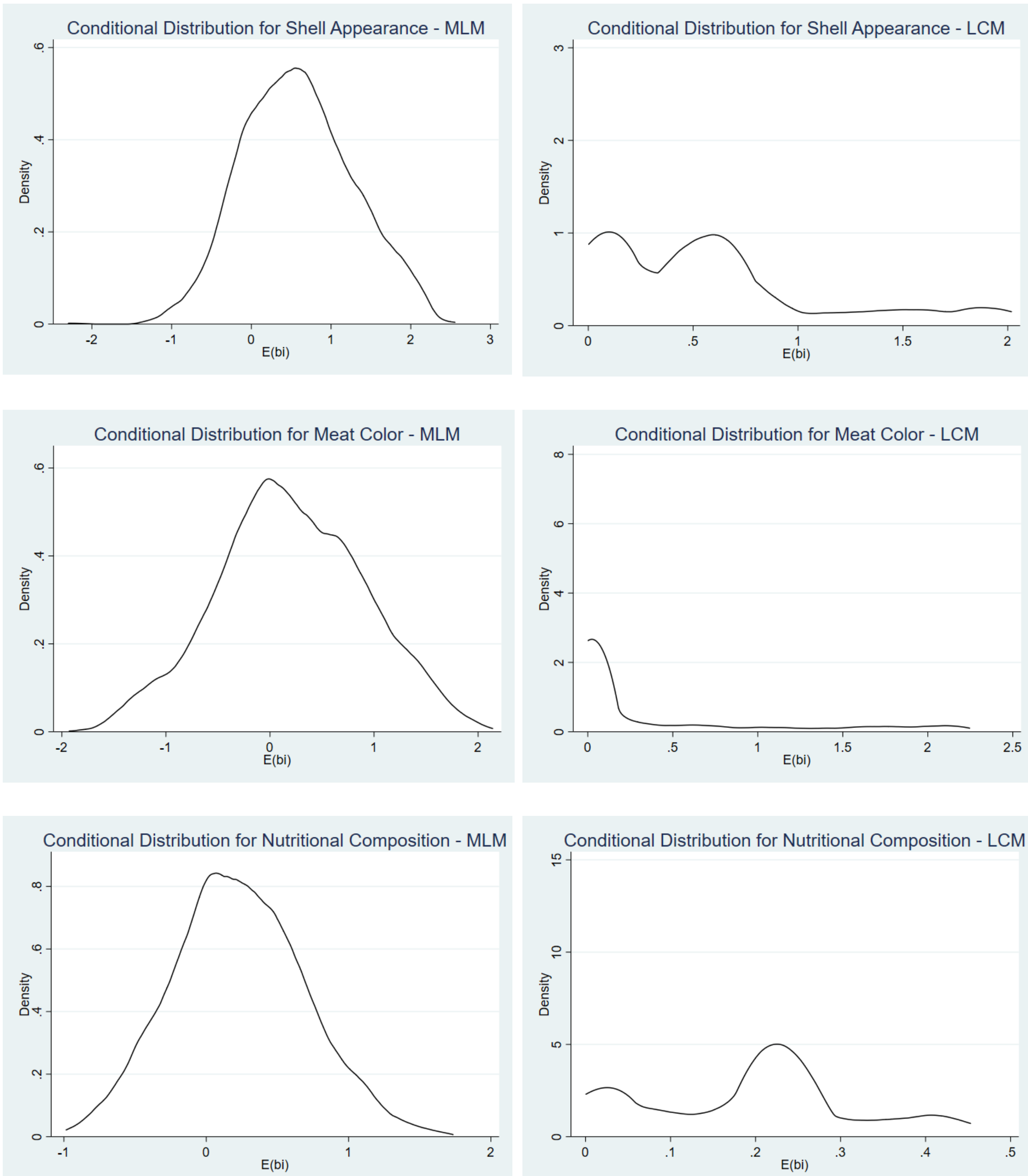

Figure 2.1 Conditional distributions for attributes in the MLM and LCM

Figure 2.1 shows a large heterogeneity in consumer preferences for the analysed attributes, suggesting that actors in the mussel supply chain could address these preferences through market segmentation.

2.4.2 Segmentation based on signs and intensity of individual-specific posterior distributions

A hierarchical cluster analysis using the ISP values from both MLM and LCM was used to identify the market segments.[11] The examination of the dendrograms' height and structure suggested a partition at an altitude of 2.65 for the MLM and 1.26 for the LCM. This examination led to six clusters for the MLM (MLC1 to MLC6) and five clusters for the LCM (LCC1 to LCC5). Details are provided in Appendix A.3, Figures A.3.1 and A.3.2. These clusters represented the predicted market segments.[12]

Table 2.2 summarises the number (percentage) of individuals in each market segment obtained from the cluster analysis. The first result is that both MLM and LCM provide different numbers of segments with different numbers of individuals. In the LCM, there is a clear predominant segment (segment 1 with

[11] Note that even though the LCM offers four classes, these classes were not used as the segments for the LCM. Instead, the same strategy to uncover the market segments for both models was pursued: using ISPs in cluster analysis. The main reason behind this decision was the recognition that class membership is probabilistic so, by using ISPs from LCM, this randomness is considered.

[12] From the LCM, the number of segments differs from the number of classes, which indicates the relevance of considering that membership into each class is probabilistic. This indication is one of the main differences between the approach followed in this study and the one used by Asioli et al. (2018).

63% of the individuals), while in the MLM the segments are more evenly distributed.

Table 2.2 Number (percentage) of individuals in each segment

Nº segments	**MLM**	**LCM**
1	263 (20.9%)	796 (63.3%)
2	325 (25.9%)	162 (12.9%)
3	163 (13.0%)	191 (15.2%)
4	160 (12.7%)	59 (4.7%)
5	235 (18.7%)	49 (3.9%)
6	110 (8.8%)	-

Note: In the MLM, one individual was excluded from the sample for being an outlier.

Adequately profiling these segments is essential to posterior strategic decision-making (Dolnicar, Grün, & Leisch, 2018). In Appendix A.3, Tables A.3.1 and A.3.2 show the mean values for the ISPs associated with each attribute. Despite the general sample showing a positive preference for all three attributes, the intensity of these preferences differed at the individual level. Moreover, in the MLM, groups of individuals disliked one or more attributes resulting from having a normal distribution. Thus, with the analysis of information provided by each segment, Table 2.3 presents the intensity of the preference as positive high (+high), positive low (+low) or negative (−). A positive preference is high or low depending on whether the ISP value is above or below the mean value for the entire sample, respectively.

From Table 2.3, it appears that only MLC5 and LCC4 represented a similar preference structure; however, for the rest of the segments, there was no clear match. This shows that segments obtained from both models, in general, do not represent the same preference structure.

Table 2.3 Preference structure for each cluster from MLM and LCM

	MLC 1	MLC 2	MLC 3	MLC 4	MLC 5	MLC 6	LCC 1	LCC 2	LCC 3	LCC 4	LCC 5
$\bar{\beta}_{appear.}$	+	+		+	+	+	+	+	+	+	+
	low	high	-	low	low	low	low	high	high	low	high
$\bar{\beta}_{color}$	+	+		-	+	+	+	+	+	+	+
	high	low	-		high	low	low	high	low	high	high
$\bar{\beta}_{nutri}$		+		+	+	+	+	+	+	+	+
	-	high	-	high	high	high	low	high	low	high	high*

*In this case, this segment's mean ISP is marginally above the sample average (0.198 vs 0.191). Thus, it could not be considered higher than the sample average but equal to it.

Table 2.4 shows the number of individuals assigned to each segment for both models. A perfect match occurs when an individual is assigned to the same type of group in each model (MLM and LCM). For instance, among the segments representing a similar preference structure, LCC4 and MLC5, only 19 individuals coincided. This result shows that each model predicts different segments in terms of preferences for the attributes.

Table 2.4 Consistency among individuals assigned to each cluster in MLM and LCM

	LCC1	LCC2	LCC3	LCC4	LCC5	*Total*
MLC1	195	37	1	22	8	*263*
MLC2	94	10	187	10	24	*325*
MLC3	156	0	0	4	3	*163*
MLC4	158	0	2	0	0	*160*
MLC5	88	114	1	**19**	13	*235*
MLC6	104	1	0	4	1	*110*
Total	*795*	*162*	*191*	*59*	*49*	*1,256*

Even though the segments do not share the same people, it is possible that they could be statistically similar in terms of the people's characteristics. To evaluate whether these segments were statistically similar, a comparison of the sociodemographic and attitudinal characteristics of individuals assigned to each of these clusters was conducted.[13]

Considering only the paired segments (LCC4 and MLC5) representing similar preference structures, Table 2.5 provides the statistical comparison tests for individuals' characteristics.

[13] In Appendix A.3, Table A.3.3 provides a general description of each segment in terms of sociodemographic and attitudinal characteristics.

Table 2.5 Statistical comparison between segments with similar preference structure

	LCC4 vs MLC5	
T test	**t**	**p-value**
age	-1.563	0.119
household size	-0.710	0.478
Chi2 test	**chi2**	**p-value**
post-secondary education	1.547	0.214
risk aversion	0.044	0.834
only fish consumption	0.335	0.563
origin of the product	0.093	0.760
trust	1.629	0.202
environmental group	*	(0.081)

* In cases where the condition of expected frequency is not satisfied, Fisher's exact values are given in parentheses.

As shown in Table 2.5, individuals assigned to the segment LCC4 were not statistically different from those assigned to an equivalent segment (in terms of preference structure) under the MLM, in this case, MLC5. These results imply that the coincidence of these two segments represents a similar type of population. Nevertheless, for all other cases, the MLM and LCM did not provide similar segments, neither in terms of preference structure nor in terms of individuals assigned to them. In Appendix A.3, Table A.3.4 shows all segment comparisons between LCM and MLM. For segments LCC1 and LCC2, there was no similar segment in the MLM, either in terms of preference or individuals' characteristics.

Segment LCC3 was statistically similar, in terms of individual characteristics, to the second segment MLC2. These two segments shared a group of individuals who were highly sensitive to shell appearance with no signs of acidification. In addition, even though both segments had a positive preference for nutritional level, they differed in preference for taste intensity. In the case of the smaller segments from LCM (LCC4 and LCC5), they were statistically similar to more than one segment from MLM in terms of the individual characteristics; however, in terms of preferences, they were very different.

The individual willingness to pay (WTP) for each attribute j was also estimated by using $WTP_{nj} = -\frac{\beta_j}{\beta_{cost}}$, where β_j is the coefficient of the j-th attributes and β_{cost} is the coefficient of the cost in the case of the MLM. For the LCM, the WTP for each attribute j was estimated by $WTP_{nj} = -\frac{\sum_{s=1}^{S}\left(\hat{\beta}_j^s \cdot \hat{\pi}_n^s\right)}{\sum_{s=1}^{S}\left(\hat{\beta}_{cost}^s \cdot \hat{\pi}_n^s\right)}$, where $\hat{\beta}_j^s$ is the coefficient for attribute j in each class (s) and $\hat{\pi}_n^s$ is the probability of belonging to each of the s classes. The average WTPs for each segment are provided in Appendix A.3, Table A.3.5. On average, the WTPs were higher in the LCM for the attributes of shell appearance and nutritional level, but slightly lower for meat colour. From both models, for a product of 250 grams, the attribute with higher WTP was shell appearance. In the MLM, the second segment was WTP up to US$8.86. In contrast, in the third segment of the LCM, all individuals belonged to a class where the price was not statistically significant. In this case, the calculation of the WTP lost economic meaning (the value was US$234.60 for shell appearance, explained by the highly inelastic preference for this attribute, where the denominator in the WTP formula was a tiny number). In the case of the nutritional level attribute, even though on average the WTP was higher for the LCM than the MLM, the sixth segment from the MLM had the highest WTP (US$5.85), while the highest WTP in the LCM came from the third segment (US$2.40). For the attribute of meat colour, the largest WTP was from segment 5 from the MLM (US$6.67), while the larger value in the LCM was in segment 2 (US$2.84).

2.5 Discussion and conclusions

The findings suggest important heterogeneity across mussel consumers, which is relevant when mussel industry actors develop strategies to address the effects of OA. Moreover, by using a two-step approach to uncover market segments based on the ISPs, the results show that segment predictions from both models (MLM and LCM) are different in terms of preference structure and the characteristics of individuals assigned to each segment.

Three segments from MLM and all segments from LCM coincide when individuals have positive tastes for all three attributes. That is, individuals prefer shell appearance, meat colour and nutritional composition without any sign of OA. These results coincide with previous research that identifies the importance of these attributes over consumption behaviour (Azpeitia, Ferrer, Revilla, Pagaldai, & Mendiola, 2016; Batzios, Angelidis, Moutopoulos, Anastasiadou, & Chrisopolitou, 2003). However, the MLM predicts other three segments in which some or all the attributes are distasteful for the individuals.[14] These findings allow us to conclude, using a comparison of the type of segments (preference structure), number of people assigned to each segment and the sociodemographics of individuals in each group, that the segmentation prediction between these two models is different. Thus, consumer groups differ according to the main methodology used, leading to a series of lessons regarding discrepancies among the methods to capture heterogeneity, gaps and suggestions about best practices that could be implemented in future research assessing market segmentation.

Previous studies compared these approaches through statistical measures of fit and behavioural outputs, concluding that it is not possible to prefer unambiguously one over the other (Greene & Hensher, 2003; Shen, 2009). The findings of our study complement these studies. The results indicate that, in general, both approaches lead to different market segments when cluster analysis is used to perform segmentation based on the ISPs—a discrepancy that could be expected since the two models have different distributional assumptions. However, this result differs from Asioli et al. (2018), who conclude that the MLM combined with cluster analysis and the classes generated by the LCM tends to provide the same results in terms of segmentation.

[14] The MLM was also estimated by using a log-normal distribution (to force all parameters estimated to be positive as those from LCM) but the model showed a worse fit.

From this study, it can be concluded that the type of model chosen for segmentation is relevant since different models provide different predictions. Further, the MLM identifies more segments than the LCM. The general marketing literature offers two main approaches for segmentation: one based on customer needs and the other on identifiability and accessibility to the seller (Bonoma & Shapiro, 1984). These approaches use different techniques based either on descriptive or predictive statistical methods and also on a priori and post-hoc segmentation procedures (Wedel & Kamakura, 2000). The most common methods are cluster analysis, mixture regressions and scaling. However, to capture unobserved heterogeneity, continuous or discrete mixture models are most appropriate. According to Wedel et al. (1999), models with a continuous distribution, such as the MLM, seem to better predict segments, mainly because they are able to obtain ISPs. While our study shows that these models are indeed appropriate to identify market segments based on ISPs, an argument for not choosing them is that their results are sensitive to the choice of the mixing distribution. In this study, the estimation of the MLM was carried out considering both the multivariate normal and the log-normal mixing distribution, choosing the first because it has a better fit to the data. However, this model ended with a segment that might have the ‘wrong’ sign (such as MLC3). This type of segment may not exist in reality because it seems to indicate the LCM results; however, it may result from the normal distribution properties. Thus, a suggestion for researchers and practitioners is trying several mixing distributions in the MLM to evaluate the robustness of their results.

One of the main difficulties of using this strategy to uncover market segments as well as other data-driven (or post-hoc) segmentation, is to interpret the segments, since the defining characteristics of the segments are unknown for the researcher (Dolnicar et al., 2018). Thus, profiling the segments must be conducted by the researcher. Because this step is crucial for marketing or decision-making purposes, more attention should be spent on this process, with continual checking for accuracy. In this study, the segments were profiled considering the tastes towards all three attributes by describing whether the consumer shows a high or low positive preference for the attributes or dislikes them. This strategy, although it considers the intensity of the preferences towards the attributes, adds difficulty in making the comparison among different models, especially when the number of attributes increases. An alternative approach to uncover the segments to obtain a simpler profile for the segments is suggested by Scarpa and Del Giudice (2004). In this strategy, the segments are pre-defined as all possible combinations in the like–dislike dimension based on the signs of the ISPs. The main advantage of this strategy is that it can help distinguishing each segment's preference patterns. However, its main disadvantage is that the number of potential segments increases substantially with the number of attributes. This augmentation could lead to a large number of small segments.

Appendix A.4 presents the segments uncovered for the MLM following this strategy.[15]

In terms of the applicability of these results, the findings suggest that there is an important heterogeneity between consumers of mussels, which is relevant in a strategy to address the OA effects on mussel characteristics. Most consumers (predicted by both approaches) prefer mussels without any sign of acidification and they are willing to pay for this attribute. Specifically, shell appearance (without any signs of acidification) is the most appreciated attribute. However, there are groups of consumers with different degrees of preferences towards the combination of the three attributes.

Limitations of this study include the inability to generalise the results, since it is based on one study case. However, the findings are in line with most studies comparing MLM and LCM and contribute to the literature by showing that the two models provide different results in terms of market segmentation. Future research could apply this segmentation strategy to different goods or industries to provide additional evidence on which model should be used. Second, as the basis for segmentation, this study relied only on the mean of the ISP estimates. Future extensions might attempt to define a more general method involving other moments of the ISPs to define segments more accurately. Third, for the segmentation, one particular cluster technique was used; hence, future studies

[15] Unfortunately, it was not possible to compare MLM and LCM using this strategy because all ISPs from the LCM estimation were positive for all three attributes.

extending this research could include other strategies for segmentation, such as the one presented in Appendix A.4.

Despite these limitations, this study provides a glimpse of how market segmentation can be defined by using ISPs from both the MLM and LCM. Further, it demonstrates that each approach has strengths, inconsistencies and biases that can overcome using best modelling practices. In the absence of a definite evaluation of which approach is better to identify market segments, the best practice is to estimate both models and analyse their insights simultaneously. Considering that both models provide different predictions, MLM and LCM are not interchangeable. Thus, at the end, no econometric approach substitutes a researcher’s judicious analysis to make sense of the results. A proper evaluation of the predicted market segments requires a deep understanding of the market.

Appendix A

Appendix A.1. Sample characteristics

Table A.1 Characterisation of the sample

	Mean	Std. Dev.	Min	Max
Age (years)	45.25	17.42	18	92
Household size (Nº)	3.79	1.76	1	14
Post-secondary education (%)	0.38	0.49	0	1
Risk aversion (%)	0.23	0.42	0	1
Only fish consumption (%)	0.07	0.26	0	1
Origin of the product (%)	0.15	0.35	0	1
Trust (%)	0.67	0.47	0	1
Environmental group (%)	0.02	0.14	0	1

Appendix A.2. Model estimations

Table A.2.1 Mixed logit and latent class model estimations

	MLM		**LC1**		**LC2**		**LC3**		**LC4**	
	mean	std. error	mean	std. error	mean	std. error	mean	std. error	mean	std. error
shell appea.	0.234	0.144	0.018	0.067	**0.820**	0.205	**0.565**	0.121	**2.045**	0.255
meat colour	0.038	0.150	-0.097	0.060	**2.297**	0.302	0.032	0.113	-0.130	0.252
nutri	0.255	0.143	**0.236**	0.044	**0.460**	0.145	0.079	0.104	-0.003	0.191
price	**-0.162**	0.021	**-0.063**	0.032	**-0.792**	0.123	**-0.202**	0.069	0.091	0.100
status quo	**-1.094**	0.072	**-2.578**	0.184	**-1.105**	0.345	**0.607**	0.219	**-1.612**	0.558
shell_ hhsize	**0.088**	0.020								
shell_ risk	**-0.498**	0.079								
shell_ onlyf	**-0.524**	0.120								
shell_ origin	**-0.411**	0.090								
colour_ risk	**0.503**	0.082								
colour_ origin	**0.342**	0.094								

colour_								
trust	**0.313**	0.071						
nutri_								
risk	**-0.236**	0.077						
nutri_								
origin	**-0.243**	0.091						
Standard deviation random parameters								
Shell	**0.931**	0.059						
meat								
colour	**0.974**	0.060						
nutritional	**0.757**	0.063						
Segmentation variables								
constant			**1.228**	0.559	1.218	0.668	**1.713**	0.578
age			-0.003	0.007	**-0.029**	0.009	-0.013	0.007
household size			-0.112	0.061	**-0.217**	0.090	**-0.247**	0.071
post-secondary education			0.141	0.242	0.005	0.305	-0.186	0.262
risk aversion			**1.175**	0.386	**1.719**	0.458	**0.914**	0.841
only fish consumption			**1.882**	0.839	**1.993**	0.924	**1.934**	0.841
origin of the product			**1.373**	0.473	**2.010**	0.517	**1.181**	0.489
trust			-0.106	0.260	0.213	0.330	**-0.664**	0.266
environmental group			0.564	1.100	1.745	1.102	1.016	1.087
LL	-6,904.5					-6,634.6		
AIC	13,873					13,363		
BIC	14,094					13,740		

* The statistically significant variables are presented in bold.
** For space, we only report sociodemographic and attitudinal variables statistically significant at 1%.

Table A.2.2. AIC and BIC to define the number of segments in the latent class model

	LL	N° parameters	AIC	BIC
2 segments	-6,844.65	19	13,727.3	13,879.8
3 segments	-6,734.23	33	13,534.5	13,799.4
4 segments	-6,634.59	47	13,363.2	**13,740.4**
5 segments	-6,571.07	60	13,262.1	13,743.8
6 segments	-6,527.12	74	13,202.2	13,796.2
7 segments	-6,492.84	88	13,161.7	13,868.1
8 segments	-6,470.26	102	12,940.5	13,963.3
9 segments	-6,437.85	116	13,107.7	14,038.8
10 segments	-6,430.01	130	13,120.0	14,163.5

In general, in both models, the estimated coefficients had the expected signs. In both cases, alternative specific constants were included, representing the status quo, to analyse whether preferences were in favour of the purchasing option. The status quo estimated coefficient was negative and statistically significant in the MLM and for three classes in the LCM, indicating that individuals had positive preferences in favour of buying mussel products. However, the third latent class had a positive and statistically significant coefficient, reflecting that those individuals preferred the non-purchase option. The mean estimates for shell appearance, meat colour and nutritional composition were positive and statistically significant, which may be expected, given that most individuals prefer mussels without signs of acidification. The price coefficient was also negative and statistically significant, as expected; however, for the LCM, this was not significant in the fourth class.

There were some differences in how the interaction with sociodemographic and attitudinal variables affected the models. In the MLM, it was found that household size, risk aversion, consumption of fish only and origin of the product affected individuals' preferences towards shell appearance, while only risk aversion, the origin of the product and trust in institutions affected preference for meat colour. In the case of nutritional composition, only risk aversion and origin of the product were relevant. To determine classes in the LCM, the variables were statistically significant, but not in the same way for each class, indicating that every segment has specific characteristics.

Appendix A.3. Segmentation from clusters

Figures A.3.1 and A.3.2 show dendrograms obtained under the MLM and LCM. The division partition, based on the dissimilarity index, is six clusters when the ISPs come from the MLM (Figure A.3.1) and five clusters for the LCM (Figure A.3.2).

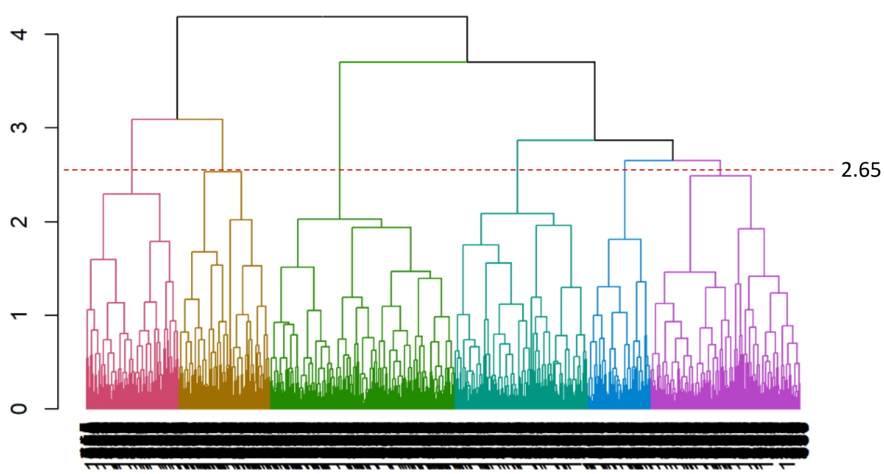

Figure A.3.1. Cluster dendrogram based on individual-specific posterior distribution from the mixed logit model

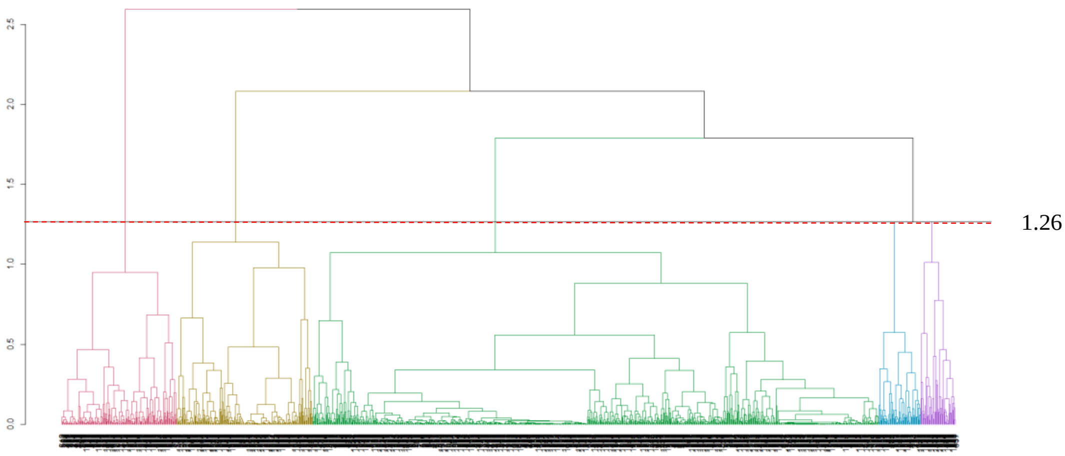

Figure A.3.2. Cluster dendrogram based on individual-specific posterior distribution from the latent class model

Table A.3.1 Mean individual-specific posterior distribution by segment from mixed logit model

	$\bar{\beta}_{appear.}$	$\bar{\beta}_{color}$	$\bar{\beta}_{nutri}$
MLC1	0.26	0.41	-0.03
MLC2	1.44	0.14	0.31
MLC3	-0.32	-0.23	-0.18
MLC4	0.51	-0.81	0.28
MLC5	0.56	1.08	0.31
MLC6	0.34	0.16	0.95
TOTAL	**0.58**	**0.20**	**0.23**

Table A.3.2 Mean individual-specific posterior distribution by segment from latent class model

	$\bar{\beta}_{appear.}$	$\bar{\beta}_{color}$	$\bar{\beta}_{nutri}$
LCC1	0.28	0.09	0.17
LCC2	0.76	1.87	0.40
LCC3	1.64	0.08	0.06
LCC4	0.56	1.14	0.30
LCC5	0.95	0.78	0.20
TOTAL	**0.59**	**0.39**	**0.19**

Table A.3.3 Sociodemographics and attitudinal characteristics by segment: Mean values

	age	household size	post-secondary education	risk aversion	only fish consumption	origin of the product	trust	environmental group
MLC1	44.67	3.62	0.36	0.38	0.08	0.22	0.66	0.02
MLC2	46.16	4.18	0.40	0.10	0.02	0.06	0.74	0.01
MLC3	47.20	3.26	0.37	0.34	0.12	0.20	0.51	0.03
MLC4	46.28	3.96	0.43	0.07	0.06	0.08	0.58	0.00
MLC5	44.08	3.61	0.35	0.30	0.11	0.20	0.77	0.06
MLC6	42.09	3.90	0.41	0.14	0.08	0.11	0.66	0.01
LCC1	46.92	3.68	0.38	0.24	0.09	0.15	0.63	0.02
LCC2	38.10	3.56	0.41	0.32	0.06	0.27	0.78	0.06
LCC3	46.74	4.38	0.37	0.10	0.02	0.05	0.72	0.01
LCC4	40.08	3.44	0.44	0.29	0.08	0.19	0.69	0.00
LCC5	42.24	4.41	0.69	0.12	0.04	0.04	0.67	0.04
Sample	**45.25**	**3.79**	**0.38**	**0.23**	**0.07**	**0.15**	**0.67**	**0.02**

Table A.3.4 Statistical tests to compare all segments

	Age t^a (p-value)	Hhsize t^a (p-value)	Post-Sec chi2[b] (p-value)	RiskAv chi2[b] (p-value)	OnlyFish chi2[b] (p-value)	Origin chi2[b] (p-value)	Trust chi2[b] (p-value)	Env.Group chi2[b] (p-value)
LCC1 vs MLC1	1.815	0.475	0.363	**19.914**	0.208	**6.722**	0.635	*
	(0.070)	(0.635)	(0.547)	**(0.000)**	(0.648)	**(0.010)**	(0.426)	(1.000)
LCC1 vs MLC2	0.665	**-4.337**	0.606	**29.944**	**17.563**	**14.858**	**10.539**	*
	(0.506)	**(0.000)**	(0.436)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.001)**	(0.373)
LCC1 vs MLC3	-0.189	**2.931**	0.058	**7.801**	1.353	2.997	**8.944**	*
	(0.850)	**(0.004)**	(0.809)	**(0.005)**	(0.245)	(0.083)	**(0.003)**	(0.188)
LCC1 vs MLC4	0.429	-1.857	1.234	**23.172**	1.543	**5.056**	2.006	*
	(0.668)	(0.064)	(0.267)	**(0.000)**	(0.214)	**(0.025)**	(0.157)	(0.235)
LCC1 vs MLC5	**2.186**	0.534	0.483	**3.862**	0.647	**4.214**	**16.005**	**14.615**
	(0.029)	(0.594)	(0.487)	**(0.049)**	(0.421)	**(0.040)**	**(0.000)**	**(0.000)**
LCC1 vs MLC6	**2.732**	-1.302	0.392	**5.781**	0.144	1.205	0.357	*
	(0.006)	(0.193)	(0.531)	**(0.016)**	(0.704)	(0.272)	(0.550)	(1.000)
LCC2 vs MLC1	**-3.836**	-0.392	1.067	1.531	0.692	1.666	**6.518**	**6.810**
	(0.000)	(0.696)	(0.302)	(0.216)	(0.406)	(0.197)	**(0.011)**	**(0.009)**
LCC2 vs MLC2	**-4.942**	**-3.517**	0.008	**38.919**	**5.183**	**40.050**	1.035	*****
	(0.000)	**(0.001)**	(0.927)	**(0.000)**	**(0.023)**	**(0.000)**	(0.309)	**(0.000)**
LCC2 vs MLC3	**-4.877**	1.761	0.529	0.187	3.605	2.149	**25.534**	1.780
	(0.000)	(0.079)	(0.467)	(0.666)	(0.058)	(0.143)	**(0.000)**	(0.182)

LCC2 vs	**-4.471**	**-2.039**	0.103	**32.544**	0.001	**20.022**	**15.137**	**10.193**
MLC4	**(0.000)**	**(0.042)**	(0.749)	**(0.000)**	(0.977)	**(0.000)**	**(0.000)**	**(0.001)**
LCC2 vs	**-3.375**	-0.303	1.202	0.160	2.782	2.443	0.006	0.008
MLC5	**(0.001)**	(0.762)	(0.273)	(0.690)	(0.095)	(0.118)	(0.938)	(0.929)
LCC2 vs	-1.912	-1.768	0.001	**12.029**	0.407	**10.583**	**4.347**	*****
MLC6	(0.057)	(0.078)	(0.978)	**(0.001)**	(0.524)	**(0.001)**	**(0.037)**	**(0.032)**
LCC3 vs	1.237	**4.385**	0.040	**45.092**	**9.816**	**25.620**	1.910	*
MLC1	(0.217)	**(0.000)**	(0.842)	**(0.000)**	**(0.002)**	**(0.000)**	(0.167)	(1.000)
LCC3 vs	0.364	1.076	0.677	0.023	*	0.672	0.101	*
MLC2	(0.716)	(0.282)	(0.411)	(0.879)	(0.751)	(0.412)	(0.750)	(0.629)
LCC3 vs	-0.250	**5.703**	0.001	**31.378**	**16.572**	**20.293**	**17.061**	*
MLC3	(0.803)	**(0.000)**	(0.975)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	(0.255)
LCC3 vs	0.250	**1.982**	1.249	1.052	**5.345**	1.726	**8.387**	*
MLC4	(0.803)	**(0.048)**	(0.264)	(0.305)	**(0.021)**	(0.189)	**(0.004)**	(0.502)
LCC3 vs	1.535	**4.181**	0.081	**25.967**	**14.967**	**22.447**	1.522	**7.028**
MLC5	(0.126)	**(0.000)**	(0.776)	**(0.000)**	**(0.000)**	**(0.000)**	(0.217)	**(0.008)**
LCC3 vs	**2.212**	**2.113**	0.537	0.948	*****	**4.130**	1.154	*
MLC6	**(0.028)**	**(0.035)**	(0.464)	(0.330)	**(0.010)**	**(0.042)**	(0.283)	(1.000)
LCC4 vs	-1.184	-0.807	1.429	1.767	*	0.265	0.241	*
MLC1	(0.066)	(0.420)	(0.232)	(0.184)	(1.000)	(0.606)	(0.623)	(1.000)
LCC4 vs	**-2.524**	**-2.766**	0.292	**16.962**	*****	*****	0.414	*
MLC2	**(0.012)**	**(0.006)**	(0.589)	**(0.000)**	**(0.024)**	**(0.004)**	(0.520)	(1.000)
LCC4 vs	**-2.780**	0.783	0.962	0.603	0.624	0.070	**6.059**	*
MLC3	**(0.006)**	(0.434)	(0.327)	(0.437)	(0.429)	(0.791)	**(0.014)**	(0.328)

LCC4 vs	**-2.504**	-1.886	0.043	**18.606**	*	**4.888**	2.599	**-**
MLC4	**(0.013)**	(0.061)	(0.835)	**(0.000)**	(0.555)	**(0.027)**	(0.107)	
LCC4 vs	-1.563	-0.710	1.547	0.044	0.335	0.093	1.629	*
MLC5	(0.119)	(0.478)	(0.214)	(0.834)	(0.563)	(0.760)	(0.202)	(0.081)
LCC4 vs	-0.732	-1.881	0.157	**5.763**	*	1.954	0.171	*
MLC6	(0.465)	(0.062)	(0.692)	**(0.016)**	(1.000)	(0.162)	(0.679)	(1.000)
LCC5 vs	-0.894	**3.053**	0.165	**12.236**	*	**8.336**	0.026	*
MLC1	(0.372)	**(0.003)**	(0.685)	**(0.000)**	(0.393)	**(0.004)**	(0.872)	(0.239)
LCC5 vs	-1.490	0.743	0.042	*	*	*	0.823	*
MLC2	(0.137)	(0.458)	(0.838)	(0.606)	(0.334)	(0.752)	(0.364)	(0.085)
LCC5 vs	-1.780	**4.382**	0.062	**8.901**	2.716	**7.141**	**4.103**	*
MLC3	(0.077)	**(0.000)**	(0.803)	**(0.003)**	(0.099)	**(0.008)**	**(0.043)**	(0.663)
LCC5 vs	-1.501	1.452	0.214	*	*	*	1.513	*
MLC4	(0.135)	(0.148)	(0.644)	(0.239)	(0.736)	(0.529)	(0.219)	(0.054)
LCC5 vs	-0.658	**2.898**	0.211	**6.624**	*	**7.466**	2.249	*
MLC5	(0.511)	**(0.004)**	(0.646)	**(0.010)**	(0.188)	**(0.006)**	(0.134)	(1.000)
LCC5 vs	0.052	1.776	0.064	0.057	*	*	0.015	*
MLC6	(0.959)	(0.078)	(0.800)	(0.811)	(0.505)	(0.229)	(0.903)	(0.225)

[a] Previously, it was tested whether the variances were equal to apply the test for equal variance (or for different variances in case they are different).
[b] If the condition of expected frequency is not satisfied, Fisher's exact value is reported in brackets.
Variables that statistically differ in both groups are highlighted in bold.

Table A.3.5 Individuals' willingness to pay for each attribute in both models (US dollars)

	Shell Appearance		Meat Colour		Nutritional composition	
	mean	**s.d.**	**mean**	**s.d.**	**mean**	**s.d.**
All sample MLM	**3.59**	**4.24**	**1.25**	**4.32**	**1.40**	**2.85**
MLC1	1.61	2.88	2.53	2.97	-0.16	1.83
MLC2	8.86	2.34	0.83	2.67	1.92	2.16
MLC3	-1.95	1.86	-1.42	2.67	-1.10	2.49
MLC4	3.12	2.34	-5.01	2.19	1.72	2.66
MLC5	3.48	2.22	6.67	2.51	1.89	2.31
MLC6	2.09	1.98	0.96	2.16	5.85	1.95
All sample LCM	**37.60**	**153.80**	**1.03**	**1.13**	**1.89**	**1.38**
LCC1	2.57	3.40	0.48	0.72	2.18	1.43
LCC2	1.18	0.28	2.84	0.06	0.61	0.04
LCC3	234.57	332.17	0.96	0.96	2.42	1.02
LCC4	1.26	0.23	2.56	0.19	0.69	0.14
LCC5	3.19	1.51	2.42	0.42	0.65	0.20

Appendix A.4 Segmentation strategy based on ISPs using the like/dislike dimension

Using the ISP from the estimated model, this strategy was used to assign each individual to one of the 2^k potential segments, where k is the number of random attributes (Scarpa & Del Giudice, 2004). In this mussel study, considering all possible combinations of preferences for the three random attributes, eight potential segments appeared. Table A.4.1 summarises the number (percentage) of individuals in each segment. The first column describes the preference profile. Since these segments are clearly defined, a comparison with other models is straightforward and based on each particular preference structure.[16]

Table A.4.1 Number (percentage) of individuals in each segment

Preference structure	Nº segment	MLM
$\bar{\bar{\beta}}_{appear.} > 0, \bar{\bar{\beta}}_{color} > 0, \bar{\bar{\beta}}_{nutri} > 0$	1	446 (35.5%)
$\bar{\bar{\beta}}_{appear.} > 0, \bar{\bar{\beta}}_{color} < 0, \bar{\bar{\beta}}_{nutri} > 0$	2	279 (22.2%)
$\bar{\bar{\beta}}_{appear.} > 0, \bar{\bar{\beta}}_{color} > 0, \bar{\bar{\beta}}_{nutri} < 0$	3	151 (12.0%)
$\bar{\bar{\beta}}_{appear.} < 0, \bar{\bar{\beta}}_{color} > 0, \bar{\bar{\beta}}_{nutri} > 0$	4	88 (7.0%)
$\bar{\bar{\beta}}_{appear.} > 0, \bar{\bar{\beta}}_{color} < 0, \bar{\bar{\beta}}_{nutri} < 0$	5	112 (8.9%)
$\bar{\bar{\beta}}_{appear.} < 0, \bar{\bar{\beta}}_{color} < 0, \bar{\bar{\beta}}_{nutri} > 0$	6	44 (3.5%)
$\bar{\bar{\beta}}_{appear.} < 0, \bar{\bar{\beta}}_{color} > 0, \bar{\bar{\beta}}_{nutri} < 0$	7	58 (4.6%)
$\bar{\bar{\beta}}_{appear.} < 0, \bar{\bar{\beta}}_{color} < 0, \bar{\bar{\beta}}_{nutri} < 0$	8	79 (6.3%)

[16] In this case, it was not possible to compare MLM with LCM following this strategy because all ISPs from LCM were positive. This means that following this strategy, in the LCM there was just one big segment with all individuals in it. However, for other marketing studies, this strategy can be useful, especially for identifying the most preferred combinations of attributes for a product.

For marketing or decision-making purposes, these segment profiles can be very useful. The study results revealed that a large group of individuals preferred mussels without any sign of acidification (36%). More than 40% of the individuals expressed a combination of positive preference for two of the attributes while one did not like it. Moreover, nearly 15% liked just one attribute while liking the other two, and 6% expressed a negative preference for all three attributes.

Characterising each segment according to the sociodemographic and attitudinal characteristics provided additional insights. Table A.4.2 shows that the first segment (MLM1) had one of the highest numbers of individuals trusting in institutions related to food safety, while the second segment (MLM2) was composed of individuals who were less risk-averse along with those having a large household size.

Table A.4.2 Mean sociodemographic and attitudinal characteristics by segment

	age	household size	post-secondary education	risk aversion	only fish consumption	origin of the product	trust	environmental group
MLM1	44.48	3.91	0.41	0.20	0.07	0.16	0.74	0.03
MLM2	45.43	4.09	0.44	0.06	0.06	0.08	0.66	0.00
MLM3	46.02	3.74	0.26	0.36	0.07	0.19	0.75	0.01
MLM4	42.48	3.36	0.48	0.44	0.05	0.16	0.68	0.07
MLM5	49.76	3.98	0.24	0.21	0.04	0.09	0.57	0.00
MLM6	43.68	3.34	0.43	0.18	0.23	0.11	0.50	0.00
MLM7	40.36	3.22	0.34	0.52	0.16	0.29	0.58	0.02
MLM8	48.68	3.03	0.34	0.29	0.11	0.20	0.43	0.03

Chapter 3:

Research Study 2. Monte Carlo Comparison of Market Segments from the Mixed Logit and Latent Class Models: The Role of Heterogeneity and Presence of Niche Segments

Abstract

This study assesses the accuracy of the mixed logit model (MLM) and the latent class model (LCM) to identify market segments in two scenarios: high and low levels of preference heterogeneity among consumers with the presence or absence of niche segments. During the last decades, the LCM has probably been the most popular a posteriori segmentation technique for capturing heterogeneity in taste consumers in the literature. This method has been used to identify both market segments and market share. In contrast, the MLM has rarely been used to identify market segments. Nevertheless, the literature is silent on the accuracy of the LCM in predicting market segments or under which circumstances this model is more appropriate. To answer these questions, we developed a Monte Carlo study to compare the LCM with the MLM. The individual-specific posterior distributions of the coefficients served to identify market segments for both models. The results show that the LCM is the best when preference heterogeneity is low and the number of market segments is correctly identified in the econometric estimation process. However, when there is a high heterogeneity level, the MLM outperforms the LCM. Moreover, in this scenario, the segmentation based on the individual-specific posterior distributions from an LCM is also better than that predicted by the original LCM. Thus, this study challenges the common practice for market segmentation and concludes that the selection between both models to uncover market segments is not trivial and is highly dependent on the level of preference heterogeneity among consumers.

Keywords: individual-specific posterior distribution; latent class model; mixed logit model; Monte Carlo study; niche segments; preference heterogeneity.

3.1 Introduction

Mixed logit models (MLMs) and latent class models (LCMs)[17] have been used extensively in the literature to capture consumer heterogeneity (Bujosa et al., 2010). Several studies have compared these models in terms of their goodness of fit, parameter significance and estimation outcomes, such as willingness to pay (WTP), elasticities and predicted probabilities (e.g. Andrews, Ainslie, & Currim, 2002; Greene & Hensher, 2003, 2013; Keane & Wasi, 2013; Otter, Tüchler, & Frühwirth-Schnatter, 2004; Shen, 2009).

However, there is scarce literature comparing segmentation prediction from these models and there is no clarity about which model is more suitable for recovering underlying market segments. The MLM considers each individual as a 'single segment' (perfect heterogeneity), meaning that each individual in the sample has their own taste coefficient for an attribute of a product. Since researchers cannot identify each of these coefficients, the population is characterised by a distribution function. In contrast, the LCM divides the sample into a fixed number of homogeneous groups of individuals or segments (Boxall & Adamowicz, 2002). All individuals belonging to that segment share the same coefficients, and heterogeneity is captured to the extent that there are various

[17] Also known as finite mixture logit model (Andrews, Ainslie, & Currim, 2002; Gupta & Chintagunta, 1994).

segments. The LCM also calculates the probability of belonging to each segment, interpreted as ‘market shares’. Choosing these two approaches is not straightforward because it is not known under which circumstances each model is more appropriate to capture consumer heterogeneity. To bridge this gap, this study compares the performance of the MLM and LCM in terms of their market segment predictions. We ran a Monte Carlo simulation study to assess the properties of each model, echoing previous calls for this type of study and research on relevant marketing issues (Kohli & Haenlein, 2021; Wedel & Kamakura, 2002)

Since Kamakura and Russell (1989), DeSarbo, Wedel, Vriens and Ramaswamy (1992) and Gupta and Chintagunta (1994), there seems to be a consensus that the LCM has some supremacy to uncover market segments. The main advantage of the LCM is that it uses the a posteriori segmentation approach, in which the estimation of the parameters is performed simultaneously, with the assignment of individuals to homogeneous classes or segments (Wedel & Kamakura, 2000).[18] The number of segments cannot be determined using the same estimation process. Therefore, researchers estimate the LCM for different segments and choose the final specification based on goodness of fit criteria (Hensher, Rose, & Greene, 2015). In our opinion, the identification of classes and membership probabilities has been loosely categorised as market segments.

[18] In contrast, a priori segmentation defines the number and type of segments in advance (generally based on sociodemographic characteristics).

In contrast, the MLM has the advantage of considering a more extensive degree of heterogeneity among individuals by allowing random parameters in the estimation process, providing more flexibility (Asioli et al., 2018; Train, 2009). However, the MLM has been limited to only a few studies on market segmentation. Some use an a priori approach to divide the sample into segments and later estimate the model for each group (Gunay & Gokasar, 2021; Hess & Polak, 2005). To uncover the segments using an a posteriori approach, unlike the LCM, the MLM requires a two-stage procedure that includes first estimating the MLM to recover the individual-specific posterior distributions (ISPs) and then using these ISPs as the basis for segmentation. Scarpa and Del Giudice (2004) use the signs of the mean of the ISPs to gather individuals with similar preference patterns by considering all possible combinations in the like/dislike dimension of the attributes.[19] Alternatively, these ISPs can be used as inputs in cluster analysis to determine the specific number of clusters (or segments) and individuals' assignment to them (Asioli et al., 2018; Crabbe et al., 2013; Richter & Pollitt, 2018).

It is important to highlight the value of the ISPs obtained from these two models and how their use has been generally underestimated in classical statistics to address market segmentation. For instance, Richter and Pollitt (2018)

[19] In the distribution of tastes, for a particular attribute, a positive value of the ISP indicates that the individual has positive taste for that attribute (like), while a negative value represents a dislike preference for that attribute. Thus, considering all attributes in a product, the preference patterns are all possible sign combinations of the ISPs.

point out the importance of ISPs in exploring heterogeneity and obtaining more detailed information about consumers' preferences. Further, Revelt and Train (2000) show that predictions based on the conditional individual distribution of preferences are more accurate than those based on population distribution. Similarly, Sarrias and Daziano (2018) extend this work to an LCM and conclude that ISPs allow better predictions. However, in the literature, the ISPs have been used mainly to compute WTP (Greene & Hensher, 2003, 2013; Shen, 2009), with scarce application to identify market segments. This omission is particularly problematic for LCMs, for which, to the best of our knowledge, there is no study exploiting this information for segmentation purposes.[20]

The aim of this study is to compare the accuracy of the LCM and MLM in uncovering market segments. While the use of ISPs is more common in an MLM context, this study extends this approach to an LCM context for segmentation. For this endeavour, a Monte Carlo study is performed under two types of heterogeneity levels. In the first situation, there is heterogeneity between segments, but homogeneity within each segment. This case is closer to a 'latent class world'. In the second situation, there is a greater degree of heterogeneity between and within segments, emulating a 'random parameter world'. Finally, this study analyses the effectiveness of these models in uncovering market segments with and without niche segments. A niche segment can be described as a group

[20] Recently, Z. Li et al. (2019) combined MLM and LCM. They estimated an LCM to divide the sample into homogeneous groups (segments) and afterwards estimated an MLM for each of these groups.

of consumers with extreme preferences whose market share is low, but large enough to be profitable for firms (Allenby & Ginter, 1995).

The study generates three results. First, to uncover market segments, the LCM is more accurate than the MLM only when there is homogeneity within classes; however, with greater heterogeneity, the MLM outperforms the LCM. This is an expected result. Nevertheless, it highlights that LCMs do not always predict the correct segments in the market, questioning the prevalence of LCM in estimating market segments. Second, when there is large heterogeneity among consumers, ISPs allow us to uncover market segments closest to the real ones, even when using LCM. This is a novel and significant result, considering that it is a common practice among marketers to rely on classes and probabilities predicted by the LCM as market segments (Magidson & Vermunt, 2004; Wedel & Kamakura, 2000). The results show that this approach has the worst prediction capability when there is substantial heterogeneity. Finally, the results did not provide evidence that any model was better at uncovering niche segments. Therefore, this is a challenge for future researchers to find a mechanism to identify niche segments.

This study contributes to the literature in three ways. First, it provides new evidence comparing the MLM with the LCM in terms of market segmentation prediction under a controlled experiment. Many studies have provided evidence in favour of either model using different data sets, as in Keane and Wasi (2013). However, in terms of segmentation, a controlled experiment allows us to determine which model provides better predictions and is not limited to specific data. Second, the study shows that the accuracy of segment prediction is sensitive to the degree of preference heterogeneity of consumers in the population. Under a large degree of preference heterogeneity, the MLM outperforms the LCM in predicting market segments. Third, the study provides evidence on the relevance of using ISPs to identify segments, even in the LCM. This issue has been widely neglected in the literature. Latent class studies rely on the classes obtained from estimation to identify market segments. However, this study shows that using the ISPs derived from the LCM provides more accurate segments than those offered by the classes themselves when there is a high level of preference heterogeneity among consumers. Thus, using the classes obtained from the LCM estimation should be carefully reconsidered when there is large heterogeneity.

3.2 Monte Carlo study

The Monte Carlo study assesses market segment predictions from the MLM and LCM. The work of Revelt and Train (2000) was considered for the MLM specification and that of Sarrias and Daziano (2018) for the LCM specification. Specifically, we adapted R scripts from Sarrias and Daziano (2018) and Sarrias (2019). In particular, the study compared the performance of both models in terms of their capacity to recover the actual market segments using the mean of the ISPs from each model.

Four experiments were designed to contrast both models. These experiments aimed to evaluate the performance of each model under two circumstances. First, the performance of each model was evaluated under two levels of heterogeneity. The data were classified as following a ‘latent class structure’ when there was heterogeneity between segments but homogeneity within them and a ‘mixed logit structure’ when there was heterogeneity between and within segments. Second, the accuracy of both models was assessed when there were large segments and when there were niches.

The common characteristics among all experiments were as follows: the simulation included 300 databases with 500 hypothetical consumers who faced 10 choice situations. Each choice situation included three alternatives and two attributes. For the MLM estimations, the simulations used 300 random draws.

Each hypothetical consumer n selected the alternative j in the choice situation t if this choice provided the highest utility, given by:

$$U_{njt} = \beta_{1n}X_{1njt} + \beta_{2n}X_{2njt} + \varepsilon_{njt} \tag{1}$$

where X_{1njt} and X_{2njt} represented observed alternative attributes. These were assumed to be dummy variables from a uniform distribution and ε_{njt} is i.i.d. extreme value type I. These two sets of variables were randomly generated for all hypothetical consumers in each choice situation and all three alternatives. $\beta's$ represents consumers’ preferences towards the attributes $X's$ where a positive sign means that the consumer likes the attribute and a negative sign denotes a dislike. $\beta_n \sim f(\beta|\theta)$ in the population, where θ are the parameters of this distribution. This function $f(.|.)$ can have different forms. When the mixing distribution is continuous, most applications consider a multivariate normal, $\beta_n \sim MVN(b, \mathrm{W})$, generating a typical MLM.[21] If the mixing distribution is discrete, the model corresponds to an LCM, where β_n is fixed within segment s but different between segments. In this case:

$$\beta_n = \beta_s \text{ with probability } w_{ns}, \text{ for } s = 1, \ldots, S \tag{2}$$

where S is the total number of segments and $\sum_s w_{ns} = 1$ and $w_{ns} > 0$.

The LCM is called the latent class logit model when w_{ns} is formulated as a semi-parametric multinomial logit:

$$w_{ns}(\gamma) = \frac{\exp(\gamma_s)}{\sum_{s=1}^{S} \exp(\gamma_s)}, \gamma_1 = 0 \tag{3}$$

with γ_s as a constant (Scarpa & Thiene, 2005).

The unconditional probabilities of the individual's sequence of choices for the MLM and LCM are presented in Equations (4) and (5), respectively.

$$\mathrm{P}_n(\theta) = \int \left\{ \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{\exp(\beta_n' \mathrm{x}_{njt})}{\sum_{\mathrm{i}}^{J} \exp(\beta_n' \mathrm{x}_{nit})} \right)^{y_{njt}} \right\} f(\beta_n) d\beta_n \tag{4}$$

$$P_n(\theta) = \sum_{s=1}^{S} w_{ns} \left[\prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{\exp(\beta_s' \mathrm{x}_{njt})}{\sum_{i}^{J} \exp(\beta_s' \mathrm{x}_{nit})} \right)^{y_{njt}} \right] \tag{5}$$

[21] Keane and Wasi (2013) summarised other mixed logit models, such as the mixed logit with a log-normal mixing, mixed-mixed logit, scale heterogeneity logit model, or the generalized multinomial latent class metric conjoint analysis logit model.

with $y_{njt} = 1$ if individual n chooses alternative j in choice situation t; and θ represents the vector of parameters at the population level.

Estimating the parameters for Equation (4) implies maximising a simulated log-likelihood function, while Equation (5) requires maximising a standard log-likelihood function.

3.2.1 Experiments

Table 3.1 summarises the four experiments. Columns 2 and 3 show the LCM experiments (low heterogeneity), while columns 4 and 5 show the random parameter experiments (high heterogeneity). In both cases, there was an experiment without a niche and another with a niche. Table 3.1 shows the segment size, type of distribution (discrete or normal), the true preference patterns for each segment and the parameters' average.

Table 3.1 General description of the experiments

	Experiment 1: LCM without niche	**Experiment 2: LCM with niche**	**Experiment 3: MLM without niche**	**Experiment 4: MLM with niche**
Segment size	S1 = 40.0% S2 = 60.0%	S1 = 15.0% S2 = 35.0% S3 = 50.0%	S1 = 26.4% S2 = 73.6%	S1 = 34.0% S2 = 15.2% S3 = 37.2% S4 = 13.6%
Distribution of true parameters	Discrete distribution	Discrete distribution	Normal distribution	Normal distribution
True preference patterns per segment	$S1: \begin{pmatrix}\beta_1 > 0;\\ \beta_2 > 0\end{pmatrix}$ $S2: \begin{pmatrix}\beta_1 < 0;\\ \beta_2 < 0\end{pmatrix}$	$S1: \begin{pmatrix}\beta_1 > 0;\\ \beta_2 > 0\end{pmatrix}$ $S2: \begin{pmatrix}\beta_1 < 0;\\ \beta_2 > 0\end{pmatrix}$ $S3: \begin{pmatrix}\beta_1 < 0;\\ \beta_2 < 0\end{pmatrix}$	$S1: \begin{pmatrix}\beta_1 > 0;\\ \beta_2 > 0\end{pmatrix}$ $S2: \begin{pmatrix}\beta_1 > 0;\\ \beta_2 < 0\end{pmatrix}$	$S1: \begin{pmatrix}\beta_1 > 0;\\ \beta_2 > 0\end{pmatrix}$ $S2: \begin{pmatrix}\beta_1 < 0;\\ \beta_2 > 0\end{pmatrix}$ $S3: \begin{pmatrix}\beta_1 > 0;\\ \beta_2 < 0\end{pmatrix}$ $S4: \begin{pmatrix}\beta_1 < 0;\\ \beta_2 < 0\end{pmatrix}$
Average true parameters	$\overline{\beta_1} = -0.400$ $\overline{\beta_2} = -0.100$	$\overline{\beta_1} = -1.375$ $\overline{\beta_2} = 0.600$	$\overline{\beta_1} = 2.995$ $\overline{\beta_2} = -0.685$	$\overline{\beta_1} = 0.494$ $\overline{\beta_2} = -0.025$

3.2.1.1 Experiment 1: Latent class structure without niches (low heterogeneity without niches)

In this experiment, there were two relatively balanced size segments with 40% and 60% market share. Because this was an LCM, their distribution was discrete, with values for $\beta_1 = 2$ and $\beta_2 = 0.5$ in the first segment and $\beta_1 = -2$

and $\beta_2 = -0.5$ in the second segment. Considering the market shares, the average parameter associated with the first attribute was equal to $\bar{\beta}_1 = -0.4$ with a standard deviation (sd_{β_1}) of 1.96, while for the second attribute, it was equal to $\bar{\beta}_2 = -0.1$ with $sd_{\beta_2} = 0.49$. In other words, there were two preference patterns: one segment included consumers who liked both attributes, while the other included those who disliked them.

3.2.1.2 Experiment 2: Latent class structure with a niche (low heterogeneity with a niche)

This experiment was similar to the previous experiment, but there were three segments with market shares of 15%, 35% and 50%, respectively. The first segment with the lowest share was the niche segment. The true parameters were, $\beta_1 = 0.5$ and $\beta_2 = 1$, $\beta_1 = -2$ and $\beta_2 = 2$ and $\beta_1 = -1.5$ and $\beta_2 = -0.5$, respectively. Considering the market shares, the average parameter associated with the first attribute is equal to $\bar{\beta}_1 = -1.375$ with $sd_{\beta_1} = 0.82$, while for the second attribute, it was equal to $\bar{\beta}_2 = 0.6$ with $sd_{\beta_2} = 1.15$. In this experiment, the niche segment included hypothetical consumers who liked both attributes. In contrast, the other two segments included those who disliked both attributes (the largest segment) and those who disliked one attribute but liked the other.

In the first two experiments, it was assumed that all hypothetical consumers were homogeneous within each segment. That is, all consumers within a segment shared the same parameters. Two or three segments represented the heterogeneity across individuals.

The random parameter model (mixed logit) allowed for broader heterogeneity across individuals in which individuals had their own parameters. The distribution of these parameters was summarised using the mean and standard deviation of the distribution. The segments were defined by consumers sharing the same preference pattern according to their parameter signs.

3.2.1.3 Experiment 3: Mixed logit structure without a niche (high heterogeneity without a niche)

In this experiment, the true parameters followed a normal distribution, simulating an MLM. From this simulation, two segments arose based on preference patterns using the signs of the betas. Segment 1 included 26.4% of the hypothetical consumers in the sample with positive preferences for both attributes, while segment 2 included 73.6% of the sample who liked attribute 1 but disliked attribute 2. The average values for the parameters associated with both attributes were $\bar{\beta}_1 = 3.0$ and $\bar{\beta}_2 = -0.7$, with standard deviations of $sd_{\beta 1} = 0.99$ and $sd_{\beta 2} = 1.02$, respectively.

3.2.1.4 Experiment 4: Mixed logit structure with a niche (high heterogeneity with a niche)

In the last experiment, the true parameters also followed a normal distribution, simulating an MLM, but the experiment included a niche. Thus, four segments arose. Segment 1 included 34% of the hypothetical consumers in the sample, with a positive preference for both attributes. Segment 2 contained 15.2% of the sample, who disliked attribute 1 but liked attribute 2. Segment 3 included 37.2% of the sample, consisting of individuals with a positive preference for attribute 1 but a negative preference for attribute 2. The last segment included 13.6% of the sample, who disliked both attributes. The average values for the parameters associated with both attributes were $\bar{\beta}_1 = 0.49\ and\ \bar{\beta}_2 = -0.02$, with standard deviations of $sd_{\beta 1} = 0.93$ and $sd_{\beta 2} = 1.03$, respectively.

3.2.2 Individual-specific posterior distributions

For each simulated dataset, the mean ISPs for both models were recovered. For the MLM, the equation for the mean ISP followed Revelt and Train (2000):

$$\widehat{\widehat{\beta_n}} = \hat{E}(\beta_n|y_n, x_n) = \frac{\frac{1}{R}\sum_{r=1}^{R} \beta_n^{[r]} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{\exp\left(\beta_n^{[r]} x_{njt}\right)}{\sum_{\mathrm{j}}^{J} \exp\left(\beta_n^{[r]} x_{njt}\right)} \right)^{y_{njt}}}{\frac{1}{R}\sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{\exp\left(\beta_n^{[r]} x_{njt}\right)}{\sum_{j}^{J} \exp\left(\beta_n^{[r]} x_{njt}\right)} \right)^{y_{njt}}}, \qquad (6)$$

where $\beta_n^{[r]}$ is the r-th draw for individual n from the posterior population distribution of β.

The LCM followed Sarrias and Daziano (2018), with the mean ISP as:

$$\widehat{\widehat{\beta_n}} = \hat{E}(\beta_n|y_n, x_n) = \frac{\sum_{s=1}^{S} \hat{\beta}_s \hat{w}_{ns} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{\exp\left(\hat{\beta}_s' x_{njt}\right)}{\sum_{i}^{J} \exp(\hat{\beta}_s' x_{nit})} \right)^{y_{njt}}}{\sum_{s=1}^{S} \hat{w}_{ns} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{\exp\left(\hat{\beta}_s' x_{njt}\right)}{\sum_{i}^{J} \exp(\hat{\beta}_s' x_{nit})} \right)^{y_{njt}}} \qquad (7)$$

After collecting these data, the segments were identified based on all possible combinations of the betas' signs, in line with Scarpa and Del Giudice (2004). This was done to contrast them with the true segments.

For each experiment in the LCM, two to four classes were estimated because these were all possible preference patterns.[22] The idea was also to evaluate the error level when the researcher wrongly chose the number of model classes. In this way, we sought to resemble real situations where researchers may not know the proper number of segments. Most studies rely on information criteria to determine the number of classes; nevertheless, some discrepancies may appear depending on the criteria chosen. For instance, if criteria such as the Akaike information criterion (AIC), the Bayesian information criterion (BIC) or the consistent Akaike information criterion (CAIC) suggest different models, the final decision depends on the researcher. Consequently, the possibility exists of selecting the wrong model (Sarstedt, 2008).

3.2.3 Model comparison

The study used three comparisons. First, the mean of the estimated coefficients from the models $\overline{(\hat{\beta})}$ and the posterior individual-specific $\overline{(\widehat{\beta_n})}$ were compared with the true parameters $\bar{\beta}$. This comparison sought to determine which model produced the lower difference between the predicted and true values. This comparison was made by observing Diff $\left|\overline{(\hat{\beta})} - \bar{\beta}\right|$ and Diff $\left|\overline{(\widehat{\beta_n})} - \bar{\beta}\right|$ for each

[22] The only exception was in Experiment 1, where the LCM with three and four classes failed to converge.

parameter. Considering that a model could have a closer prediction for one parameter but not for the other, an additional measure was added, combining the difference across both parameters (Equation 8), as shown below.

$$Com\_Diff \;=\; \sqrt{\frac{\left(\widehat{\beta_1}-\overline{\beta_1}\right)^2+\left(\widehat{\beta_2}-\overline{\beta_2}\right)^2}{2}} \tag{8}$$

Considering the findings of Revelt and Train (2000) and Sarrias and Daziano (2018), it was expected that the ISPs would outperform the population coefficients for all cases.

Second, considering the average of all datasets, preference patterns predicted using the ISPs were compared with the true segments, both in terms of their composition and size. In this case, it was expected that the MLM would outperform the LCM where there was large heterogeneity, given that the MLM is more flexible than the LCM for modelling heterogeneity (Shen, 2009).

Finally, the analysis included the correct prediction of the number of individuals in each segment using the root mean square error (RMSE) for each dataset (Equation 9), as shown below:

$$RMSE_Q \;=\; \sqrt{\frac{\sum_{s\,=\,1}^{S}(\%SegP_S-\%SegR_S\,)^2}{S}} \tag{9}$$

where Q is the number of databases; S is the number of segments or preferences patterns; and $\%SegP$ and $\%SegR$ are the percentage of hypothetical individuals in the predicted segment s and the real segment s, respectively. Table 3.2 summarises the comparison criteria.

Table 3.2 Comparison criteria between both models

Criterion	Measurement
C1. Estimated coefficients and ISP mean values vs true parameters	Diff $\left\|\overline{(\hat{\beta})} - \bar{\beta}\right\|$; Diff $\left\|\overline{(\widehat{\beta_n})} - \bar{\beta}\right\|$; and Com_Diff
C2. Preference patterns predicted by ISP vs true preference patterns segments	Number segments predicted and segments' size
C3. Individual assignment to the real segment	$\overline{RMSE_Q}$

3.3 Results

3.3.1 Coefficient predictions

The first analysis sought to determine which model produced closer predictions of the parameters in each experiment. The measure used in the analysis shows the difference between the parameters (and the mean ISPs) predicted by each model and the true parameters[23]. Table 3.3 shows the difference between the coefficients and true parameters and the difference between the mean ISPs and true parameters. A measure of accuracy combining both parameters was added (*Comb_Diff*).

As expected, in the first and second experiments, the LCM with two and three classes produced estimates closest to the true parameters, either in terms of the estimated coefficients or the mean ISPs. In both cases, the differences and

[23] Table B.1 in Appendix B summarises the parameters estimated in each model for the four experiments along with the ISP mean values.

the combined difference measures were smaller for LC2 and LC3. This result was expected because these two first experiments mimicked a latent class structure (heterogeneity between segments but homogeneity within them). Therefore, the LCM outperformed the MLM when the correct number of segments was selected. However, two additional results are obtained. First, comparing the performance of the unconditional estimates versus the ISPs in the LCM, the first experiment shows that the mean ISPs produced the lowest difference with respect to the real parameters, while the opposite was true for the second experiment. This result suggests that there is no strong evidence to support the ISP's superiority over parameter estimates in the LCM with the structure defined in this experiment. Second, in Experiment 2, although the LC3 was better than the other models, the MLM was the second-best option to adjust the data to the real parameters, compared with the LCM, but with the wrong number of classes.[24] This result indicates that even when the data follow a latent class structure, choosing the correct number of classes is essential and that the MLM may be better when there is uncertainty regarding the number of classes.

[24] The advantages of one model over the other are also observed in the BIC values, with the chosen models having the lowest BIC. Table B.2 in the Appendix B summarises the BIC values for each model.

Table 3.3 Comparison between the mixed logit model and the latent class model in terms of the predicted coefficients and mean ISP

		Coefficient prediction			Mean ISP prediction		
		Diff $\left\lvert\overline{(\hat{\boldsymbol{\beta}}_1)} - \boldsymbol{\beta}_1\right\rvert$	**Diff** $\left\lvert\overline{(\hat{\boldsymbol{\beta}}_2)} - \boldsymbol{\beta}_2\right\rvert$	$\boldsymbol{Com\_Diff}$	**Diff** $\left\lvert\overline{(\widehat{\boldsymbol{\beta}_{1n}})} - \boldsymbol{\beta}_1\right\rvert$	**Diff** $\left\lvert\overline{(\widehat{\boldsymbol{\beta}_{2n}})} - \boldsymbol{\beta}_2\right\rvert$	$\boldsymbol{Com\_Diff}$
Exp1	MLM	0.147561	0.004913	0.073821	0.149210	0.005030	0.074647
	LC2	**0.005438**	**0.002532**	**0.002999**	**0.005437**	**0.002532**	**0.002998**
Exp2	MLM	0.038097	0.043559	0.028934	0.038097	0.043559	0.029204
	LC2	0.124198	0.108705	0.082526	0.124197	0.108710	0.082527
	LC3	**0.007453**	**0.004207**	**0.004279**	**0.007476**	**0.004203**	**0.004288**
	LC4	0.041693	0.045851	0.030986	0.041803	0.045929	0.031052
Exp3	MXL	**0.001755**	0.009141	**0.004654**	**0.001598**	0.008443	**0.004296**
	LC2	0.334796	**0.004357**	0.167412	0.334798	**0.004322**	0.167413
	LC3	0.121236	0.027283	0.062134	0.121211	0.027337	0.062128
	LC4	0.140260	0.021727	0.070966	0.140229	0.021693	0.070949
Exp4	MXL	**0.004247**	0.010996	**0.005894**	**0.003757**	0.010322	**0.005492**
	LC2	0.069676	0.007559	0.035042	0.069679	0.007558	0.035044
	LC3	0.023412	0.014607	0.013798	0.023404	0.014598	0.013792
	LC4	0.012931	**0.005176**	0.006964	0.012915	**0.005212**	0.006964

Experiments 3 and 4 focused on a larger heterogeneity structure with heterogeneity between and within segments. Table 3.3 shows that the MLM better and more clearly resembled the actual combination of both parameters for the two experiments. In particular, the mean ISPs produced the lowest error level. Although beta 2 was better predicted in LC2 for Experiment 3 and LC4 in

Experiment 4, the high error for both models in predicting the first parameter gave the MLM the lowest combined error (Com_Diff). Therefore, the MLM better resembled the true data. The LCMs closest to the actual parameters were LC3 and LC4 for Experiments 3 and 4, respectively, matching the exact number of segments. From these results, it can be concluded that the ISPs outperformed the population coefficients because they provided estimates closer to the actual parameters when there was large heterogeneity. Further, the LCM would be the second-best substitute only if the number of segments were correct.

These results suggest that ISPs outperform population parameters in the case of high preference heterogeneity; however, when preferences within segments are more homogeneous, this superiority is not quite evident.

3.3.2 Market segmentation predictions

To assess the segmentation prediction from both models, the mean ISP values served to gather all hypothetical individuals with the same preference patterns based on the coefficients' signs to later evaluate their accuracy using criteria C2 and C3 shown in Table 3.2. First, the analysis focused on the number of segments predicted and their respective sizes.

It is important to clarify that, for the MLM and LCM, the segments were uncovered using the ISPs (hereafter these models are named *ISP-based*). However, the 'original classes' uncovered by the LCM through the membership probabilities were also included (hereafter named *mbrshp*).

Tables 3.4 and 3.5 summarise the segments predicted using the mean ISPs as the basis for segmentation (*ISP-based*) and the original classes from the LCM estimation (*mbrshp* as an abbreviation for the probability of LCM membership).[25]

Table 3.4 focuses on the first two experiments (low-preference heterogeneity). In both experiments, the LCM outperformed the MLM. In the first experiment, the MLM showed very poor precision in uncovering the correct number of segments based on the ISP values and their sizes. In contrast, the LCM with the correct number of classes showed a very close fit to the true segments, especially the original classes from the LCM estimation (*mbrshp*) compared with those uncovered from the ISP (*ISP-based*). In Experiment 2, which included a niche, the membership probabilities from the LC3 were very close to the true segments, with no problems in detecting the niche; however, the segmentation based on the ISP values was less accurate in terms of size. From these results, it can be concluded that the LCM outperforms the MLM when there is a simple heterogeneity level.

[25] The LC2, LC3 and LC4 notation refer to the LCM estimated, either with two, three or four classes. Then, when the ISP values served as basis for segmentation (according to the signs of ISPs), the number of predicted segments may differ from the number of classes originally estimated.

Table 3.4 Average segment size predicted by each model in Experiments 1 and 2

		Preference patterns (segments)			
		$\binom{\boldsymbol{\beta_1} > \mathbf{0};}{\boldsymbol{\beta_2} > \mathbf{0}}$	$\binom{\boldsymbol{\beta_1} < \mathbf{0};}{\boldsymbol{\beta_2} > \mathbf{0}}$	$\binom{\boldsymbol{\beta_1} > \mathbf{0};}{\boldsymbol{\beta_2} < \mathbf{0}}$	$\binom{\boldsymbol{\beta_1} < \mathbf{0};}{\boldsymbol{\beta_2} < \mathbf{0}}$
Exp1	Real size	40.00%	0.00%	0.00%	60.00%
	MLM size (*ISP-based*)	21.76%	10.48%	18.19%	49.57%
	LC2 size (*ISP-based*)	39.98%	0.03%	0.03%	59.96%
	LC2 size (*mbrshp*)	40.03%	0.00%	0.00%	59.97%
Exp2	Real size	15.00%	35.00%	0.00%	50.00%
	MLM size (*ISP-based*)	3.42%	65.84%	0.27%	30.46%
	LC2 size (*ISP-based*)	0.00%	49.05%	0.00%	41.92%
	LC3 size (*ISP-based*)	9.03%	58.78%	0.00%	41.22%
	LC4 size (*ISP-based*)	9.10%	58.13%	0.08%	32.69%
	LC2 size (*mbrshp*)	0.00%	49.49%	0.00%	50.51%
	LC3 size (*mbrshp*)	15.53%	34.95%	0.00%	49.52%
	LC4 size (*mbrshp*)	14.77%	31.49%	0.00%	53.74%*

* In this case, two classes from this model both had coefficients with negative sign. Therefore, they were added up in the same preference pattern.

Table 3.5 shows the segmentation predictions under a large degree of heterogeneity. The results of Experiment 3 show that, in general, all four models using ISP values agreed on the existence of two main segments, even though they overestimated the size of the largest segment. At first sight, it is unclear which model was better, and it was necessary to evaluate the error in allocating the hypothetical individuals in the segments (see the analysis of Table 3.6). For the original classes in the LCM (*mbrshp*), the model with two classes did not correctly predict the market shares. However, the model with three classes correctly predicted the first segment (both parameters had a positive sign) but divided the second segment into two classes. Thus, by merging these last two classes, the size better resembled the true segment size. The model with four classes incorrectly predicted the number of segments and market shares when the classes with the same preference patterns were merged.

For Experiment 4, the LCM based on the membership probabilities provided the worst segmentation predictions, especially for the smallest segments. However, when the segmentation was based on the ISPs, there was an improvement. Even though the segmentation from LC4 based on ISPs predicted the correct number of segments with sizes relatively close to the actual segments, the MLM had better results.

Table 3.5 Average segment size predicted by each model in Experiments 3 and 4

		Preference patterns (segments)			
		$\binom{\boldsymbol{\beta_1} > \mathbf{0};}{\boldsymbol{\beta_2} > \mathbf{0}}$	$\binom{\boldsymbol{\beta_1} < \mathbf{0};}{\boldsymbol{\beta_2} > \mathbf{0}}$	$\binom{\boldsymbol{\beta_1} > \mathbf{0};}{\boldsymbol{\beta_2} < \mathbf{0}}$	$\binom{\boldsymbol{\beta_1} < \mathbf{0};}{\boldsymbol{\beta_2} < \mathbf{0}}$
Exp3	Real size	26.40%	0.00%	73.60%	0.00%
	MLM size (*ISP-based*)	17.60%	0.00%	82.36%	0.01%
	LC2 size (*ISP-based*)	12.00%	0.00%	88.00%	0.00%
	LC3 size (*ISP-based*)	17.80%	0.00%	82.20%	0.00%
	LC4 size (*ISP-based*)	14.70%	0.00%	84.30%	0.01%
	LC2 size (*mbrshp*)	48.39%	0.00%	51.61%	0.00%
	LC3 size (*mbrshp*)	29.04%	0.00%	70.96%*	0.00%
	LC4 size (*mbrshp*)	47.28%*	0.00%	52.72*	0.00%
Exp4	Real size	34.00%	15.20%	37.20%	13.60%
	MLM size (*ISP-based*)	37.10%	12.10%	38.80%	12.00%
	LC2 size (*ISP-based*)	47.23%	1.12%	49.78%	0.54%
	LC3 size (*ISP-based*)	38.92%	9.91%	41.20%	9.97%
	LC4 size (*ISP-based*)	36.90%	11.36%	39.60%	11.42%
	LC2 size (*mbrshp*)	49.70%	0.00%	50.30%	0.00%
	LC3 size (*mbrshp*)	34.33%	0.00%	35.40%	30.28%
	LC4 size (*mbrshp*)	49.60%*	0.00%	27.45%	22.94%

* In these cases, the classes with the same sign pattern were merged since they represented the same preference pattern.

These experiments provide evidence that, when there is a large degree of heterogeneity, the MLM outperforms the LCM with and without the presence of a niche. However, to provide a more exact measure of the predominance of one model over the other, the third criterion was used, calculated as the average RMSE.

The level of error in each model was assessed for each experiment and all databases. Table 3.6 summarises the average RMSE. For the first two experiments, Table 3.6 confirms the results from Table 3.4; that is, with the correct number of classes, the LCM provided a closer prediction of the true segments with minimal error level, compared with the MLM, which demonstrated very poor performance. Additionally, in the LCM, the original classes and the segments predicted using the ISPs were very similar to those in Experiment 1, with an error level marginally higher for the ISP-based. However, with the existence of a niche segment (Experiment 2), the RMSE was lower for the original classes.

For Experiments 3 and 4, the results show that the MLM predicted segments with the lowest error level, followed by the LCM with the correct number of classes and using the mean ISPs. Interestingly, in all LCMs, segmentation using the ISPs produced lower error levels than the original classes from the model estimation (using membership probabilities). Thus, these results show that in the context of LCM, using the ISPs to uncover market segments is better than using the classes from the estimation when there is a large level of heterogeneity among individuals.

Table 3.6 Average RMSE for each model across all databases

	Experiment 1		Experiment 2		Experiment 3		Experiment 4	
	Average	**S.D.**	**Average**	**S.D.**	**Average**	**S.D.**	**Average**	**S.D.**
MLM (*ISP-based*)	0.153	0.02	0.192	0.02	**0.062**	**0.02**	**0.030**	**0.01**
LC2 (*ISP-based*)	0.0022	0.002	0.150	0.03	0.110	0.08	0.155	0.04
LC3 (*ISP-based*)	-	-	0.087	0.03	0.065	0.05	0.080	0.04
LC4 (*ISP-based*)	-	-	0.152	0.18	0.093	0.07	0.069	0.06
LC2 (*mbrshp*)	**0.0019**	**0.001**	0.107	0.01	0.145	0.06	0.172	0.04
LC3 (*mbrshp*)	**-**	**-**	**0.017**	**0.01**	0.068	0.05	0.118	0.03
LC4 (*mbrshp*)	-	-	0.030	0.03	0.117	0.04	0.115	0.03

3.4 Discussion

This study compared the performance of the MLM and LCM in terms of market segment predictions. A Monte Carlo simulation study was run to assess the properties of each model. Previous comparisons used criteria such as the goodness of fit or behavioural measures, including WTP or elasticities. Comparisons of their market segment predictions are scarce in the literature, likely because of the superiority of the LCM to identify classes and membership probabilities that have been loosely categorised as market segments and because the MLM requires a post-estimation analysis (Greene & Hensher, 2003, 2013; Keane & Wasi, 2013; Shen, 2009). The Monte Carlo study from this study adds new evidence about both models' performance in uncovering market segments, showing that the LCM does not always produce better segment predictions.

The analysis started by comparing both models through standard measures, goodness of fit and estimated parameters. Experiments 1 and 2 showed that the LCM outperformed the MLM in their model fit and provided estimated coefficients closer to the true values. This dominance of the LCM over the MLM was also found in Greene and Hensher (2003) and Shen (2009). However, when higher heterogeneity among individuals is introduced, as in Experiments 3 and 4, the MLM outperformed the LCM, even if the correct number of classes was used in the LCM. This is one of the main results of the present study. It is important to consider the context and conditions under which these results prevail. In other words, it is necessary to know whether the underlying heterogeneity follows a 'latent class world' or a 'random parameters world'. Otherwise, the incorrect model could be applied and heterogeneity may not be correctly predicted.

As expected, when there are clear and identifiable classes in which individuals share the same parameters (Experiments 1 and 2), the LCM, produces the best fit (in terms of BIC) and the lowest error in terms of the distance between estimates and true parameters. However, this is conditional on identifying the correct number of classes. In this case, even when niche segments exist, the performance of the LCM far exceeds that of the MLM, considering the classes predicted by the model or discovering the segments by using the mean ISPs. However, if the researcher fails to choose the correct number of classes during the estimation,[26] the MLM generates better results using ISPs. This result is highly relevant considering that the researcher never knows in advance the correct number of classes (or segments) and has to rely on information criteria (AIC or BIC) to determine it (Boxall & Adamowicz, 2002; Gupta & Chintagunta, 1994; Kamakura & Russell, 1989; Swait, 1994).

When the state of nature is closer to a random parameter situation (different individual parameters as in Experiments 3 and 4), the MLM predicts coefficients and ISPs closer to the true parameters and has the best goodness of fit. Other authors, such as Keane and Wasi (2013), also found the MLM to be superior to the LCM when comparing the goodness of fit. Thus, this study supports the hypothesis that the MLM captures higher heterogeneity better than the LCM. The MLM largely outperforms the LCM, even when the LCM estimates the correct number of classes.

Considering the focus of this study, which is market segmentation, it is found that heterogeneity plays a decisive role. Literature comparing the MLM and LCM in terms of market segment prediction is scarce, explained partly by the paucity of studies using the MLM to uncover segments (for instance, Richter & Pollitt, 2018; Scarpa & Del Giudice, 2004). This study shows how useful random parameter models are when there are large differences in consumer preferences. Asioli et al. (2018) followed an alternative segmentation strategy that requires a

[26] For cases in which the researcher relies on certain information criteria, Sarstedt (2008) provides evidence that the sample size or the presence of niches may affect class selection depending on the criterion chosen.

post-estimation analysis. In their findings, the segmentation obtained from the LCM and MLM was not significantly different. Nevertheless, their work highlights some advantages of these sequential procedures.

The use of an MLM to uncover market segments requires a post-estimation analysis using ISPs. There are a few options for using these ISPs to find the segments. This study followed the Scarpa and Del Giudice (2004) strategy, in which the segments are formed with all possible combinations of preference patterns based on the signs of the ISPs. An alternative approach is to exploit both the signs and magnitudes of the ISPs. In this case, the ISPs can be used to perform a cluster analysis to uncover the segments, as in Asioli et al. (2018).

Other studies have highlighted the benefits of using the ISPs (Revelt & Train, 2000; Richter & Pollitt, 2018; Sarrias & Daziano, 2018). The present study demonstrates their accuracy in uncovering market segments when using an MLM. More importantly, the study confirms that in scenarios with large heterogeneity, the use of the ISPs also reduces the errors to uncover segments when an LCM has erroneously been fitted instead of the more appropriate MLM. In this setting, the highest errors are found when we directly associate the classes and their probabilities with market segments in the LCM.

This finding provides a novel result for the marketing literature because marketers commonly rely on the classes estimated by the LCM as market segments (Magidson & Vermunt, 2004; Wedel & Kamakura, 2000). In this study, the evidence shows that these classes are less accurate in uncovering the true preference patterns than using ISPs. The predicted classes are closer to the real segments only when the heterogeneity structure is less complex (Experiments 1 and 2).

3.4.1 Limitations and future extensions

This study designed experiments with specific characteristics that can be modified to evaluate the findings' robustness. For instance, this study uses a simple choice experiment with 10 choice sets, three alternatives and only two attributes. However, the complexity of this choice experiment can be increased if the number of attributes is higher. Thus, would the accuracy of the LCM remain if there is heterogeneity within segments? Would it be better to estimate an MLM if the researcher suspects large heterogeneity in the sample? Future studies can explore the accuracy of these models when the choice experiment is more complex in terms of the number of attributes that consumers must evaluate. This increment in the choice experiment's complexity opens up another challenge: to evaluate the role of using attribute processing strategies, such as attribute non-attendance, as a coping mechanism to face a more complex task and its impact on segmentation.

In terms of using ISPs, this study considers their signs to determine all the possible combinations of tastes and uncover the segments, as in Scarpa and Del Giudice (2004). However, a decision-maker or marketer could also be interested in the intensity of the preference, and not just the like or dislike information. In this case, an extension of ISPs would be to use them as inputs in a cluster analysis to uncover the segments, as in Asioli et al. (2018) or Crabbe et al. (2013).

Finally, another limitation of this study is that it only compared the two most frequently used models to capture unobserved heterogeneity. However, other random parameter models have gained increasing attention during the last decade, such as the latent class random parameter model (LC-RPL). This model combines an LCM and MLM to allow for heterogeneity within classes. Evidence shows that it outperforms the other two models in terms of model fit and in-sample predictions (Bujosa et al., 2010). Thus, future studies could extend our findings by comparing an LC-RPL with an MLM to uncover market segments when there is large heterogeneity among consumers.

3.5 Conclusions

This study assessed two of the most popular models used to capture consumer heterogeneity—the MLM and the LCM—to determine which technique is better for uncovering market segments. In a Monte Carlo study, we designed four experiments to evaluate which model better predicts market segments. A relatively simple choice experiment (10 choice sets, three alternatives and two attributes) was used to analyse the accuracy of both models with and without niche segments and also while allowing heterogeneity within segments.

The main findings show that when heterogeneity exists within segments, the MLM outperforms the LCM in terms of the coefficients, ISPs and segmentation prediction. This result is independent of whether niche segments are present or not.

The study also demonstrates that using ISPs from an LCM estimation to uncover market segments reduces the error level of approaching the true segments, compared with using the estimated classes. This result holds when there is large heterogeneity, because when the individuals in the same segment are completely homogeneous, the original classes provide the closest segments.

These results are useful for marketers, considering that segmentation is one of the most useful tools to match products to the right consumers. Having more accurate knowledge about consumer preferences towards a product and its attributes can help marketers highlight the most desirable attributes to the right consumers in advertising or even to create new products considering these more desirable attributes (and levels).

Appendix B

Table B.1. Mean estimated parameters and ISPs from MLM and LCM

	Model	β_1 True	β_1 Coeff.	β_1 ISP	β_2 True	β_2 Coeff.	β_2 ISP
Exp1*	MLM	-0.400	-0.5475605	-0.5492095	-0.100	-0.1049126	-0.1050296
	LC2		-0.4054375	-0.4054370		-0.1025318	-0.1025317
Exp2	MLM	-1.375	-1.413097	-1.413954	0.600	0.5564414	0.5564785
	LC2		-1.250802	-1.250803		0.4912951	0.4912902
	LC3		-1.382453	-1.382476		0.5957928	0.5979680
	LC4		-1.333307	-1.333197		0.6458510	0.6459293
Exp3	MLM	2.9952	2.993473	2.993630	-0.6848	-0.6939556	-0.6932572
	LC2		2.660432	2.660430		-0.6804580	-0.6804928
	LC3		2.873992	2.874017		-0.6575318	-0.6574776
	LC4		2.854968	2.854999		-0.6630874	-0.6631215
Exp4	MLM	0.4936	0.4893967	0.4898869	-0.0246	-0.0136181	-0.0142922
	LC2		0.4239678	0.4239648		-0.0170551	-0.0170562
	LC3		0.4702311	0.4702393		-0.0100073	-0.0100165
	LC4		0.4807129	0.4807283		-0.0194379	-0.0194012

* For this experiment, LCMs with three and four classes had problems converging.
** More decimals are included to better show the difference between the use of coefficients and ISPs.

Table B.2. BIC values for MLM and LCM in all experiments

Experiment	Model	Average BIC value
Exp1	MLM	9419.28
	LC2	**9158.73**
Exp2	MLM	9523.94
	LC2	9626.58
	LC3	**9478.72**
	LC4	9501.89
Exp3	MLM	**74944.4**
	LC2	7556.4
	LC3	7538.5
	LC4	7551.7
Exp4	MLM	**10510.6**
	LC2	10676.9
	LC3	10579.7
	LC4	10571.9

Chapter 4:

RESEARCH STUDY 3. SEGMENTATION ACCOUNTING FOR ANA BEHAVIOUR: THE ROLE OF ATTRIBUTE IMAGES AND STATED ANA INFORMATION

Abstract

This study evaluates the effects of accounting for attribute non-attendance (ANA) on uncovering market segments. In particular, it assesses the role of using visual aids and self-reported information to identify and accommodate ANA behaviour in a latent class model (LCM). Current literature uses the classes from an LCM to accommodate this type of consumer behaviour. However, several issues remain unsolved. One of these issues concerns how to better identify ANA that reflects an actual preference towards the attribute compared to an ANA behaviour used to deal with a complex task. This study uses a between-subject design to evaluate the use of visual aids to reduce complexity, thereby better accounting for ANA and uncovering market segments. Moreover, there is no definitive answer indicating how to accommodate ANA in an LCM. There are different strategies, but there is no discussion about which is better. Thus, this study compares the exclusion and the step-wise approaches to accommodate ANA in an LCM, exploiting the self-reported ANA to guide this last approach. The main findings suggest that model efficiency can be improved by using attributes' images in a choice experiment and posteriorly self-reported ANA information during the estimation. Considering that market segmentation is a powerful tool used by marketers to customise marketing strategies, this efficiency improvement strengthens the uncovered segments.

Keywords attribute non-attendance; choice experiment; inferred ANA; latent class model; stated ANA; visual aids

4.1 Introduction

Understanding what drives consumers' decisions is a challenge for researchers. To study consumers' preferences and choices, discrete choice experiments (DCEs) are a valuable tool used in marketing since the work of Louviere and Woodworth (1983). Despite the assumption that full rationality predominates in most DCE studies, the idea of bounded rationality (Simon, 1955) recognises a variety of decision or screening rules followed by consumers to simplify choice tasks (Gilbride & Allenby, 2004; Hensher, 2006). In particular, attribute non-attendance (ANA) is an attribute processing strategy or screening rule in which consumers ignore one or more attributes during a choice task (Hensher et al., 2005). Thus, during the last 15 years, ANA in DCE has attracted attention from different fields, such as transportation, health economics and environmental economics, among others (Lew & Whitehead, 2020). Many studies show that not accounting for ANA during the estimation process may reduce model efficiency by producing biased estimates and affecting the derivation of behavioural outputs, such as willingness to pay (WTP) estimates (Hensher, 2014; Scarpa et al., 2009). However, how market segmentation can be affected by ANA has not attracted all the attention it deserves in the literature, despite the importance of segmentation for marketers. A precise segmentation can greatly benefit marketing strategies, such as product innovation, promotion and pricing strategies; hence, it becomes important to evaluate the effects of accounting for ANA in estimating market segments (Yankelovich & Meer, 2006). Thus, this study attempts to answer: What are the impacts of ANA (or not accounting for it) on market segmentation? In addition, there are issues about how to treat ANA in the modelling process. For instance, what is the best way to identify ANA? To what extent can self-reported ANA be included in the estimation? How do experimental design features affect ANA behaviours?

Thus, responding to recent calls for more research on ANA (Elshiewy et al., 2017; Lew & Whitehead, 2020), this study explores the effects of ANA on market segmentation under the choice modelling framework. In particular, the study assesses the role of two elements to identify and accommodate ANA: (i) the use of visual aids (images) to represent the attributes in the choice experiment survey and (ii) the use of self-reported ANA in a latent class model (LCM) to accommodate ANA analytically. A more detailed description of the general framework and these two elements follows.

The choice modelling provides a framework that accounts for the heterogeneity in consumer preferences, which makes it valuable for different reasons. First, DCE[27] is a significant source of data about the importance of product attributes during consumers' choices. DCE is based on random utility theory, which assumes rational consumers maximise their utility when making choices (McFadden, 1974). That means that the chosen alternative in each choice task will represent the one that provides the highest utility level, with utility level

[27] DCE could be considered equivalent to choice-based conjoint (CBC) since both have a structure based on attributes and levels. However, Louviere et al. (2010) state that they are not synonymous because their theoretical foundations are different.

being a function of product attributes. Second, to statistically model unobserved preference heterogeneity, the LCM (also known as the finite mixture model) is one of the most popular methods for segmenting the market (Elshiewy et al., 2017; Kamakura & Russell, 1989). Thus, considering this traditional framework and that current literature agrees that most consumers do not always make trade-offs between all product attributes but just with a subset of them in choice decisions (Hensher, 2006, 2014), the presence of ANA requires some extensions to this traditional framework. These extensions may come either from the experimental design of models or their adjustment to better accommodate ANA.

First, the experimental design may help to reduce ANA behaviour used as a coping strategy to simplify complex tasks. The literature recognises that ANA may appear for different reasons, but only a few studies have explored why ANA occurs (Alemu et al., 2013; Heidenreich et al., 2018). One reason is that ANA might appear as a coping mechanism to simplify complex choice tasks, for instance, information overload, time restrictions, unfamiliarity with the product, etc. (Hensher, 2006). A second reason is that ANA might reflect a genuine preference towards an attribute that is not relevant for the consumer (Alemu et al., 2013). Given that the first reason does not reflect consumers' preferences but appears for external stimuli, different studies evaluate how complex tasks may induce it. Manipulation of the number of choice sets, number of alternatives, number of attributes and attribute levels has been proved to affect the complexity of choice tasks leading to ANA behaviour (Grebitus & Roosen, 2018; Hensher, 2006). However, there is no evidence on how the presentation format of the choice experiment may affect complexity and ANA. Thus, this study adds images to lessen the complexity of the tasks to reduce ANA. The picture superiority effect (Whitehouse, Maybery, & Durkin, 2006) suggests that images are easier to remember and process and thus, in a DCE, presumably reduce complexity (Uggeldahl, Jacobsen, Lundhede, & Olsen, 2016). Moreover, displaying attributes in text and visual stimuli together is more effective in attracting people's attention (Shr, Ready, Orland, & Echols, 2019). In addition, using images provides a more realistic buying situation (Jansen, Boumeester, Coolen, Goetgeluk, & Molin, 2009; Orzechowski, Arentze, Borgers, & Timmermans, 2005).

A second extension comes from the adjustment of models to analyse the data when ANA occurs. Currently, the LCM can be used to identify and accommodate ANA. In particular, each class represents a specific ANA pattern[28] by assigning zero utility weight to the ignored attributes, so the model infers ANA analytically (Campbell et al., 2011; Caputo et al., 2018; Hensher & Greene, 2010; Scarpa et al., 2009). However, the operationalisation of this strategy differs across studies in terms of identifying ANA patterns. Some studies follow an 'exclusion approach', starting with the estimation of the LCM considering all possible ANA

[28] ANA patterns refer to different combinations of attributes that are either ignored or attended during a choice task. For instance, in a choice situation with three attributes, there are eight ANA patterns. There is a total attendance pattern where all three attributes are attended during the choice. There is a total non-attendance pattern where all three attributes are ignored by the consumer. Three additional ANA patterns represent partial non-attendance of one attribute. Finally, the remaining three ANA patterns represent partial non-attendance of two attributes simultaneously.

patterns, to progressively eliminating the classes with low membership probability. Thus, this approach evaluates different models until the best model is found through a measure of fit (Caputo, Nayga, & Scarpa, 2013; Caputo et al., 2018; De Marchi et al., 2019; Heidenreich et al., 2018; Kragt, 2013; Mueller Loose, Scholderer, Corsi, & Lockshin, 2012). Alternatively, a 'step-wise approach' adds ANA patterns sequentially, until the best model is found (Campbell et al., 2011; Hensher & Greene, 2010; Hensher, Rose, & Greene, 2012; Lagarde, 2013; Scarpa et al., 2009, 2013; Thiene, Franceschinis, & Scarpa, 2019; Weller et al., 2014). However, it is unclear which ANA patterns should be added in each step, especially when there is a large number of attributes generating different estimation results. Only a few studies combine inferred ANA and self-reported ANA (also known as stated ANA) by using this last source of information in the estimation of the LCM. For instance, in Hensher, Collins and Greene (2013), the authors use self-reported ANA to define the parameters' restrictions and conclude that stated ANA adds little to the model. Conversely, Hole, Kolstad and Gyrd-Hansen (2013) use stated ANA information as dummies in an endogenous attribute attendance model, allowing stated and inferred ANA simultaneously. They conclude that the stated ANA provides valuable information because it shows that respondents are aware of this behaviour, but it should be used carefully. Therefore, considering the mixed evidence about using inferred ANA complemented with stated ANA, and given the limited discussion related to the specification of classes in the LCM, this study proposes a step-wise approach in an LCM inferring ANA, complemented with self-reported ANA information. Moreover, since no research has compared the exclusion approach with a step-wise approach, this study compares both approaches. Thus, by gathering more evidence related to different model specifications, the effect of ANA on model performance and market segmentation can be assessed, which is vital for decision-makers to implement successful strategies.

By assessing the role of these elements in the identification and accommodation of ANA in LCM to uncover market segments, two findings emerge. First, the study shows that using images to describe the levels of the attributes improves the performance of the model. This, in turn, leads to more precise estimation results of market segmentation. Second, by using the self-reported ANA to guide the step-wise approach to identify ANA patterns, the inferred ANA strategy improve the model fit compared with the traditional exclusion approach. Thus, these results suggest that by incorporating both elements, the LCM becomes a viable solution to identify and accommodate ANA behaviour.

This study contributes to the literature in two ways. First, it provides evidence that ANA patterns reported by consumers are a valuable source of information to define classes in a latent class estimation. Although some studies have included stated ANA in LCMs, either as dummies in the model or as a way of defining the most ignored attributes, this study follows a different strategy. Specifically, it uses ranking of self-reported ANA patterns to guide the step-wise approach. This strategy is especially relevant when the number of attributes is large and researchers must define a subset of ANA patterns to be in the specification. To the best of the researcher's knowledge, no studies use self-reported ANA combined with inferred ANA in this type of strategy. Hensher et al. (2013) conducted a similar study; however, it did not consider the information of all possible ANA patterns, only the ignored attributes individually. Second, the study contributes by providing evidence that using attribute images in a DCE facilitates consumers' choice decisions. It also improves the model's performance in identifying consumers' real preferences when ANA is considered in the estimation. In particular, since images improve consumers' understanding of the DCE, this study suggests that the inferred ANA model—estimated from a choice experiment including image—is superior to the model from a choice experiment displaying attribute levels in text format only.

The study begins with a literature review about ANA, market segmentation and the role of images in choice experiments. Next, the data and methods are described, followed by the results. The study concludes with a general discussion of the contributions, implications, limitations and future research directions.

4.2 Theoretical background

All consumers are different and, given their diversity of needs and tastes, this heterogeneity creates challenges for market segmentation. Heterogeneity may stem from easily observed variables such as age, gender, place of residence or other sociodemographic or geographic characteristics. However, a significant part of consumers’ heterogeneity is not observed by the researcher; therefore, it requires additional methods to capture it.

The methods and bases for market segmentation have continuously evolved to accommodate the unobserved heterogeneity in behavioural analysis. The work of Kamakura and Russell (1989) generates a mass increment of research using an LCM that allows us to uncover patterns of preferences based on consumer choices. The classes obtained from the model represent market segments reflecting the heterogeneity of consumers. The theoretical foundation of this discrete choice model is random utility theory (McFadden, 1974). However, based on the works of Hensher et al. (2005) and Hensher (2006), an increasing number of studies has questioned the underlying, fully compensatory assumption that consumers may ignore some attributes during the choice process—the so-called ANA. Not accounting for ANA reduces the model’s efficiency by producing bias estimates (Scarpa et al., 2009). Thus, to account for ANA, two issues need to be solved: how to measure it and how to model it in the data analysis (Chrzan & White, 2016).

4.2.1 Attribute non-attendance

There are two principal sources to detect ANA: stated ANA and inferred ANA. Stated ANA, first proposed by Hensher et al. (2005), consists of recovering from respondents what attributes they ignored during the choice experiment by asking them directly during the survey. Some studies gather this information once the choice experiment finishes (e.g. Hensher et al., 2005), while others include stated ANA questions at the end of each choice task (Puckett & Hensher, 2008; Scarpa, Thiene, & Hensher, 2010). The first case is known as ‘serial stated ANA’ and the second as ‘choice-task stated ANA’ (Caputo et al., 2018). In the case of the inferred ANA, there are no additional questions about ignoring or attending the attributes during the survey; instead, ANA is retrieved analytically from the model (Hensher & Greene, 2010; Hole, 2011; Scarpa et al., 2009). Recently, a third source has appeared—the visual ANA[29]—which relies on using eye-tracking or virtual reality technology (Balcombe, Fraser, & McSorley, 2015; Krucien, Ryan, & Hermens, 2017; Van Loo, Nayga, Campbell, Seo, & Verbeke, 2018; Yegoryan, Guhl, & Klapper, 2020).

To account for ANA, either stated or inferred, the modelling process uses LCMs or random parameter models (RPMs). Both models consider observed or unobserved consumers’ heterogeneity which is vital to uncover market segments. There are various strategies for introducing ANA in the modelling process of either model. Table 4.1 shows a general summary of these strategies and, in the last row, the strategy proposed in this study is introduced.

4.2.1.1 Stated ANA

The stated ANA approach retrieves information from participants of a choice experiment related to the attributes they ignored during the choice tasks.

[29] This study does not include an analysis of this third source of ANA, focusing only on stated and inferred ANA.

Specifically, the participants answer questions about this behaviour, mainly by denoting the attributes not considered in their choice.

To accommodate stated ANA, acknowledging taste heterogeneity among consumers, the most used model is the RPM. The parameter associated with the attribute described by the respondent as ignored (or not attended) is set to zero, meaning that the marginal utility of that attribute is fixed to zero (Campbell, Hutchinson, & Scarpa, 2008; Hensher et al., 2005; Kragt, 2013). Other authors follow a similar approach but with different nuances, such as Carlsson, Kataria and Lampi (2010), who use this strategy and also evaluate the accuracy of these restrictions, or Balcombe, Burton and Rigby (2011), who propose a generalisation of the RPM through a Bayesian approach. To avoid using restrictions on the parameters stated as ignored, Campbell and Lorimer (2009) suggest estimating a model with two separate attribute parameters per respondent, one for the attribute ignored and one for the attribute attended.

One of the principal criticisms of the stated ANA approach is that not always provides reliable information, which may lead to misspecifications (Caputo et al., 2018; Hensher & Rose, 2009; Van Loo et al., 2018). The serial stated ANA, where the respondent answers the questions about ANA at the end of the experiment, can be inconsistent if an attribute is declared as ignored when the truth is that it is only of low importance to the consumer. In this case, the marginal utility is not zero but a low value. In addition, this approach assumes that an ANA answer means that the respondent ignored the attribute in all choice tasks, but this does not consider respondent progress throughout the experiment (Puckett & Hensher, 2009). To relax this last restriction, the choice-task stated ANA can be used. This involves formulating the ANA questions immediately after each choice decision task. However, the main problem of this last approach is that it affects the choice tasks by biasing the answers, as shown in Table 4.1.

Table 4.1 Summary of modelling strategies to accommodate ANA

Modelling strategy	ANA measure	General description	Source
RPM with fixed coefficient	Stated ANA	The contribution of the ignored attribute to the marginal utility is fixed to zero.	Campbell et al. (2008); Hensher et al. (2005)
RPM with separate attribute parameters for attenders and non-attenders	Stated ANA	Instead of imposing restrictions on the parameters reported as ignored, the authors estimate two separate coefficients for those who indicate they ignored an attribute and those who attend it.	Campbell & Lorimer (2009); Hess & Hensher (2010)
RPM and coefficient of variation	Inferred ANA	From the conditional estimates of an RPM, a coefficient of variation (CV) is obtained per individual. If CV > 2, then the individual is considered a non-attender of the attribute.	Hess & Hensher (2010)
Equality constrained latent class (ECLC)	Inferred ANA	Classes represent different ANA patterns. Non-zero attributes take the same value across classes.	Scarpa et al. (2009)
Endogenous attribute attendance model (EAA)	Inferred ANA	This is an extension of the ECLC model in which the decision of attending the attributes is endogenous.	Hole (2011)
Mixed endogenous attribute attendance model (MEAA)	Inferred ANA	This model extends the EAA by enabling heterogeneity across individuals within the same class.	Hole et al. (2013)
LCM with classes based on self-reported ANA	Inferred ANA complemented by stated ANA	In this LCM, the classes represent different ANA patterns, guided by the self-reported ANA information provided by each respondent.	

4.2.1.2 Inferred ANA

Unlike the stated ANA approach, which mainly relies on the RPM, the inferred ANA relies principally on the LCM to accommodate ANA. In this model, classes represent different ANA patterns (different combinations of attribute attendance/non-attendance). The first adaptation of an LCM to accommodate ANA is the Equality Constrained Latent Class Model (ECLC) proposed by Scarpa et al. (2009). Here, the parameters for ignored attributes are constrained to zero in each class according to the respective ANA pattern. However, the parameters for the attended attributes are assumed equal across classes. Some studies relax this last restriction to allow for preference heterogeneity between classes (Campbell et al., 2011; Scarpa et al., 2013). Despite the simplicity of this model, one of its main problems is that the number of classes can be unmanageable as the number of attributes increases, especially if the researcher wants to include all possible ANA patterns. Hole (2011) extends this model by considering an endogenous approach. The endogenous attribute attendance model (EAA) considers two steps in the process. In the first step, the respondent chooses a subset of attributes to consider during the proposed alternatives evaluation in the choice experiment. In the second step, the choice made is conditional on the subset of attributes defined in the first stage. This model allows us to include all attribute subsets, avoiding the restriction of the previous ECLC. An extension of this model is the mixed EAA (MEAA) which allows preference heterogeneity not just between classes but also within classes (Hole et al., 2013). This last strategy is based on the latent class random parameter model (LC-RPM) proposed by Bujosa et al. (2010), also known as latent class mixed multinomial logit model

(LC-MMNL) proposed by Greene and Hensher (2013). Here, each class includes the random distribution of the taste coefficients.

In all these inferred ANA models, classes represent different ANA patterns. However, a more profound academic discussion of its suitability for market segmentation is required. Are these ANA patterns appropriately representing market segments? A couple of studies introduce more flexibility by allowing for both taste heterogeneity and ANA (Caputo et al., 2013; Hensher et al., 2013). This flexibility implies defining multiple classes for the same ANA pattern. For instance, Hensher et al. (2013) assess the possibility of including more than one fully attended attribute class, just as in a regular LCM, while Caputo et al. (2013) also evaluate adding more than a specific ANA pattern (not just for a fully attended attribute class).

The flexibility gained from using either the LC-RPM or multiple classes for the same ANA pattern has some counteractions. For instance, in Bujosa et al. (2010), the LC-RPM showed convergence failures with more than two classes. Moreover, when the researcher wants to include multiple ANA patterns, there is no objective process to decide which should be replicated. Thus, one of the main issues arising from using an LCM to accommodate ANA is how to decide the number of classes and which ANA patterns to include in the modelling. Generally, the LCM uses information criteria measures to choose the best model to determine the optimal number of classes, thereby reducing subjectivity in this decision (Dillon & Mukherjee, 2006). These criteria include Schwarz's Bayesian information criterion (BIC), the Akaike's information criterion (AIC) or other extensions such as AIC3 or Bozdogan's consistent AIC (CAIC). Each one of these has a different penalisation for the number of parameters estimated (Andrews & Currim, 2003; Wedel & Kamakura, 2000). The number of segments to retain is achieved when the chosen criterion is minimised. Although this strategy for choosing the number of segments is generally accepted, the same cannot be said for the ANA patterns to include in these classes.

From the literature, two strategies emerge to define the ANA patterns to accommodate in the classes. First, the 'exclusion approach' (e.g. Caputo et al., 2013, 2018; Kragt, 2013; Mueller Loose et al., 2012) begins with all possible ANA patterns in the model. Then, an elimination procedure starts by removing the classes with zero or very low membership probability. This elimination continues until the model with the best fit is found. Second, the 'step-wise approach' is a strategy that includes pre-defined ANA patterns in a sequential procedure (Hensher & Greene, 2010; Weller et al., 2014). In this case, the ANA patterns that are included vary among the studies. Some studies begin with a model including one totally attended class plus a partially non-attended class by each attribute and a fully non-attended class. Then, the researcher includes classes combining two or more non-attended attributes, searching for the model with the best fit[30]

[30] For instance, if there are three attributes (A1, A2, A3), there are eight possible ANA patterns in total. The researcher starts with one model with five classes (fully attended, ignoring A1, ignoring A2, ignoring A3 and ignoring A1-A2-A3). Then, a second model can include all previous classes with a membership probability significantly different from zero plus classes ignoring two attributes simultaneously and so on. The final model is the one with the best fit.

(e.g.Campbell et al., 2011; Lagarde, 2013; Scarpa et al., 2009, 2013). Other studies do not follow any of these two approaches when the number of attributes is low (less than four) because they include all ANA patterns, as in Hensher et al. (2012).

The previous review shows that the success of the step-wise approach relies heavily on the researcher's decision about which and how many ANA patterns to include in the model. Thus, one question arising is: Which should follow the researcher, the exclusion approach or the step-wise approach? To the best of the researcher's knowledge, no study has attempted to compare the effectiveness of both. Consequently, this study compares the exclusion approach with a step-wise approach. Moreover, since there is no consensus about how the step-wise approach should be applied, this study also proposes a strategy by incorporating an objective element to guide the decision about which ANA patterns include—the self-reported ANA information.

There is substantial evidence that, regardless of the chosen approach, model efficiency can be improved by accounting for ANA rather than ignoring it (Hensher, 2014; Scarpa et al., 2009). However, more research is required about this behaviour. Most studies use either stated or inferred ANA, but only a few combine both approaches (Hensher et al., 2013; Hole et al., 2013). Although the literature has questioned the reliability of self-reported ANA to identify genuine ANA behaviour (Hensher et al., 2013; Hess & Hensher, 2010), to deny the richness of this information would be imprudent. Moreover, different authors have suggested combining stated and inferred ANA (Hensher, 2010; Lew & Whitehead, 2020).

Thus, this study uses self-reported information to guide the choice of ANA patterns to add to the modelling. This is expected to reduce the current subjectivity of the step-wise approach by combining stated and inferred ANA.

4.2.2 Use of images in a choice experiment

How the human brain processes information is under constant study in cognitive science. Similarly, how the brain acquires information and the role played by the presentation format is also widely studied. Authors such as Sojka and Giese (2006) suggest that individuals respond differently to visual and verbal stimuli. For visual stimuli, the literature supports the advantage of using images to recall and recognise—the so-called the ‘picture superiority effect’ (McBride & Dosher, 2002; Whitehouse et al., 2006). Confirming this effect, the dual-coding theory of Paivio (1975) acknowledges that images are easier to remember than words, which is beneficial in memory tasks. The idea that images allow individuals to evoke sensory experiences, such as taste or smell, increases the meaning of the information received, making them superior to words alone (M. Kim & Lennon, 2008; Whitehouse et al., 2006). Moreover, the education literature argues that using a combination of visual aids and text improves individuals’ learning compared with texts or images alone (Mayer, 2009).

In choice tasks faced by individuals, such as those performed during a choice experiment, the literature also recognises the benefits of using images.

First, visual aids help to provide information about the attributes (and levels) when it is difficult to describe them in words, thereby reducing possible wrong interpretations (Green & Srinivasan, 1978; Jansen et al., 2009). Second, images bring individuals closer to what they observe in the real world (Green & Srinivasan, 1978; Jansen et al., 2009; Vriens, Loosschilder, Rosbergen, & Wittink, 1998). Third, observing images reduces fatigue (Green & Srinivasan, 1978). Fourth, visual aids help to capture individuals' attention (Pieters & Wedel, 2004). Moreover, including both images and text to describe attributes seems to enhance the information, reducing the possible non-attendance of individuals (Shr et al., 2019). Nevertheless, images must be used with caution because they can include visual cues, such as size, colour or texture that may affect the main message (Green & Srinivasan, 1978; Jansen et al., 2009).

Keeping information in the working memory of the individual is critical during a choice task, and images can help in this matter (Arentze, Borgers, Timmermans, & DelMistro, 2003). One of the reasons why respondents may decide not to consider all attributes during a choice experiment is the cognitive burden of the task. Images can facilitate this task. Different studies have assessed how complex tasks can induce respondents to use ANA as a coping strategy. Hensher's (2006) study is one of the first to address this issue. The author assesses different scenarios by manipulating the number of choice sets, alternatives, attributes, attribute levels and their range. The increment in these elements makes the choice task more difficult, thereby creating a cognitive burden for the respondent. Hensher (2006) finds that if the experiment becomes more complex, respondents tend to use coping strategies such as ANA. In a more recent study, Grebitus and Roosen (2018) examine the impact of the number of attributes and alternatives on the attribute processing strategies, with similar findings.

Another element that can either simplify or complicate a choice task is the presentation of the experiment. There are different ways to manipulate and display a choice experiment, thereby affecting the results (Hensher, 2014). The order of attributes, horizontal or vertical arrangement or the use of text or images to represent the attributes can be used to manipulate how respondents perceive (or attend) the information. To control for order effects, most studies randomise the list of attributes between respondents. There is also consensus that attributes should be presented in rows and alternatives in columns. However, the discussion about using images to represent the attributes is not completely settled. Although Vriens et al. (1998) do not include a discussion about ANA, they provide a starting point by evaluating how images can affect relative attribute importance, segmentation and reliability and accuracy. They find that images produce higher relative importance ratings (just for some attributes) and more heterogeneity among consumers. This leads them to conclude that images improve consumers' understanding of the attributes. In a more recent study about the use of images on wine labels, Jaud and Melnyk (2020) find that labels combining text and images increase both the appeal of the label and the buying intention (compared with text-only labels). This approach also facilitates consumer product evaluations. Some studies indicate that images in choice experiments provide a more realistic buying experience (Jansen et al., 2009; Orzechowski et al., 2005); however, others suggest that there is no improvement in consumer understanding (Veldwijk et al., 2015)

Thus, this study evaluates if using attribute images facilitates the consumer decision process by minimising the possibility of ANA as a coping strategy. The expected result is that including images to support the presentation of attributes helps respondents understand and visualise the product better, thereby yielding a superior model to a text-only presentation format.

4.3 Data and Method

This study conducts a choice experiment on yoghurt to assess the role of attribute images and self-reported ANA in an LCM estimation to uncover market segments.

4.3.1 Experimental design

The experiment consisted of a between-subjects design with manipulation of the presentation format at two levels: text only versus text and images. The study selected yoghurt as the target product for three reasons. First, yoghurt can be considered a low-involvement product, whose attributes are relatively familiar to most people (Calvo-Porral, Ruiz-Vega, & Lévy-Mangin, 2018; Mittal, 1989). This was intended to reduce the time required by respondents to familiarise themselves with the yoghurt attributes shown in the experiment, thereby reducing cognitive burden and fatigue. Second, as respondents may already know which attributes they prefer in yoghurts, the ANA behaviour may be closer to reflecting their real preferences. Third, using images may help to recall their routine purchase choices (Whitehouse et al., 2006), making the decision easier.

The yoghurt had five attributes and price, all of them in different levels as shown in Table 4.2. The selection of these attributes was in line with the findings of other empirical studies. Various studies on yoghurt consumption agree that flavour and nutritional components such as sugar and fat content are highly valued by consumers (Ballco, Caputo, & de Magistris, 2020; Ballco, de Magistris, & Caputo, 2019; Orquin, Chrobot, & Grunert, 2018). Packaging and organic certification are generally considered less important (Van Loo, Diem, Pieniak, & Verbeke, 2013). Thus, the experiment included highly relevant and less relevant attributes of the same product.

Table 4.2 Yoghurt attributes presented in each alternative of the choice experiment

	Level 1	**Level 2**	**Level 3**	**Level 4**
Fat content	Fat Free	5% Fat		
Flavour	Berries	Plain (natural)	Vanilla	
Organic information	Not organic	Organic	Certified organic	
Packaging (container)	Not recyclable	Recyclable		
Sugar	No added sugar	5% added sugar		
Price (100 grs)	\$0.7	\$0.9	\$1.2	\$1.5

The choice experiment consisted of 12 choice tasks.[31] Each task included three alternatives of yoghurt plus a ‘none’ option. The design was created using the Sawtooth (2019) CBC software following the balanced overlap method, meaning that within-subjects was nearly orthogonal across attributes and level-balanced. This method is generally recognised as optimal for mixing both the complete enumeration and the random methods, such that the orthogonality is well controlled, duplicate alternatives are not allowed within the same task and possible mechanic responses based on observing only one attribute are reduced. In addition, to control for order effects, the design of within-choice tasks was randomised. Thus, the attributes listed vertically were randomised between subjects but kept in the same order within all tasks for the same respondent. Only the attribute price was always presented at the bottom.

4.3.2 Sampling and procedure

The total sample consisted of 800 participants recruited from the online platform, Prolific. All participants are over 18 years of age and residents of Australia. They were randomly assigned to one of the two conditions describing the attributes as either text only (TO) or text and images (T&I). The survey included two questions to exclude respondents disliking or not consuming yoghurt. The first control question was related to how often they ate yoghurt. In the question, the respondents were required to select their answer on a five-point

[31] The first two tasks were fixed among all respondents as a warm-up exercise and were not included in the subsequent econometric analysis.

scale (ranging from 1 being *always* to 5 being *never*). Thus, individuals who stated never having eaten yoghurt were removed from the sample (six from the TO condition and nine from the T&I condition). The second question asked to what extent they liked eating yoghurt (on a seven-point scale). This question was designed to remove individuals who disliked eating yoghurt very much or did not like eating yoghurt at all. In this question, a total of eight respondents fulfilled the criteria; however, they had already been eliminated through the first control question. Thus, after eliminating individuals who either never ate yoghurt or did not like it, the final sample was 785, including 394 in the TO condition and 391 in the T&I condition. A general description of the respondents is provided in Table 4.3.

Table 4.3 Sample description of respondents categorised by condition

	TO condition	**T&I condition**
Age (average)	32.3 years	31.7 years
Gender		
Female	51.02%	48.59%
Male	47.72%	50.38%
Other	1.27%	1.02%
Income level(*)		
Less than $399	24.62%	20.97%
Between $400 and $599	15.99%	13.55%
Between $600 and $799	12.18%	8.70%
Between $800 and $999	11.68%	12.02%
Between $1,000 and $1,299	11.93%	16.11%
Between $1,250 and $1,499	7.87%	8.18%
Between $1,500 and $1,999	9.14%	13.04%
More than $2,000	6.60%	7.42%
Marital status		
Single	52.54%	52.43%
Married/permanent live-in partner	42.64%	46.29%
Separated/divorced/widowed	4.82%	1.28%
Educational level		
Secondary school or lower	16.50%	16.88%
Certificate level	10.66%	10.23%
Diploma or advanced diploma	6.85%	8.95%
Bachelor degree	46.95%	44.50%
Masters degree or higher	19.04%	19.44%

* Income level is shown in AUD.

4.3.2.1 Choice tasks

Each participant completed the online survey. The first section of the survey included the choice experiment described in the previous section. Figure 4.1 shows a standard choice task offered in both experimental settings. The presentation format followed the traditional display; that is, attributes in rows and alternatives in columns. Across the two conditions, respondents were exposed to the attributes displayed either as TO or T&I. For the TO condition, each attribute level was always displayed in one row. For the T&I condition, each attribute included the verbal description and a corresponding image of equal size below the text.

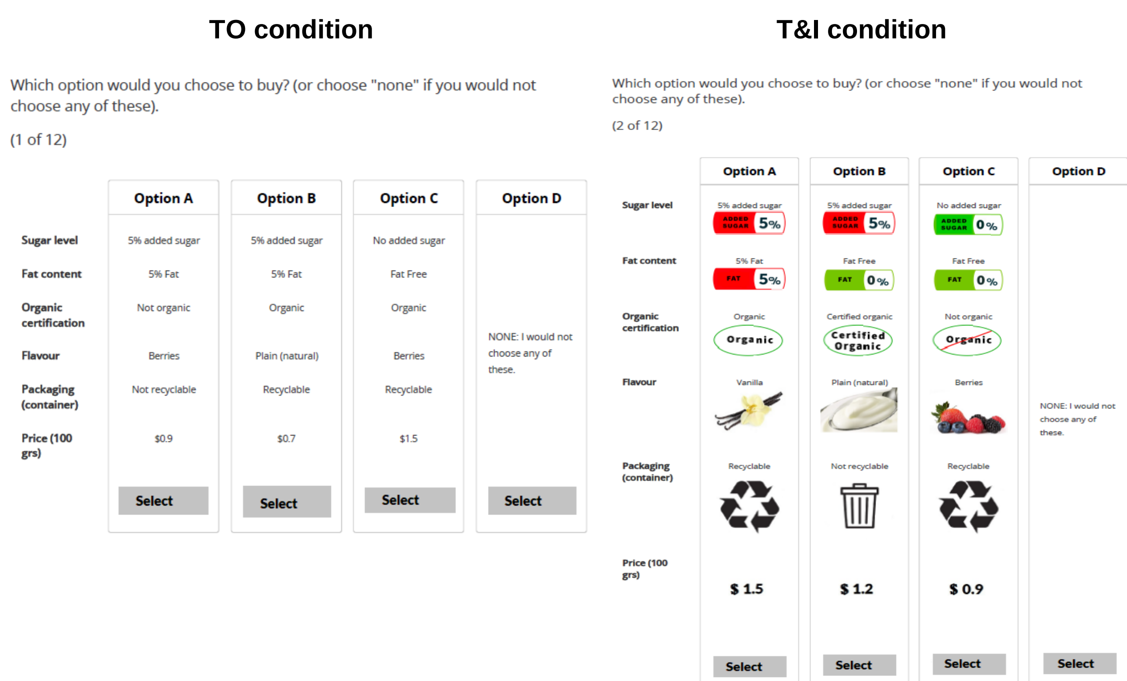

Figure 4.1 Example of a choice task for each type of condition

4.3.2.2 Measures

Immediately after completing the 12 choice tasks, the respondents answered a question to determine which of the attributes in the experiment they had ignored during the choice tasks. This type of information is commonly used to analyse stated ANA (Campbell et al., 2008; Carlsson et al., 2010; Hensher, Rose, & Bertoia, 2007; Hensher et al., 2005; Hess & Hensher, 2010; Hole et al., 2013; Rose, Hensher, Greene, & Washington, 2012; Scarpa et al., 2010). The question was as follows: *From all the attributes that were offered to you*, *please select the attribute(s) that you did NOT consider (or that you ignored) during your choice tasks (you can select more than one attribute if relevant).* In addition, the respondents answered a rating question about the importance of every attribute during their choices. Specifically, they rated all the attributes on a five-point scale, with 1 being *very important* and 5 being *not important at all*, to indicate how they influenced their previous choices. This question about attribute importance was used to validate the consistency of self-reported ANA questions since low importance attached to an attribute can signal potential non-attendance (Pike, Kotsi, Oppewal, & Wang, 2020). The survey ended with some general questions related to their consumption behaviour and sociodemographics.[32]

[32] Appendix C.1 shows the questions included in the survey applied to the sample and the participant consent form.

The respondents did not have any time constraint to answer the questions, thereby avoiding time pressure as a potential external stimulus for ANA as a coping mechanism.

4.4 Results

This section begins with the analysis of the time spent to complete the choice experiment, followed by the analysis of the stated importance and stated ANA information. Later, it continues with the LCM used to accommodate ANA using two approaches.

4.4.1 Time spent on the choice experiment

The time spent to complete the choice experiment under each condition is listed in Table 4.4. As expected, the respondents spent more time on the first choice task (fixed), and as they progressed through the experiment, the time decreased.

Table 4.4 Time spent by respondents on each choice task per condition (mean and median values)

	CT1	CT2	CT3	CT4	CT5	CT6	CT7	CT8	CT9	CT10	CT11	CT12	Total DCE
TO	34.1	23.7	18.9	22.3	18.9	16.1	15.0	17.5	15.1	15.6	13.2	14.2	222.2
	28	18	15	14	12	12	12	11	11	10	10	10	189
T&I	39.6	25.2	20.2	19.4	16.8	18.2	15.4	16.1	16.8	15.3	16.3	12.2	231.7
	33	20	16	14	13	13	12	11	11	11	11	10	202

Note: The value presented above represents the average time, while the median is presented below. Both are presented in seconds.

For all the tasks, the average time used to answer was not statistically different between both conditions, except for the first task (34.1 seconds in the TO condition versus 39.6 seconds in the T&I) and the last task (14.2 and 12.2 seconds, respectively). In terms of the median time, only the first choice task took, statistically, more time in the T&I condition compared with the TO condition (33 versus 28 seconds, respectively). A similar result is in the choice experiment of Vass, Davison, Vander Stichele and Payne (2020), who compared a plain-text survey with an animated storyline survey in a health study. Their findings revealed no statistically significant difference in the mean time spent on the choice tasks under both types of surveys. Thus, these findings show that the respondents' engagement was similar in terms of the time spent on each choice task under both conditions. Table 4.5 shows the tests comparing the mean and median time spent on each choice task in both conditions.

Table 4.5 Comparison of spent time per choice task.

	CT1	**CT2**	**CT3**	**CT4**	**CT5**	**CT6**	**CT7**	**CT8**	**CT9**	**CT10**	**CT11**	**CT12**	**Total DCE**
t	2.23	0.82	1.14	1.02	0.97	1.03	0.39	0.53	0.80	0.16	1.48	2.35	0.98
	(0.03)	(0.41)	(0.25)	(0.31)	(0.33)	(0.31)	(0.70)	(0.60)	(0.43)	(0.87)	(0.14)	(0.02)	(0.33)
χ^2	12.75	2.25	1.46	0.10	2.35	1.95	0.51	0.80	0.25	0.22	0.81	0.01	2.95
	(0.00)	(0.13)	(0.23)	(0.75)	(0.13)	(0.16)	(0.48)	(0.37)	(0.62)	(0.64)	(0.37)	(0.94)	(0.09)

Note: The t-test is for mean time while the Pearson χ^2 test is for the median time. The value presented in parentheses is the *p* value.

4.4.2 Stated importance and stated attribute non-attendance

Respondents rated each attribute on a five-point scale. In both conditions, the importance order of the attributes was matching.[33] The highest importance was attached to the attribute, *flavour* (mean_TO = 3.64 and mean_T&I = 3.81), followed by *sugar* (mean_TO = 3.60 and mean_T&I = 3.59) and *packaging* (mean_TO = 3.19 and mean_T&I = 3.05). The lowest importance was assigned to the attributes, *fat* (mean_TO = 2.88 and mean_T&I = 2.94) and *organic* (mean_TO = 2.47 and mean_T&I = 2.63). However, there was a statistical difference in the means of two of the attributes.[34] For the most important attribute, *flavour*, and the less important attribute, *organic*, the importance assigned in the T&I condition was higher than in the TO condition.

Figure 4.2 shows the distribution of the attributes' stated importance per condition, in which the categories *very important* and *important* were merged and renamed *very important or important*, while the categories *of little importance* and *not important at all* were merged and renamed *of little importance*. According to this information, it could be expected that, regardless the condition faced by the respondent, the most ignored attributes would be *organic*, *fat* and *packaging*.

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[33] Nevertheless, the test could not reject that the mean importance values for *flavour* and *sugar* were statistically equal for the TO condition. Thus, statistically, both attributes shared the same importance for respondents under the same condition. The same applied for the attributes *packaging* and *fat* for the T&I condition, where both attributes, statistically, shared the same importance level.

[34] Appendix C.3, Table C.3.1 shows the results of the Kruskal–Wallis test. The test evaluates whether the mean ranks are different between both groups. For the attributes, *flavour* and *organic,* the mean ranks were statistically different (p values of 0.029 and 0.048, respectively). However, for the attributes *sugar*, *packaging* and *fat,* the test was unable to reject the hypothesis of equal mean ranks.

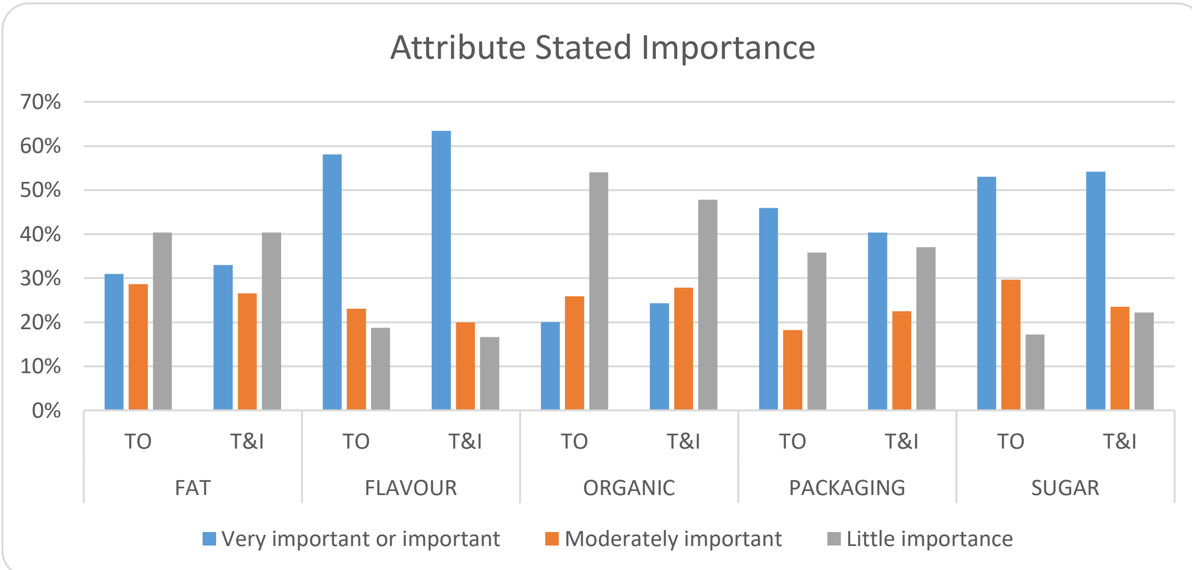

Figure 4.2 Attributes' stated importance per condition

Along with the attribute importance question, the respondents also answered which attribute(s) they ignored during the experiment (stated ANA). A high percentage indicated having ignored at least one attribute during their choices.[35] In the TO condition, this percentage was 77.92%, while in the T&I condition it was slightly higher, at 78.52%. However, after performing a chi-square test comparing both proportions, the chi-square was 0.014, with a *p* value of 0.907, showing that it was not statistically significant. Most individuals ignored one or two attributes and only a few showed lexicographic preferences. Table 4.6 summarises the percentage of respondents ignoring attributes.

[35] The price was not considered in this analysis so as to only focus on the specific attributes of the product.

Table 4.6 Stated attribute non-attendance

	TO condition	T&I condition
No attributes ignored	22.08%	21.48%
Only one attribute ignored	28.93%	32.74%
Two attributes ignored	30.20%	27.62%
Three attributes ignored	13.96%	13.04%
Four attributes ignored	4.57%	4.60%
All five attributes ignored	0.25%	0.51%

Table 4.7 shows the frequency of respondents ignoring each attribute either by itself or along with others. In both conditions, when respondents indicated having ignored just one attribute, the most ignored was *organic*, coinciding with the less rated attribute in terms of importance. The second most ignored attribute in the TO condition was *fat*, while in the T&I condition it was *packaging*, followed by *fat*. This result was not unexpected, compared with the importance ranking, since both attributes shared the second last place. The less ignored attributes, in both conditions, were *flavour* and *sugar*, which also coincided with the most important attributes.

Table 4.7 Frequency of stated ANA in both conditions

	TO condition		T&I condition		Total
	N° respondents	**%**	**N° respondents**	**%**	**N° respondents**
Fat	135	34.26%	125	31.97%	260
Flavour	85	21.57%	72	18.41%	157
Organic	181	45.94%	157	40.15%	338
Packaging	110	27.92%	142	36.32%	252
Sugar	83	21.07%	83	21.23%	166

Note: The number of individuals ignoring the attribute includes not just those who stated they ignored only one attribute, but also those who ignored that attribute in combination with other attributes.

For the respondents who stated that they ignored two attributes simultaneously, the majority indicated *organic* and *packaging* (26.9% in the TO condition and 33.3% in the T&I condition, which corresponds to 8.1% and 9.2% from the total sample, respectively). Appendix C.2 summarises all 32 possible ANA patterns with the percentage of individuals under each pattern. The top eight ranked ANA patterns in both conditions coincided with the two bigger classes (full attendance and ignoring only *organic*). The remaining six places also coincided in the ANA patterns but they were placed in different positions, except for one ANA pattern that was not in both conditions. An unexpected finding in this top eight ANA pattern ranking was that one class ignored only *flavour*, which was stated as the most important attribute for both conditions, along with *sugar.* This result indicates that even if this attribute was relevant for most consumers, a group of them ignored it when choosing a yoghurt.

Considering the attribute importance information and the self-reported ANA, one could expect a strong correlation between both variables. Specifically, a negative and significant relationship between both was expected. Thus, a logit model was used to evaluate the consistency of the stated ANA information, in line with Carlsson et al. (2010). Table 4.8 reports the logit estimations, where the dependent variable is the probability of ignoring one of the attributes. These variables are explained by the importance assigned to the respective attribute (*Imp_att*) and sociodemographic variables such as age, gender, educational level, income, marital status and whether the respondent had children. Attitudinal variables can also explain why a respondent attends (or ignores) a particular attribute. Thus, the model included some attitudes towards organic products, sport activities, and recycling. For instance, it could be expected that a person who plays sport regularly would care more about healthy attributes than a person who plays sport sporadically. In the same vein, a person who consumes organic products often would also be more likely to pay attention to organic labels on yoghurts. The same applies to a person who recycles often, who would therefore be more likely pay attention to packaging. In addition, the model includes a dummy variable named *image* to capture potential differences between both TO and T&I conditions. Appendix C.4 describes these variables and reports the logit estimation for each survey and attribute.

Table 4.8 Summary of the logit estimations for each attribute.

	Fat		Flavour		Organic		Packaging		Sugar	
	Coef.	s.e	Coef.	s.e	Coef.	s.e	Coef.	s.e	Coef.	s.e
Imp_att	**-1.515**	**0.115**	**-1.113**	**0.098**	**-1.492**	**0.117**	**-1.243**	**0.095**	**-1.027**	**0.095**
Age	-0.013	0.011	0.004	0.011	-0.002	0.009	0.001	0.010	-0.017	0.011
Female	-0.078	0.194	-0.252	0.211	-0.077	0.190	-0.130	0.200	-0.044	0.205
Single	-0.277	0.228	0.296	0.258	0.321	0.225	-0.195	0.243	-0.291	0.239
Edu_univ	0.147	0.207	0.250	0.234	0.309	0.200	0.160	0.211	-0.127	0.213
No_kids	0.127	0.228	-0.355	0.245	-0.074	0.226	0.043	0.240	0.205	0.242
Income	-0.085	0.198	-0.197	0.215	0.296	0.192	-0.057	0.203	0.139	0.209
Freq_ sport	-0.214	0.204	0.075	0.222	-0.152	0.196	0.029	0.207	-0.168	0.213
Freq_ recycle	0.158	0.261	-0.521	0.274	0.295	0.243	-0.138	0.241	-0.285	0.260
Freq_ organic	0.336	0.236	-0.237	0.248	-0.372	0.276	-0.186	0.257	**0.472**	**0.240**
Image	0.026	0.198	-0.036	0.214	-0.176	0.191	**0.481**	**0.203**	-0.031	0.209
Const	**3.546**	**0.591**	**2.767**	**0.672**	**2.908**	**0.556**	**2.580**	**0.577**	**2.775**	**0.631**
Pseudo R2	0.323		0.240		0.329		0.332		0.219	

* Note: Dependent variable: probability of ignoring the attribute according to stated ANA questions. $p < 0.05$ in bold numbers.

From the results in Table 4.8, three conclusions can be drawn. First, when individuals assign more importance to an attribute, there is a lower probability of ignoring that attribute during a choice task. This result emerged for all five attributes, confirming a recent study by Pike et al. (2020), which reports that attributes considered more important by consumers are also more attended; hence, they are considered during a choice decision. Thus, those attributes considered less significant by consumers have a greater probability of been ignored.

Second, the probability of ignoring a particular attribute seems not to be affected by the presentation format of the survey, except for the attribute, *packaging.* In particular, the probability of ignoring this attribute increases if the respondents face the T&I condition compared with the TO. It would seem that respondents who were more familiar with recycling images reacted closer to what they would do in an actual buying situation for this type of product.

Third, all sociodemographic coefficients were statistically insignificant, as were most attitudinal variables. These results support those of Carlsson et al. (2010). A possible explanation of this result is that there seems no particular individual characteristic leading a respondent to ignore an attribute. The only exception is the importance given to the attributes, which is highly significant.

4.4.3 ANA and market segmentation

The LCM estimation is used to obtain market segments while accounting for ANA. The utility function for the general model is given in Equation (1). For simplicity, subscripts for each individual, alternative and choice situation, were omitted. Dummy variables represented the five attributes through their levels. The base categories were *plain* (natural), *not organic*, *no added sugar*, *fat-free* and *not recyclable*. This model allowed heterogeneity between classes for the main attributes, except for the variables *SQ* (representing the status quo or non-buying situation) and *Price*, which were fixed for all the classes. Additionally, the models did not incorporate covariates to predict latent class membership.

$$U = \beta_{Vanilla}Vanilla + \beta_{Berries}Berries + \beta_{Organic}Organic + \beta_{Orgcertif}Orgcertif + \beta_{Sugar}Sugar + \beta_{fat}Fat + \beta_{pack}Packaging + \overline{\beta_{SQ}}SQ + \overline{\beta_{Price}}Price + \varepsilon \quad (1)$$

After the estimation of several LCMs with different numbers of classes, the best model was selected according to the lowest BIC value. If the classes predicted in this best model included several small segments, the posterior description and analysis would focus on the largest segments (covering at least half of the sample).

This study followed two strategies to accommodate ANA in the LCM: the exclusion strategy and the step-wise strategy.

4.4.3.1 Exclusion strategy and step-wise strategy

The exclusion strategy used in this study involved the estimation of several LCMs, differing in the number of classes included. The first LCM included all possible ANA patterns. From this first model, the second LCM excluded the classes with class membership probability statistically equal to zero. Then, each consecutive LCM dropped the smaller size class until a model was reached with only two classes. The chosen best model was the one with the lowest BIC value.

In this first strategy, ANA was fully inferred analytically and did not include any additional information from the respondents. Figure 4.3 represents this procedure.

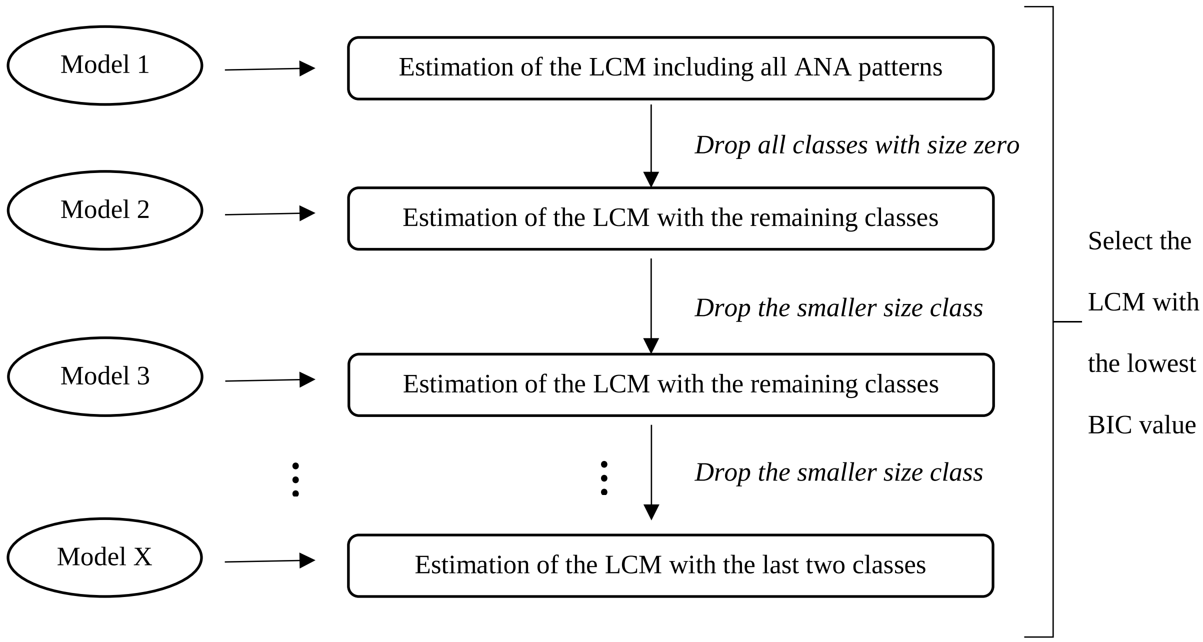

Figure 4.3 Graphical representation of the exclusion strategy

The step-wise approach used in this study followed a reverse strategy. The ANA patterns were added sequentially based on the stated ANA information. Specifically, from the self-reported ANA, all 32 ANA patterns were ranked from the most to the least frequent, as the information in Table 4.9 with the first-ranked ANA patterns (see Appendix C.2 for the entire ranking).

Table 4.9 Most frequent ANA patterns in both conditions

ANA patterns TO condition	**% respondents TO condition**	**ANA patterns T&I condition**	**% respondents T&I condition**
Full attendance	22.08	Full attendance	21.48
Ignored only organic	11.42	Ignored only organic	11.25
Ignored organic & packaging	8.12	Ignored only packaging	9.46
Ignored only fat	5.84	Ignored organic & packaging	9.21
Ignored fat & organic	5.84		
Ignored only flavour	5.08	Ignored only flavour	5.63
Ignored fat & sugar	5.08		

* Note that fourth and fifth places share more than one ANA pattern under the TO condition.

From this ranking, the step-wise approach began with the estimation of the first LCM, including the two larger ANA patterns. Next, the third ANA pattern was added to the previous model to estimate a new LCM. Then, the fourth was added and so on, until all ANA patterns were included. The model with the lowest BIC value was the final chosen model. Figure 4.4 represents this second strategy.

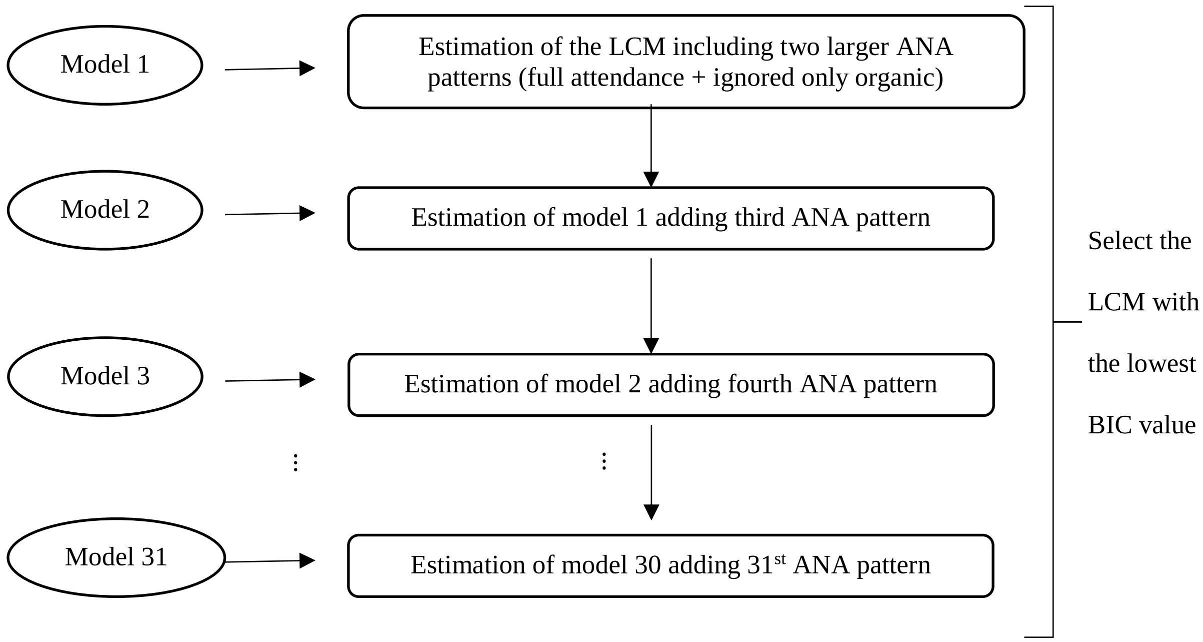

Figure 4.4 Graphical representation of the step-wise strategy based on self-reported ANA

The study begins by estimating a traditional LCM, without accounting for ANA, as a benchmark. Then, the study presents the estimation of the LCMs accounting for ANA following both strategies, as described above. All the estimations used Latent Gold software (Vermunt & Magidson, 2005).

4.4.3.2 Benchmark estimation

The estimation began with the traditional LCM, not accounting for ANA, as a benchmark. From 2 to 18 classes, for the TO condition sample, the lowest BIC value was obtained with 12 classes (BIC = 8262.2), while for the T&I condition sample, the lowest BIC value was obtained with 15 classes (BIC = 8101.9). Raftery's rule states that if a difference between two BIC values is lower than 2, then that difference can be considered weak (Raftery, 1995). In the present case, applying this rule, more parsimonious models could be chosen; that is, models with a low number of classes. For the TO condition, the best model would be the LCM with 10 classes, while for the T&I condition, it would be a model with 14 classes. Table 4.10 shows the BIC values for this benchmark models.

Table 4.10 BIC values for LCMs from 2 to 18 classes for both conditions (without accounting for ANA)

N°classes	TO condition	T&I condition	N°classes	TO condition	T&I condition
2	9060.70	9010.90	11	8262.49	8122.86
3	8717.37	8752.10	**12**	**8262.17**	8106.67
4	8570.98	8590.45	13	8267.52	8104.32
5	8458.75	8474.48	***14***	8281.36	***8103.67***
6	8385.51	8385.46	**15**	8295.42	**8101.89**
7	8336.72	8309.13	16	8310.90	8110.14
8	8291.59	8244.28	17	8328.25	8120.68
9	8272.86	8194.19	18	8345.04	8130.09
10	***8263.39***	8153.61			

* Bold represents the optimal number of classes under the BIC criterion, while italic bold represents the final selected benchmarks.

Thus, the benchmark models had 10 classes and 14 classes for the TO and T&I conditions, respectively. A summary of these two models is shown in Table 4.11, where the status quo coefficient was negative and statistically significant, as was the price coefficient (both fixed for all classes). The coefficient signs of each attribute level differed between classes, where a positive sign reflected a positive preference for the attribute level while a negative sign indicated that the respondent disliked that attribute level compared with the baseline.

Table 4.11 Classes predicted without accounting for ANA

TO condition									T&I condition							
	Class size (%)	**Vanilla**	**Berries**	**Organic**	**Organic certified**	**Sugar added**	**5% Fat**	**Packaging recyclable**		**Class size (%)**	**Vanilla**	**Berries**	**Organic**	**Organic certified**	**Sugar added**	**5% Fat**	**Packaging recyclable**
C1	20.3	NS	N	P	P	N	N	P	C1	17.0	P	P	P	NS	N	N	P
C2	19.4	P	P	P	NS	P	P	P	C2	17.0	N	NS	P	P	N	N	P
C3	10.0	N	NS	NS	N	N	N	P	C3	8.5	P	P	P	P	N	NS	P
C4	9.6	P	P	P	P	N	NS	P	C4	7.7	P	N	P	P	NS	N	P
C5	9.5	P	P	NS	P	N	NS	P	C5	6.9	NS	NS	P	P	N	NS	P
C6	9.1	NS	NS	P	P	NS	NS	P	C6	5.8	P	P	NS	NS	NS	NS	P
C7	8.6	P	P	P	P	N	N	P	C7	5.7	NS	NS	NS	NS	N	P	P
C8	7.0	NS	N	P	P	N	P	NS	C8	5.3	N	P	NS	NS	N	N	NS
C9	4.7	P	P	NS	P	NS	N	NS	C9	5.2	N	N	P	P	N	NS	P
C10	1.8	N	N	P	P	NS	NS	P	C10	4.6	P	P	P	P	N	N	P
									C11	4.5	NS	NS	N	NS	N	P	NS
									C12	4.5	N	N	NS	NS	N	N	P
									C13	3.7	N	NS	N	N	N	NS	N
									C14	3.6	NS	NS	P	P	P	P	NS

* Symbol meanings: '*P*' is a positive significant preference for the attribute; '*N*' is a negative significant preference for the attribute; and '*NS*' means that the parameter is statistically not significant at 5%.
** Comparison base for each attribute: vanilla and berry / plain (natural); organic and organic certified / not organic; sugar added / no sugar added; 5% fat / fat-free; and packaging recyclable / not recyclable.

4.4.3.3 Strategy 1. LCM accounting for ANA using an exclusion approach

This strategy began with the estimation of the LCM with all 32 ANA patterns. For the TO condition, the lowest BIC value was 8169.9 with 16 classes, while for the T&I condition, the lowest BIC value was 8017.5 with 18 classes (Appendix C.6, Table C.6.1 summarises the BIC values for all estimated LCMs for both conditions). In both cases, there was an improvement in the model fit compared with their respective benchmarks. This result is similar to prior studies, supporting the idea that accounting for ANA enhances the models. Additionally, the model estimated in the T&I condition provided a better fit than the model from the TO condition. This provides the first indication that including visual aids in a choice experiment can better capture consumer behaviour.

The estimation results showed the expected signs. For the status quo coefficient, the mean was negative and statistically significant for both conditions, indicating that the respondents were likely to choose a purchase alternative instead of a non-purchase option. The price coefficient was also negative and statistically significant, as expected. For the rest of the attributes, on average, the vanilla and berry flavours were preferred over plain (natural). The same phenomenon occurred with organic quality, where organic or organic certified yoghurts were preferred over non-organic ones. The nutritional variables, sugar and fat, both presented negative coefficients, showing that respondents preferred yoghurts with no added sugar and 0% fat over yoghurts with 5% added sugar and 5% fat, respectively. Finally, concerning the packaging, respondents preferred yoghurts with recyclable packaging over those that were not recyclable. These are the average preferences, but at a segment level, some differences appears.

Table 4.12 summarises the preference structure of each predicted class (segment), considering the tastes towards the attributes. The presentation order of these segments was according to their class sizes. Both conditions predicted a different number of segments and their composition was also different. One condition yielded 16 segments and the other 18. Moreover, the segment with the higher market share gathered respondents attending all the attributes in the T&I condition, but in the other condition, this group was in fifth place. Adding up all the membership probabilities where each attribute was ignored, in the TO condition, the three most ignored attributes were *flavour* (52.8%), *fat* (39.3%) and *organic* (38.1%). For the T&I condition, this was *fat* (50.1%), *packaging* (32.7%) and *sugar* (31.8%). In contrast, the two least ignored attributes were *sugar* (15.9%) and *packaging* (31.4%) for the TO condition, and *flavour* (20.1%) and *organic* (29.4%) for the T&I.

Table 4.12 Classes predicted by condition using an exclusion approach (inferred ANA)

	TO condition									T&I condition							
	Class size (%)	**Vanilla**	**Berries**	**Organic**	**Organic certified**	**Sugar added**	**5% Fat**	**Packaging recyclable**		**Class size (%)**	**Vanilla**	**Berries**	**Organic**	**Organic certified**	**Sugar added**	**5% Fat**	**Packaging recyclable**
C1	14.5	-	-	-	-	N	N	P	C1	17.1	N	NS	P	P	N	N	P
C2	13.8	-	-	P	P	N	-	P	C2	9.2	P	P	P	P	N	-	P
C3	10.7	P	P	NS	N	NS	P	-	C3	7.2	P	P	-	-	-	NS	NS
C4	10.6	-	-	P	P	N	NS	P	C4	6.5	-	-	P	P	N	-	-
C5	8.4	P	P	P	P	N	N	P	C5	6.4	NS	NS	NS	NS	-	-	-
C6	6.5	-	-	P	P	-	-	P	C6	5.7	-	-	NS	NS	N	-	P
C7	5.6	N	NS	-	-	N	-	-	C7	5.5	P	P	NS	NS	-	NS	P
C8	5.4	P	P	-	-	N	-	P	C8	5.5	NS	N	P	P	-	-	P
C9	5.0	-	-	-	-	N	P	-	C9	5.0	N	P	-	-	N	-	-
C10	4.8	P	P	P	P	P	-	NS	C10	4.9	N	N	-	-	N	-	P
C11	3.2	P	NS	NS	P	-	-	-	C11	4.7	P	NS	-	-	-	-	P
C12	3.0	NS	P	-	-	-	NS	-	C12	4.6	-	-	P	P	N	N	-
C13	3.0	NS	NS	-	-	N	N	P	C13	4.1	P	P	-	-	N	N	P
C14	2.5	-	-	NS	NS	P	NS	-	C14	3.4	-	-	P	P	P	P	NS
C15	1.7	P	P	-	-	-	P	P	C15	3.4	NS	NS	-	-	N	P	-
C16	1.5	NS	NS	NS	NS	-	NS	-	C16	2.5	NS	N	P	P	-	NS	-
									C17	2.3	N	P	N	N	N	-	-
									C18	2.2	N	NS	NS	NS	NS	N	-

* Symbol meanings: '*P*' is a positive significant preference for the attribute; '*N*' is a negative significant preference for the attribute; '*NS*' means that the parameter is statistically not significant at 5%; and '-' means that the attribute was ignored.
** Comparison base for each attribute: vanilla and berry / plain (natural); organic and organic certified / not organic; sugar added / no sugar added; 5% fat / fat-free; and packaging recyclable / not recyclable.

4.4.3.4 Strategy 2. LCM using a step-wise approach based on stated ANA information

The previous strategy did not consider the stated ANA information obtained from respondents at the end of the experiment. Hence, this second strategy uses what respondents said they ignored during the choice tasks to define the ANA pattern to be included in the model. Thus, the first LCM included two classes characterised as the two first-ranked ANA patterns (according to the stated ANA ranking in Appendix C.2). For both conditions, these two first classes included full attendance and ignoring only the organic attribute. Several LCMs were then estimated, adding an extra class each time, following the ranked ANA patterns.

Table 4.13 summarises the best models (with the lowest BIC value) for each condition. In the TO condition, the best LCM had 15 classes, with a BIC value of 8162.8. For the T&I condition, the best model had 17 classes, with a BIC value of 8002.6; however, the LCM with 15 classes had a difference of less than 2 in the BIC value. Thus, following Raftery's rule, this model was also deemed acceptable (see Appendix C.6, Table C.6.2 for all BIC values for the estimated LCMs). In both cases, these models had a better fit than the benchmarks; they were also better than Strategy 1 used previously.

Table 4.13 Classes predicted by condition using a step-wise approach based on stated ANA information (inferred ANA combined with stated ANA information)

TO condition									T&I condition								
	Class size (%)	**Vanilla**	**Berries**	**Organic**	**Organic certified**	**Sugar added**	**5% Fat**	**Packaging recyclable**		**Class size (%)**	**Vanilla**	**Berries**	**Organic**	**Organic certified**	**Sugar added**	**5% Fat**	**Packaging recyclable**
C1	21.9	-	-	P	P	N	N	P	C1	19.0	NS	P	P	P	N	N	P
C2	11.9	P	P	P	P	N	NS	P	C2	12.4	P	P	-	-	N	-	-
C3	10.6	P	P	P	N	P	NS	-	C3	9.1	P	P	P	P	N	-	P
C4	9.1	P	P	-	-	N	N	P	C4	8.2	-	-	-	-	N	NS	P
C5	8.0	P	P	P	P	P	-	P	C5	7.0	-	-	P	P	N	NS	P
C6	5.2	-	-	P	P	N	-	P	C6	6.0	P	P	NS	N	-	-	-
C7	5.0	P	P	-	-	N	-	-	C7	6.0	N	P	-	-	-	-	-
C8	4.5	-	-	-	-	N	-	P	C8	5.6	NS	N	P	P	-	-	P
C9	4.5	N	NS	-	-	NS	-	P	C9	5.5	N	N	-	-	N	N	P
C10	4.4	NS	N	-	-	N	P	-	C10	5.0	P	NS	-	-	NS	-	P
C11	4.2	-	-	-	-	N	N	-	C11	4.3	-	-	-	-	N	P	-
C12	4.2	-	-	-	-	N	P	P	C12	3.7	NS	NS	P	P	P	P	-
C13	2.9	NS	P	-	-	-	-	NS	C13	3.0	P	P	-	-	N	N	-
C14	2.3	P	NS	-	-	-	-	-	C14	2.8	N	NS	N	N	N	-	-
C15	1.5	N	N	NS	NS	-	-	P	C15	2.5	NS	N	-	-	-	-	P

* Symbol meanings: '*P*' is a positive significant preference for the attribute; '*N*' is a negative significant preference for the attribute; '*NS*' means that the parameter is statistically not significant at 5%; and '-' means that the attribute was ignored.
** Comparison base for each attribute: vanilla and berry / plain (natural); organic and organic certified / not organic; sugar added / no sugar added; 5% fat / fat-free; and packaging recyclable / not recyclable.

Similar to the findings from Strategy 1, on average, the coefficients showed the expected signs. In addition, the largest segment in the T&I condition included individuals attending to all attributes. Nevertheless, this strategy differed from the one used previously in the number of segments predicted. In both conditions, the number of classes coincided (15 classes) and was lower than the number of classes from Strategy 1. The inferred ANA level was also different. For the TO condition, the three most ignored attributes were *organic* (41%), *flavour* (40%) and *fat* (33.9%), while for the T&I condition, these were *fat* (49.3%) *organic* (46.9%) and *packaging* (38.1%).

Table 4.14 summarises the main statistics for both strategies and conditions estimated. Confirming prior studies, accounting for ANA improves model performance regardless of the strategy followed by the researcher to account for ANA. However, two more results enhance the current understanding of how to identify and accommodate ANA. The first shows that, for all cases, the addition of visual aids to the experiment produces a better model fit compared with using text only. The second proves that, regardless of the survey format, Strategy 2 yields better estimation results than Strategy 1. This indicates that using stated ANA information and combining it with inferred ANA enriches the estimation process. Thus, of all cases under study, the LCM estimation using self-reported ANA information in the T&I condition proved to be the best model to explain preferences towards yoghurt.

Table 4.14 Summary of the best fit models

	LCM benchmark (not accounting for ANA)		LCM for Strategy 1 (inferring ANA)		LCM for Strategy 2 (inferring ANA using stated ANA information)	
	TO	**T&I**	**TO**	**T&I**	**TO**	**T&I**
N° classes	10	14	16	18	15	15
N° parameters	81	113	85	102	77	80
LL	-3889.65	-3714.60	-3830.95	-3704.33	-3851.32	-3763.09
BIC	8263.39	8103.67	8169.89	8017.46	8162.81	**8003.67**

Concerning the role of using images in the estimation to account for ANA, Table 4.14 summarises the level of ANA for each model. The percentages in the table show the proportion of individuals ignoring each attribute.[36] From these results, the inferred ANA is sensitive to the strategy followed and to the stimuli provided. In addition, compared with the stated importance assigned to each attribute, the model using Strategy 2 in the T&I condition predicted ignored (and not ignored) attributes, consistent with this indicator. From the stated importance question, the less important attributes were *organic*, *fat* and *packaging* and from the LCM estimations, the model using Strategy 2 for the T&I condition was the

[36] Considering that each individual has a posterior probability of being a member of each class within the model, this proposal acknowledges this 'fuzzy' membership to calculate the proportions of inferred ANA. Specifically, at an individual level, all membership probabilities for the classes in which the attribute was ignored were added to obtain the percentage of inferred ANA.

only one that predicted these same three attributes as the most ignored (although the order was not the same). In the same way, this model was the closest to the stated ANA frequencies. This last result was not surprising since that information was used to define the ANA patterns for inclusion in the model. This model also has the best fit. Therefore, these three findings give the confidence to state that this model was a good representation of the preferences towards yoghurt.[37]

Table 4.15 Inferred ANA results under both strategies and conditions compared with the stated ANA

	TO condition			T&I condition		
	Stated ANA	**LC16 (Strat.1)**	**LC15 (Strat.2)**	**Stated ANA**	**LC18 (Strat.1)**	**LC15 (Strat.2)**
Fat	34.3%	39.5%	33.9%	32.0%	50.1%	49.3%
Flavour	21.6%	53.0%	40.0%	18.4%	20.1%	19.5%
Organic	45.9%	37.9%	41.0%	40.2%	29.4%	46.9%
Packaging	27.9%	31.4%	26.4%	36.3%	32.7%	38.1%
Sugar	21.1%	16.0%	6.7%	21.2%	31.8%	20.1%

4.4.4 Characteristics of the best model

The best model was the LCM from the T&I condition under Strategy 2. This model included 15 segments, where the larger segment had a class size of 19% and the smaller had 2.5%. Of all the segments, five have a share market below

[37] Appendix C.5 summarises the results of the tests for equality of proportions. This test compares the ANA level inferred by each strategy and condition and the stated ANA information gathered from respondents.

5% and only five were above 7%. The existence of so many segments could lead to some issues in practising marketing strategies. For this reason, the following description considers the first five segments to analyse their preferences for yoghurt and the ANA behaviour (these groups form 56% of the sample). The main characteristics of these five segments are presented in Table 4.16.

The largest segment (19%) represented consumers attending all attributes. Consumers in this segment had positive preferences for organic berry yoghurt, with no sugar added, no fat and offered in a recyclable container. Most consumers were single (59%) with a university educational level (70%). Based on its characteristics, this segment can be named the *everything is important* group.

The second segment (12%) represented consumers only caring about flavour and sugar level—the two most important attributes stated by respondents. They did not care whether the yoghurt was organic or not, nor did they care about the type of packaging or the fat content. In particular, this segment preferred vanilla and berry flavours over natural (plain) and yoghurt with no added sugar. Sixty percent were male, who declared that flavour was a very important attribute in the yoghurt they bought. Thus, this segment can be described as the *concerned with flavour* group.

The third segment (9%) was similar to the first, except that consumers ignored the fat content of the yoghurt. In addition, they also preferred vanilla flavour over natural. Compared with the first segment, this group was predominantly male (57%), but they considered the level of sugar highly relevant (85%). Thus, this segment can be described as the *sugar aware* group.

The fourth segment (8%) represented consumers considering sugar, fat and packaging as the most relevant attributes regardless of the flavour or organic origin. They preferred yoghurt with no added sugar and no fat, in a recyclable package. This segment included a high number of females (59%). This was also the largest segment viewing packaging as very important (66%). Further, this segment had the highest percentage of respondents stating that they always recycled (69%). Thus, this segment can be described as the *environmentally friendly* group.

Finally, the fifth segment (7%) represented consumers preferring organic yoghurt with no sugar added in a recyclable package. The principal characteristic of this group was that they accorded a very high importance to the organic information (86% stated this attribute was very important or important). They played sports regularly (75% at least once a week). Thus, this group can be described as *natural and healthy*.

Table 4.16 Description of main yoghurt segments

	Segment 1 *Everything is important*	Segment 2 *Concerned with flavour*	Segment 3 *Sugar aware*	Segment 4 *Environmentally friendly*	Segment 5 *Natural and healthy*
Coefficients:					
Vanilla	0.034	3.189***	1.071***	0.000	0.000
Berries	0.599**	3.889***	0.920**	0.000	0.000
Organic	0.948***	0.000	1.318***	0.000	4.055***
Organic	1.089***	0.000	0.904**	0.000	4.759***
Certified	-1.530***	-0.514**	-4.678***	-0.527*	-0.831***
Added sugar	-1.241***	0.000	0.000	-0.167	-0.333 .
High Fat	1.712***	0.000	1.244***	3.776***	0.636**
Pack.					
Recyclable					
Relative importance:					
Vanilla	0.003	0.266	0.074	0	0
Berries	0.052	0.325	0.063	0	0
Organic	0.082	0	0.091	0	0.270
Organic	0.094	0	0.062	0	0.317
Certified	0.133	0.043	0.322	0.060	0.055
Added sugar	0.108	0	0	0.019	0.022
High Fat	0.148	0	0.086	0.426	0.042
Pack.					
Recyclable					
Some socio-demographics and consumer characteristics:					
Age (years)	29.8	31.3	33.0	34.0	29.4
% Female	50.7	40.0	51.3	59.4	42.9
% Single	59.2	52.0	56.4	56.3	57.1
% Sport week	70.4	58.0	64.2	56.3	75.0
% Recycling	85.9	78.0	89.8	93.8	89.3

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.1$

These five segments reflect the main characteristics of Australian yoghurt consumers. Although most consumers were concerned about each attribute of the yoghurt they bought, some groups focused more on certain characteristics of the product. When an LCM accounts for ANA behaviour, it highlights the importance attached to the remaining not-ignored attributes, making the segments more distinctive. For instance, the second segment in this study represented consumers who were highly aware of flavour, preferring either vanilla or berry over natural, and caring to a lesser extent about the sugar content but ignoring the remaining attributes. This result is not surprising considering that, for instance, Orquin et al. (2018) note that when consumers are asked to choose the yoghurt they prefer, the most preferred attribute is flavour. Another segment was very aware of the organic attribute, a product characteristic previously studied by other authors. Van Loo et al. (2013) indicate that women are more likely to buy organic yoghurt because of the safety and health characteristics of this type of yoghurt. However, in the present study, this segment comprised less than half women. This result shows that organic yoghurt is not only preferred by women but also by men. None of the five segments viewed fat content as an attribute of high importance. This result is in line with the study of Ballco et al. (2019) on natural yoghurt, which confirms that only the smallest segment accords high importance to the attribute of fat content.

4.5 Discussion

This study evaluates the effects of accounting for ANA in uncovering market segments using a controlled choice experiment. It assesses the role of using visual aids and self-reported ANA information to identify and accommodate ANA in an LCM.

Prior literature has extensively proved that model fit improves when the estimations account for ANA, either under a stated or inferred approach (Hensher & Greene, 2010; Hole, 2011; Lagarde, 2013; Scarpa et al., 2009, 2013). The present study confirms this statement by comparing the best fitted LCMs without considering ANA (benchmark models) with those accounting for ANA, regardless of the strategy followed. However, it also adds new evidence by using self-reported ANA information combined with inferred ANA (Strategy 2). The findings show that an LCM using ANA information provided by respondents during the survey performs better than models only inferring ANA analytically. This result is in contrast to the finding of Hensher et al. (2013), who conclude that stated ANA information has a weak link to the selection of ANA classes. In this study, the model using stated ANA information to guide the inclusion of ANA classes in the LCM estimation was superior, irrespective of whether the attributes were presented as text only or as text and images. In another study with similar results, Hole et al. (2013) report improved model performance when self-reported ANA information is added as dummy variables to the membership probability function.

This result indicates that stated ANA information in an LCM helps to better identify market segments.

The present study used two strategies to account for ANA in an LCM, one based on an exclusion approach and the other on step-wise approach. The results show that the selected strategy is important, particularly when the study includes numerous attributes. The total number of ANA patterns was 2^k, with *k* representing the number of attributes. Thus, the main problem with the exclusion approach arises when *k* is high, causing consistency problems in the estimation (degrees of freedom, convergence, achievement of local maximum, very low class membership probabilities, etc.). Meanwhile, the step-wise approach can lead to an overwhelming number of estimations using alternative restrictions if there is no clarity on the ANA patterns that must be included in the model. This study used the second strategy, guided by self-reported ANA information, to define the ANA patterns to include in the model. Then, the LCM estimation inferred the definitive ANA classes. This approach shows consistent results, not just in terms of the stated ANA, but also the stated importance information.

The literature has debated what truly constitutes such ANA information—is it a reflection of genuine preferences or is it just a coping mechanism to deal with a complex task? Our study demonstrates that if the complexity of the choice experiment is reduced, the ANA will more faithfully represent genuine preferences, thereby yielding a better model. Choice task complexity can be manipulated in different ways, for instance, by controlling the number of attributes and levels, the number of alternatives and the number of choice sets, or by presenting the attributes horizontally or vertically, in a particular order and in a particular format, as text only or as text and images. This study assessed the last option.

In general, there is a consensus about the number of attributes, alternatives and choice sets to be included to ensure an efficient design and reduce respondents' burden during a choice experiment. A large number of attributes increases the cognitive burden (DeShazo & Fermo, 2002). Therefore, generally, no more than 10 attributes are included with at least two levels. This study used five yoghurt attributes at two or three levels as well as the price. Generally, there should be three or four alternatives (including a non-purchase option) to ensure comparison, while the number of choice sets should be carefully defined to avoid fatigue and to represent an optimal design. It is recommended to include about 8 to 15 choice sets.

In terms of attribute deployment, the standard way to display attributes/alternatives is by presenting the alternatives in columns and the attributes in rows. Sandorf, Sourd and Mahieu (2018) affirm that display orientation does not influence ANA. Consequently, in this study, the traditional display was kept. To avoid order effects, the attributes were randomised between respondents.

Regarding the decision to display attributes as text or images, Vriens et al. (1998) conclude that images help respondents to better understand the attributes while text improves their judgement. In this study, the results show that the model fit improves if a combination of text and images is used, demonstrating that the use of visual aids simplifies the task for respondents and more faithfully represents their actual preferences. More recent studies conclude that images do not change the preferences of respondents but improve choice consistency (Vass et al., 2020). These studies also demonstrate a reduction in the degree of error variance, making it easier to carry out a choice experiment (Uggeldahl et al., 2016), and thereby explaining why model fit improves with images. Y. Li and Xie (2020) demonstrate similar results for the use of images in social media posts, concluding that images attract more attention (reflected in more likes and retweets), and thereby facilitating readers' engagement. Thus, the present study provides additional evidence, corroborating the usefulness of images, not just to improve the understanding of the tasks, but also to better account for ANA.

Apart from this main contribution, the study also addresses the connection between attribute importance and ANA. Regarding attribute importance, the attributes were ranked from those reported as most important to least important. This ranking produced the same order under both conditions (TO and T&I) although the importance of two attributes (flavour and organic) was slightly higher in the T&I condition. Next, the analysis turned to the attributes stated as ignored during the choice tasks; the attributes that were most ignored also received the lowest importance, while the attributes that were least ignored were those considered more important for respondents. This result provides evidence of a correlation between these two measures. Thus, to corroborate this result, a logit model was estimated, with the findings showing a strong negative correlation between the importance assigned to each attribute and the probability of ignoring it during a choice task. This result is similar to the findings of Carlsson et al. (2010), who also report a negative correlation between the percentage of people ignoring an attribute and its importance. Both results also match the non-attendance level per attribute found in the LCM using Strategy 2 under the T&I condition.

4.5.1 Limitations and future extensions

Although the second strategy to account for ANA in the LCM provided better results, there was a limitation in terms of the segmentation process. This strategy is relatively easy to implement and less cumbersome than other strategies; however, its precision in uncovering marketing segments can be improved. First, it considers a unique association between one class and one ANA pattern. This limitation may result in a simplified picture of the actual preference patterns. For instance, in the estimation, there is only one segment representing all five attributes attended. That segment includes consumers who like vanilla and berry flavours, prefer organic yoghurt with or without certification, do not like yoghurt with added sugar or high fat content and prefer yoghurt in recyclable packaging. However, do some consumers have different preference patterns to these five attended attributes? Caputo et al. (2013) acknowledge this potential heterogeneity and include more than one class to represent the same ANA pattern. They first choose a model after evaluating all possible ANA patterns, ending up with three classes. Then, they repeat some of the ANA patterns in the chosen model, generating a final model with five classes. This model proved to have a better fit than the original. The problem with this strategy is that it can be very cumbersome when the original model includes several segments, as in the case of this study, thereby reducing the substantiality of the market segments. A potential solution to this problem is to use the individual-specific posterior distributions from the LCM estimation to use them as a basis for posterior segmentation. Since this information allows us to reflect on the preferences for the attributes, it can be used as input in a cluster analysis to identify more accurate market segments.

Another limitation of the study is that it only includes stated and inferred ANA information to uncover market segments. There is a growing body of literature assessing the potential benefits of including visual ANA through eye-tracking technology or even virtual reality (Balcombe et al., 2015; Krucien et al., 2017; Van Loo et al., 2018; Yegoryan et al., 2020). The inclusion of these new data sources could enrich the proposed strategy and allow a better understanding of consumer behaviour.

4.6 Conclusion

This study assesses the effect of accounting for ANA in market segmentation, including the potential role of attribute images in a choice experiment, as well as self-reported ANA information. Using a between-subjects design, the study proposed a strategy to estimate an LCM, controlling for ANA analytically, but complementing it with stated ANA information. The findings suggest that using images in a choice experiment to present attributes (and levels) would help reduce the cognitive burden of the tasks, improving the way to uncover market segments. By identifying more accurate market segments, marketers would be able to design more targeted strategies based on the most preferred attributes.

Appendix C

Appendix C.1. Questionnaire and participant consent form.

<u>**Name of Project:**</u> **Market segmentation from discrete choice experiments: Does attribute non-attendance matter?**

You are invited to participate in a study consumer choice of yoghurt. The purpose of this study is to investigate how consumers make choice decisions of yoghurt based on their attention to product attributes.

The study is being conducted by Ms. Nelyda Campos Requena (Department of Marketing at Macquarie University, nelydaaurora.camposrequena@hdr.mq.edu.au) as a part of her PhD project to meet the requirements of PhD under the supervision of Dr. Jun Yao (Department of Marketing, 9850 8489, jun.yao@mq.edu.au) with Dr. Felipe Vasquez Lavin (School of Business at Universidad del Desarrollo, Chile, fvasquez@udd.cl).

If you decide to participate, you will be asked to complete a computer-based survey with a duration about 10 minutes. You will be asked to complete 12 hypothetical choice tasks of yoghurt with different attributes' levels. In addition to these choice tasks, you will be asked some general questions about yoghurt consumption as well as sociodemographics. Participation in this study is completely anonymous and no information associated with your identity will be collected. Upon the completion of the study, you will be paid £1.5 for your participation.

Any information or personal details gathered in the course of the study are confidential, except as required by law. No individual will be identified in any publication or dissemination of the results. Only the researchers listed above will have the access to the data to ensure the confidentiality. Responses for this survey are stored in North America and not in Australia. A summary of the results of the data can be made available to you on request via email to nelydaaurora.camposrequena@hdr.mq.edu.au. The data will be made available for use in future Human Research Ethics Committee-approved projects.

Participation in this study is entirely voluntary, you are not obliged to participate. You are free to withdraw at any time without having to give a reason and without consequence. However, it will not be possible to withdraw from this study after completing and submitting the survey since your participation is anonymous and is not possible to be linked to an individual.

If you agree to participate, please click the below 'Next' button to proceed. If you do not agree to participate, please close the window to quit.

The ethical aspects of this study have been approved by the Macquarie University Human Research Ethics Committee. If you have any complaints or reservations about any ethical aspect of your participation in this research, you may contact the Committee through the Director, Research Ethics & Integrity (telephone (02) 9850 7854; email ethics@mq.edu.au). Any complaint you make will be treated in confidence and investigated, and you will be informed of the outcome.

Next

Now, you will be completing 12 choice tasks; each choice task consists of yoghurts that have different attributes (for example, sugar, fat, flavour, package, etc.).

Imagine that you are going to buy some yoghurt. In each page, there are three different alternatives of yoghurts, so you can select your preferred one.

Next

{Figure 4.1 shows an example of the 12 choice tasks offered in this section to the participants for both conditions}

Next

Please, think back to the choices you just made across the 12 choice tasks.

From the attributes that were offered to you, please select the attribute(s) that **you did NOT consider (or that you ignored)** during your choice tasks (you can select more than one attribute if relevant)

☐ Fat content
☐ Packaging (container)
☐ None, because I considered all attributes
☐ Flavour
☐ Price
☐ Organic certification
☐ Sugar level

Next

How important were the below attributes to influence your previous choices during the 12 tasks?

	Very important	Important	Moderately important	Of little importance	Not important at all
Fat content	○	○	○	○	○
Flavour	○	○	○	○	○
Organic certification	○	○	○	○	○
Packaging (container)	○	○	○	○	○
Price	○	○	○	○	○
Sugar level	○	○	○	○	○

Next

Now, we will ask you some general questions about your consumption of yoghurt.

In general, how often do you eat yoghurt?

Always	Often	Sometimes	Rarely	Never
○	○	○	○	○

In general, to what extent do you like eating yoghurt?

Extremely like	Like very much	Like	Neither like or dislike	Dislike	Dislike very much	Do not like at all
○	○	○	○	○	○	○

Are you the usual buyer of the yoghurt you consume?

Yes	No
○	○

Please, think about food and groceries (such as yoghurt, biscuits, canned food, etc.) that are purchase for your household.

Which of the following best describes your usual role in choosing the brands and products to buy?

- ◯ I have sole discretion over which brands and products are purchased for my household.
- ◯ I have a strong influence on which brands and products are purchased for my household.
- ◯ I jointly decide which brands and products are purchased for my household.
- ◯ I do not decide (or I am not involved) on the brands and products purchased for my household.
- ◯ None of the above.

When was the last time you bought a yoghurt? (select the closest option)

- ◯ During the last 7 days
- ◯ During the last 15 days
- ◯ During the last month
- ◯ At least, 2 months ago
- ◯ More than 2 months ago
- ◯ More than 6 months ago

Next

Now, I would like to ask you some other general questions.

In general, how often do you practice sport activities?

Every day	Several days per week	Once a week	Occasionally	Never
◯	◯	◯	◯	◯

How often do you purchase organic products?

Always	Often	Sometimes	Rarely	Never
◯	◯	◯	◯	◯

In general, how often do you recycle the packaging of the food you buy?

Always	Often	Sometimes	Rarely	Never
◯	◯	◯	◯	◯

Next

Finally, please answer some demographic questions.

What is your gender?

Male	Female	Other
○	○	○

What is your age? [ ] years

What is your weekly income before tax?

- ○ Less than $399
- ○ Between $400 and $599
- ○ Between $600 and $799
- ○ Between $800 and $999
- ○ Between $1,000 and $1,249
- ○ Between $1,250 and $1,499
- ○ Between $1,500 and $1,999
- ○ More than $2,000

How many dependent children live at your home?

None	1-2	3 or more
○	○	○

Which of the following best describes your marital status?

- ○ Single
- ○ Married/Permanent live-in partner
- ○ Separated/Divorced/Widowed

What is the highest degree or level of school you have completed?

- ○ Secondary school or lower
- ○ Certificate level
- ○ Advanced diploma and diploma
- ○ Bachelor degree
- ○

Masters degree or higher

(End of questionnaire)

Appendix C.2. Stated ANA patterns and distribution for each condition

Table C.2.1. Stated ANA patterns and ranking for each condition

	Type of ANA pattern	% respondents TO condition	Ranking	% respondents T&I condition
APS1	Full attendance	22.08	1 / 1	21.48
APS2	Ignored only fat	5.84	4 / 7	5.12
APS3	Ignored only flavour	5.08	5 / 5	5.63
APS4	Ignored only organic	11.42	2 / 2	11.25
APS5	Ignored only packaging	4.82	6 / 3	9.46
APS6	Ignored only sugar	1.78	11 / 14	1.28
APS7	Ignored fat & flavour	2.03	10 / 15	1.02
APS8	Ignored fat & organic	5.84	4 / 10	2.56
APS9	Ignored fat & packaging	1.02	13 / 9	2.81
APS10	Ignored fat & sugar	5.08	5 / 6	5.37
APS11	Ignored flavour & organic	3.05	8 / 10	2.56
APS12	Ignored flavour & packaging	1.78	11 / 13	1.53
APS13	Ignored flavour & sugar	1.27	12 / 17	0.51
APS14	Ignored organic & packaging	8.12	3 / 4	9.21
APS15	Ignored organic & sugar	1.27	12 / 16	0.77
APS16	Ignored packaging & sugar	0.76	14 / 14	1.28
APS17	Ignored fat & flavour & organic	2.03	10 / 17	0.51
APS18	Ignored fat & flavour & packaging	0.51	15 / 19	0.00
APS19	Ignored fat & flavour & sugar	0.76	14 / 13	1.53
APS20	Ignored fat & organic & packaging	2.03	10 / 9	2.81
APS21	Ignored fat & organic & sugar	3.30	7 / 8	3.07

APS22	Ignored fat & packaging & sugar	1.02	13 / 11	2.30
APS23	Ignored flavour & organic & packaging	2.54	9 / 12	1.79
APS24	Ignored flavour & organic & sugar	0.51	15 / 18	0.26
APS25	Ignored flavour & packaging & sugar	0.25	16 / 18	0.26
APS26	Ignored organic & packaging & sugar	1.02	13 / 17	0.51
APS27	Ignored fat & flavour & organic & packaging	0.76	14 / 15	1.02
APS28	Ignored fat & flavour & organic & sugar	0.76	14 / 16	0.77
APS29	Ignored fat & flavour & packaging & sugar	0.00	17 / 18	0.26
APS30	Ignored fat & organic & packaging & sugar	3.05	8 / 11	2.30
APS31	Ignored flavour & organic & packaging & sugar	0.00	17 / 18	0.26
APS32	All attributes ignored	0.25	16 / 17	0.51

* Notice that some places share more than one ANA pattern.

Appendix C.3. Comparison of stated attribute importance between both conditions

Table C.3.1. Comparing stated attribute importance between both conditions through a Kruskal–Wallis test

	Rank sum TO condition	Rank sum T&I condition	Chi-squared with ties	Probability
Fat	152790.50	155714.50	0.440	0.507
Flavour	**148170.00**	**160335.00**	**4.746**	**0.029**
Organic	**148733.00**	**159772.00**	**3.922**	**0.048**
Packaging	159166.50	149338.50	1.933	0.165
Sugar	155054.00	153451.00	0.005	0.945

Appendix C.4. Logit estimations

Table C.4.1. Description of the variables from the logit estimations

Variable name	Description
Dependent variable Ignored_attribute	For every five attributes, the dependent variable takes value 1 if the respondent states that the attribute was ignored during the choice.
Independent variables	
Imp_att	Each attribute (*att*) represents a numerical variable with values from 1 to 5, where 1 represents *not important at all* and 5 represents *very important*.
Age	Numerical variable that represents the age of the respondent in years.
Female	Dummy variable taking value 1 if the respondent is female, 0 otherwise.
Single	Dummy variable taking value 1 if the respondent is single, 0 otherwise.
Edu_univ	Dummy variable taking value 1 if the respondent has a bachelor or higher level of education, 0 otherwise.
No_kids	Dummy variable taking value 1 if the respondent has no children, 0 otherwise.
Income	Dummy variable taking value 1 if the respondent has an income above AUD$1,000 weekly, 0 otherwise.
Freq_sport	Dummy variable taking value 1 if the respondent plays sport activities at least once a week, 0 otherwise.
Freq_recycle	Dummy variable taking value 1 if the respondent always or often recycles the packaging of the food they buy, 0 otherwise.
Freq_organic	Dummy variable taking value 1 if the respondent always or often purchases organic products, 0 otherwise.
Image	Dummy variable taking value 1 if the survey answered by the respondents includes images in the attribute presentation.

Table C.4.2. Logit estimations from TO and T&I conditions

	Fat		Flavour		Organic		Packaging		Sugar	
	TO	**T&I**	**TO**	**T&I**	**TO**	**T&I**	**TO**	**T&I**	**TO**	**T&I**
Imp_ att	**-1.60**	**-1.42**	**-1.21**	**-1.01**	**-1.68**	**-1.35**	**-1.34**	**-1.19**	**-1.22**	**-0.89**
	(0.167)	**(0.161)**	**(0.145)**	**(0.136)**	**(0.181)**	**(0.156)**	**(0.151)**	**(0.125)**	**(0.152)**	**(0.124)**
Age	-0.01	-0.01	0.004	0.01	0.003	-0.004	0.01	-0.004	-0.03	-0.01
	(0.015)	(0.016)	(0.015)	(0.017)	(0.013)	(0.014)	(0.014)	(0.015)	(0.019)	(0.015)
Female	0.25	-0.44	-0.28	-0.26	-0.19	0.04	-0.18	-0.14	-0.05	-0.02
	(0.28)	(0.284)	(0.301)	(0.307)	(0.274)	(0.270)	(0.306)	(0.274)	(0.303)	(0.290)
Single	0.22	**-0.79**	0.39	0.02	0.55	0.18	-0.45	-0.22	0.06	-0.55
	(0.335)	**(0.334)**	(0.384)	(0.375)	(0.344)	(0.314)	(0.394)	(0.327)	(0.375)	(0.325)
Edu_ univ	0.23	0.10	0.40	0.17	0.16	0.41	0.61	-0.09	-0.17	-0.17
	(0.311)	(0.300)	(0.337)	(0.340)	(0.290)	(0.289)	(0.328)	(0.291)	(0.320)	(0.308)
No_ kids	-0.02	0.28	-0.18	-0.51	-0.06	-0.04	-0.01	0.17	-1.00	0.48
	(0.339)	(0.319)	(0.351)	(0.348)	(0.337)	(0.310)	(0.382)	(0.316)	(0.369)	(0.330)
Income	0.06	0.12	-0.45	0.23	0.35	0.27	**-0.72**	0.09	0.42	0.11
	(0.335)	(0.304)	(0.350)	(0.337)	(0.312)	(0.283)	**(0.358)**	(0.294)	(0.358)	(0.108)
Freq_ sport	-0.06	-0.45	-0.03	0.26	-0.03	-0.26	0.39	-0.168	-0.08	-0.35
	(0.302)	(0.292)	(0.314)	(0.324)	(0.291)	(0.272)	(0.320)	(0.283)	(0.314)	(0.297)
Freq_ recycle	0.01	0.45	-0.49	-0.57	0.24	0.41	-0.41	0.06	-0.57	-0.01
	(0.372)	(0.386)	(0.381)	(0.407)	(0.349)	(0.353)	(0.349)	(0.345)	(0.380)	(0.378)
Freq_ organic	-0.15	**0.86**	-0.10	-0.31	-0.27	-0.44	0.09	-0.33	0.59	0.40
	(0.344)	**(0.336)**	(0.351)	(0.369)	(0.400)	(0.395)	(0.401)	(0.345)	(0.353)	(0.335)
Const	**3.46**	**3.39**	**2.88**	**2.30**	**3.15**	**2.39**	**2.59**	**3.08**	**3.90**	**1.93**
	(0.826)	**(0.886)**	**(0.922)**	**(1.021)**	**(0.774)**	**(0.815)**	**(0.839)**	**(0.827)**	**(0.977)**	**(0.873)**
Pseudo R2	0.368	0.306	0.275	0.212	0.362	0.300	0.379	0.302	0.279	0.184

Appendix C.5. Summary of the test for equality of proportions

Table C.5.1. Comparing ANA in terms of both conditions

	Stated ANA TO vs stated ANA T&I	Inferred ANA strat.1 TO vs inferred ANA strat.1 T&I	Inferred ANA strat.2 TO vs inferred ANA strat.2 T&I
Fat	0.369	8.980	18.854
	(0.544)	(2.73E-03)	(1.41E-05)
Flavour	1.035	88.338	38.526
	(0.309)	(2.20E-16)	(5.40E-10)
Organic	2.449	5.604	2.553
	(0.118)	(0.018)	(0.110)
Packaging	5.971	0.156	11.539
	(0.015)	(0.693)	(0.001)
Sugar	6.73E-30	26.602	29.141
	(1.000)	(2.50E-07)	(6.73E-08)

Table C.5.1 shows that when comparing the ANA levels between the TO condition and the T&I condition, the *packaging* attribute is the only attribute differing in terms of the stated ANA proportion. However, when ANA is inferred from the LCM using either Strategy 1 or Strategy 2, the proportions of ANA differ for almost all the attributes depending on the format.

Table C.5.2. Comparing stated and inferred ANA for each condition

	TO condition		**T&I condition**	
	Stated ANA vs inferred ANA strat.1	**Stated ANA vs inferred ANA strat.2**	**Stated ANA vs inferred ANA strat.1**	**Stated ANA vs inferred ANA strat.2**
Fat	1.889 (0.169)	0.005 (0.946)	25.894 (3.61E-07)	23.654 (1.15E-06)
Flavour	80.02 (2.2E-16)	30.453 (3.42E-08)	0.249 (0.618)	0.080 (0.777)
Organic	5.343 (0.021)	1.826 (0.177)	9.620 (0.002)	3.278 (0.070)
Packaging	0.821 (0.365)	0.154 (0.695)	0.986 (0.321)	0.172 (0.679)
Sugar	3.240 (0.072)	32.956 (9.43E-09)	10.611 (0.001)	0.107 (0.744)

Table C.5.2 shows that stated ANA and inferred ANA are consistent for Strategy 2 when the attributes are shown with images; they only differ in the ANA proportion for the *fat* attribute.

Appendix C.6. Selection of the LCM for both conditions

Table C.6.1 BIC values for the LCMs for both conditions in Strategy 1

N° classes	TO condition	N° classes	T&I condition
32 classes	8340.77	32 classes	8143.2
24 classes	8241.2	25 classes	8058.3
23 classes	8223.4	21 classes	8019.7
22 classes	8221.7	20 classes	8026.2
20 classes	8200.0	19 classes	8019.8
19 classes	8200.2	**18 classes**	**8017.5**
18 classes	8183.7	17 classes	8022.9
17 classes	8177.0	15 classes	8026.5
16 classes	**8169.9**	14 classes	8022.5
15 classes	8177.7	13 classes	8029.2
14 classes	8172.2	12 classes	8074.8
13 classes	8174.3	11 classes	80867.0
12 classes	8178.6	10 classes	8125.8
11 classes	8196.4	9 classes	8150.1
10 classes	8223.7	8 classes	8201.9
9 classes	8255.7	7 classes	8275.5
8 classes	8312.7	6 classes	8360.5
7 classes	8402.9	5 classes	8511.4
6 classes	8442.1	4 classes	8597.3
5 classes	8473.4	3 classes	8783.5
4 classes	8590.9	2 classes	9212.1
3 classes	8913.3		
2 classes	9140.0		

Table C.6.2 BIC values for the LCMs for both conditions in Strategy 2

N° classes	TO condition	N° classes	T&I condition
2 classes	9056.7	2 classes	9011.4
3 classes	8736.0	3 classes	8747.0
4 classes	8568.7	4 classes	8582.3
5 classes	8437.6	5 classes	8438.1
6 classes	8364.0	6 classes	8345.0
7 classes	8302.1	7 classes	8261.5
8 classes	8266.0	8 classes	8191.3
9 classes	8253.5	9 classes	8143.3
10 classes	8222.1	10 classes	8120.3
11 classes	8192.5	11 classes	8061.5
12 classes	8183.5	12 classes	8044.6
13 classes	8172.7	13 classes	8035.1
14 classes	8168.0	14 classes	8012.4
15 classes	**8162.8**	***15 classes***	***8003.7***
16 classes	8179.1	16 classes	8006.2
17 classes	8167.4	**17 classes**	**8002.6**
18 classes	8168.5	18 classes	8003.3
19 classes	8192.9	19 classes	8019.5

* Given that after 18 classes the BIC values start to increase again and the impracticality of a large number of segments, no more estimations were performed.

Chapter 5:

CONCLUSIONS

5.1 Summary

Discovering what consumers want and what attributes of a product persuade them to buy that product instead of another is probably one of the most valuable sources of information for marketers or decision-makers. By mimicking the choice situations faced by consumers when they buy a product, researchers can gather specific information about their preferences and tastes. Choice experiments (or choice-based conjoint experiments) are an effective way of capturing this information which, combined with an appropriate model, can be used to identify groups of consumers based on their taste patterns. In the marketing literature, the latent class model (LCM) has been applied most frequently to predict market segments, but is it the most suitable model for this purpose? Can it be improved?

This thesis assessed the reliability and effectiveness of using the traditional LCM to identify market segments taking into account the potential effects of additional elements. The three studies that were conducted as part of this thesis demonstrated that certain methodological interventions play a significant role in achieving more accurate market segmentation by promoting best modelling practices. These included:

- the ability to select the appropriate model to represent the level of heterogeneity in consumer tastes;
- the contribution of individual-specific posterior distributions (ISPs), recovered from either the random parameter model or the LCM, as a basis

for market segmentation, especially in the presence of high heterogeneity among consumers;

- the recognition of attribute non-attendance (ANA) behaviour during choice tasks faced by consumers in a choice experiment, including the role of self-reported information related to this behaviour; and
- the use of visual aids (images) to show the attributes of a product during choice tasks as a mechanism to better accounting for ANA, thereby representing genuine preferences.

The first two studies emphasised the strengths and weaknesses of using an LCM to predict market segments compared with using an alternative model, the mixed logit model (MLM). In the literature, both models have proved to be effective in modelling both observed and unobserved heterogeneity, making them appropriate for market segmentation. However, although the MLM does not predict market segments directly, as the LCM does, this thesis demonstrated its suitability for segmenting consumers under certain scenarios. This segmentation is possible in a two-stage procedure by exploiting ISPs. In particular, when there is high heterogeneity among consumers, the MLM was shown to outperform the LCM in predicting homogeneous groups. However, the LCM was shown to be superior under certain conditions.

From an empirical study, the results showed that both models differed in their market segments predictions, leading to the first conclusion that the model selection does matter. Based on a controlled set of four experiments (Monte Carlo study), some directions emerged, indicating which model to select. The classes from the LCM provided a faithful representation of the actual groups of consumers with similar preference patterns when the level of heterogeneity among them was low. Thus, in the presence of heterogeneity between segments but homogeneity within them, the best model to predict market segments was the traditional LCM. However, when heterogeneity was high, both between and within segments, this model was less effective than other alternatives exploiting the ISPs as a basis for segmentation. The ISPs recovered from both the mixed logit and latent class estimations were used in a second stage to obtain the market segments. This provided better results than the traditional LCM. From these results, two additional conclusions emerged. First, the MLM outperforms the LCM when consumer preferences are highly heterogeneous. Second, an LCM exploiting its ISPs to segment highly heterogeneous consumers outperforms a traditional LCM using the predicted classes as segments. In this last case, using the ISPs recognises the probabilistic nature of the class membership—a factor that is ignored in traditional segmentation. It should be remembered that each individual may belong to more than one class with a given probability in LCMs. However, traditional segmentation assigns them to a single class—the one in which they have the highest posterior class membership probability. For instance, let us consider a latent class estimation with two classes. The posterior class membership probabilities for a particular individual are 49% for the first class and 51% for the second class. During the segmentation, this person will be assigned as a member of the second class. This assignment to the second class does not consider that the individual's preferences also match the other group at a high percentage. Therefore, using ISP as a basis for segmentation recognises this 'fuzzy' membership of more than one class.

The previous conclusions considered that consumers attended all attributes of a product to make a buying decision; however, the literature provides extensive evidence that ANA is frequent during choice experiments. The third study conducted as part of this thesis addressed the effects of ANA on segmentation.

Prior literature has used LCMs to account for ANA; however, more discussion is needed about its impacts. The third study evaluated the role of two factors in improving the identification and accommodation of ANA in these models. One manipulated the design of the choice experiments to reduce ANA as a coping mechanism during complex tasks. In this case, the study assessed the use of visual aids to simplify the information provided to consumers, contrasting this approach with the standard text only presentation format. The other factor that was evaluated was the use of self-reported ANA information combined with the analytical method adopted in LCMs. The results of this empirical study showed a clear improvement in the goodness of fit when the LCM accounts for ANA by using both stated and inferred ANA and when the choice experiment displays the product attributes using text and images. This improvement identified market segments more accurately. This is because the combination of both elements more faithfully represented genuine ANA behaviour and hence, the preferences towards the attributes.

This last study led to a new conclusion. Appropriate design of the choice experiment plus an appropriate strategy to account for ANA can enhance the LCM, leading to the better identification of market segments. Specifically, a suggestion to researchers and practitioners is to include images of the offered attributes during choice tasks to simplify the process and bring it closer to an actual buying experience. Moreover, during the model estimation to identify segments, they should not disregard information stated as ignored by consumers during the choice task since this can provide valuable and objective insights into modelling decisions.

5.2 Future research directions

The methodological suggestions arising from this thesis are a mere fraction of the potential improvements in modelling to identify market segments more accurately, especially considering the strategic potential of more accurate segmentation. Thus, future investigations should consider the following issues:

- *Analysis of additional models to identify market segments*: This thesis compared only two models that account for observed and unobserved heterogeneity in the quest to identify market segments. The MLM assumed a normal distribution for the random parameters, opening up the possibility of assessing additional distributions, such as log-normal, triangular or Johnson Sb, among others. However, a convenient extension of this research is to evaluate a model that combines the MLM and the LCM. The latent class random parameter model has gained attention during the last decade for combining the best elements of both models. Thus, assessing this model, especially in a setting of high preference heterogeneity, opens up new possibilities to identify market segments. Still, it is relevant to evaluate whether the potential benefits of using this model overcome the computational costs that it entails.

- *Extending the use of individual-specific posterior distributions*: This thesis showed the benefits of exploiting ISPs for segmentation, either in an MLM or an LCM context. Nevertheless, the thesis only considered the first moment of these distributions; that is, the mean values of the ISP. Thus, a natural extension would be to include other moments in the analysis.
- *More applications*: In all cases, providing more evidence would support the proposed methodologies. Such additional evidence could come from different empirical studies or controlled experiments. For instance, a Monte Carlo study might introduce more attributes and levels to consider more complex settings or even add new models.
- *More data*: This thesis confirmed that additional consumer data (e.g. ISPs or self-reported ANA) enhance the analysis and the possibility of uncovering more accurate market segments. Thus, including new data to understand consumer behaviour would help to reduce uncertainty or subjectivity in different stages of the modelling. During the last years,

access to eye-tracking technology or virtual reality has provided new sources of information. For instance, visual ANA from eye-tracking technology produces additional and more objective data related to what attributes consumers ignore during buying decisions. This type of data, combined with self-reported ANA and inferred ANA, could enrich the analysis and prediction of market segments.

5.3 Conclusion

This thesis examined different methodological elements to improve the identification of market segments, from the design of choice experiments to the methods used to analyse the data. It also showed that the LCM is an appropriate method under certain circumstances and, like other models, has strengths and weaknesses.

The best modelling practices are ultimately based on the researcher's decision. However, this thesis suggests that researchers should consider additional elements in the examination, such as giving careful consideration to heterogeneity in tastes or possible ANA behaviour to adjust the modelling.

Market segmentation is a valuable tool for marketers in designing appropriate business strategies; therefore, more precise segmentation achieved through the methodologies proposed in this thesis could be used to improve marketing strategies, such as product innovation, promotion or pricing. However, this benefit can be applied beyond the field of marketing. Understanding consumer preferences may also be relevant for other disciplines, such as environmental economics, health economics or food studies.

Despite the contributions and extensions recommended by this thesis to perform consumer preferences analysis, more research is still needed to improve predictions.

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