United Arab Emirates beef consumer consumption behaviours and product preferences: A Latent Class Analysis of New Zealand beef mince

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Contents

List of Tables

List of Figures

Key Points

- The Agribusiness and Economics Research Unit (AERU) at Lincoln University, with the support of research partners under the *Unlocking Export Prosperity from the Agri-food Values of Aotearoa New Zealand* research programme has estimated willingness-to-pay (WTP) values for selected credence attributes of Beef mince product by United Arab Emirates (UAE) consumers, with a focus on identifying preferences for attributes considered *distinctively New Zealand.*

- Preferences for many of the credence attributes considered here are not readily observable from market prices, and so the economic non-market valuation method of Discrete Choice Experiments was used. This involved an online survey of UAE residents in August 2021.

- As well as consumer willingness-to-pay values, this survey reports findings on:
    - Beef purchase by cut and consumption frequency
    - Prices usually paid across 25 beef cuts
    - Country-of-origin purchase frequency and quality ranking
    - Use of digital media and smart technologies for beef shopping

- Regular fat beef mince was the most purchased beef product (64 per cent. While consumers are paying on average AED48/kg, one in ten consumers are usually paying above AED100/kg. The highest average price was for sirloin steaks at AED84/kg, and was purchased at least monthly by 18 per cent of respondents. The majority of expenditure on beef products was through hypermarkets (21 per cent), grocery stores (18 per cent), and specially stores (15 per cent).

- Many respondents purchase NZ beef products (58 per cent), with cubed beef, low fat mince, and burger product being purchased at least monthly by over a third of respondents. A quarter of respondents purchase NZ sirloin or ribeye steak at least monthly.

- The average number of meals per week containing beef was 4.5, although one in five respondents had beef containing meals at least daily.

- UAE beef was by far the most purchased country-of-origin with 65 per cent of respondents frequently purchasing, followed by Australia (45 per cent), Pakistan (43 per cent) and New Zealand (40 per cent). Almost one in four consumers had never purchased a NZ beef product, and a further 20 per cent rarely purchased.

- Many consumers use mobile devices to search for information about beef products (58 per cent Often, 34 per cent Sometimes), and to make beef purchases (41 per cent Often, 34 per cent Sometimes). Consumers are using a range of smart technologies with smart phones to make purchases and search for information (36 per cent Often). Use of barcodes is higher than either QR codes or RFID/NFC technologies, with 29 per cent of consumers often making purchases using barcodes, and searching for product information (31 per cent).

- The main sources of online digital media related to beef products include food company website (65 per cent), YouTube (59 per cent), and food blogs (53 per cent). There is a relatively high use of mobile applications across the sample, particularly for purchasing (51 per cent), recipes (49 per cent), and discounts/coupons (48 per cent). Further, there is high interest in potential uses even where current use is relatively low, such as for environmental information with 56 per cent interested in this use.

- 54 per cent of consumers purchase beef products online, largely due to the convenience of home delivery (22 per cent), access to promotions (19 per cent), and greater variety available (16 per cent). Although hypermarkets were the main online retailer used (60 per cent Often), many consumers used international retailers (25 per cent Often), and Amazon (21 per cent).
- The survey included a Discrete Choice Experiment to assess the willingness-to-pay by consumers for different attributes associated with beef mince. The consumers were then segmented, using a Latent Class Model, into three classes each with different characteristics and preferences. Results demonstrate significant consumer support for the types of product attributes that can be considered as distinctively New Zealand.
- We find substantial preference differences between consumer segments. The first segment is the largest of the three consumer groups. These consumers have the strongest preferences of the three segments spanning most of the attributes considered, and they have the highest willingness-to-pay for Māori produced beef of the three segments. Consumers in this segment are more likely to have higher usual beef spend, higher purchase frequency, higher income, and to rate NZ beef quality high.
- The second consumer segment comprises a third of consumers and has broad preferences spanning all but two attributes considered. While they have relatively modest levels of WTP, these consumers are the only segment to value a Carbon Neutral attribute. The third segment is the smallest of the three segments and while these consumers have the narrowest set of attribute preferences at just three, they are the only segment to value a feedlot raised claim. They also prefer GE-free feed to be given to cattle.
- Average marginal willingness-to-pay for each of the three consumer segments is presented in the following table as the percentage change in price per kg for inclusion of an attribute claim.

Beef mince Attribute	Segment One 55%	Segment Two 32%	Segment Three 13%
Carbon Neutral		23% (-1%, 47%)	
Water Quality Protection	26% (3%, 48%)	15% (7%, 22%)	
Organic Production	78% (37%, 118%)	11% (0%, 22%)	
Māori Production	56% (25%, 85%)	13% (5%, 22%)	
Feedlot Raised	92% (22%, 210%)		40% (17%, 62%)
100% Pasture Raised	60% (28%, 92%)	9% (3%, 15%)	28% (8%, 48%)
100% Grass-fed	55% (23%, 83%)		
Grain-fed	41% (12%, 68%)	16% (10%, 23%)	
No added hormones	70% (27%, 113%)	11% (1%, 22%)	
No added antibiotics	84% (40%, 128%)	21% (10%, 32%)	
Enhanced Animal Welfare	45% (20%, 68%)	19% (13%, 25%)	
GMO-free	43% (17%, 68%)	7% (1%, 13%)	24% (7%, 42%)
Social responsibility	41% (17%, 63%)	9% (3%, 15%)	

Average marginal WTP/kg beef mince.
95% Confidence Interval in brackets.

Chapter 1
Introduction

This study is part of a research programme entitled *Unlocking Export Prosperity from the Agri-food Values of Aotearoa New Zealand*. It is funded by the Ministry of Business, Innovation and Employment (MBIE) Endeavour Fund for science research programmes.

The research aims to provide new knowledge on how local enterprises can achieve higher returns by ensuring global consumers understand the distinctive qualities of the physical, credence and cultural attributes of agri-food products that are "Made in New Zealand".

Agricultural exports are an important contributor to the New Zealand (NZ) economy. While NZ historically relied on key markets such as the United Kingdom for export trade, NZ has more recently significantly expanded its export markets and the United Arab Emirates (UAE) offers potential to become established as an important beef product destination. It is critically important for NZ exporters to understand export markets and the different cultures and preferences of those consumers to safeguard market access, and for realising potential premiums.

This report describes the application of a survey of United Arab Emirates beef mince consumers designed to examine consumption behaviour and consumer Willingness-to-Pay (WTP) for credence attributes. While *search attributes* such as price or colour can be observed directly, and *experience attributes* such as flavour can be assessed when consumed, *credence attributes* such as environmental sustainability cannot be immediately seen or experienced at the point of sale. For products promoting credence attributes, the role of verification including labelling is of significant importance.

Our approach is to apply a Discrete Choice Experiment economic valuation method, analysed using a statistical approach called Latent Class Modelling that describes profiles for different consumer segments identified in the data and provides estimates of attribute WTP across these segments.

Chapter 2
Beef Survey Method

To understand how consumers value NZ credence attributes, this study used a structured self-administered online survey that included a Discrete Choice Experiment, conducted in the UAE in June 2021. The survey was administered through Qualtrics™, a web-based survey system, and focused on beef mince consumers with purchase frequency of at least monthly.

The survey was developed by the research team drawing from a literature review on consumer trends for animal meat products, results from previous surveys examining consumer attitudes in overseas markets, and consultation with industry partners and stakeholders, especially those on the AERU advisory board.

Sampling involved recruiting participants from an online consumer panel database provided by an international market research company (dynata.com). Panel members are recruited by online marketing across a range of channels and panels are profiled to ensure adequate representativeness. Panels are frequently refreshed, with the participation history of members reviewed regularly. Respondents for each survey are compensated with a retail voucher for completing a survey.

2.1 Using Discrete Choice Experiments to examine consumer preferences

Discrete Choice Experiments are a survey-based valuation approach that have been widely used to value consumer preferences for food and beverage product attributes. They are particularly useful for examining the role of new attributes, and attributes that are not easily observable in market prices such as the attributes explored in the current report. The ability of this method to identify which individual attributes are more important in consumer choices, and to estimate consumers' WTP for these, has seen this approach to valuation become increasingly favoured by researchers.

Designing a Discrete Choice Experiment survey involves deciding which product attributes are of interest, combining these into different product offerings, and asking consumers to pick which offering they prefer from a range of alternatives. In this study, the attributes associated with beef mince products are different production practices and price (Table 2-1). These attributes were selected in consultation with the relevant industries and informed by previous similar surveys including scoping surveys that used a combination of open text and structured questions to identify which attributes UAE consumers considered distinctive of NZ beef.

Table 2-1 Beef mince attribute descriptions used in the Discrete Choice Experiment

Beef mince attributes	Attribute descriptions
Animal Feed	100% Grass-fed beef is lower in calories, contains more healthy omega-3 fats, vitamins A and E, beta-carotene and antioxidants. Grain fed beef have higher fat content and marbling which can produce a richer taste.
Animal Housing	Animals can be raised mainly in feedlots, or mainly in pastures.
Animal Welfare	Animal welfare practices can be enhanced above the minimum legal standards.
t	Beef may be raised with or without added antibiotics and/or hormones.
GMO-Free	Animals are not genetically modified, and do not consume genetically modified feed.
Social Responsibility	Socially responsible farms actively include public interest into decision making.
Environmental Sustainability	Environmentally sustainable farms actively minimise the environmental effects of beef production. The beef may be labelled as being produced using a system that is either Carbon Neutral, Enhances Biodiversity or Protects Water Quality
Organic Production	No synthetic fertilisers, hormones, antibiotics or animal by-product supplementation during the entire life of the animal including in their feed.
Māori Production	The beef may be labelled as being produced on Māori farms. Māori, New Zealand's indigenous people, value sharing food with family, friends and visitors. For Māori, sharing food is more than just good hospitality but is viewed as an essential component of society and of individual prestige, with the food representing a gift that binds people together.
Price	AED per kilogram beef mince

Changes in beef attributes are described using the levels in Table 2-2. Price levels were determined by market prices, and from what scoping survey respondents said that they usually paid. An example of alternative product offerings presented to respondents is shown in Figure 2-1. Each set of offerings comprises three options, of which respondents chose their preferred one. Two options present alternative beef mince products, while the third is a 'none of these' option. Each respondent answered ten choice sets. Product choices are statistically analysed, and consumers' WTP for each attribute is estimated. A more detailed description of theoretical foundation and statistical procedure of Discrete Choice Experiments can be found in Appendix A.

Table 2-2 Beef mince attribute levels used in the choice experiment

Beef tenderloin attributes	Attribute levels			
Enhanced Animal Welfare	No Label	Certified		
GMO-free	No Label	GMO-free		
Social Responsibility	No Label	Certified		
Additives	No Label	No Added Antibiotics	No Added Hormones	
Animal Housing	No label	100% Pasture Raised	Feed-lot raised	
Animal Feed	No label	100% Grass-fed	Grain-fed	
Farming System	Conventional	Organic	Māori	
Environmental Sustainability	No Label	Carbon Neutral	Biodiversity Enhancement	Water Quality
Price AED per kg beef mince	AED30	AED60	AED90	

Set 1 of 10 Imagine you need to purchase some **beef mince** from your usual retailer. Given the information that is provided, **which of the following New Zealand produced beef mince options do you prefer?**
Mark your choice using the buttons below, and please bear in mind the price that is associated with your choice and how that would fit into your budget. More Info

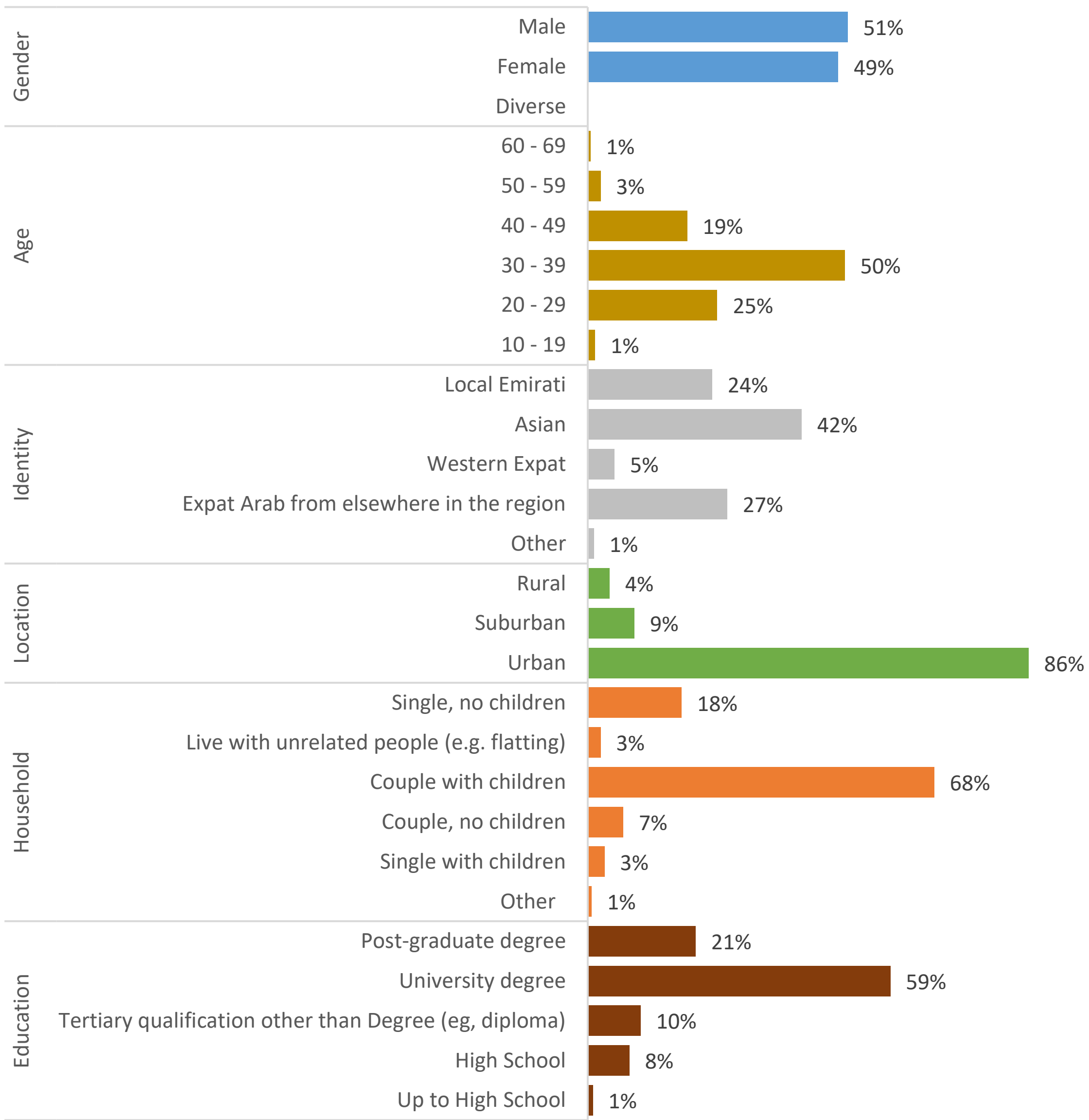
	Option A	Option B	
Farming System	Conventional	Māori	
Social Responsibility		Socially Responsible	
Enhanced Animal Welfare	Enhanced Animal Welfare		
Additives	No added hormones		
Animal Housing	100% Pasture raised		
Animal Feed	Grain-fed		
Environmentally Sustainable	Biodiversity Enhancement	Carbon Neutral	
GMO-Free		GMO-Free	
Price	90AED/kg	30AED/kg	
Selection:	○	○	○ I would choose a different beef mince

Figure 2-1 Example of a choice experiment question shown to respondents

Chapter 3
Survey Results

3.1 Sample demographic description

- The sample comprised a wide range of demographics, which is important to ensure that the sampling process has broadly canvased the relevant population (Figure 3-1).
- It is important to note that we are not attempting to represent the overall UAE population, but rather those that purchase beef mince at least monthly.



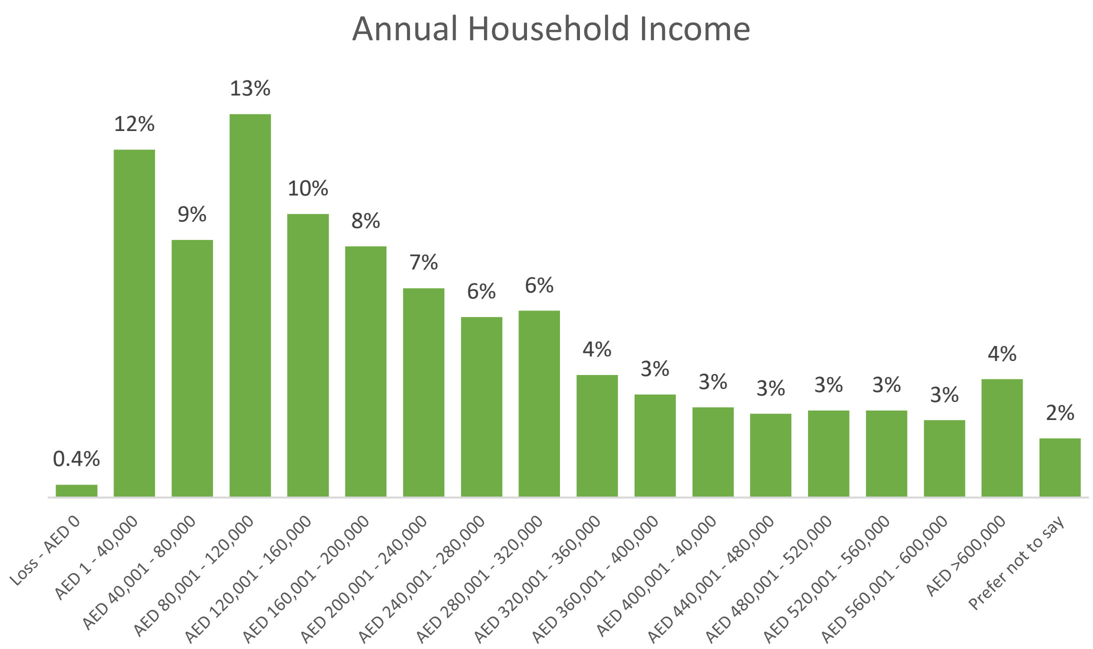


Figure 3-1 Sample demographics

3.2 Purchase and consumption behaviour

3.2.1 Purchase and consumption frequency

- After *regular fat mince*, *burger* was the most often purchased beef product, followed by *low fat mince* and *regular cubes* (Figure 3-2).

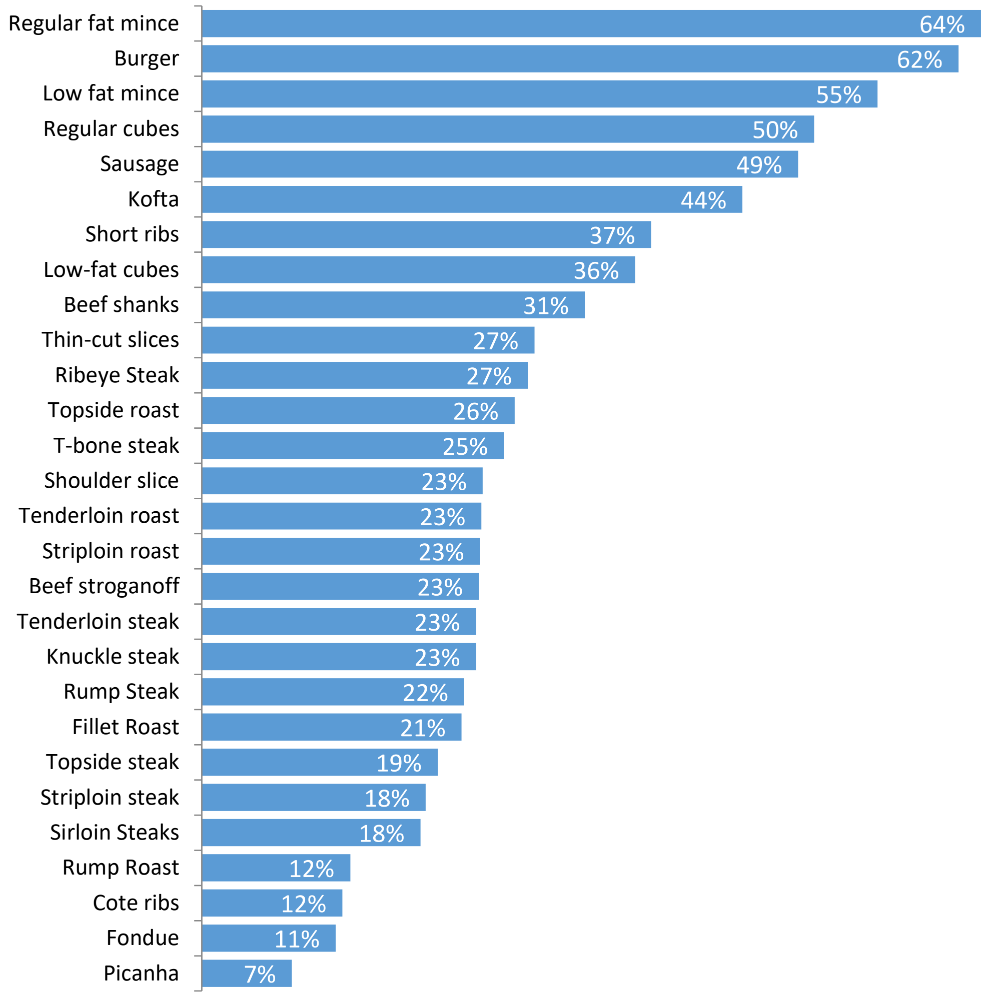


Figure 3-2 Beef product purchases in previous month

- Respondents were asked if they eat beef that is not halal, and nearly 70 per cent of respondents stated "no" (Figure 3-3).

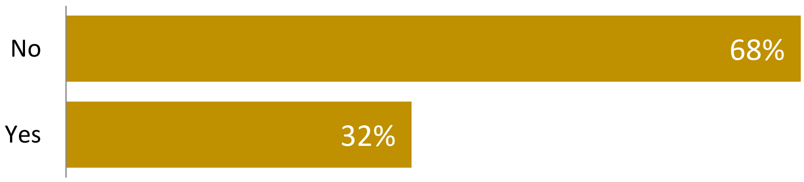


Figure 3-3 Consumption of beef that is non-halal

- Consumers were asked to indicate how many meals in a typical week contained beef (Figure 3-4).
- The average number of meals containing beef was 4.5/week, with the most frequent amount being three.

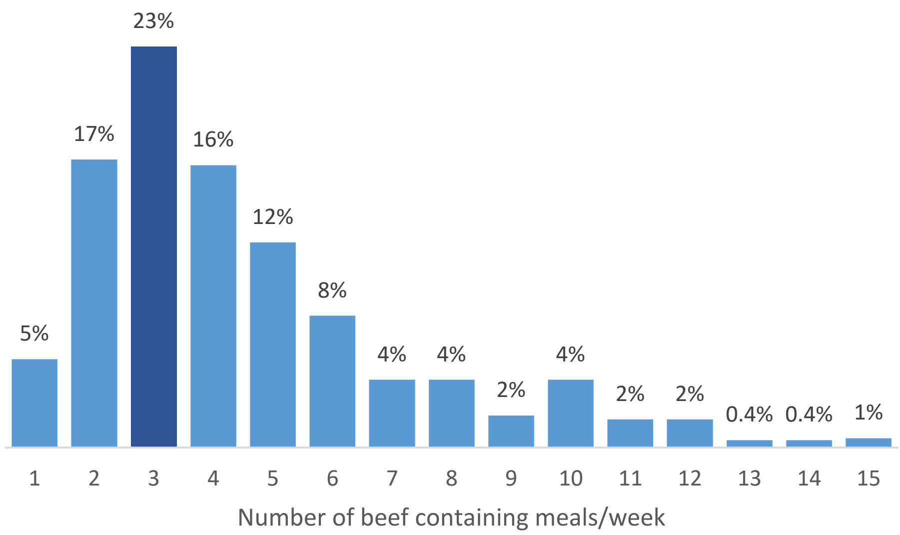


Figure 3-4 Number of meals containing beef consumed per week

3.2.2 Prices usually paid for beef cuts

- Consumers were asked to indicate the price per kg that they usually paid for different beef cuts. The average of these prices shows that price usually paid is highest for *sirloin steak* and lowest for *sausage* (Figure 3-5).

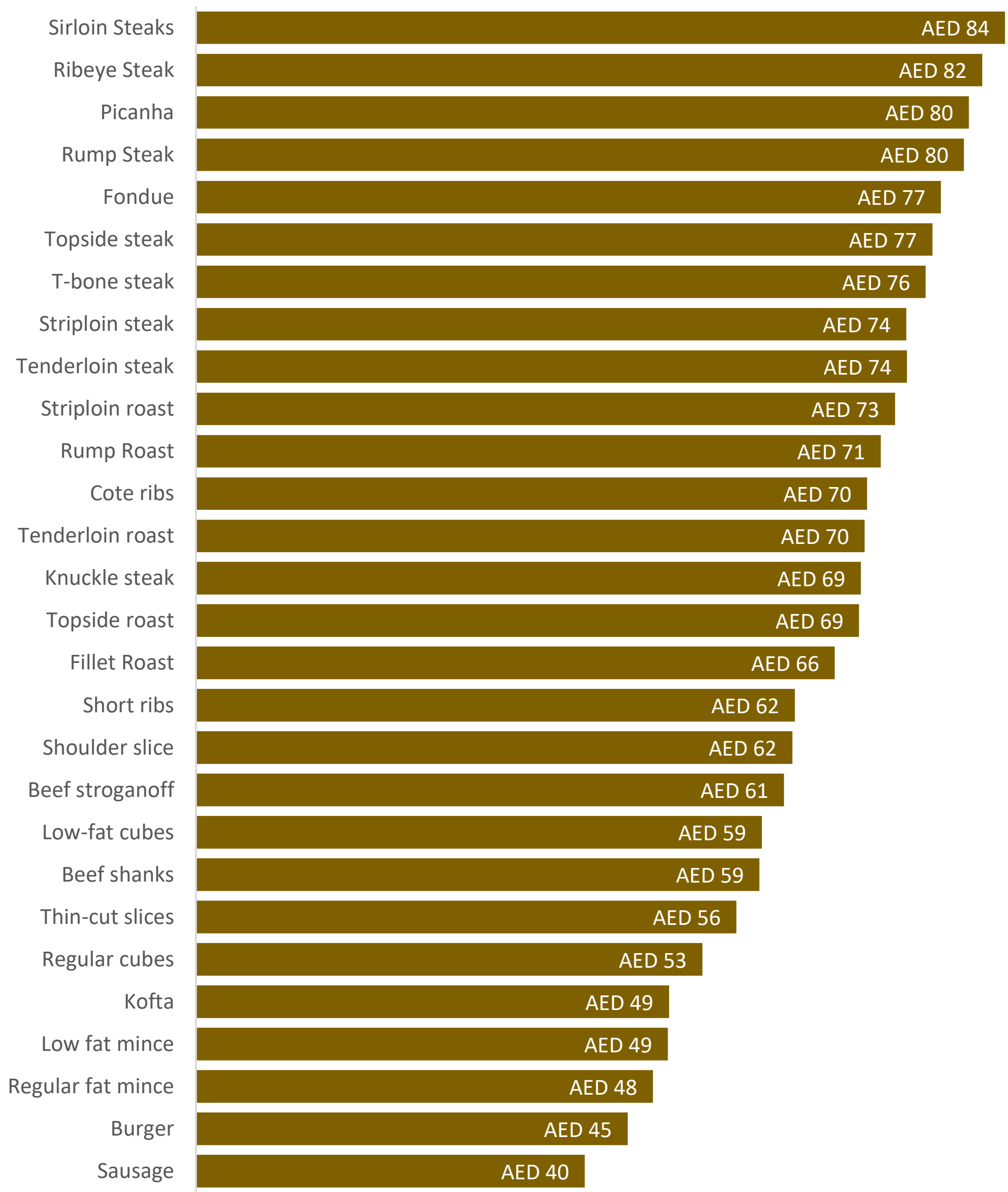


Figure 3-5 Average price per kg usually paid for beef cuts

- Looking in more detail at beef mince (both regular and low fat), the majority of respondents pay less than AED 60/kg and 2 per cent pay over AED 160/kg (Figure 3-6).

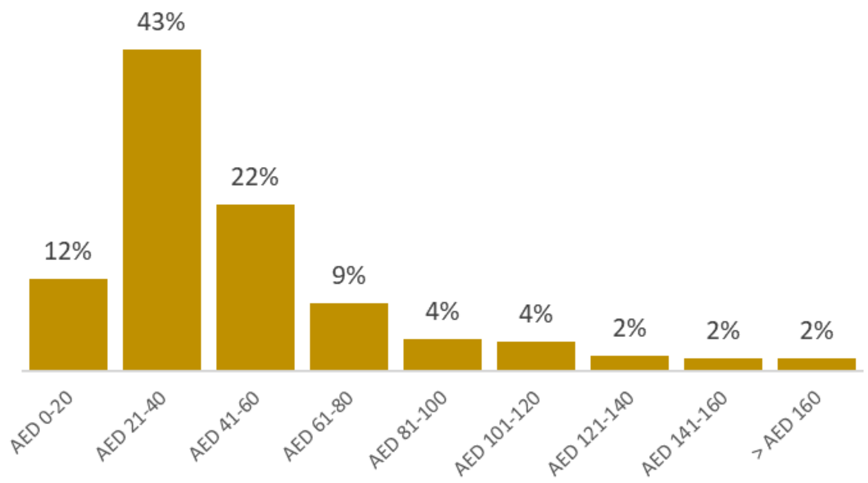


Figure 3-6 Price per kg usually paid for beef mince

3.2.3 Country-of-origin beef purchase frequency

- NZ has the fourth highest country-of-origin beef purchase frequency (Figure 3-7). And is purchased at least occasionally by 58 per cent of consumers.

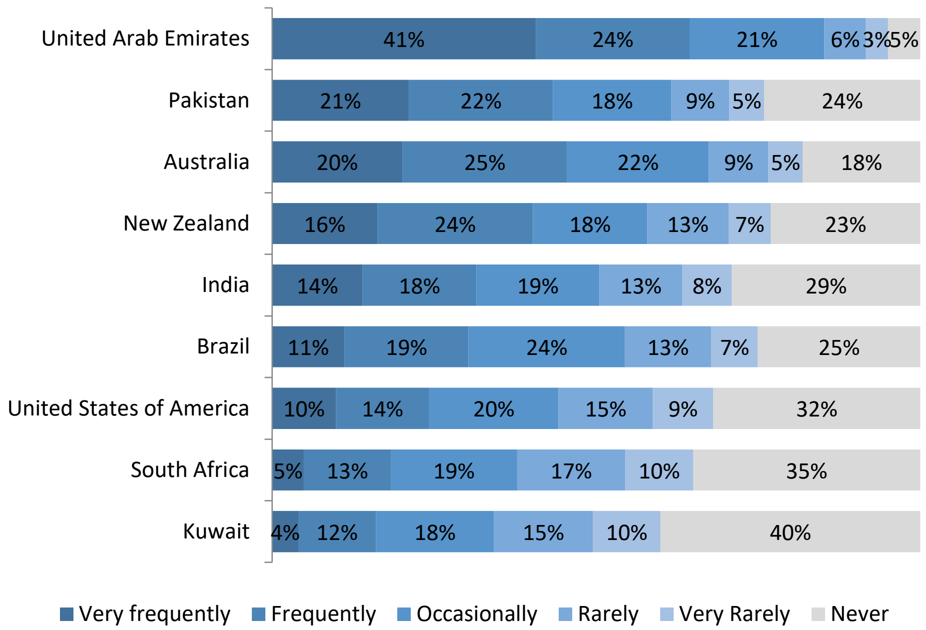


Figure 3-7 Country-of-origin beef purchase frequency

3.2.4 New Zealand beef cuts purchased

- Consumers who had purchased NZ beef at least occasionally (58 per cent, n=533) were asked to indicate which NZ origin beef cuts that they had purchased in the previous month (Figure 3-8).
- The most popluar NZ beef cut purchased was regular cubed beef with 37 per cent purchasing this in the previous month.

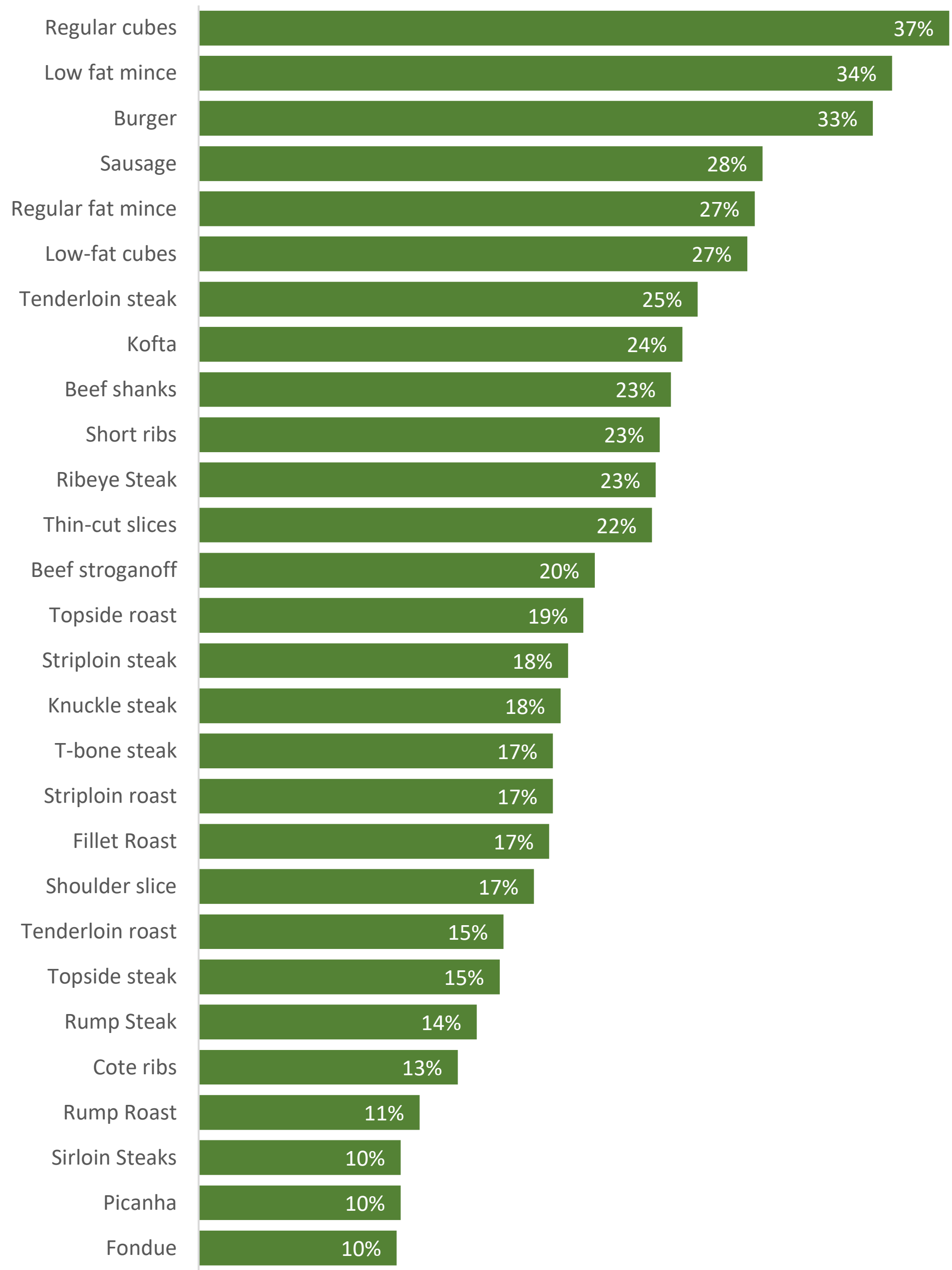


Figure 3-8 NZ beef cuts purchased

3.2.5 Country-of-origin beef quality ranking

- Consumers were asked to rank the quality of beef raised in countries presently in-market (Figure 3-9).
- Beef raised in NZ has a high-quality ranking overall when compared with the other main importing countries considered, and is ranked highest by about a fifth of respondents, and in the top three by 48 percent of respondents.

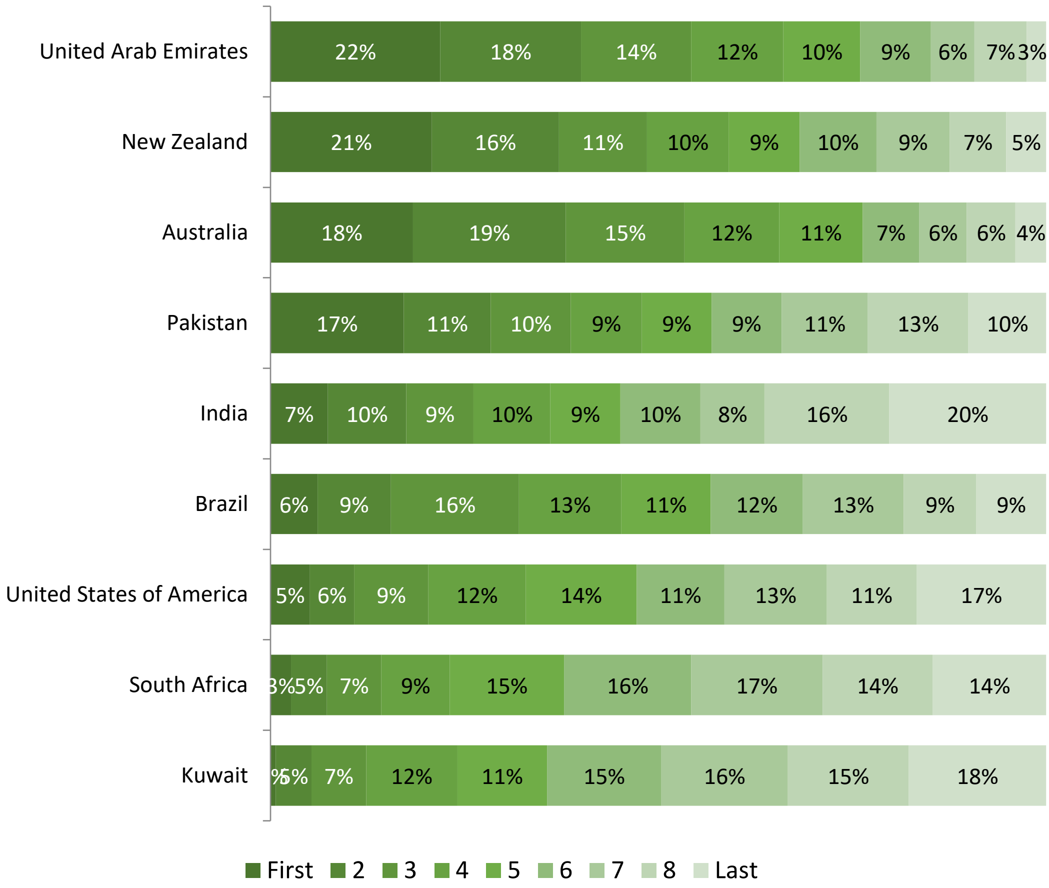


Figure 3-9 Beef country-of-origin ranking

3.3 Use of digital media and smart technologies for beef shopping

3.3.1 Internet access by device and use

- Internet use among respondents was high, with over 90 per cent using the internet at least weekly (Figure 3-10).

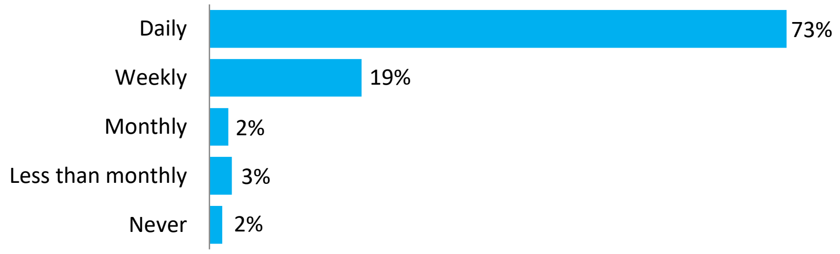


Figure 3-10 Frequency of internet access

- Considering specifically the use of mobile devices (e.g. smartphones), respondents generally had relatively high use of mobile devices to search for information and purchase beef products (Figure 3.11), with 41 per cent often making purchases this way.

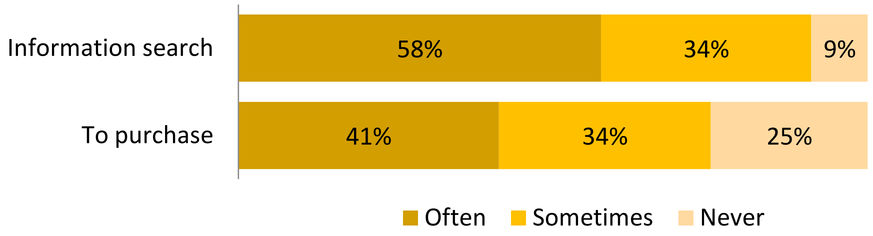


Figure 3-11 Use of smartphones for information search and purchase

3.3.2 Use of mobile device smart technologies for beef

- Barcodes are often used to make beef purchases or search for information by about 30 per cent of consumers (Figure 3-12).

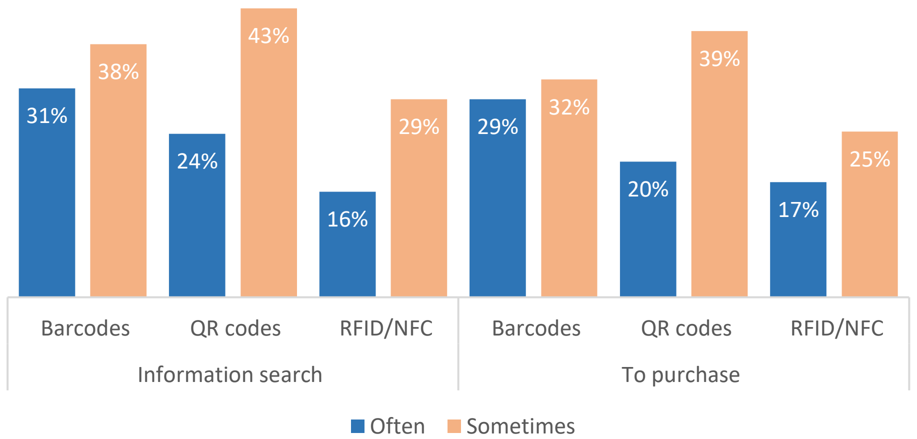


Figure 3-12 Use of smart technologies for information searching and purchase

3.3.3 Sources of online digital media related to beef

- Respondents were asked to indicate which online sources they used to either search for information about *how a beef produced* was produced, or for deciding which products to purchase (Figure 3-13).
- Generally, consumers use the same types of digital media to search for information both on how a beef product is produced as well as deciding which product to purchase.
- Looking at the highest use sources for each, almost 60 per cent of consumers are using You Tube when looking for production information, and 65 per cent are using food company websites to inform their purchase decisions.

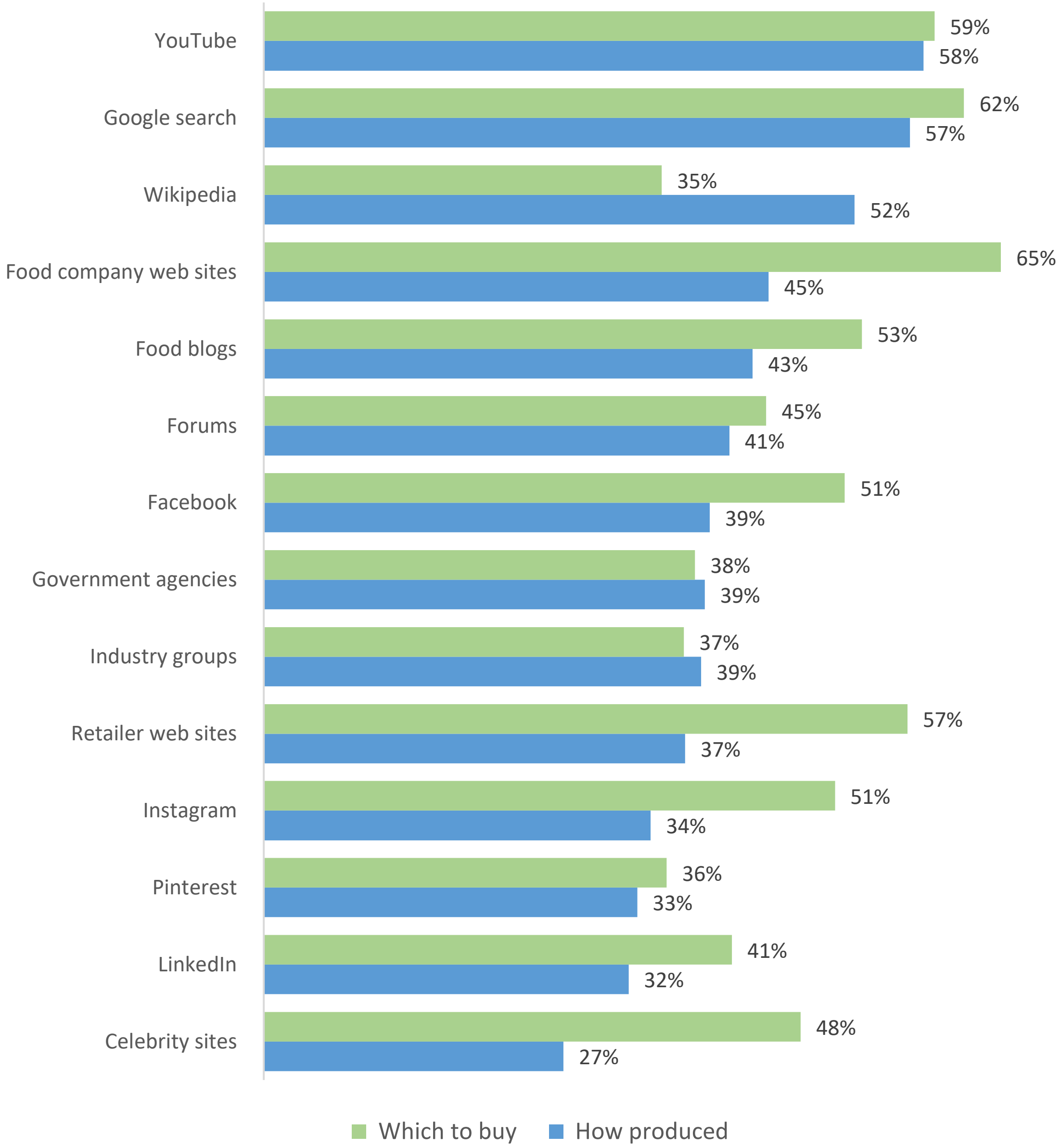


Figure 3-13 Use of digital media for information searching and purchasing

3.3.4 Mobile app use related to beef products

- There is a relatively high use of mobile applications across the sample, and high interest in potential uses where current use is relatively low, such as traceability information (Figure 3-14).
- The most common uses of a smartphone app related to beef products is to make purchases, find recipes, and to access discounts.

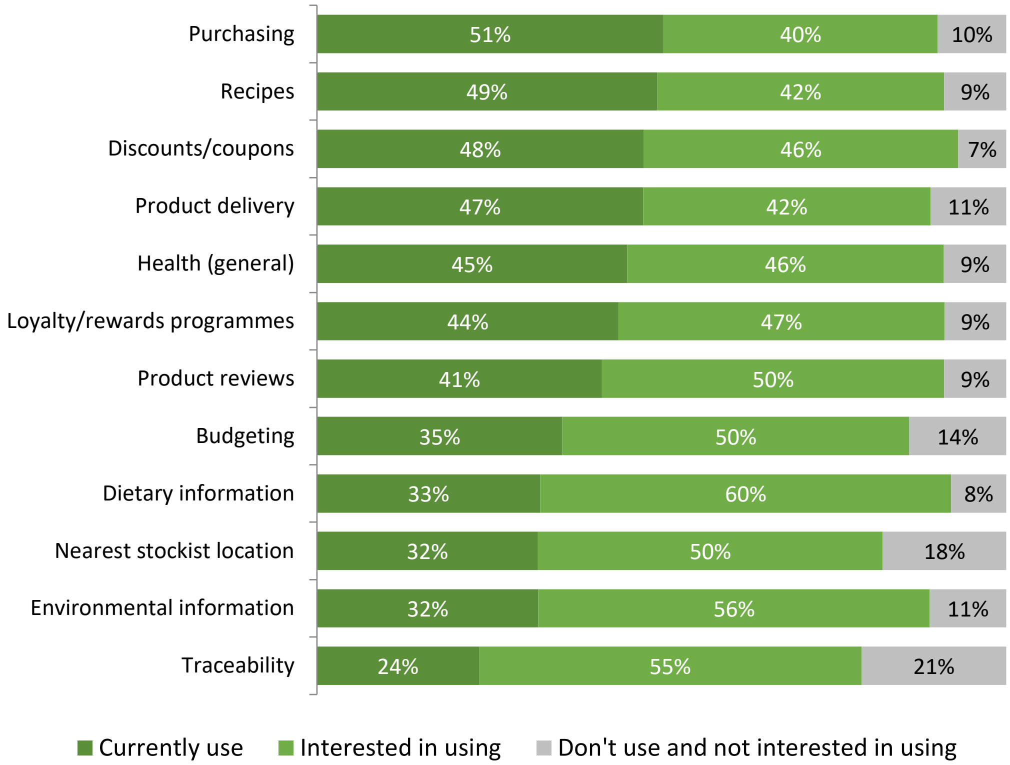


Figure 3-14 Current and potential use of mobile applications

3.3.5 Beef expenditure by purchase channel

- Respondents were asked to allocate their beef expenditure according to their usual purchase channels (Figure 3-15). The graph below shows the average expenditure by channel.
- This shows that on average, the highest level of expenditure occurs with hypermarkets.

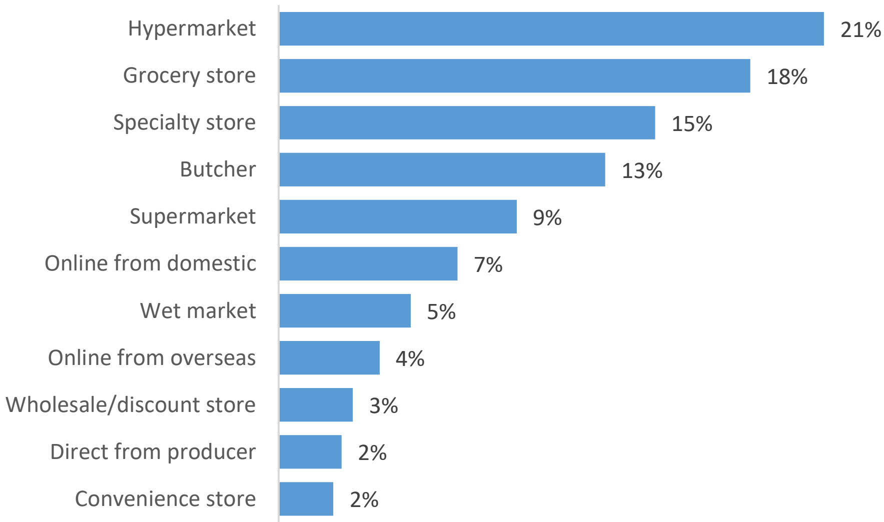


Figure 3-15 Beef expenditure by retail channel

- 54 per cent of consumers purchase beef products online. Convenience of home delivery and access to promotions are important reasons for those choosing to shop for beef online (Figure 3-16).

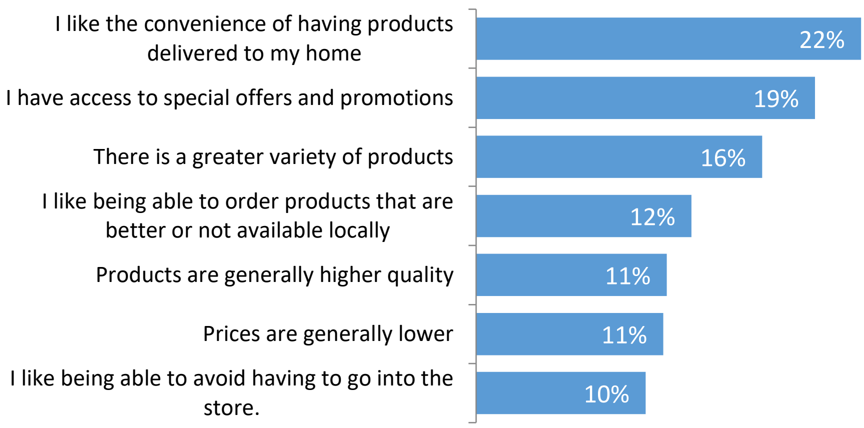


Figure 3-16 Main reason for shopping online for beef

- For those shopping for beef online, hypermarkets and supermarkets are the main retail channels used (Figure 3-17).
- Three quarters of consumers are using international retailers at least sometimes to purchase beef online.

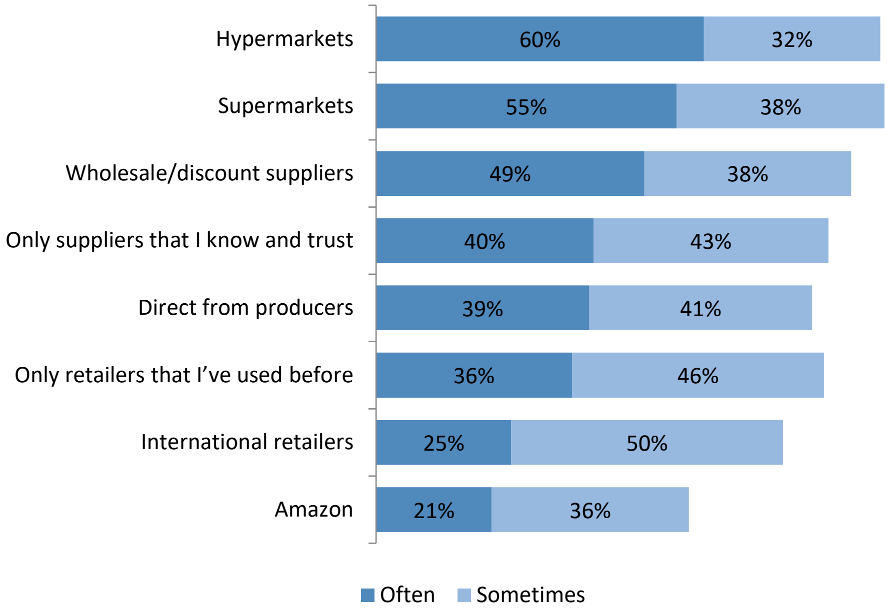


Figure 3-17 Use of online retail channels

3.4 Discrete Choice Experiment analysis of beef mince choices

In this section we present findings of the Discrete Choice Experiment. Our objective is to identify which beef mince attributes drive product choices, by how much, and by who. We do this using a statistical method called Latent Class Modelling that identifies consumer segments in the data based on which product offerings consumers preferred. The model parameter estimates can be found in Appendix B. Discrete Choice Experiments can be somewhat more difficult to answer compared with the usual question formats that people have typically seen before, so it is important to check whether respondents have been able to complete the exercise reliably. Overall, the choice task and product attribute understanding was high, respondents felt that they were able to express what was important to them concerning beef mince attributes, and most respondents felt certain that their responses reflected real-world choices if these beef mince products were available (Figure 3-18).

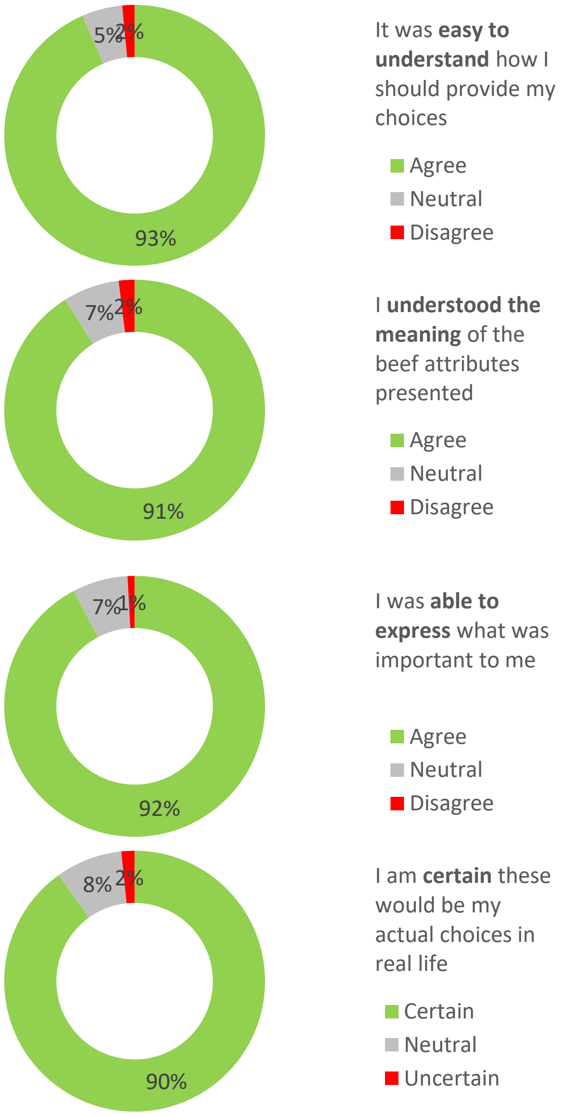


Figure 3-18 DCE task and attribute understanding, preference ability, choice certainty

3.4.1 Consumer willingness-to-pay values

Estimates of WTP tell us how much more the average consumer is willing to pay for per kg of beef mince with a particular attribute, over beef mince that does not have this attribute (Table 3-1, Figure 3-19, Figure 3-20). For example, members of Segment One are willing to pay, on average, AED47.8 more for beef mince that is produced with Water Quality Protection standards over one that is not. There is some uncertainty in WTP estimates, and the Confidence Intervals reported indicate that we can be 95 per cent sure that the true WTP falls within this interval, in this case between AED7 and AED89.

We can see that the Latent Class Modelling has identified three distinct consumer groups. Reported under each segments column heading is the size of each segment, Segment One has an estimated size of 55 per cent, the second segments size is 32 per cent and the third is 13 per cent. These segment sizes tell us the probability that a randomly selected UAE beef mince purchaser belongs to that consumer segment.

Table 3-1 Beef mince attribute willingness-to-pay by consumer group

Beef mince Attribute	Segment One 55%	Segment Two 32%	Segment Three 13%
Carbon Neutral		AED13.5* (-0.8, 28)	
Water Quality Protection	AED15.67** (2, 29)	AED8.80*** (4, 13)	
Organic Production	AED46.67*** (22, 71)	AED6.45* (-0.2, 13)	
Māori Production	AED33.33*** (15, 51)	AED8.04*** (3, 13)	
Feedlot Raised	AED55.00* (13, 126)		AED23.8*** (10, 37)
100% Pasture Raised	AED36.00*** (17, 55)	AED5.69*** (2, 9)	AED16.8*** (5, 29)
100% Grass-fed	AED33.10*** (14,50)		
Grain-fed	AED24.33*** (7, 41)	AED9.73*** (6, 14)	
No added hormones	AED42.23*** (16, 68)	AED6.5*** (0.5, 13)	
No added antibiotics	AED50.67*** (24, 77)	AED12.5*** (6, 19)	
Enhanced Animal Welfare	AED26.70*** (12, 41)	AED11.3*** (8, 15)	
GMO-free	AED26.06*** (10, 41)	AED4.47** (0.8, 8)	AED14.6*** (4, 25)
Social responsibility	AED24.67*** (10, 38)	AED5.42*** (2, 9)	

Average marginal WTP/**kg** beef mince AED 2021.
95% Confidence Interval in brackets.
***, **,* denote statistical significance at the 1%, 5% and 10% levels indicating that a willingness-to-pay estimate is significantly different from zero.

United Arab Emirates Consumer Willingness-to-pay Segments

1. Cultural Consumer — **55% of consumers**

This segment is the largest of the three consumer groups. These consumers have the strongest preferences of the three segments spanning most of the attributes considered. They have the highest willingness-to-pay Māori produced beef of the three segments.

Consumers in this segment are more likely to:

- Have higher usual beef spend
- Have higher income
- Have higher purchase frequency
- Rate NZ beef quality high

2. Carbon Concerned — **32% of consumers**

This segment has broad preferences spanning all but two attributes considered. While they have relatively modest levels of WTP, these consumers are the only segment to value a Carbon Neutral attribute.

Consumers in this segment are more likely to:

- Be male
- Rate NZ lower than other segments
- Have lower usual beef spend

3. Feed-lot Focused — **13% of consumers**

This is the smallest of the three segments. While these consumers have the narrowest set of attribute preferences at just three, they are the only segment to value a feedlot raised. attribute. They also prefer GE-free feed to be given to cattle.

Consumers in this segment are more likely to:

- Have lower purchase frequency
- Have lower consumption frequency
- Be younger

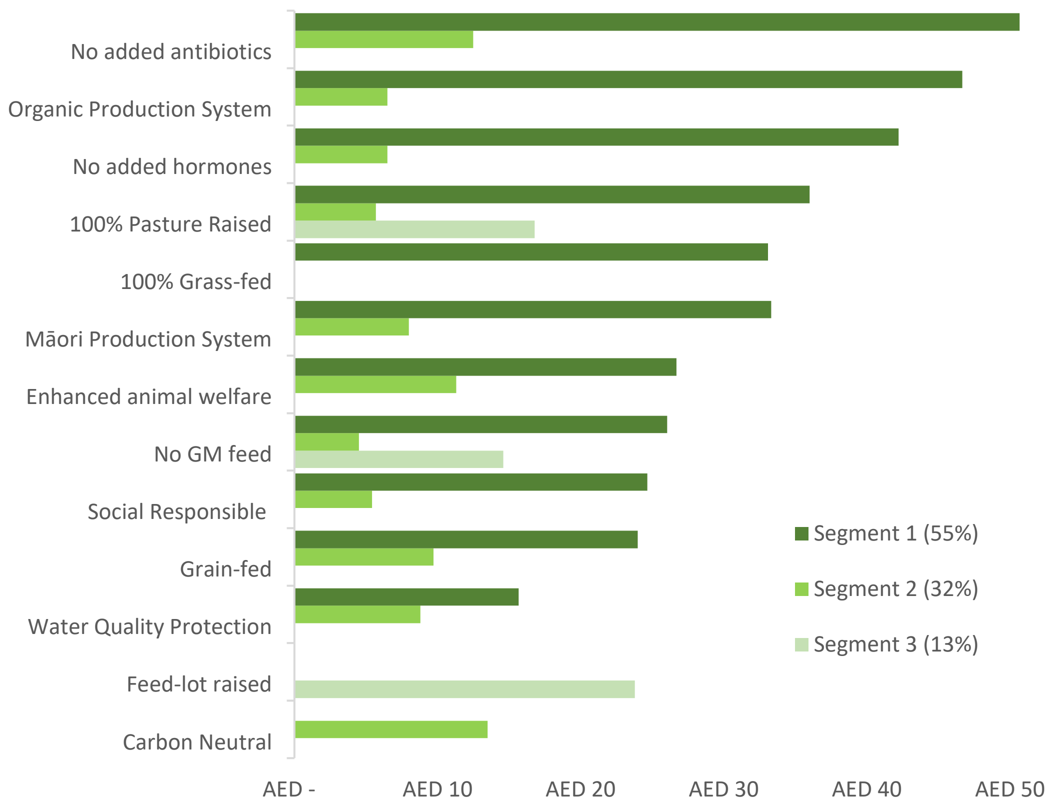


Figure 3-19 UAE consumers' willingness-to-pay for beef mince attributes

To provide an indication of the overall preferences and willingness-to-pay values, the Latent Class Modelling presented above is combined to form an aggregate estimate for each attribute (Figure 3-20). These estimates are formed by weighting willingness-to-pay values for each class by their class size and summing across segments. What this reflects is that the relative WTP ranking result is same as that for segment one alone, because segment one is significantly larger and has much stronger preferences than the other two consumer segments.

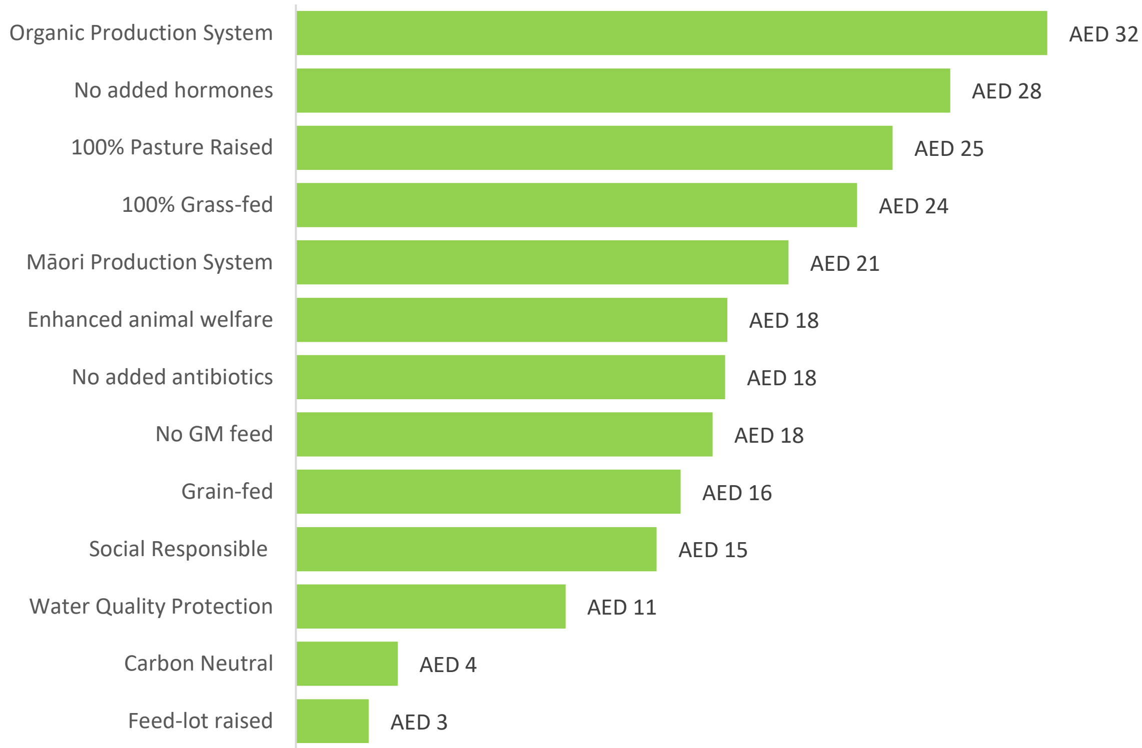


Figure 3-20 Segment weighted aggregate willingness-to-pay

Chapter 4
Conclusions

This report presents the findings of a structured online survey of United Arab Emirates beef mince consumers. The survey objective was to provide insights into consumers' purchase and consumption behaviours. The information gathered included examining perceptions of important drivers of product characteristics, the role of digital media and smart technologies, and consumers' preferences for distinctively New Zealand credence attributes.

Overall, results clearly indicate that New Zealand beef is held in high regard as a high-quality offering with characteristics that consumers prefer and value. The statistical analysis of consumers beef mince choices using the Discrete Choice Experiment and Latent Class Modelling provides a robust analytical framework to identify consumer segments with differing characteristics and product preferences. Profiling high value consumers informs marketing strategy aimed at engaging consumers with the highest willingness-to-pay for the product attributes that New Zealand can deliver.

This survey is the second in the research programme to survey UAE beef mince consumers, with the first survey in 2019[1]. The two samples are very similar on demographic measures including gender, location, education, age, and household composition. Comparing results found here to the previous survey show that:

- The most often purchased beef products are the same across both samples. Average prices paid for less premium cuts such as mince, burger and sausage have remained largely unchanged between 2019 and 2021 survey. While significant increases of around 20 per cent are seen for more premium cuts such as sirloin, ribeye, and Picanha. However, the relative prices paid across a range of different cuts are largely similar.
- Purchases of New Zealand beef products has increased moderately between surveys, with a 17 per cent increase in the number of consumers purchasing NZ beef at least occasionally.
- Consumers ranking of beef quality by country-of-origin remains unchanged between 2019 and 2021, with New Zealand beef quality ranked relatively highly. UAE beef is ranked highest, with NZ and Australian beef being ranked very closely and just below UAE.
- There is a significant increase in the use of digital media and smart technologies related to beef. Use of QR codes for information search and purchasing is about 10 per cent higher in 2021.
- The top uses of smartphone apps related to beef recipes, purchasing and discounts has remained unchanged. In contrast, app use has significantly increased for traceability and environmental information.
- Use of online digital media sources has increased significantly for many sources, and the number of consumers seeking information on how a product is produced has increased substantially.
- The proportion of consumers buying beef online has increased from 27 per cent in 2019 to 54 per cent in 2021. Hypermarkets and supermarkets continue to dominate both the online and physical retail channels.

[1] Tait, Peter, Caroline Saunders, Paul Dalziel, Paul Rutherford, Timothy Driver and Meike Guenther (2020). *United Arab Emirates beef consumer consumption behaviours and product preferences: A Latent Class Analysis.* AERU Research Report No. 359, prepared for Unlocking Export Prosperity Research Programme. Lincoln University: Agribusiness and Economics Research Unit.

At the time of the first survey in 2019, the COVID-19 pandemic had not reached the UAE. The pandemic officially started in the UAE in January 2020 when the first confirmed case was recorded. In the preceding months leading to the second survey conducted in August 2021, there were about 6,000 new cases weekly, and over 2,000 deaths. Covid has significantly affected changes in consumers' food and eating behaviours around the world. Food and nutrition now play a greater role in providing health benefits and in strengthening the immune system. Some of the changes in WTP between 2019 and 2021 estimates may be attributable to these factors. Demand for food that provides preventative health has increased and this can have the effect of lifting overall WTP values across product attributes. Comparison of WTP estimates between 2019 and 2021 show that of the thirteen attributes considered, about half are broadly consistent between surveys, while there are substantial increases in WTP for attributes that can be considered to relate to human health including organic, and no hormones or antibiotics (Figure 4-1).

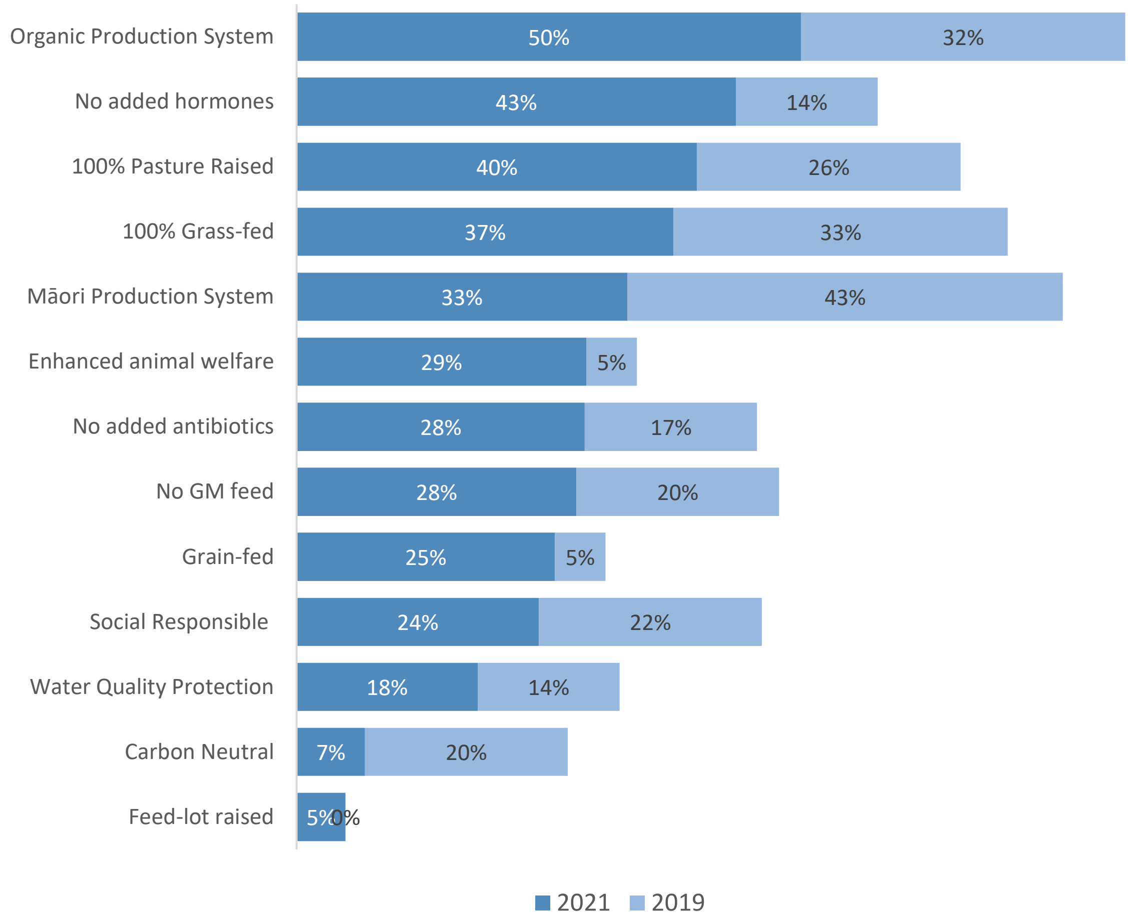


Figure 4-1 Comparing 2021 and 2019 WTP

Appendix A
Statistical Method

This appendix provides technical details of statistical analysis of choice data. The appendix includes a brief description of the theoretical foundations of choice analysis followed by statistical probability estimation approaches, focusing on contemporary models applied in this report. Lastly, the method used in generating monetary estimates is described.

A-1 Conceptual Framework

In Choice Experiments (CEs), researchers are interested of what influences, on average, the survey respondents' decisions to choose one alternative over others. These influences are driven by people's preferences towards the attributes but also the individual circumstances such as their demographics or perceptions of the choice task (e.g., the level of difficulty or understanding) (Hensher et al. 2015).

Each alternative in a choice set is described by attributes that differ in their levels, both across the alternatives and across the choice sets. The levels can be measured either qualitatively (e.g., poor and good) or quantitatively (e.g., kilometres). This concept is based on the characteristics theory of value (Lancaster 1966) stating that these attributes, when combined, provide people a level of utility[2] *U* hence providing a starting point for measuring preferences in CE (Hanley et al. 2013; Hensher et al. 2015). The alternative chosen, by assumption, is the one that maximises people's utility[3] providing the behavioural rule underlying choice analysis:

$$U_j > U_i \tag{0.1}$$

where the individual *n* chooses the alternative *j* if this provides higher utility than alternative *i*. A cornerstone of this framework is Random Utility Theory, dated back to early research on choice making (e.g., Thurstone 1927) and related probability estimation. This theory postulates that utility can be decomposed into systematic (explainable or observed) utility *V* and a stochastic (unobserved) utility ε (Hensher et al. 2015; Lancsar and Savage 2004).

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{0.2}$$

where *j* belongs to a set of J alternatives. The importance of this decomposition is the concept of utility only partly being observable to the researcher, and remaining unobserved sources of utility can be treated as random (Hensher et al. 2015). The observed component includes information of the attributes as a linear function of them and their preference weights (coefficient estimates).

$$V_{nsj} = \sum_{k=1}^{K} \beta_k x_{nsjk} \tag{0.3}$$

with *k* attributes in vector x for a choice set s. Essentially, the estimated parameter β shows "the effect on utility of a change in the level of each attribute" (Hanley et al. 2013, p. 65). This change can be specified as linear across the attribute levels, or as non-linear using either dummy coding or effect coding

[2]Related terminology used in psychology discipline is *the level of satisfaction* (Hensher et al. 2015).
[3] In choice analysis, utility is considered as *ordinal utility* where the relative values of utility are measured (Hensher et al. 2015).

approaches. The latter coding approach has a benefit of not confounding with an alternative specific constant (ASC) when included in the model (Hensher et al. 2015).

A-2 Statistical Modelling of Choice Probabilities

The statistical analysis aims to explain as much as possible of the observed utility using the data obtained from the CE and other relevant survey data. In order to do so, the behavioural rule (eq. 1.1) and the utility function (eq. 1.2) are combined (Hensher et al. 2015; Lancsar and Savage 2004) to estimate the probability of selecting an alternative *j*:

$$\Pr_{nsj} = \Pr\left(U_{nsj} > U_{nsi}\right) = \Pr\left(V_{nsj} + \varepsilon_{nsj} > V_{nsi} + \varepsilon_{nsi}\right) = \Pr\left(\varepsilon_{nsi} - \varepsilon_{nsj} < V_{nsj} - V_{nsi}\right) \forall j \neq i \quad (0.4)$$

where the probability of selecting alternative *j* states that differences in the random part of utility are smaller than differences in the observed part. A standard approach to estimate this probability is a conditional logit, or multinomial logit (MNL) model (McFadden 1974). This model can be derived from the above equations (1.2 and 1.3) by assuming that the unobserved component is independently and identically distributed (IID) following the Extreme Value type 1 distribution (see e.g. Hensher et al. 2015; Train, 2003). Although the MNL model provides a "workhorse" approach in CE, it includes a range of major limitations (see e.g. Fiebig et al. 2010; Greene and Hensher 2007; Hensher et al. 2015):

- Restrictive assumption of the IID error components
- Systematic, or homogenous, preferences allowing no heterogeneity across the sample
- Restrictive substitution patterns, namely the existence of independence of irrelevant alternatives property where introduction (or reduction) of a new alternative would not impact on the relativity of the other alternatives
- The fixed scale parameter obscures potential source of variation

Some or all of these assumptions are often not realised in collected data. These restrictive limitations can be relaxed in contemporary choice models. In particular, the random parameter logit (RPL) model (aka, the mixed logit model) has emerged in empirical application allowing preference estimates to vary across respondents (Fiebig, et al. 2010; Hensher et al. 2015; Revelt and Train, 1998). This is done by specifying a known distribution of variation to be parameter means. The RPL model probability of choosing alternative *j* can be written as:

$$\Pr_{nsj} = \frac{\exp(\beta_n' x_{nsj})}{\sum_J \exp(\beta_n' x_{nsj})} \quad (0.5)$$

where, in the basic specification, $\beta_n = \beta + \eta_n$ with η being a specific variation around the mean for k attributes in vector x (Fiebig, et al. 2010; Hensher et al. 2015). Typical distributional assumptions for the random parameters include normal, triangular and lognormal distributions, amongst others. The normal distribution captures both positive and negative preferences (i.e., *utility* and *disutility*) (Revelt and Train, 1998). The lognormal function can be used in cases where the researcher wants to ensure the parameter has a certain sign (positive or negative), a disadvantage is the resultant long tail of estimate distributions (Hensher et al. 2015). The triangular distribution provides an alternative functional form, where the spread can be constrained (i.e., the mean parameter is free whereas spread is fixed equal to mean) to ensure behaviourally plausible signs in estimation (Hensher et al. 2015). Further specifications used in modelling include parameters associated with individual specific characteristics (e.g, income) that can influence the heterogeneity around the mean, or allowing correlation across the random parameters. The heterogeneity in mean, for example, captures whether individual specific characteristics influence the location of an observation on the random distribution (Hensher et al. 2015). In this study, the frequency of visits to rivers, streams and lakes was used to explain such variance.

Another way to write this probability function (in eq. 1.4) (Hensher et al. 2015) involves an integral of the estimated likelihood over the population:

$$L_{njs} = \int_{\beta} \mathrm{Pr}_{nsj}\left(\beta\right) f\left(\beta \middle| \theta\right) d\beta \tag{0.6}$$

In this specification, the parameter θ is now the probability density function conditional to the distributional assumption of β. As this integral has no closed form solution, the approximation of the probabilities requires a simulation process (Hensher et al. 2015; Train, 2003). In this process for data *X*, *R* number of draws are taken from the random distributions (i.e. the assumption made by the researcher) followed by averaging probabilities from these draws; furthermore these simulated draws are used to compute the expected likelihood functions:

$$L_{nsj} = E(\mathrm{Pr}_{nsj}) \approx \frac{1}{R} \sum_{R} f(\beta^{(r)} | X) \tag{0.7}$$

where the $E(\mathrm{Pr}_{nsj})$ is maximised through Maximum Likelihood Estimation. This specification (in eq. 1.6) can be found in Hensher et al. (2015). In practice, a popular simulation method is the Halton sequence which is considered a systematic method to draw parameters from distributions compared to for example, pseudo-random type approaches (Hensher et al. 2015).

A-3 Econometric Extensions

Common variations of the RPL model include specification of an additional error component (EC) in the unobserved part of the model. This EC extension captures the unobserved variance that is alternative-specific (Greene and Hensher 2007) hence relating to substitution patterns between the alternatives (Hensher et al. 2015). Empirically, one way to explain significant EC in a model is SQ-bias depicted in the stochastic part of utility if the EC is defined to capture correlation between the non-SQ alternatives (Scarpa et al., 2005).

Another extension which has gained increasing attention in recent CE literature, is the Generalized Mixed Logit (GMXL) model (Czajkowski et al. 2014; Hensher et al. 2015; Juutinen et al. 2012; Kragt 2013; Phillips 2014). This model aims to capture remaining unobserved components in utility as a source of choice variability by allowing estimation of the scale heterogeneity alongside the preference heterogeneity (Fiebig et al. 2010; Hensher et al. 2015). This scale parameter is (inversely) related to the error variance, and in convenient applications such as MNL or RPL, this is normalised to one to allow identification (Fiebig et al. 2010; Louviere and Eagle 2006). However, it is possible that the level of error variance differs between or within individuals, due to reasons such as behavioural outcomes, individual characteristics or contextual factors (Louviere and Eagle 2006).

Recent GMXL application builds on model specifications presented in Fiebig et al. (2010), stating that β_n (in eq. 1.4) becomes:

$$\beta_n = \sigma_n \beta + \gamma \eta_n + (1-\gamma)\sigma_n \eta_n \tag{0.8}$$

where σ is the scale factor (typically = 1) and $\gamma \in \{0,1\}$ is a weighting parameter indicating variance in the residual component. In the case the scale factor equals 1, this reduces to the RPL model. The importance of the weighting parameter is the impact on the scaling effect on the overall utility function (population means) versus the individual preference weights (individual means): when γ parameter approaches zero the scale heterogeneity affects both means, whereas when this approaches one the scale heterogeneity affects only the population means (Hensher et al. 2015; Juutinen et al. 2015). Interpretation of these parameters includes

- If γ is close to zero, and statistically significant, this supports the model specification with the variance of residual taste heterogeneity increases with scale (Juutinen et al. 2012); and
- If γ is not statistically significant from one, this suggests that the unobserved residual taste heterogeneity is independent of the scale effect, that is the individual-level parameter estimates differ in means but not variances around the mean (Kragt, 2013)

The scale factor specification (eq. 1.7) can also be extended to respondent specific characteristics associated with the unobserved scale heterogeneity (Hensher et al. 2015; Juutinen et al. 2015):

$$\sigma_n = \exp\{\bar{\sigma} + \tau\omega_n\} \tag{0.9}$$

where $\bar{\sigma}$ *is* the mean parameter in the error variance; and ω is unobserved scale heterogeneity (normally distributed) captured with coefficient τ (Hensher et al. 2015; Juutinen et al. 2015; Kragt, 2013). Juutinen et al. (2012), for example, in context of natural park management found that respondents' education level and the time spent in the park explained the scale heterogeneity ($\tau > 0$, p-value < 0.01). In this study, the respondents indicated levels of choice task understanding and difficulty were used to explain scale heterogeneity.

A-4 Estimation of Monetary Values

Typically the final step of interest in the CE application is the estimation of monetary values of respondent preferences for the attributes considered in utility functions. These are commonly referred to as marginal willingness-to-pay (WTP). WTP estimation is based on the marginal rate of substitution expressed in dollar terms providing a trade-off between some attribute k and the cost involved (Hensher et al. 2015) and is calculated using the ratio of an attribute parameter and the cost parameter. WTP can take into account interaction effects, if statistically significant, such as with the respondent demographics. WTP of attribute *j* by respondent *i* is calculated as the ratio of the estimated model parameters accommodating the influence of the random component (Cicia et al. 2013) as:

$$WTP_i^j = -\left(\frac{\beta_j + \varepsilon_{ij}}{\beta_{price} + \varepsilon_{ip}}\right) \tag{0.10}$$

The estimated mode parameters can also be used to estimate compensating surplus (CS) as a result of policy or quality change in a combination of attributes, using (Hanemann, 1984):

$$\mathbf{CS} = \frac{-1}{\beta cost}\left[\ln\sum_{j=1}^{J}\exp\left\{V_j^0\right\} - \ln\sum_{j=1}^{J}\exp\left\{V_j^1\right\}\right] \tag{0.11}$$

which calculates the difference in utilities before the policy or quality change (V_0) and after the policy or quality change (V_1) (Hanley et al. 2013; Lancsar and Savage 2004). Similar to WTP, the monetary estimation of this change is possible by using the estimate for the monetary attribute $\beta_{cost.}$. Lastly, there are some challenges associated with the empirical estimation of the WTP in the RPL based models. One approach is to use a fixed cost, which simplifies the WTP estimation (Daly et al. 2012) but which may not be as behaviourally a plausible consideration as allowing heterogeneous preferences towards the cost attribute (Bliemer and Rose, 2013; Daziano and Achtnicht, 2014). Conceptually, the estimated cost parameter is a proxy for the marginal utility of income for respondents and economic theory suggests individuals will respondent differently to varying income levels. The use of a random cost parameter however, presents complications in deriving population distribution moments from the ratio of two random parameters.

Appendix B
Latent Class Model of Beef Mince Choices

Table B-1 Latent Class Model of UAE beef mince consumer product choices

Utility parameters[1]	Class 1	Class 2	Class 3
Carbon Neutral	0.14 (0.19)	0.74* (0.40)	-0.17 (0.23)
Biodiversity Enhancement	0.07 (0.16)	0.41 (0.31)	-0.08 (0.21)
Water Quality Protection	0.15***(0.05)	0.48***(0.13)	0.25 (0.16)
Organic production system	0.44***(0.07)	0.35* (0.19)	-0.03 (0.22)
Māori production system	0.31***(0.05)	0.44***(0.13)	-0.24** (0.11)
Feed-lot raised	0.21 (0.33)	0.56 (0.43)	0.57***(0.16)
100% Pasture Raised	0.34***(0.04)	0.31***(0.10)	0.41***(0.16)
100% Grass-fed	0.51* (0.31)	0.77 (0.59)	0.32 (0.21)
Grain-fed	0.23***(0.05)	0.53***(0.12)	0.15 (0.15)
No added hormones	0.40***(0.07)	0.36** (0.17)	-0.21 (0.19)
No added antibiotics	0.47***(0.07)	0.68***(0.18)	0.05 (0.18)
Enhanced animal welfare	0.25***(0.03)	0.61***(0.01)	-0.01 (0.12)
No GM feed	0.24***(0.03)	0.24***(0.11)	0.36***(0.12)
Social Responsibility	0.23***(0.03)	0.30***(0.09)	0.08 (0.13)
Price/kg mince	-0.009***(0.001)	-0.055***(0.00)	-0.024***(0.00)
Opt-Out	-2.59***(0.25)	-3.96***(0.26)	-0.14 (0.20)
Class Membership			
Ethnocentrism scale	-0.04** (0.02)	-0.06***(0.02)	
Male		0.47* (0.27)	
Asian	1.01***(0.27)	0.64** (0.27)	
Beef consumption frequency	0.28***(0.07)		
Price usually paid $/kg	0.02** (0.01)		
NZ purchase Frequency	0.24***(0.07)	0.25***(0.07)	
Average class probability	0.55	0.32	0.13
Model Fit Statistics			
Log Likelihood function	-6,515		
Log Likelihood chi^2 stat (74 d.f.)	7,161***		
McFadden Pseudo R^2	0.36		
Number of observations	9,190		
Number of respondents	919		

***, **,* denote statistical significance at the 1%, 5% and 10% levels respectively for the null hypothesis that a parameter estimate is not significantly different from zero.

Standard errors in brackets.

[1] Parameter mean estimates indicates the estimated average value in the model for each different parameter

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