Assisting Healthier and More Sustainable Online Food Choices Through Digital Quality Signals: Exploring Preferences and Segments

Sigurdsson, Menon, Larsen & Fagerstrøm, 2024

Last edition before print in Australasian Marketing Journal

Abstract:

The current paper contributes to signalling theory by demonstrating the importance of digital quality signals in influencing consumer preferences for sales and segmentation in the context of marketing fresh fish online. We conducted a choice-based conjoint analysis with a latent class segmentation to analyse the significance of digital quality signals compared to traditional attributes online. The analysis of 1,411 global consumers revealed that product rating was among the most important factors when purchasing fresh salmon fillets online. Latent class segmentation identified four distinct segments, the largest being ‘value for money’, where product rating and pricing were most important. The other segments were ‘environmentally friendly’, prioritising procurement methods and place of origin; ‘want it now’, where delivery was the most important factor; and ‘quality conscious’, which relied on three attributes—origin, delivery, and product rating. This study enhances understanding of the impact of socially mediated stimuli. It demonstrates the ability of digital quality signals to compensate for the absence of sensory evaluation in online store environments or deficiencies in knowledge or experience. The findings will benefit the food industry and online grocery retailers in promoting healthier and more sustainable products such as fish online.

Keywords: *signalling theory*, *digital quality signals, product rating online, healthy and sustainable consumption, segmentation*

1 Introduction

The Covid-19 pandemic disrupted the purchasing habits of consumers by forcing them to prioritise online channels for their shopping (Pantano et al., 2020; Sheth, 2020). This shift dramatically changed the relationship between grocery shoppers and food retailers (Melton, 2020). For example, in 2019, 81 % of US consumers had never bought groceries online (Morgan, 2020). However, this reality changed dramatically in 2020, with 79 % of US consumers purchasing groceries online. In the UK, take-home grocery sales increased by 16.9 % during the 12 weeks leading up to 12 July 2020 (McKevitt, 2020). Similarly, food and beverage e-commerce in the United States saw a 170 % increase since 2019, accounting for 9.6 % of all grocery sales in 2021 (Goldberg, 2022). Millennials are the driving force behind this trend, with 61 % purchasing groceries online, compared to 55 % for Generation X and 41 % for Baby Boomers (Nielsen & Food Marketing Institute, 2018). Despite the growing popularity of online food purchases, this market faces several challenges. In an online environment, consumers must form quality expectations by making inferences from different quality signals. This evaluation differs from physical retail environments, where consumers can more actively use their senses, such as smell and touch. For example, it is challenging for consumers to evaluate quality attributes like freshness, taste, and consistency when buying fresh fish online.

The increased emphasis on online retailing has not only involved digitalisation but has also changed how retailers sell products. Sorensen (2017) describes this transition as moving from a passive to an active mode of retailing, where consumers demand more shopper-assisted environments. This demand entails digital signals such as online product reviews, ratings, and recommendations to make quality judgments. Such digital quality signals, originating from either consumer behaviour or retailer initiatives, play a crucial role in shaping consumer perceptions of product quality within the online retail landscape (Dai et al., 2022). The growth of digital quality signals in recent years has significantly impacted consumers' purchasing decisions. For instance, a recent meta-study concludes that the valence and volume of online product reviews are key predictors of sales (Ratchford et al., 2022). Although academic research on the effectiveness of quality signals in influencing online food preferences is valuable, it remains scarce (Sigurdsson et al., 2020), for example, regarding consumers' preferences for quality signals against other online attributes and segmentation analysis.

Although the issues surrounding unsustainable fishing practices and aquaculture are of concern (Lang, 2010; Willett et al., 2019), the Lancet Commission on healthy diets from sustainable food systems highlights fish as a crucial component of the planetary health diet, alongside vegetables, fruits, legumes, whole grains, and nuts (Willett et al., 2019). The Commission recognises the global discrepancy between current dietary patterns and the recommended fish intake, a gap that persists across all regions except East Asia Pacific. Fish offers the potential to replace less nutritious protein sources in diets and boasts a lower carbon footprint than beef, thus contributing to a more sustainable food system. As fish consumption increases, it can contribute to a healthier planet and global population. Enhanced fish intake offers many health benefits for consumers, ultimately contributing to their overall well-being (Willett et al., 2019). However, according to Pitts et al. (2018), online grocery shopping presents both a positive and negative impact on consumers purchasing healthy food, such as, for example, fresh fish. On the one hand, it holds the potential to enhance healthy choices by mitigating unhealthy impulse purchases, employing effective nutrition labelling strategies, and serving as a means to overcome food access limitations for individuals with restricted access to physical stores. On the other hand, it also risks promoting unhealthy choices related to factors such as consumers' reluctance to buy fresh produce through online platforms. In this context, digital quality signals play a pivotal role in addressing consumers' hesitance to purchase fresh fish online, thereby promoting healthier and more sustainable choices in online food shopping. By providing transparent and credible information, these digital signals serve as a valuable mechanism to build confidence among online shoppers. Clear and accurate details about the quality and sourcing of fresh fish not only alleviate concerns related to online purchases but also empower consumers to make informed decisions aligned with their health and sustainability preferences.

Based on the discussion above, this study addresses two key questions advancing the theory and practice of signalling theory: 1) What is the relative importance of digital quality signals in purchasing healthier, more sustainable food items online? 2) How do different consumer groups respond to different digital quality signals?

The current study is built upon the multi-attribute product concept and highlights the value of digital quality signals compared to traditional salient product attributes. Using latent class analysis, we divided consumers into four segments, with the largest group (49.90 %) primarily relying on product rating (more than price). Moreover, product rating was among the most important attributes (either second or third) in the other three segments. This result indicates that product rating is the most important factor for the largest segment and among the most important for the other three consumer segments. Our profiling also reveals a generational gap in reliance on product ratings. However, those who rely more on product ratings are more inclined to shop in physical stores rather than online. These findings underscore Sorensen's (2017) advice to design physical retail stores in line with modern e-commerce practices; that is, it is time for offline stores to learn from online stores.

Our study contributes to the signalling theory by empirically highlighting the relative impact of digital quality signals on fresh fish purchases. According to Ratchford (2022), many studies have been done on product reviews (sentiment and volume) and fewer on other digital quality signals. We address this need for more knowledge by demonstrating the impact of online customer ratings, quantity sold online, and quality signals from firms in shaping consumer behaviour within online grocery retailing. This empirical evidence enhances our understanding of signalling theory's applicability in e-commerce, particularly discerning quality signals for perishable products like fresh fish. In addition, our study responds to the research gap identified in the 'bright side of marketing' discourse (Thaichon et al., 2022) by demonstrating how online grocery retailers can employ digital quality signals to promote the purchasing of products aligning with the planetary diet, such as responsibly resourced fish (Willett et al., 2019). Given the significance of product rating in the current study, it should stimulate further research on different levels related to digital quality signals for active, responsible retailing. We discuss the possible reasons for these findings in the discussion section.

For online grocery managers, the key takeaway is the efficacy of product ratings as a social quality signal in online fresh fish marketing. Notably, nearly half of the consumers in this study belong to the 'Value for Money' segment, emphasising the importance for managers of online fresh fish-selling firms to leverage digital quality signals originating from other consumers. This approach allows them to reach the largest customer segment effectively. This study underscores the importance of comprehending the influence of socially mediated stimuli, offering valuable insights for the food industry and online grocery retailers aiming to promote healthy and sustainable products in online settings.

2 Theoretical Framework

In this section, we first introduce how signalling aids consumers in forming impressions of product quality that influence purchasing groceries online. There is a dearth of academic research on the effects of signals stemming from other consumers and authority signals stemming from retailer recommendations. Then, we define and discuss the term 'digital quality signals' before reviewing relevant literature on three types of quality signals included in the current study: other consumers' experiences, quantity sold online, and the retailer's recommended choice.

2.1 Signalling theory

Difficulties in assessing the true quality of a product or a service because of a lack of expertise or the unobservability of important product attributes can easily lead to asymmetric information (Boulding & Kirmani, 1993). This point implies that producers and retailers can possess more product information than potential buyers. Signals can transfer relevant information when sellers and buyers possess asymmetric information (Boulding & Kirmani, 1993; Connelly et al., 2011). Therefore, marketing is concerned with signalling to influence consumers' perceptions of a product (Erdem & Swait, 1998). All elements of the marketing mix can be used for signalling purposes; for example, high prices (Gavious & Lowengart, 2012), higher warranties (Boulding & Kirmani, 1993), and country-of-origin (Lawley et al., 2012), can signal higher quality. Retailer reputation also affects how product quality is perceived (Chu & Chu, 1994). Moreover, advertisements can serve as implicit signals that enhance the appeal of the advertised firm or product to consumers (Sahni & Nair, 2020). For example, a study by Sigurdsson et al. (2020) found that placing a 'Store Choice' sign near fresh produce in a physical grocery store significantly boosted sales of these items. Signalling is, therefore, a marketing technique that transfers information about unobservable product quality attributes to the consumer to assist consumer choice (Rao et al., 1999).

Consumers' quality perceptions can also be influenced by other consumers' purchase behaviours and experiences. What other consumers do (purchase) and their expressed thoughts about a product can act as social signals (also known as social proof) reflecting the correct choice in a specific situation (Sherif, 1935). The term 'proof' refers to the idea that if other people are doing it (or saying it), it must be the correct behaviour for that situation. Social signals are considered most influential in uncertain situations where an individual cannot determine the appropriate behaviour (Cialdini & Goldstein, 2002; Sherif, 1935). This point is driven by the assumption that other people possess more knowledge about the problem or have information the individual does not have (Banerjee, 1992).

The argument for using signalling theory as a foundation in the present study is that it is particularly relevant in the online food market, where consumers often face challenges in assessing the quality and freshness of perishable goods like fresh fish. Signalling theory offers a theoretical framework for delving into the intricacies of consumers' fresh fish purchases online. By investigating signalling mechanisms and their impact on online purchasing behaviour, we contribute to a more nuanced understanding of this evolving and dynamic food marketplace.

2.2 Quality signals online

The concept of social commerce in online retail environments includes signalling as one of its core elements. According to Sorensen (2017), Amazon has brought 'personal selling' back to retailing by guiding consumers rather than relying on self-service retail. When performing active retailing (Sorensen, 2017), the retailer guides the consumer's choice by providing information, advice, and knowledge that serve as a product recommendation for the consumer. Some of these signals are based on peer behaviour and recommendations, such as product ratings, product reviews, related items based on other customers' actual purchases, and the 'Best Seller' in any category. These opinion and action-based signals (Dai et al., 2022) coexist with the retailers' own recommended choices. In the context of the current study, a digital quality signal is defined as a marketing signal in online retail environments that originates either from other consumers (behaviours/experiences) or retailers, intending to influence consumers' perceptions of product quality. E-commerce companies increasingly incorporate digital quality signals into their websites, building on the mechanism of social signals (Zhang et al., 2018; Zhou & Zou, 2023).

Implementing features such as reviews and ratings is regarded as a 'best practice' among e-commerce sites and is recognised as a major driver of conversions/sales (Appleseed, 2015; Jang et al., 2018; Niraj & Singh, 2015; Ratchford et al., 2022; Salminen et al., 2022). When consumers shop in physical stores, they can examine a product and decide whether or not to purchase it. However, it is challenging for consumers to ascertain and experience the quality of products online. Consumers often worry about product quality without being able to physically inspect products prior to purchase, and these difficulties increase uncertainty (Zhang et al., 2022). In digital retail environments, they must rely on online quality examination (Teo & Yu, 2005) along with quality signals from other consumers' behaviours and experiences (Gavilan et al., 2018). Thus, consumers seek information that will help them decide or find a solution to their problem. Digital quality signals are, therefore, central to understanding consumer choice in online retailing.

There are different types of quality signals online. However, to address our two research questions, we have chosen to analyse three types of digital quality signals. Two originate from consumers' behaviours—online customer ratings and quantity sold online—providing insights into preferences. The third digital quality signal comes from online retailers—product recommendations. This approach offers a comprehensive understanding of the online fresh fish market by examining both consumer-driven metrics and the strategies employed by online retailers. This approach enriches our analysis, providing a nuanced perspective on the dynamics between consumers and online retailers.

2.2.1 Digital quality signals stemming from consumers

This study tests two digital quality signals. Product rating, which draws on user-generated content, and quantity sold online, which is based on other consumers' purchase behaviour. User-generated content is defined as free content created by consumers outside of professional routines and practices (Christodoulides et al., 2012). Digital quality signals in the form of social signals go beyond user-generated content, as online retailers can achieve this signalling based on behavioural data from websites. Therefore, signalling 'quantity sold' is not user-generated but company-generated content based on other customers' collective behaviours.

2.2.1.1 Online product rating

Online product rating indicates customers' average quantitative evaluation of a product or an experience. Online customer product ratings now play a bigger part in how consumers make choices. More consumers are participating in creating product feedback online, and more prospective buyers are relying on the information shared by others when making their choices. Thus, the impact of product ratings on consumer choice has received considerable attention, and the literature that studies the impact of product ratings on overall product quality and customer satisfaction is rich (Kostyra et al., 2016). For instance, Gavilan et al. (2018) found that consumers in the hospitality industry trust low numerical ratings more than high ratings but also tend to shortlist those hotels with better ratings. In other contexts, higher ratings express a higher level of expertise and confidence (Robertson et al., 2021) and sales increases in books (Chevalier & Mayzlin, 2006), beer (Clemons et al., 2006), smartphones (Kaushik et al., 2018), box office (Chintagunta et al., 2010), video games (Zhu & Zhang, 2010), and clothes (Kemper, 2017). Pertinent to this research, prior work has shown the importance of product rating in driving consumers' preferences for fresh fish (Sigurdsson et al., 2020). In a review and synthesis of this literature, King et al. (2014)

organised the existing literature in antecedents of ratings (causes) from a sender and receiver perspective and consequences of ratings (effects) from a sender and receiver perspective. The present study's unit of analysis is the receiver (consumer), and our focus is the consequence/effects of online consumer product ratings.

Furthermore, a study by Paget (2023) shows that 87 per cent of consumers would not consider a business with an average rating below three stars, claiming that a company should have at least a rating of three stars before they consider doing business with them, and 38 per cent require at least four stars. However, Maslowska et al. (2016) found that the relationship between ratings and sales can be nonlinear. Their results showed that products with an average rating of 4.5 and 5 on a five-point scale were significantly less likely to be purchased than those with 4 to 4.5-star ratings. In the context of an online beauty forum, Cheung et al. (2014) found that both peer-consumer purchases (what others say they have purchased) and the number of ratings influenced consumers' purchase decisions. In the same vein, Gavilan et al. (2018) explored the influence of numerical ratings and review volume on consumers' hotel booking choices, revealing that low ratings were trustworthy regardless of the number of reviews, while high ratings were trustworthy only when a high number of reviews supported them. A study by Fagerstrøm et al. (2016) explored the potential influence of online customer ratings on consumer choice-making. The findings indicate that variation in online customer ratings related to delivery reliability significantly influenced participants' choices when selecting a webshop to purchase consumer electronics. Despite the mixed results, most show (Amblee & Bui, 2011; Paget, 2023) its positive effects, and businesses are increasingly striving to mediate sales by capitalising on product ratings, thereby offering consumers a chance to lower risk by relying on peers.

Based on this discussion, we assume that online product ratings are a digital quality signal that significantly impacts consumers' choices when purchasing fresh fish online.

Customer ratings serve as influential signals, acting as social proof and guiding buyers in assessing the quality of fresh fish products. Beyond individual choices, positive ratings contribute to enhancing the credibility and reputation of online sellers, fostering trust and encouraging repeat business.

2.2.1.2 Quantity sold online

Displaying the quantity sold can psychologically affect the consumers, who may believe a product is relatively popular due to the high volume purchased by other consumers (inference of popularity). Popularity is often associated with greater value in a retail context. For example, popularity signals can increase the perceived quality of both the product (Dean, 1999) and the seller (Tucker & Zhang, 2011) and induce customers to buy the product (Castro et al., 2013; Myers & Sar, 2013; Tucker & Zhang, 2011). Consumers were even willing to pay more for mobile applications that were displayed as the most popular compared to those without any information about popularity (Carare, 2012). In a physical store environment, Sigurdsson et al. (2020) and Salmon et al. (2015) found that a 'most sold' banner (signalling other consumers' preferences) for fish fillets and low-fat cheese, respectively, increased the sales of these products. Such banners are widely used in retailing as they are an informative indicator of product popularity. Castro et al. (2013) showed how the appearance of shelf displays (organised versus disorganised) could influence how consumers value products on the shelf displays. In the latter case, relatively few items of a specific product left on a shelf could signal that other consumers are buying the product, which could, in turn, activate inferences that the product is scarce due to its popularity (Castro et al., 2013). The positive influence of digital quality signals based on other consumers' collective purchase behaviour has been found in various products and services, such as electronics, software programs, beauty products, books, and hotels (Cheung et al., 2014; Hanson & Putler, 1996; Jeong & Kwon, 2012; Viglia et al., 2014; Wu & Lee, 2016).

Studies have shown that the degree of impact varies among product types. According to Steinhart et al. (2014), social influence has a greater impact on customers purchasing functional and practical products than those buying self-expressive products, such as fashion items and clothes. Sigurdsson et al. (2020) tested quality signals from peer-consumer purchases in the context of online grocery sales. They investigated the relative impact of the 'Top Seller' signal on consumers' preferences for fresh fish relative to other salient product attributes (such as price, procurement method, delivery time, and country of origin) in the online marketplace. In line with the principle of social signalling (Cialdini & Goldstein, 2004) and active retailing (Sorensen, 2017), a higher quantity sold should be expected to result in greater consumer utility. The term 'utility' refers to the perceived usefulness or desirability values that consumers assign to various aspects or features of a product. Expanding on the established literature, we assume that the quantity sold online serves as a digital quality signal influencing consumers' decisions in purchasing fresh fish online. This real-time measure of popularity communicates product reliability and appeal, shaping consumer confidence.

2.2.2 Digital quality signals stemming from firms

Firm-based quality signals are used extensively in marketing as a persuasion strategy, both offline and online. Previous studies have examined how different non-peer recommendations, such as product sales (Huang & Chen, 2006), editorial recommendations (Smith et al., 2005), recommendation agents (Swaminathan, 2003), and search recommendations (Dellaert & Häubl, 2012), positively influences consumer decision processes. More recently, Sigurdsson et al. (2020) found that the item signage ('The Store's

Choice', 'Top Seller', or 'no signage') was important when purchasing fresh fish online. Since Sigurdsson et al. (2020) combine two quality signals, one stemming from consumers ('Top Seller') and one stemming from the firm ('The Store's Choice') in one attribute in their conjoint design, it is difficult to disentangle the effects of the two types of digital quality signals. Further studies must examine the impact of digital quality signals from firms, such as signalling 'the store's recommendation'. The retailers perceived as credible and competent possess a persuasive force to affect consumer choice by recommending a certain product (Sigurdsson et al., 2020). The meta-study by Floyd et al. (2014) shows the potential impact of expertise. They found that products evaluated by experts had higher sales effects than those evaluated by other consumers. Thus, retailers could be perceived as possessing more relevant information than the consumer. Senecal and Nantel (2004) also provide some empirical evidence, where they found the recommender system offered by the retailer to be more influential on product choices than the traditional recommendation sources such as 'human experts' and 'other consumers'.

Therefore, in this study, digital quality signals from online groceries are assumed to impact consumer purchases of fresh fish by enhancing transparency and credibility in product information, fostering confidence, and driving demand within this online marketplace.

3 Method

3.1 Data Collection

An online survey was employed to gather data from 1,411 consumers (56 % females, 43 % males, 1 % other or declined to reveal their gender) using the Amazon Mechanical Turk (MTurk) crowdsourcing service. Studies have shown that services such as MTurk are efficient, reliable, and valid platforms (e.g., Buhrmester et al., 2011; Hauser & Schwarz, 2016; Holden et al., 2013; Ramsey et al., 2016; Thomas & Clifford, 2017). The survey consisted of two parts. The first part assessed the importance of digital quality signals compared to other relevant attributes related to online fresh fish purchases with a choice-based conjoint (CBC) study. The second part asked consumers about their fish consumption behaviour, purchase frequency, and demographics. The age demographics were measured to replicate different generations (Lyons, 2016): Generation Z (under 20), Generation Y or Millennials (20-35), Generation X (36-50), and Baby Boomers (51 or older). The distribution was as follows: 1 % of the consumers belonged to Generation Z, 61 % to Generation Y, 27 % to Generation X, and 10 % to Baby Boomers.

3.2 Choice-Based Conjoint Design

We designed the survey using Sawtooth Software Lighthouse Studio 9.5.2 and employed Choice-Based Conjoint analysis to identify the most important attributes (Green & Srinivasan, 1978) according to the participants. The product attributes used were primarily identified based on a literature review, while the attributes for digital quality signals were identified by conducting a pre-study survey of 50 participants. The study's methodology was identical to the one used in the main study. The pre-study findings showed that product rating was the most preferred among the digital quality signals, followed by quantity sold online and product recommendation. In addition to digital quality signals, relevant product quality attributes such as delivery time, price, country of origin, procurement method, and packaging were included to increase the ecological validity of the study. Multiple studies (e.g., Kleppe et al., 2002; Leek et al., 2000; Sayin et al., 2010; Sigurdsson et al., 2020) say that a few well-documented attributes may primarily influence households' fish and other seafood purchase. In an online setting, these include our chosen attributes: pricing, place of origin, procurement method, packaging, and delivery. Table 1 displays eight attributes and their corresponding levels and key references. These eight attributes and their corresponding levels constituted a 5 x 3 x 3 x 3 x 3 x 2 x 2 x 2 design.

---Insert Table 1---

Since the prices of wild and farmed salmon differ considerably in quality, we adopted a conditional pricing approach to make the price attribute dependent on the procurement method, thereby resembling a real-life situation. Low, medium, and high prices were operationalised at €18, €24, and €30 per kilogram for wild salmon and €8, €14, and €20 for farmed salmon, respectively. The study comprised 14 tasks each featuring three product concepts and a ‘none alternative’. The ‘none’ option in CBC tasks reflects the real-world scenario, as buyers are not obliged to choose products that do not meet their criteria. According to the Lighthouse Studio manual, it is recommended to have 8-15 choice tasks for paper-based studies and even fewer for web or mobile-based studies. Given that our study was web-based, we opted for 14 choice tasks, considering respondent fatigue. An example of the choice task is shown in Figure 1.

Consumers were asked to select the most attractive concept for each task. Three hundred unique design versions of the questionnaire were generated, and a specific questionnaire was repeated once for every 300 participants. While it is possible to efficiently estimate scores using a single questionnaire version for all respondents, there are practical advantages to utilising multiple questionnaire versions. With multiple versions, each respondent encounters a different set of questions, significantly increasing the diversity in how items are combined within sets across respondents, thereby reducing the potential for context biases (Sawtooth Software, 2023).

The product attributes and the digital quality signals attributes were presented randomly within a concept, and the attribute list was randomised once per respondent; these measures controlled for order effects. In constructing and displaying choice tasks, a random task generation method implementing a balanced overlap design was used, permitting some degree of level overlap (repeating levels within a choice task). This design increased the precision of both main and interaction effects. Three instructional manipulation checks (IMCs), also called screeners, were employed to maintain participant engagement throughout the study. Instead of excluding inattentive participants, a training method (Oppenheimer et al., 2009) was adopted to prompt all participants to focus on the survey. This approach involved persistently presenting the same screener question until participants successfully completed the checks.

---Insert Figure 1---

4 Results

4.1 Choice-Based Conjoint Analysis

Table 2 displays the utility estimates and the relative importance of both the product and digital quality signals attributes. Utilities were estimated using a Hierarchical Bayes (HB) estimation model; for a review, see Allenby and Ginter (1995) and Lenk et al. (1996). The first column of Table 2 lists the attributes and their levels. The table reveals that delivery time holds the highest importance, scoring 21.99, followed by product rating at 21.08, procurement method at 17.64, place of origin at 14.88, and price at 12.15. The store's recommendation scored 4.01, packaging scored 3.80, and quantity sold online scored 4.45.

---Insert Table 2---

Concerning the digital quality signals attributes, which are comparable to traditional product attributes, the results indicate that product rating is the second-most important attribute. This finding supports the general assumption that digital quality signals, particularly those originating from other consumers, serve as social proof guiding consumer choice in online fresh fish purchases (Cialdini & Goldstein, 2002; Jeong & Kwon, 2012).

4.2 Preference Segmentation

Table 3 presents a latent class segmentation of choice data, dividing consumers into four distinct segments based on strong preferences for specific product and digital quality signal attributes. We used the latent class analysis feature within Sawtooth Software and the Consistent Akaike Information Criterion (CAIC) to determine the number of groups. CAIC, proposed by Bozdogan (1987) and its application further explored by Ramaswany et al. (1993), is among the most widely used measures for deciding how many segments to accept (Sawtooth Software, 2021). Unlike other measures, a smaller value of CAIC is preferred. We ran the computation six times, estimating solutions for 2 to 6 segments. In each case, we retained only the solution with the highest Chi-Square. The CAIC decreased dramatically until four groups, after which it became nearly flat for groups 5 and 6. We used this inflexion point to indicate the right number of groups rather than its absolute magnitude. The table reveals that Segment 1 ('Value for Money'), comprising 49.90 % of the consumers, demonstrated a strong preference for product rating, with an attribute importance of 31.86 %. Price (20.34 %) and procurement method (16.76%) were significant attributes for this segment. For Segment 2 ('Environmentally Friendly'), the procurement method was the most preferred attribute, scoring 43.34 % in importance. In Segment 3 ('Want it Now'), delivery emerged as the most preferred attribute, with a notably high importance score of 66.54 %.

Segment 4 (‘Quality Conscious’) displayed more balanced consumer preferences across price (25.55 %), delivery (22.99 %), and product rating
(22.78 %).

---Insert Table 3---

Table 3 highlights product rating as an important digital quality signal attribute across all four segments. Notably, for the largest segment identified, ‘Value for Money’, product rating is the most significant factor, ranking higher than price and delivery. Product rating is also important in the ‘Quality Conscious’ segment, following place of origin and delivery time. The subsequent section offers a profile of each of the four segments to examine any differences in consumer characteristics among them.

4.3 Consumer Segmentation Profiling

According to Table 4, compared to the other segments, the ‘Value for Money’ segment comprises consumers who are more likely to purchase fish online (18.2 % as opposed to 14.0 % overall), are relatively younger and have a well-balanced female-to-male ratio. The gender distribution in all other segments is skewed towards females. For example, females comprise 72 % and 61 % of participants in the ‘Environmentally Friendly’ and ‘Quality Conscious’ segments (mixed). Moreover, the ‘Value for Money’ segment reports slightly more frequent fish consumption and online grocery purchases than the other segments. In other words, this segment is the least likely to report purchasing fish at a physical store compared to the other three segments.

---Insert Table 4---

A one-way between-groups analysis of variance (ANOVA) was conducted to explore the impact of the frequency of fish consumption on the importance of product rating. The frequency of fish consumption was categorised into five groups: Group 1 (Daily), Group 2 (Once a week), Group 3 (2-3 times a week), Group 4 (More than three times a week), and Group 5 (Never). A statistically significant difference was observed at $p < 0.05$ in the importance scores for product rating across the five groups based on the frequency of consumption: F (4, 1406) = 3.22, $p = 0.012$. Although the results reached statistical significance, the actual difference in mean scores between the groups was relatively small. The effect size, calculated using eta-squared, was 0.01. Post-hoc comparisons using the Tukey HSD test revealed that the mean scores for Group 2 ($M = 1.21$, $SD = 0.34$) and Group 4 ($M = 1.13$, $SD = 0.36$) were statistically different from that of Group 5 ($M = 1.28$, $SD = 0.32$).

Further results of a follow-up regression analysis, with product rating as the dependent variable, are presented in Table 5. Although our primary focus is Segment 1, we include corresponding values for the other segments for comparability. Only the results for Segment 1 are statistically noteworthy, as confirmed by the joint F-test at the bottom of Table 5. About Segment 1, both age groups and the place of purchase exhibit significant and positive correlations with product ratings. Specifically, individuals under 36 appear to emphasise other consumers' product ratings more than their older counterparts within the same segment. This trend is evident from the differences in the magnitude of the coefficients for age groups '*19 or under'* and *20-35'*. Regarding the relationship between product rating and the purchase of fish online and offline, those who report purchasing fish at a physical store also tend to rely on online product ratings, as opposed to those who already buy fish online.

---Insert Table 5---

5 Discussion, managerial implications, limitations, and future research

5.1 Discussion

We examined three types of digital quality signals; two focused on consumer behaviour (product rating and quantity sold online), and the third came from the firm (product recommendation). Our findings affirm that digital quality signals can influence consumer choice in purchasing fresh fish online. Specifically, product rating emerged as the second most important factor among all attributes tested, after delivery time. It was more important than pricing, procurement method, and place of origin. The following sections detail the outcomes for each of the three digital quality signals tested.

Product rating: While the advantages of product ratings are generally well-established, their impact on online food selection has been less explored. Therefore, our study underscores the significant value that product ratings offer consumers when purchasing fresh fish online. Product rating emerged as the most important attribute for the largest consumer segment identified through latent class analysis, comprising nearly 50 % of our sample. In two other segments, it ranked as the second most important factor; in the remaining, it was the third most important. These results are consistent with the findings of Cialdini and Goldstein in 2002 and Jeong and Kwon in 2012, reinforcing the idea that the quality signals based on other consumers' perceptions are pivotal in guiding consumer choices in this context. Our study not only confirmed the findings of Sigurdsson et al. (2020) but also enriched them by offering a segmented and profiled analysis rather than aggregated results. Specifically, product rating appears to be a key online quality signal for price-sensitive consumers, as evidenced by the 'Value for Money' segment, providing a more nuanced understanding.

Quantity sold: While previous studies have demonstrated the influence of signalling other consumers' collective purchase behaviour (e.g., Carare, 2012; Jeong & Kwon, 2012; Sigurdsson et al., 2020), our findings indicate that the 'quantity sold online' attribute did not significantly impact buying intentions. This finding is unexpected given the prevalence of such digital quality signals across various online platforms, such as YouTube views, Spotify play counts, and Amazon Best Seller Rankings. Our study employed three levels of 'quantity sold', denoted as average sales of 30/60/90 kgs/day. This method of signalling popularity leaves much room for individual interpretation regarding how popular the item is among other consumers. The popularity signals used by Carare (2012), Jeong & Kwon (2012), and Sigurdsson et al. (2020) are more direct. For instance, it does not require much effort to grasp the meaning of app rankings based on the number of downloads (as used by Carare, 2012). Similarly, signalling that the product is a 'bestseller' or 'top seller', as seen in the study by Sigurdsson et al. (2020), explicitly communicates a product's popularity, leaving little room for individual interpretation. On the other hand, signalling 'quantity sold' requires consumers to engage in more inferential thinking as they translate this information into an understanding of other consumers' behaviour. Consequently, our results may suggest that quality signals based on popularity must be spelt out clearly to have the intended effect on consumers' buying intentions. Alternatively, the variations in the three levels of 'quantity sold' (30/60/90 kgs) might be too subtle to affect consumers' buying intentions significantly.

Firm-based product recommendation: The store's recommendation attribute also significantly impacted participants. However, as anticipated, the impact was notably less than that of the product rating attribute. This discrepancy could be because this information comes from the company, while product ratings are derived from other customers who usually do not receive monetary gains for rating products. Consumers may approach the recommendation with greater scepticism when it originates from the firm itself. They might question the firm's objectivity or wonder if short-term gains motivate the recommendation more than a genuine interest in serving the consumer's best interests.

Other salient attributes: Of the traditional product attributes examined in the study, delivery time had the highest importance score. Previous studies have shown that delivery time is important, particularly in the case of fish. Due to its perishable nature, fish requires prompt delivery to ensure immediate refrigeration (Ghazali et al., 2006). According to these results, it is unsurprising that companies like Amazon are investing heavily in technologies to shorten delivery times. Moreover, 25 per cent of consumers claim they are willing to pay significant premiums for same-day or instant delivery, especially for groceries (Joerss et al., 2016). This proportion is increasing, particularly as younger consumers are more likely to choose faster delivery options. As previously discussed, the rest of the product attributes significantly impacted customers. However, the study first compared digital quality signal attributes (product ratings, quantity sold, and the store's product recommendations) to traditional product attributes that companies control. Interestingly, product rating had a higher impact score than all other product attributes apart from delivery time. Further, although delivery time was the most important factor, the impact of product rating is particularly interesting, as allowing customers to rate previously purchased products can be considerably less expensive than offering same-day delivery.

5.2 Managerial Implications

Our study demonstrates that product ratings, as a social quality signal, can be effective for online fresh fish sellers. The overall importance score for product rating stood at 21.08 %, almost equal to the delivery time as one of the most important attributes to customers purchasing fresh fish online. This observation underscores the value of quality signals originating from other consumers in aiding customers' decision-making processes.

Information on other consumers' views and behaviours can help customers decide and provide a sales mediation to the buying process. Sorensen (2017) calls it a 'ghost in the aisle', suggesting that social signals can facilitate and even finalise a sale.

Although online retailers selling fresh salmon fillets cannot control how many stars each consumer gives a particular product, they can decide to include ratings (and reviews) on their online sales platform. They must avoid situations where a few very dissatisfied consumers substantially affect the average rating. Retailers can increase the ratings by following best practices in encouraging and motivating consumers to engage in ratings, such as via quick response codes and relevant health communication (Fagerstrøm et al., 2023). The volatility (rate of change) of the average online ratings depends on the number of ratings (Leberknight et al., 2012). This volatility tends to decrease exponentially with more ratings until it reaches a point where it becomes stable. At this point, each new review would have little effect on the product's average rating. Introducing a product-rating feature is not enough; it needs to be able to motivate, grab attention, and facilitate responses, choices, and consumption (Pawar et al., 2023). Research examining the factors driving consumers to generate word-of-mouth content on online platforms highlights the significant influence of altruistic motivations (Hennig-Thurau et al., 2004; Yoo and Gretzel, 2008), particularly an honest concern for others. In this context, this concern involves a genuine desire to assist other customers in making informed purchase decisions (Hennig-Thurau et al., 2004). Given that our study's predominant segment is 'Value for Money', it can be inferred that encouraging online ratings from this segment can be achieved by consistently providing excellent value at competitive prices. Aligning with our findings, which underscored the prominence of 'Value for Money' consumers who prioritised product ratings and pricing, sustaining a commitment to offering quality products at attractive prices will likely elicit positive engagement from this consumer segment.

This study discovered that nearly half (49.90 %) of consumers fell into the 'Value for Money' segment. As discussed, this segment demonstrated a strong preference for social proof concepts, such as product rating, more so than any other area in the study. Decision-makers for firms selling fresh fish should take special note of this. By utilising quality signals stemming from other consumers while selling, managers can adequately reach the largest customer segment, those looking for value. As seen in Table 1, the price of fish can act as a barrier for many potential consumers (Claret et al., 2012; Leek et al., 2000; Sigurdsson et al., 2020; Verbeke & Vackier, 2005). Using product rating while selling fish, an establishment can effectively address those potential concerns with this large consumer group.

An additional implication derived from this study is that a better understanding of the impact of socially mediated stimuli would help the food industry and online grocery retailers promote healthy and sustainable products in online settings. This research contributes to the existing literature on social influence in general and online grocery shopping by exploring how the combination of digital quality signals and product attributes influence different consumer preferences for fresh fish (as a healthy food item) online. It answers the call for more research on the 'bright side of marketing' (Thaichon et al., 2022) by examining digital quality signals that retailers can utilise to increase the consumption of products belonging to the planetary diet, such as fish (Willett et al., 2019).

Another important finding of this research that may be very useful to retailers is the breakdown of the importance score of digital quality signals between customer segments. For example, value-focused online fish retailers may find it useful to promote the popularity and rating of certain products. In contrast, a retailer more focused on environmentally friendly seafood may focus efforts elsewhere. Retailers and their customer segments may react differently to social-proof marketing. However, given this, managers can begin to draw a strategic marketing plan that effectively uses social-proof marketing.

5.3 Limitations and Future Research

In CBC, the experimental choices mimic an actual buying situation. However, it is not without limitations. The CBC provides no information about the intensity of preferences nor tells us whether any other products would be acceptable (Orme, 2016). Despite this limitation, this study provides a good picture of the relative importance and consumer perception of different factors and levels. Future studies should include additional questions to measure the depth of preferences and second choices. Given the research method, consumers did not directly evaluate real products and compare the different attributes. Evaluations could change when consumers transition from a survey setting to an actual buying situation. Further studies could, therefore, be conducted in realistic environments (real online stores selling fresh fish) where people make real choices and are affected by the promotion of competing stimuli. Sigurdsson et al. (2020) showcase what this transition could look like, from conjoint analysis to in-store experimentation with favourable results.

Additionally, quantity sold proved insignificant, despite previous results demonstrating that cues signalling product popularity can considerably impact consumers. We suspect the reason to be the small difference in levels used in the study. In this case, the lowest level was 30 kg sold daily, while the highest was 90 kg daily. Higher levels and more differences between levels might yield different results. Future studies could also include other, and more direct, popularity cues, such as displaying the 'most sold product' or 'bestseller' next to the product. Labelling a certain product as a 'bestseller' or 'most sold' would suggest that many people bought this product on previous occasions. Such quality signals (based on popularity) are alternatives to displaying the quantity sold and leave less up to the individual consumer/respondent to make inferences about product popularity. Future studies should examine which quality signals based on popularity have the strongest impact on consumer choice regarding various types of healthy seafood. Further research should also examine review volume as a digital quality signal heuristic in combination with average rating scores. Although only average rating scores were examined in this study, we acknowledge that the number of ratings that each average is based on might influence consumers' choice behaviour. An average rating of 3.5 based on hundreds of ratings could be more influential on behaviour than an average rating of 4.0 with a relatively low number of ratings. Hence, this result warrants further empirical investigation regarding fresh fish and other seafood items sold online.

In our study, we have used product recommendation as an attribute, but only at one level: 'recommended by the store' from a company recommendation perspective. However, retailer recommendations can have many facets, and future studies should incorporate other product recommendations such as 'new arrival' and 'most economical choice', etc. Since the results stem from examining only one variant of a particular seafood product, we do not claim any generalisability towards other seafood products. Food regulations vary across countries, making the findings somewhat applicable in certain situations. We further acknowledge that there might be other consumer-related factors exerting an influence on consumers' choice behaviour. These factors include consumers' risk aversion tendency, degree of self-control, and brand or product familiarity.

6 Conclusion

To increase the value of fish purchases, the current study compared segmented effects of digital quality signals to more traditional product attributes that companies control in retail environments, where consumers make their final purchase decisions. When people cannot assess a product in person, they often use extrinsic cues in their decision-making (Cialdini & Goldstein, 2002; Sherif, 1935). The results contribute to this literature by showing that digital quality signals influence online retailing involving fresh fish. Purchasing fresh fish from an online provider is associated with uncertainty, and digital quality signals can help reduce consumers’ perceived risks (Dean, 1999).

The findings from this study suggest that companies looking to increase their online retailing of fish should utilise digital quality signals to assist consumers in their decision-making processes. The conclusions drawn from this study indicate the promise of utilising **digital** quality signals stemming from other consumers (social proofs) in online retailing for fresh fish, something that has traditionally been a difficult online purchase. The latent class segmentation identified four distinct segments, the largest being ‘Value for Money’, where product rating and pricing were most important. The findings should encourage online grocery retailers to implement more responsible active retailing, guiding consumers, and promoting sustainable healthy food products online.

References

Allenby, G., Ginter, J. (1995). Using extremes to design products and segment markets. *Journal of Marketing Research, 32*(4)*,* 392–403. https://doi.org/10.2307/3152175

Amblee, N. F., & Bui, T. (2011). Harnessing the influence of social proof in online shopping: the effect of electronic word of mouth on sales of digital microproducts. *International Journal of Electronic Commerce*, *16*, 91-113. doi: 10.2307/23106395

Appleseed, J. (2015, March 25). Users' Perception of Product Ratings (New Qualitative & Quantitative Findings)[Web log post]. https://baymard.com/blog/user-perception-of-product-ratings

Banerjee, A.J. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*, *107(3)*, 797–817. https://doi.org/10.2307/2118364.

Boulding, W., & Kirmani, A. (1993). A consumer-side experimental examination of signaling theory: Do consumers perceive warranties as signals of quality? *Journal of Consumer Research*, *20*(1), 111–123. https://doi.org/10.1086/209337.

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality data? *Perspectives on Psychological Science, 6*(1), 3–5. https://doi.org/10.1177/1745691610393980.

Carare, O. (2012). The impact of bestseller rank on demand: evidence from the app market. *International Economic Review*, *52*(3), 717–742. https://doi.org/10.1111/j.1468-2354.2012.00698.x.

Castro, I., Morales, A., & Nowlis, S. (2013). The influence of disorganized shelf displays and limited product quantity on consumer purchase. *Journal of Marketing, 77*(4), 118–133. https://doi.org/10.1509/jm.11.0495.

Cheung, C. Xiao, B. & Liu, I. (2014). Do actions speak louder than voices? The signaling role of social information cues in influencing consumer purchase decisions. *Decision Support Systems*, *65*, 50–58. https://doi.org/10.1016/j.dss.2014.05.002

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research, 43*(3), 345–354. https://doi.org/10.1509/jmkr.43.3.345

Chintagunta, P. K., Gopinath, S., & Venkataraman, S. (2010). The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science*, *29*(5), 944–957. https://doi.org/10.1287/mksc.1100.0572

Christodoulides, G., Jevons, C., & Bonhomme, J. (2012). Memo to marketers: quantitative evidence for change: How user-generated content really affects brands. *Journal of Advertising Research*, *52*(1), 53–64. https://doi.org/10.2501/JAR-52-1-053-064

Chu, W., & Chu, W. (1994). Signaling quality by selling through a reputable retailer: An example of renting the reputation of another agent. *Marketing Science*, *13*(2), 121–202. https://doi.org/10.1287/mksc.13.2.177

Cialdini, R. B., & Goldstein, N. J. (2002). The science and practice of persuasion. *The Cornell Hotel and Restaurant Administration Quarterly*, *43*(2)*,* 40–50. https://doi.org/10.1016/S0010-8804(02)80030-1

Cialdini, R. B., & Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annual Review of Psychology*, *55*, 591–621. https://doi.org/10.1146/annurev.psych.55.090902.142015

Claret A., Guerrero L., Aguirre E., Rincón L., Hernández M.D., Martínez I., Peleteiro, J. B., Grau, A., & Rodríguez- Rodríguez, C. (2012). Consumer preferences for sea fish using conjoint analysis. Exploratory study of the importance of country of origin, obtaining method, storage conditions and purchasing price. *Food Quality and Preference*, *26*(2), 259–266. https://doi.org/10.1016/j.foodqual.2012.05.006

Claret, A., Guerrero, L., Ginés, R., Grau, A., Hernández, M. D., Aguirre, E., Peleteiro, J. B., Fernández-Pato, C., & Rodríguez- Rodríguez, C. (2014). Consumer beliefs regarding farmed versus wild fish. *Appetite*, *79*, 25–31. https://doi.org/10.1016/j.appet.2014.03.031

Clemons, E. K., Gao, G. G., & Hitt, L. M. (2006). When online reviews meet hyperdifferentiation: A study of the craft beer industry. *Journal of Management Information Systems*, *23*(2), 149–171. https://doi.org/10.2753/MIS0742-1222230207.

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling Theory: A Review and Assessment. *Journal of Management*, 37(1), 39–67. https://doi.org/10.1177/0149206310388419.

Dai, H., Xiao, Q., Yan, N., Xu, X., & Tong, T. (2022). What influences online sales across different types of e-commerce platforms. *International Journal of Electronic Commerce*, 26(3), 311-330. https://doi.org/10.1080/10864415.2022.2076196

Dean, D. H. (1999). Brand endorsement, popularity, and event sponsorship as advertising cues affecting consumer pre-purchase attitudes. *Journal of Advertising*, *28*(3), 1–12. https://doi.org/10.1080/00913367.1999.10673585

Dellaert, B. G. C., & Häubl, G. (2012). Searching in choice mode: Consumer decision processess in product search with recommendations. *Journal of Marketing Research*, *49*(2), 277–288. doi: https://www.jstor.org/stable/23142850

Erdem, T., & Swait, J. (1998). Brand equity as a signaling phenomenon. *Journal of Consumer Psychology*, *7*(2), 131–157. https://doi.org/10.1207/s15327663jcp0702_02

Fagerstrøm, A., Eriksson, N., Khamtanet, S., Jitkuekul, P., Sigurdsson, V., & Larsen, N. M. (2023). The relative impact of health communication conveyed via quick response codes: A conjoint experiment among young thai consumers doing grocery shopping. *Health Marketing Quarterly, 40*(2), 206–225. https://doi.org/10.1080/07359683.2022.2085460.

Fagerstrøm, A., Ghinea, G., & Sydnes, L. (2016). Understanding the impact of online reviews on customer choice: A probability discounting approach. *Psychology & Marketing, 33*(2), 125–134. https://doi.org/10.1002/mar.20859

Floyd, K., Freling, R., Alhoqail, S., Cho, H. Y., & Freling, T. (2014). How online product reviews affect retail sales: A meta-analysis. *Journal of Retailing*, 90(2), 217–232. https://doi.org/10.1016/j.jretai.2014.04.004

Gavilan, D., Avello, M., & Martinez-Navarro, G. (2018). The influence of online ratings and reviews on hotel booking consideration. *Tourism Management, 66,* 53–61. https://doi.org/10.1016/j.tourman.2017.10.018

Gavious, A., & Lowengart, O. (2012). Price-quality relationship in the presence of asymmetric dynamic reference quality effects. *Marketing Letters*, 23(*1*), 137–161. 10.1007/s11002-011-9143-4.

Ghazali, E., Mutum, D., & Mahbob, N. A. (2006). Exploratory study of buying fish online: are Malaysians ready to adopt online grocery shopping? *International Journal of Electronic Marketing and Retailing, 1*(1), 67–82. http://doi.org/10.1504/IJEMR.2006.010096

Goldberg, J. (2022, February 18). *E-commerce sales grew 50% to $870 billion during the pandemic.* Forbes. https://www.forbes.com/sites/jasongoldberg/2022/02/18/e-commerce-sales-grew-50-to-870-billion-during-the-pandemic/?sh=2e19a8794e83.

Green, P. E., & Srinivasan, V. (1978). Conjoint analysis in consumer research: Issues and outlook. *Journal of Consumer Research, 5*(2), 103. https://doi.org/10.1086/208721.

Hanson, W. A., & Putler, D. S. (1996). Hits and misses: Herd behavior and online product popularity. *Marketing Letters*, *7*(4), 297–305. https://www.jstor.org/stable/40216416

Hauser, D. J., & Schwarz, N. (2016). Attentive Turkers: MTurk participants perform better on online attention checks than subject pool participants. *Behavior Research Methods, 48,* 400–407. https://doi.org/10.3758/s13428-015-0578-z.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the internet?. *Journal of Interactive Marketing*, 18(1), 38–52.

Holden, C. J., Dennie, T., & Hicks, A. D. (2013). Assessing the reliability of the M5-120 on Amazon's Mechanical Turk. Computers in Human Behavior, 29(4), 1749–1754. https://doi.org/10.1016/j.chb.2013.02.020.

Huang, J-H., & Chen, Y-F. (2006). Herding in online product choice. *Psychology & Marketing*, *23*(5), 413–428. doi: 10.1002/mar.20119.

Jang, S., Liu, T., Kang, J. H., & Yang, H. (2018). Understanding important hotel attributes from the consumer perspective over time. *Australasian Marketing Journal, 26*(1), 23–30. https://doi.org/10.1016/j.ausmj.2018.02.001

Jeong, H. J., & Kwon, K. N. (2012). The effectiveness of two online persuasion claims: Limited product availability and product popularity. *Journal of Promotion Management, 18*(1), 83–99. https://doi.org/10.1080/10496491.2012.646221

Joerss, M., Neuhaus, F., & Schröder, J. (2016, October 19). *How customer demands are reshaping last-mile delivery.* McKinsey & Company. https://www.mckinsey.com/industries/travel-logistics-and-transport-infrastructure/our-insights/how-customer-demands-are-reshaping-last-mile-delivery

Kaushik, K., Mishra, R., Rana, N. P., & Dwivedi, Y. K. (2018). Exploring reviews and review sequences on e-commerce platform: A study of helpful reviews on Amazon.in.

Journal of Retailing and Consumer Services. 45, 21–32. https://doi.org/10.1016/j.jretconser.2018.08.002.

Kemper, J. (2017). The power of online customer reviews in fashion e-commerce - An empirical analysis across categories and brands. Proceedings of the 25th European Conference on Information Systems (ECIS).

King, R. A., Racherla, P., & Bush, V. D. (2014). What we know and don't know about online word-of-mouth: A review and synthesis of the literature. *Journal of Interactive Marketing, 28*(3), 167–183. https://doi.org/10.1016/j.intmar.2014.02.001

Kleppe, I. A., Iversen, N. M., & Stensaker, I. G. (2002). Country images in marketing strategies: Conceptual issues and an empirical Asian illustration. Journal of Brand Management, 10(1), 67–74.

Kostyra, D. S., Reiner, J., Natter, M., & Klapper, D. (2016). Decomposing the effects of online customer reviews on brand, price, and product attributes. *International Journal of Research in Marketing*, *33*(1), 11–26. https://doi.org/10.1016/j.ijresmar.2014.12.004

Lang, T. (2010). Sustainable diets and biodiversity: The challenge for policy, evidence and behaviour change. In Burlingame, B. and Dernini, S. (Eds.), *Sustainable diets and biodiversity – Directions and solutions for policy, research and action* (pp. 20-26). FAO. https://www.fao.org/3/i3004e/i3004e.pdf

Lawley, M., Birch, D., & Hamblin, D. (2012). An exploratory study into the role and interplay of intrinsic and extrinsic cues in Australian consumers' evaluations of fish. *Australasian Marketing Journal, 20*(4), 260–267. https://doi.org/10.1016/j.ausmj.2012.05.014

Leberknight, C. S., Sen, S., & Chiang, M. (2012). On the volatility of online ratings: An empirical study. In *E-Life: Web-Enabled Convergence of Commerce, Work, and*

Social Life - 10th Workshop on E-Business, WEB 2011, Revised Selected Papers (Vol. 108 LNBIP, pp. 77–86). (Lecture Notes in Business Information Processing; Vol. 108 LNBIP). Springer Verlag.

Leek, S., Maddock, S., & Foxall, G. (2000). Situational determinants of fish consumption. *British Food Journal*, *102*(1), 18–39. https://doi.org/10.1108/00070700010310614

Lenk, P., Desarbo, W., Green, P., & Young, M. (1996). Hierarchical bayes conjoint analysis: Recovery of partworth heterogeneity from reduced experimental designs. *Marketing Science, 15*(2)*,* 173–191. https://doi.org/10.1287/mksc.15.2.173.

Luomala, H. (2007). Exploring the role of food origin as a source of meanings for consumers and as a determinant of consumers' actual food choices. *Journal of Business Research, 60*(2), 122–129. https://doi.org/10.1016/j.jbusres.2006.10.010.

Lyons, K. (2016, March 7). Generation Y: A guide to much maligned demographic. *The Guardian*. https://www.theguardian.com/world/2016/mar/07/millennials-generation-y-guide-to-much-maligned-demographic

Maslowska, E., Malthouse, E., & Bernritter, S. (2016). Too good to be true: the role of online reviews' features in probability to buy. *International Journal of Advertising*, *36*(1), 142–163. https://doi.org/10.1080/02650487.2016.1195622

McKevitt, F. (2020, July 21). *UK grocery sales reach a record of £31.6 billion over the most recent 12 weeks.* https://www.kantar.com/uki/inspiration/fmcg/uk-grocery-sales-reach-new-high-as-shoppers-remain-cautious.

Melton, J. (2020, August 20). *2020 changed the face of grocery retailing – likely forever.* https://www.digitalcommerce360.com/article/online-food-report/

Morgan, B. (2020, December 14). *3 lasting changes to grocery shopping after Covid-19. Forbes.* https://www.forbes.com/sites/blakemorgan/2020/12/14/3-lasting-changes-to-grocery-shopping-after-covid-19/?sh=388af4b654e7.

Myers, J. R., & Sar, S. (2013). Persuasive social approval cues in print advertising: Exploring visual and textual strategies and consumer self-monitoring. *Journal of Marketing Communications*, *19*(3), 168–181. https://doi.org/10.1080/13527266.2011.581303.

Nguyen, T. T., Haider, W., Solgaard, H. S., Ravn-Jonsen, L., & Roth, E. (2015). Consumer willingness to pay for quality attributes of fresh seafood: A labeled latent class model. *Food quality and preference*, *41*, 225-236. doi: 10.1016/j.foodqual.2014.12.007.

Nguyen, D. H., de Leeuw, S., Dullaert, W., & Foubert, B. P. J. (2019). What is the right delivery option for you? Consumer preferences for delivery attributes in online re-tailing. *Journal of Business Logistics*, 40(*4*), 299-321. https://doi.org/10.1111/jbl.12210.

Nielsen & Food Marketing Institute. (2018). *The Digitally Engaged Food Shopper Developing Your Omnichannel Collaboration Model.* Retrieved April 17, 2018.

Niraj, R., & Singh, J. (2015). Impact of user-generated and professional critics reviews on Bollywood movie success. *Australasian Marketing Journal, 23*(3), 179–187. https://doi.org/10.1016/j.ausmj.2015.02.001

Oppenheimer, D. M., Meyvis, T., & Davidenko, N. (2009). Instructional manipulation checks: Detecting satisficing to increase statistical power. *Journal of Experimental Social Psychology*, *45*(4), 867–872. https://doi.org/10.1016/j.jesp.2009.03.009

Orme, B. K. (2016). *CBC/HB v.5.* https://content.sawtoothsoftware.com/assets/276545e9-0445-474c-b01c-f5b24c3eba6d.

Paget, S. (2023, February 7). Local Consumer Review Survey 2023. https://www.brightlocal.com/learn/local-consumer-review-survey/.

Pantano, E., Pizzi, G., Scarpi, D., & Dennis, C. (2020). Competing during a pandemic? Retailers' ups and downs during the COVID-19 outbreak. *Journal of Business Research*, *116*, 209–213. https://doi.org/10.1016/j.jbusres.2020.05.036.

Pawar, S., Fagerstrøm, A., Sigurdsson, V., & Arntzen, E. (2023). Analyzing motivating functions of consumer behavior: Evidence from attention and neural responses to choices and consumption. *Frontiers in Psychology, 14.* https://doi.org/10.3389/fpsyg.2023.1053528.

Pitts, S. B. J., Ng, S. W., Blitstein, J. L., Gustafson, A., & Niculescu. (2018). Online grocery shopping: Promise and pitfalls for healthier food and beverage purchases. *Public Health Nutrition*, 21 (*18*), 3360-3376. doi: 10.1017/S1368980018002409.

Ramaswamy, V., W. S. DeSarbo, D. J. Reibstein, and W. T. Robinson. (1993). An empirical pooling approach for estimating marketing mix elasticities with PIMS data. *Marketing Science*, 12, 103-124.

Ramsey, S. R., Thompson, K. L., McKenzie, M., & Rosenbaum, A. (2016). Psychological research in the Internet age: The quality of web-based data. *Computers in Human Behavior,* 58, 354–360. https://doi.org/10.1016/j.chb.2015.12.049

Rao, A. R., Qu, L., & Ruekert, A. R. (1999). Signaling unobservable product quality through a brand ally. *Journal of Marketing Research*, 36(*2*), 258–268. https://doi.org/10.1177/002224379903600209

Ratchford, B., Soysal, G., Zentner, A., & Gauri, D. K. (2022). Online and offline retailing: What we know and directions for future research. *Journal of Retailing*, 98(*1*), 152-177. https://doi.org/10.1016/j.jretai.2022.02.007

Rickertsen, K., Alfnes, F., Combris, P., Enderli, G., Issanchou, S., & Shogren, J. F. (2017) French consumers' attitudes and preferences toward wild and farmed fish. *Marine Resource Economics*, 32(*1*), 59–81. https://doi.org/10.1086/689202.

Robertson, J., Ferreira, C., & Paschen, J. (2021). Reading between the lines: Understanding customer experience with disruptive technology through online reviews. *Australasian Marketing Journal*, 29(3), 215–224. https://doi.org/10.1177/1839334921999487.

Sahni, N. S., & Nair, H. S. (2020). Does advertising serve as a signal? Evidence from a field experiment in mobile search. *The Review of Economic Studies*, 87(3), 1529-1564. https://doi.org/10.1093/restud/rdz053

Salmon, S. J., De Vet, E., Adriaanse, M. A., Fennis, B. M., Veltkamp, M., & De Ridder, D. T. D. (2015). Social proof in the supermarket: promoting healthy choices under low self-control conditions. *Food Quality and Preferences*, *45*, 113–120. https://doi.org/10.1016/j.foodqual.2015.06.004

Salminen, J., Kandpal, C., Kamel, A. M., Jung, S. G., & Jansen, B. J. (2022). Creating and detecting fake reviews of online products. *Journal of Retailing and Consumer Services, 64,* 102771. https://doi.org/10.1016/j.jretconser.2021.102771

Sawtooth Software, Inc. (2021). The latent class technical paper v4.8. https://sawtoothsoftware.com/resources/technical-papers/latent-class-technical-paper

Sawtooth Software, Inc. (2023). *Lighthouse Studio v9.15.0*. https://sawtoothsoftware.com/help/lighthouse-studio/manual/index.html.

Sayin, C., Emre, Y., Mencet, M. N., Karaman, S., & Tascioglu, Y. (2010). Analysis of factors affecting fish purchasing decisions of the household: Antalya district case. Journal of Animal and Veterinary Advances, 9(12), 1689–1695.

Senecal, S., & Nantel, J. (2004). The influence of online product recommendations on consumers' online choices. *Journal of Retailing*, *80*(2), 159–169. https://doi.org/10.1016/j.jretai.2004.04.001.

Sheth. J. (2020). Impact of Covid-19 on consumer behavior: Will the old habits return or die? *Journal of Business Research*. *117*. 280–283. https://doi.org/10.1016/j.jbusres.2020.05.059.

Sherif, M. (1935). A study of some social factors in perception. *Archives of Psychology (Columbia University), 187*, 60.

Sigurdsson, V., Menon, R. G., & Fagerstrøm, A. (2017). Online healthy food experiments: Capturing complexity by using choice-based conjoint analysis. *The Behavior Analyst, 40*(2), 373–391. https://doi.org/10.1007/s40614-017-0114-9.

Sigurdsson, V., Larsen, N. M., Alemu, M. H., Gallogly, J. K., Menon, R. G. V., & Fagerstrøm, A. (2020). Assisting sustainable food consumption: The effects of quality signals stemming from consumers and stores in online and physical grocery retailing. *Journal of Business Research*, *112*, 458–471. https://doi.org/10.1016/j.jbusres.2019.11.029.

Silayoi, P., & Speece, M. (2004). Packaging and purchase decisions: An exploratory study on the impact of involvement level and time pressure. British Food Journal, 106(8), 607-628.https://doi.org/10.1108/00070700410553602.

Simmonds, G., Woods, A. T., & Spence, C. (2018). 'Show me the goods': Assessing the effectiveness of transparent packaging vs. product imagery on product evaluation. *Food Quality and Preference*, *63*, 18–27. https://doi.org/10.1016/j.foodqual.2017.07.015

Smith, D., Menon, S., & Sivakumar, K. (2005). Online peer and editorial recommendations, trusts, and choice in virtual markets. *Journal of Interactive Marketing*, *19*(3), 15–57. doi: https://doi.org/10.1002/dir.20041.

Sorensen, H. (2017). *Inside the mind of the shopper* (2nd ed.). Pearson Education, Inc.

Steinhart, Y., Kamins, M., Mazursky, D., & Noy, A. (2014). Effects of product type and contextual cues on eliciting naive theories of popularity and exclusivity. *Journal of Consumer Psychology*, *24*(4), 472–483. https://doi.org/10.1016/j.jcps.2014.04.004

Swaminathan, V. (2003). The impact of recommendation agents on consumer evaluation and choice: The moderating role of category risk, product complexity, and consumer knowledge. *Journal of Consumer Psychology*, *13*(1-2), 93–101. https://doi.org/10.1207/S15327663JCP13-1&2_08

Teo, T., Yu, Y. (2004). Online buying behavior: A transaction cost economics perspective. *Omega, 33*(5)*,* 451–465. https://doi.org/10.1016/j.omega.2004.06.002

Thaichon, P., Quach, S., & Ngo, L. V. (2022). Emerging research trends in marketing: A review of Australasian Marketing Journal. *Australasian Marketing Journal, 30*(3), 214–227. https://doi.org/10.1177/14413582221110450

Thomas, K. A., & Clifford, S. (2017). Validity and Mechanical Turk: An assessment of exclusion methods and interactive experiments. *Computers in Human Behavior, 77*, 184–197. https://doi.org/10.1016/j.chb.2017.08.038

Tucker, C., & Zhang, J. (2011). How does popularity information affect choices? A field experiment. *Management Science*, *57*(5), 828–842. https://doi.org/10.1287/mnsc.1110.1312

Uchida, H., Onozaka, Y., Morita, T., & Managi, S. (2014). Demand for ecolabeled seafood in the Japanese market: A conjoint analysis of the impact of information and interaction with other labels. *Food Policy, 44,* 68–76. doi: 10.1016/j.foodpol.2013.10.002.

Verbeke, W., & Vackier, I. (2005). Individual determinants of fish consumption: Application of the theory of planned behaviour. *Appetite*, *44*(1), 67–82. https://doi.org/10.1016/j.appet.2004.08.006

Verbeke, W., Vermeir, I., & Brunso, K. (2007). Consumer evaluation of fish quality as basis for fish market segmentation. Food Quality and Preference, 18(4), 651–661. https://doi.org/10.1016/j.foodqual.2006.09.005

Viglia, G., Furlan, R., & Ladrón-de-Guevara, A. (2014). Please, talk about it! When hotel popularity boosts preferences. *International Journal of Hospitality Management*, *42*, 144–164. https://doi.org/10.1016/j.ijhm.2014.07.001

Willett, W., Rockström, J., Loken, B., Springmann, M., Lang, T., Vermeulen, S., Garnett, T., Tilman, D., DeClerck, F., Wood, A., Jonell, M., Clark, M., Gordon, L. J., Fanzo, J., Hawkes, C., Zurayk, R., Rivera, J. A., De Vries, W., Sibanda, L. M., … Murray, C. J. L. (2019). Food in the Anthropocene: The EAT-Lancet Commission on healthy diets from sustainable food systems. *The Lancet, 393*(10170), 447–492. https://doi.org/10.1016/S0140-6736(18)31788-4

Wu, L., & Lee., C. (2016). Limited edition for me and best seller for you: The impact of scarcity versus popularity cues on self versus other-purchase behaviour. *Journal of Retailing*, *92*(4), 486–499. https://doi.org/10.1016/j.jretai.2016.08.001.

Yoo, K. H., & Gretzel, U. (2008). What motivates consumers to write online travel reviews?. *Information Technology & Tourism*, 10(4), 283-295.

Zhang, Y., Voorhees, C. M., Lin, C., Chiang, J., Hult, G. T. M., & Calantone, R. J. (2022). Information search and product returns across mobile and traditional online channels. *Journal of Retailing, 98*(2), 260–276. https://doi.org/10.1016/j.jretai.2021.05.001

Zhang, H., Zhao, L., & Gupta, S. (2018). The role of online product recommendations on customer decision making and loyalty in social shopping communities. *International Journal of Information Management, 38*(1), 150–166. https://doi.org/10.1016/j.ijinfomgt.2017.07.006

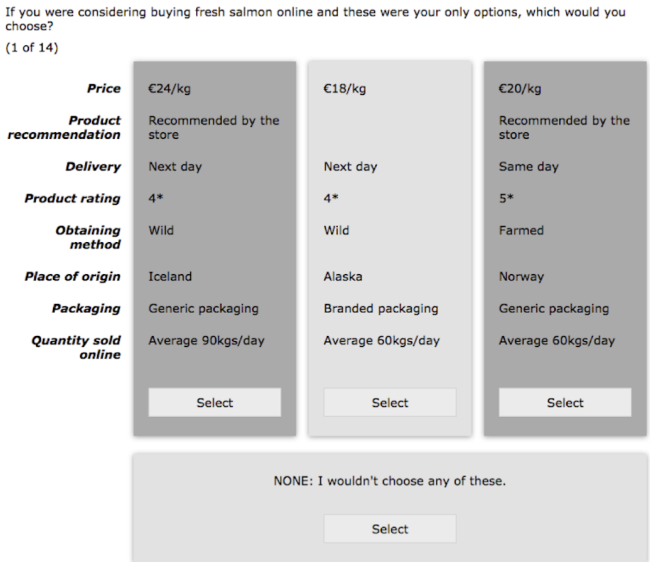
Zhou, B., & Zou, T. (2023). Competing for recommendations: The strategic impact of personalized product recommendations in online marketplaces. *Marketing Science, 42*(2), 360–376. https://doi.org/10.1287/mksc.2022.1388

Zhu, F., & Zhang, X. (2010). Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing*, *74*, 133–148. https://doi.org/10.1509/jmkg.74.2.133

Figures

Figure 1. Example of a choice task

In the next section, we will be asking you specifically about purchasing fresh fish online. We would like you to imagine that you are considering buying fresh fish from an online store. We will show you different options related to buying fish online and ask **which one you would purchase**. It is important that you answer in the way you would if you were **actually buying fresh fish from an online store**.



If you were considering buying fresh salmon online and these were your only options, which would you choose?

(1 of 14)

Price	€24/kg	€18/kg	€20/kg
Product recommendation	Recommended by the store		Recommended by the store
Delivery	Next day	Next day	Same day
Product rating	4*	4*	5*
Obtaining method	Wild	Wild	Farmed
Place of origin	Iceland	Alaska	Norway
Packaging	Generic packaging	Branded packaging	Generic packaging
Quantity sold online	Average 90kgs/day	Average 60kgs/day	Average 60kgs/day
	Select	Select	Select

NONE: I wouldn't choose any of these.

Select

Tables

Table 1. Attributes and levels (choice sets) used in the conjoint analysis design.

Attribute name	Attribute description	Levels	Examples of references
Quantity sold online	This is often perceived as an indication of popularity and can be translated by the consumer as an inference of quality.	Avg 30 kgs/day Avg 60 kgs/day Avg 90 kgs/day	Cheung et al. (2014); Jeong & Kwon (2012); Salmon et al. (2015); Sigurdsson et al. (2020); Viglia et al. (2014); Wu & Lee (2016)
Product Recommendation	Indicates whether the product is recommended by the store or not.	Recommended by the store No level shown	Senecal & Nantel (2004); Sigurdsson et al. (2020)
Product rating	Indicates how consumers in a similar situation regard a product or an experience. This signal shows others their level of satisfaction with the item in question. These signals are often presented online as stars, thumbs up or down, or an overall score.	Three stars Four stars Five stars	Chevalier and Mayzlin (2006); Fagerstrøm et al. (2016); Gavilan et al. (2018); Kostyra et al. (2015)
Price	This can be seen as an indicator of the quality of fish products. However, it is a barrier for some consumers.	Low Price Medium Price High Price	Claret et al. (2012); Leek et al. (2000); Sayin et al. (2010); Verbeke & Vackier (2005)
Place of origin	Indicates where the fish product has been sourced from. The source of fish products indicates quality and food safety for some consumers.	Iceland Norway Scotland Alaska Japan	Claret et al. (2012); Kleppe et al. (2002); Luomala (2007); Pieniak et al. (2013); Uchida et al. (2014)
Procurement method	Denotes the way that the fish was obtained. The procurement method has been perceived as an indicator of quality, with wild being assumed to be superior. Consumers are increasingly interested in sustainability and ethical issues, which has shifted this mindset.	Wild Farmed	Claret et al. (2014); Davidson et al. (2012); Nguyen et al. (2015); Rickertsen et al. (2017)

Packaging	Indicates the type of packaging used for the product. Changes in packaging have been shown to influence consumer preference.	Branded Packaging Generic Packaging	Silayoi & Speece (2004); Simmonds et al. (2018)
Delivery	Delivery time can be defined as the amount of time between order placement and receipt of the product.	Same day Next day Within three days	Nguyen et al. (2019); Sigurdsson et al. (2020)

Table 2. Conjoint impact estimates and relative importance of attributes/features

Attributes	Levels	Utility Estimates	Importance score (%)
Place of origin			14.88
	Iceland	3.28	
	Norway	-2.45	
	Scotland	-2.48	
	Alaska	37.92	
	Japan	-36.27	
Procurement method			17.64
	Wild	12.56	
	Farmed	-12.56	
Price			12.15
	Low price	36.89	
	Medium price	1.50	
	High price	-38.39	
Quantity sold online			4.45
	Avg 30 kgs/day	-3.05	
	Avg 60 kgs/day	-0.12	
	Avg 90 kgs/day	3.17	
Product recommendation			4.01
	Recommended by the store	10.64	
	No level shown	-10.64	
Packaging			3.80
	Branded packaging	7.58	

	Generic packaging	-7.58	
Delivery			21.99
	Same day	68.66	
	Next day	13.17	
	Within three days	-81.83	
Product rating	3*	-81.31	21.08
	4*	13.65	
	5*	67.66	
None		-146.70	

Table 3. Mean part-worth utilities and importance of attributes/features for four consumer segments

		Utilities				Attribute importance			
Attributes/	**Levels**	**Segment 1 - Value for money**	**Segment 2 - Environmentally friendly**	**Segment 3 - Want it now**	**Segment 4 - Quality conscious**	**Value for money (%)**	**Environmentally friendly (%)**	**Want it now (%)**	**Quality conscious (%)**
Place of origin	Iceland	0.92	19.07	-0.75	7.53	9.63	17.84	6.82	25.55
	Norway	-10.84	1.92	-0.40	-9.61				
	Scotland	6.81	-4.36	-9.94	-72.41				
	Alaska	40.08	63.03	32.83	132.01				
	Japan	-36.97	-79.67	-21.74	-57.51				
Procurement method	Wild	-67.05	173.37	-1.49	25.40	16.76	43.34	0.37	6.35
	Farmed	67.05	-173.37	1.49	-25.40				
Price	Low price	78.08	20.41	13.71	60.55	20.34	5.05	3.35	12.84

	Medium price	6.60	-0.42	-0.60	-18.35				
	High price	-84.68	-20.00	-13.11	-42.19				
Quantity sold online	Avg 30 kgs/day	-4.11	-6.72	-7.66	4.28	1.24	1.42	1.53	2.98
	Avg 60 kgs/day	-1.70	2.03	4.57	9.79				
	Avg 90 kgs/day	5.82	4.68	3.09	-14.07				
Product recommendation	Recommended by the store	18.48	8.90	10.07	9.66	4.62	2.23	2.52	2.41
	No level shown	-18.48	-8.90	-10.07	-9.66				
Packaging	Branded packaging	10.71	4.45	6.86	16.33	2.68	1.11	1.72	4.08
	Generic packaging	-10.71	-4.45	-6.86	-16.33				
Delivery						12.86	13.21	66.54	22.99

	Same day	41.57	38.21	247.30	98.42				
	Next day	19.75	29.25	37.71	-12.89				
	Within three days	-61.32	-67.45	-285.01	-85.53				
Product rating	3*	-128.79	-70.94	-76.31	-96.09	31.86	15.80	17.15	22.78
	4*	2.70	15.48	15.39	9.94				
	5*	126.09	55.45	60.93	86.15				
None		-455.07	-125.14	-155.92	335.17				
Segment Sizes (%)		**49.90**	**19.60**	**17.20**	**13.40**				

Table 4. Consumer segment profiles

Variable	Category/Group	Consumer segments (column % in brackets)				Total	P-value
		Value for money	Environmentally friendly	Want it now	Quality conscious		
Frequency of grocery purchase	I do not buy grocery items online	218 (30.79)	101 (36.86)	80 (33.2)	75 (39.89)	474 (33.59)	0.123
	I sometimes buy grocery items online	422 (59.6)	150 (54.74)	142 (58.92)	104 (55.32)	818 (57.97)	
	I buy most of my grocery items online	68 (9.6)	23 (8.39)	19 (7.88)	9 (4.79)	119 (8.43)	
Fish purchase online	I have bought fresh fish online	129 (18.22)	28 (10.22)	27 (11.2)	14 (7.45)	198 (14.03)	0
	No, but I would like to buy fresh fish online	212 (29.94)	83 (30.29)	66 (27.39)	35 (18.62)	396 (28.07)	
	No, I prefer to buy fish from the store	367 (51.84)	163 (59.49)	148 (61.41)	139 (73.94)	817 (57.9)	
Age	19 or under	12 (1.69)	1 (0.36)	4 (1.66)	1 (0.53)	18 (1.28)	0
	20-35	475 (67.09)	127 (46.35)	147 (61)	109 (57.98)	858 (60.81)	

	36-50	165 (23.31)	107 (39.05)	67 (27.8)	46 (24.47)	385 (27.29)	
	51 or older	53 (7.49)	39 (14.23)	23 (9.54)	31 (16.49)	146 (10.35)	
	Refuse to answer	3 (0.42)	0 (0)	0 (0)	1 (0.53)	4 (0.28)	
Gender	Male	351 (49.58)	78 (28.47)	112 (46.47)	72 (38.3)	613 (43.44)	0
	Female	353 (49.86)	196 (71.53)	129 (53.53)	114 (60.64)	792 (56.13)	
	Other	1 (0.14)	0 (0)	0 (0)	1 (0.53)	2 (0.14)	
	Refuse to answer	3 (0.42)	0 (0)	0 (0)	1 (0.53)	4 (0.28)	
Income	Less than € 30,000	237 (33.47)	59 (21.53)	99 (41.08)	58 (30.85)	453 (32.1)	0
	Between € 30,000 and € 60,000	262 (37.01)	89 (32.48)	71 (29.46)	61 (32.45)	483 (34.23)	
	Between € 60,001 and €90,000	115 (16.24)	67 (24.45)	40 (16.6)	35 (18.62)	257 (18.21)	
	Between € 90,001 and €120,000	52 (7.34)	36 (13.14)	23 (9.54)	13 (6.91)	124 (8.79)	
	Above € 120,001	24 (3.39)	13 (4.74)	7 (2.9)	11 (5.85)	55 (3.9)	
	Refuse to answer	18 (2.54)	10 (3.65)	1 (0.41)	10 (5.32)	39 (2.76)	

Frequency of fish consumption	Daily	30 (4.24)	8 (2.92)	10 (4.15)	4 (2.13)	52 (3.69)	0.023
	Once a week	434 (61.3)	168 (61.31)	143 (59.34)	99 (52.66)	844 (59.82)	
	2-3 times a week	123 (17.37)	58 (21.17)	42 (17.43)	32 (17.02)	255 (18.07)	
	More than three times a week	34 (4.8)	8 (2.92)	10 (4.15)	8 (4.26)	60 (4.25)	
	Never	87 (12.29)	32 (11.68)	36 (14.94)	45 (23.94)	200 (14.17)	
Total		708 (50.18)	274 (19.42)	241 (17.08)	188 (13.32)	1411 (100)	

Table 5. Segment comparison concerning product rating

	Consumer segments			
Dependent variable: Product rating	**Value for money**	**Environmentally friendly**	**Want it now**	**Quality conscious**
Age group (reference group: 36-50)				
19 or under	0.542*	0.649	0.0699	-0.881
	(0.308)	(0.931)	(0.497)	(0.822)
20-35	0.163*	0.246**	0.0631	-0.125
	(0.092)	(0.116)	(0.141)	(0.150)
51 or older	0.00641	-0.229	0.108	-0.0595
	(0.171)	(0.190)	(0.268)	(0.210)
Gender (reference group: male)				
Female	0.0437	0.0912	0.0464	-0.303**
	(0.077)	(0.121)	(0.133)	(0.127)
Income (reference group: Less than € 30,000)				
Between € 30,000 and € 60,000	0.0321	-0.152	0.2	0.0466
	(0.089)	(0.147)	(0.152)	(0.150)
Between € 60,001 and €90,000	0.0729	0.0197	0.308*	-0.174
	(0.112)	(0.159)	(0.182)	(0.180)
Between € 90,001 and €120,000	-0.194	0.252	0.656***	-0.232
	(0.150)	(0.186)	(0.220)	(0.257)
Above € 120,001	0.282	-0.283	0.208	-0.438
	(0.214)	(0.276)	(0.372)	(0.276)

Refuse to answer	-0.17	-0.00709	1.331	0.425
	(0.260)	(0.301)	(0.980)	(0.314)
Occupation (reference group: Employee)				
Self-employed	0.00104	-0.0694	-0.0479	-0.189
	(0.105)	(0.143)	(0.170)	(0.176)
Homegoing/Housewife	0.0999	0.285*	0.07	0.312
	(0.135)	(0.171)	(0.212)	(0.197)
Retired	0.0494	0.0343	-0.166	0.167
	(0.244)	(0.277)	(0.435)	(0.328)
Student	-0.0838	0.0231	0.232	0.255
	(0.152)	(0.296)	(0.289)	(0.256)
Other	0.301	0.164	0.212	0.14
	(0.237)	(0.318)	(0.378)	(0.291)
Frequency of grocery purchase (reference group: I do not buy grocery items online)				
I sometimes buy grocery items online	0.0575	-0.0317	-0.0137	0.0767
	(0.086)	(0.115)	(0.139)	(0.130)
I buy most of my grocery items online	0.0333	-0.427**	-0.268	0.192
	(0.149)	(0.216)	(0.259)	(0.299)
Fish purchase online (reference group: Yes, I have bought fresh fish online)				
No, but I would like to buy fresh fish online	0.179	-0.208	-0.265	0.254
	(0.118)	(0.196)	(0.222)	(0.278)
I prefer to buy fish from the store	0.316***	-0.169	-0.335	0.00327
	(0.115)	(0.192)	(0.218)	(0.252)

Frequency of fish consumption (reference group: daily consumers)				
Once a week	-0.102	-0.294	-0.3	-0.298
	(0.192)	(0.321)	(0.322)	(0.421)
2-3 times a week	0.112	-0.335	-0.451	-0.494
	(0.205)	(0.329)	(0.345)	(0.433)
More than three times a week	-0.245	-0.406	-0.499	-1.205**
	(0.251)	(0.436)	(0.447)	(0.518)
Never	0.25	-0.329	0.013	-0.384
	(0.221)	(0.351)	(0.368)	(0.434)
Constant	-1.737***	-1.501***	-1.543***	-0.916*
	(0.222)	(0.394)	(0.364)	(0.470)
N	703	274	241	185
R-squared	0.054	0.089	0.098	0.141
F test (Prob > F)	0.017	0.332	0.379	0.248

*** p<0.01, ** p<0.05, * p<0.1; Standard errors in parentheses