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Overcoming the barriers of shopping fresh foods online

An explorative study of the Norwegian online grocery market

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Abstract

Online grocery shopping is a rather new phenomenon but has had considerable growth during the last few years. As a result of the pandemic, online grocery shopping had an uplifting trend due to the need for less physical contact, however it is still lagging behind other categories in terms of consumer adoption. Several researchers have identified barriers for shopping online, and the specific barriers for online grocery shopping are often related to buying fresh foods – as these products cannot be touched and evaluated by the customer before purchase. These barriers can lead to a lack of trust and higher perceived risk for the consumers, which might result in them not purchasing it. This creates the research question regarding how companies can reduce these barriers, to increase consumers' purchase intention for fresh foods. Previous research suggests several ways to do this, and the following paper aims to explore these using different concepts of service offerings. The concepts are money-back guarantee, product reviews (positive and negative), real-time images and physical touch, which were tested through a randomized, online experiment. The data collected were analyzed by conducting an ANOVA, and other additional analyses such a multinomial logistic regression and frequency tables.

The findings indicated no significant differences between the five concepts on the dependent variables trust, need for touch, purchase intention, overall liking, and perceived usefulness. Yet, the results showed that age had a significant negative effect on purchase intention, overall liking, and perceived usefulness, meaning that older participants scored lower on these variables. Further, consumers' purchase frequency had a significant effect on all the dependent variables, with active shoppers scoring more positively on all dependent variables. Lastly, an interesting finding was related to the currently used service offering, money-back guarantee, which was most preferred when participants were shown all concepts together. The findings had managerial implications for managers as they showed that all concepts could be equally viable. They also highlighted the importance of customer heterogeneity and how to tailor the service offerings according to the different customers. In addition, the findings may also indicate no immediate need to invest in more complex solutions to overcome the barriers of shopping fresh food online, such as real-time images or physical touch solutions.

1.0 Introduction

In the digital era, shopping online has become more and more common. This is an easy way of shopping where the consumer only needs to make a few clicks online, and soon, the products are on their way. This has become especially common in the apparel industry (Chevalier, 2021), which has experienced a growth rate of 14% from 2018-2022 in the U.S. (Chevalier, 2022). Shopping for groceries online (e-grocery), however, is rather a new phenomenon (Kahn, 2018; Singh & Söderlund, 2020). The idea is the same; the consumer visits a website and purchases whatever he or she needs, however, products with an expiration date are now included, which differs this retail industry from the others. Grocery shopping is part of the fast-moving consumer goods (FMCG) industry, where products have a short shelf life, and are high in demand. Examples of products are beverages and perishable goods (CFI, 2022). This latter product category makes offering online services more complicated, as these often have a short life span, and might travel a long way. Yet, several retailers have adopted this offering, and created a website and delivery service of their own to meet the increasing customer needs. In the U.S., retailers such as Walmart and Kroger provide online grocery shopping (Walmart, 2022; Kroger, 2022), while in smaller countries such as Norway, these services are offered by Oda, Coop Matlevering and Meny (Oda, 2022; Coop, n.d.; Meny, 2022) to name a few.

Shopping online vs. offline in physical grocery stores are argued to be very different experiences, as the act of comparing prices and product attributes are different. Moreover, the retailer must also consider the design and layout for the website, as well as the actual delivery service (Singh & Söderlund, 2020). The consumer also limits their ability to use their senses in the decision-making process, having only their eyes to rely on a picture that is showcasing a product in the most desirable way. In offline shopping (traditional grocery stores), the consumer can feel, smell, and see the product from all angles, and in some cases even taste (if taste tests of products are offered). These senses are all lost in the case of e-grocery.

Yet, studies show that grocery products have been the fastest growing e-commerce product, reaching a 300% sales growth in 2020, and is predicted to grow more than double in dollar shares in the U.S (Redman, 2020a). A main reason for this fast growth is the Covid-19 pandemic, where many countries advised their citizens to primarily stay at home (Risnes, 2021). In a study, 66% of respondents stated the pandemic was one of their main reasons for shopping groceries online (Redman, 2020b). This can indicate that when the pandemic is over, many could continue their previous habits and shop in traditional stores. However, the study also indicates that 90% will continue to shop online, even after the pandemic is over (Redman, 2020b). Thus, the industry is in itself growing, apart from the pandemic. Retailers must therefore consider how this can affect them in the future and meet the future needs that the consumers might introduce. One such need is the trust of purchasing a high-quality fresh food product. Some studies reveal that this product group is the slowest growing category of all products in online grocery shopping. Only 10% out of the overall 46% buying online groceries in 2018, had fresh produce in their virtual shopping cart (Park et al., 2021). Thus, lack of trust in quality could be considered a barrier for purchasing fresh food online. To lower this barrier, retailers in Norway, such as Oda and Meny, promise quality of their fresh products by giving consumers the opportunity of a refund if they are not satisfied with the product (Oda, 2022; Meny 2022). However, is this promise enough for the consumer? This act of service can be argued to be quite common across all industries, where consumers can return a product within a timeframe, based solely on a change of mind (Liu et al., 2020; Chen & Chen, 2017). Are there other ways to lower the barriers in order to increase the sales of fresh foods online? This frames our research question as the following:

"How to overcome the barriers to shop fresh foods online in order to increase purchase intention in the Norwegian market?"

In the following paper, we firstly review and discuss previous research regarding online vs. offline shopping behavior, both in general and for groceries, as well as the different barriers of shopping online. The method of research in this paper includes a prestudy that establishes the barrier's existence in the Norwegian market, which gives grounds for the main study. Further, we elaborate on the methodology for the main study with its 203 participants, and the findings from the study which is analyzed using different statistical models. Lastly, a discussion is made regarding the results, in addition to the study's limitations and suggestions on further research on the subject.

2.0 Literature review

Traditional grocery shopping is often regarded as a stressful chore, typically involving large crowds, long lines at the checkout and fighting for parking. However, with internet access and adoption rapidly increasing worldwide (Coppola, 2021), grocery retailers have evolved their business model into being multichannel. Some of the world's largest grocery retailers such as Whole Foods (Amazon Fresh) and Walmart now offer their services both in the traditional Brick-and-Mortar stores, as well as online. Other retailers, such as the Norwegian company Oda, offer pure online grocery services – without any physical store (Oda, n.d.). Online grocery shopping provides consumers with the ability to have groceries brought to them, instead of having to get them themselves. There are also no limitations connected to localization and opening hours (Hanus, 2016) – making online shopping more convenient and time saving (Citrin et al., 2003). Further, in an observational study of consumer behavior online, Anesbury et al. (2016) concluded that online shopping in the grocery context seems to primarily reflect a desire for time efficiency on the part of the shopper. Thus, the advantages of online grocery shopping suggests that consumers would embrace this new way of conducting their weekly or daily chore.

Surprisingly, the adoption of online grocery shopping has been slower than anticipated. According to Aull (2021), the slow uptake can be due to customer reservations about buying fresh food online, along with high e-commerce fees and non-intuitive website designs. However, during the peak of the pandemic, US grocery stores experienced 20 to 30 percent of their business shift to online, driven by a sudden demand for contactless shopping (Aull, 2021). A similar pattern also transpired in Norway, where the demand for online grocery shopping increased by 15% (Risnes, 2021). Despite the increasing demand for online grocery shopping services during the pandemic, the segment is still lagging behind compared to other retail sectors such as fashion and apparel, beauty and personal care and financial services in terms of consumer acceptance (Coppola, D, 2022a). Recent research published by the marketing intelligence agency Mintel shows that consumers still have concerns about evaluating the quality of fresh products. Typical household items (e.g., toilet roll, cleaning products etc.) and food cupboard items (e.g., tinned foods, crisps etc.) are still most frequently ordered, while fresh fruit, vegetables, meat, and fish are at the bottom of grocery products typically purchased online in 2019-2020 (Mintel, 2021). Further, a study carried out in December 2021 revealed that over one third (34%) of Norwegian grocery shoppers want to see, feel, and try a product before buying it (Coppola, D, 2022b). Thus, it is evident that there exist some barriers for consumers to shop groceries online – stunting the adoption of this service.

2.2 Barriers in online shopping

Researchers have identified numerous barriers or obstacles that consumers encounter when purchasing online, such as the Need for Touch (NFT) (eg. Peck & Wiggins, 2011; Zheng & Bensebaa, 2022), delivery fees (Huang & Oppewal, 2006) as well as security and privacy concerns (Miyazaki, 2001). These barriers have an effect on consumers' perceived risk, customer experience, confidence in judgement and product evaluations – possibly influencing consumers purchasing decisions (Rose et al., 2011). Rudolph et al (2004) looked at barriers for both active and inactive users of online shopping, and the researchers divided the barriers into four main categories: digital, security, online channel, and experience barriers. Their findings indicated that internet users are most concerned with security and privacy, thus, they may be reluctant to provide personal information such as name, address, and credit card information. These findings are similar to the ones from Miyazaki and Fernandez (2006) and Ariffin et al (2018), which also showed that consumers are most concerned with privacy issues surrounding online shopping. On the other side, findings from Swaminathan et al (1999) imply that consumers are less concerned about the security of their online transactions. In a recent meta-analysis by Maseeh et al (2021), the researchers concluded that privacy concerns are negatively associated with customer attitudes towards, and the usage of e-commerce platforms. Further, delivery fees have also been identified as a barrier to online grocery shopping (Huang & Oppewal, 2006). Although security and privacy risks together with delivery fees have been identified as barriers to online shopping by several researchers, other barriers might be more relevant in explaining why the adoption of online grocery shopping is lagging behind other retail e-commerce sectors.

2.3 Barriers in online grocery shopping

It could be argued that online grocery shopping specifically has some additional barriers, other than the ones just mentioned. A key difference between purchasing groceries online compared to traditional physical stores is that sensory stimulation is more limited in the online environment (Citrin et al., 2003). Some grocery products like canned goods and householding articles are highly standardized, and most consumers have previous experience with these – thus no need to touch them. However, other typical grocery items such as fruit and vegetables belong to the perishable goods category. These products must be seen, touched, or smelled in order to evaluate the product quality, and consumers can experience a lack of perceived control when they lose the ability of quality assurance (Martinez et al., 2018). This relates to the construct of Need for Touch (NFT), and research has shown that touching products often are a central part of consumers purchase decisions, serving as a way to gain information, increase quality perceptions, purchase intention, and satisfaction (e.g., Hanus, 2016; Citrin et al., 2003; Vieira, 2012).

2.3.1 Need for Touch

Since Hornik (1992) introduced NFT in consumer research, the construct has been widely examined and applied. NFT is generally defined as consumers' preference for interacting physically with a product through the touch system (Peck & Wiggins, 2011; Jin & Phua, 2015), and the ability to touch a product has been shown to increase positive attitudes and purchase intentions toward product (Grohmann et al., 2007; Peck & Childers, 2003). Consumers often use touch as a way to evaluate product quality (Vieira, 2012), and the opportunity to get sensory information through touching can influence the purchase decision by creating more certainty and familiarity with the product (Peck & Childers, 2003).

Due to customer heterogeneity, Peck and Childers (2003) divided the NFT construct into two main categories, instrumental and autotelic. The first refers to functionality, where the need for touch is based upon that the object should be evaluated by touching it to buy the product. The latter, autotelic, refers to the emotional aspect of touch, touching the object for the sake of touch alone (Peck & Childers, 2003). The following study will be based upon scales related to instrumental NFT, as touching fresh foods is considered a quality assurance, rather than emotional touch.

In order to overcome the barriers of NFT, some online grocery retailers guarantee a product's freshness and quality. Yet, studies have found that consumers still perceive a risk of failure to meet these requirements (Huang and Oppewal, 2006). Retailers such as the Norwegian company Oda claim product freshness for their perishable food, however, consumers do perceive a risk of groceries deteriorating prior to delivery (Mortimer, 2015).

2.3.2 Perceived risk and trust

Researchers have agreed upon the fact that perceived risk has a significant impact on customer behavior (Mitchell, 1999). Studies examining differences between online and offline environments have also concluded that perceived risk was greater when purchasing online (Laroche et al., 2005; Miyazaki & Fernandez, 2006). Similarly, Mortimer et al (2016) confirmed that perceived risk is a potential barrier to repurchase intentions online. When consumers are not able to touch the products they order (due to intangibility), researchers have found that perceived risk is likely to increase (de Ruyter et al., 2001; McDougall & Snetsinger, 1990). According to Lim (2003), consumers perceive risk because they face uncertainty and potentially undesirable outcomes or consequences as a result of their behavioral decisions. As consumers become more uncertain and perceive more risk, the less likely they are to purchase. The construct of risk has been divided into different categories such as financial risk, performance risk, psychological risk, social risk, physical risk, and time loss risk (Rose et al., 2011). Through focus groups discussion, Lim (2003) identified three sources of consumers' perceived risk in online shopping, namely technology, vendor, and product risk. Further, Hanus (2016) looked specifically at online grocery shopping and found that there is a product risk performance as perishable goods are difficult to evaluate the quality of and can deteriorate under transportation.

Perceived risk is also related to the concept of trust, and these two concepts are often tightly discussed in the literature (Rose et al., 2011; Lim, 2003). However, the existing literature shows that research has different views about the relationship between perceived risk and trust. While researchers such as Stewart

(2000) considers risk to be moderating the relation between consumers' trust and willingness to purchase from online retailers, others like Kim and Prabhakar (2000) suggest that adoption of online shopping is determined by a balance between perceived risk and trust. Researchers have also looked at product performance risk more specifically, and van der Heijden et al (2003) suggested that high feelings of trust reduce concerns about product performance. Newer research has adopted the term "online trust", a construct that typically has been conceptualized as a mediator in research models between selected antecedents and consequences (Kim & Peterson, 2017). Several researchers have concluded that increasing trust is a way of decreasing consumers' perceived risk (Rose et al., 2012; Corbitt et al., 2003).

2.3.3 Purchase intention

According to the study by Sam and Tahir (2009), one of the main contributors in predicting a consumer's purchase intention is trust. Other research also argues that a consumer's online purchase intention, in fact, reflects their trust (Schlosser et al., 2006). Purchase intention is, like the name suggests, described as a person's intent of buying something, or as "the probability that a person is going to buy something" (Sam & Tahir, 2009). One can therefore argue that to increase a consumer's purchase intention, one needs to increase their level of trust.

Research also suggests that other factors which may influence the consumers' online purchase intention, is the design of the website, its usefulness, empathy, and the quality of the information given (Barnes & Vidgen, 2005; Sam & Tahir, 2009). Moreover, several studies of online service quality also used dimensions such as ease of use, process controllability, quality of the outcome, information quality, consumer service (Su et al., 2008), or personalization, trust, responsiveness, and reliability (Lee & Lin, 2005) to only name a few.

This study will focus on the dimensions concerning the motivation of (or lack of) buying a specific product category online, namely fresh food. This will be analyzed without regard to the outlay of the website, the financial security, or the customer service, although these dimensions are key when understanding a consumer's purchase intention. We will instead focus on the dimensions of trust and need for touch, which is argued to have a large effect on purchase intention

(Peck & Childers, 2003; Sam & Tahir, 2009). Elements such as website design will be controlled for in the study to minimize it affecting the results. This will be discussed in more detail in the methodology section.

As Naminas (1959) argues, solely asking consumers about their purchase intention would not suffice, as such intentions are complex and may change by unforeseeable events. Thus, two more constructs are included to further capture consumers' purchase intention, in addition to trust and NFT. One such construct used in this study, is regarding the consumer's attitude – their *overall liking*, and the other one is how the consumers think a concept is helpful to them – its *perceived usefulness*.

2.3.4 Overall liking and perceived usefulness

Common in consumer science is the use of liking measurements, which represents one of the main methods when studying choice behavior (Chillà et al. 2019). Overall liking is arguably a measure of the consumers' attitude, which research suggests carry a strong influence when predicting their behavior. Attitudes describe how someone feels about things and how they react to a stimulus (Udell, 1965), and are often measured on a bipolar continuum scaling from positive to negative sides – also called semantic differential scale (Udell, 1965; Priester et al., 2004).

However, a study conducted by Davis et al. (1989) found that attitudes only partially mediated behavior intentions. Further, the same study found that consumers' perceived usefulness strongly influenced their intentions. Thus, this construct could also be an important measure when capturing purchase intention. In their study regarding consumers acceptance of computer systems, Davis et al. (1989) defined perceived usefulness as *"a user's subjective probability that using a specific application system will increase his or her job performance*". Although created in a different context, the same definition can arguably be used in this study regarding online shopping for fresh food. Perceived usefulness could thus be described as how consumers believe that something is going to be helpful to them, in order to execute a task.

2.4 Conceptual framework

As previous literature reveals certain barriers when shopping for fresh foods online, retailers must find ways to decrease these, by increasing the level of trust. Some methods are already used in today's market, such as money-back guarantee, however it can be assumed, based on previous research, that other methods could be more viable, such as product reviews, real-time images, and physical touch. These concepts will all be discussed accordingly.

2.4.1 Money-back guarantee

A strategy used by online retailers for groceries today is to increase the level of trust by having a money-back guarantee (MBG). This strategy, also called the "satisfaction guarantee", is a promise that the consumer will get a full refund if they are not satisfied with the product (Heiman et al., 2001; Walsh & Möhring, 2017). It offers a signal of quality (Moorthy and Srinivasan 1995), resulting in reducing the consumer's perceived risk before purchasing the product (Heiman et al., 2001). The strategy is commonly used in today's market, especially by online retailers, as the consumer's perceived risk increases when the physical senses can no longer be used, such as touch and smell (Ofek et al., 2011; Shulman et al., 2010). However, studies also show that the use of MBG actually increases the return rate of products (Walsh & Möhring, 2017). This means that the strategy in fact could facilitate that more customers return the purchased product. A promise of quality given by the retailer can increase consumers' expectations, and if these are not met, the incentive to return the product can outweigh the value of keeping it (Shulman et al., 2011). This could in turn negatively affect the consumer's level of trust in quality for that particular retailer in the future. Furthermore, the policy could also have a negative financial effect, as returns are quite costly for the company (Walsh & Möhring, 2017). For e-grocery, this would especially be true, as returned perishable goods often cannot be resold due to deterioration and safety concerns. Thus, this might not be the most viable option to increase purchase intention. Yet, as the method is widely used, it will here serve as a benchmark when compared to other concepts. This study will take a more explorative approach to understand if and how consumers can overcome the existing barriers. Thus, the first research question (RQ) is formulated as:

RQ_1: *How does the existing concept, MBG, affect consumers' a) trust b) NFT and c) purchase intention for the fresh food product category?*

2.4.2 Product reviews

Since its introduction, online reviews have come to play an important part for consumers when shopping online. Walsh and Möhring (2017) found in their study that product reviews decreased the return rate and is often used as a signal of quality to decrease the level of perceived risk. Through this strategy, the consumer can read peer reviews of the product, which are a virtual source of customers' experience and opinion of it (Weathers et al., 2015). Consumers can use this information to improve their decision-making process regarding a certain product (Mudambi & Schuff 2010; Weathers et al. 2015; Sahoo et al. 2018). Previous studies also show that such reviews are powerful to affect sales and influence choices (Chevalier and Mayzlin, 2006; Senecal and Nantel, 2004). According to a consumer review survey, consumers are now reading online reviews more than ever, increasing from 60% in 2020 to 77% in 2021. Moreover, 77% of the respondents reported that online reviews play a "very important" or "important" part when making decisions regarding food (Pitman, 2022). This reflects how consumers rely more on other people's experience with a product and trust their opinion, rather than solely trusting the company from which the product comes from. This can be due to the consumers perception of how consumer reviews are not directly controlled by the company itself. As mentioned, some studies demonstrate how consumers feel that a product's review rating is the strongest signal of its quality, compared to other product attributes such as price (de Langhe et al., 2015). This would arguably make the consumers less influenced by marketing and become more rational decision-makers. However, online reviews can also be used as a practical tool by the company being reviewed. By constantly monitoring consumers' opinions and attitudes towards their products, companies get updated information and can more easily understand and make changes that are needed in order to increase the sales level.

None of the Norwegian online retailers of groceries offers product reviews today. However, this strategy might induce a higher level of trust in the quality of the products. Thus, it could be argued that this strategy could decrease the barriers of purchasing fresh produce online, leading to an increase in sales of this product category. Yet, this strategy would be more likely to be successful if the reviews are positive and encouraging. If not, the opposite effect could occur, where the reviews only scare the consumers away. Several studies have shown that negative reviews have a greater impact on sales than positive reviews (Chevalier and Mayzlin, 2006; Yin et al., 2016; Filieri et al., 2021). Only 3% of consumers report that they would consider a company with an average rating of 2 stars or less (Pitman, 2022). We want to explore if these findings are similar in the e-grocery market, and if positive and negative product reviews affect the barriers differently. Thus, further research questions are formulated as:

RQ_2: *How will product reviews affect consumers' a) trust b) NFT and c) purchase intention for the fresh food product category comparing to the other concepts?*

RQ_3*: How will positive and negative product reviews differ with regards to affecting a) trust b) NFT and c) purchase intention?*

2.4.3 Real-time images

Another concept that can lower the barriers of shopping fresh foods online is real-time images. Previous research has shown that the use of real-time images of perishable products could improve the ability for the consumer to evaluate the quality of the products (Park et al., 2021) This implies that e-grocery retailers would offer updated, high-resolution photographs of their products. Park et al. (2021) argue that this method could build consumers' trust in quality for e-groceries, and facilitate a higher purchase intent for perishable goods, such as fruits and vegetables. Several researchers found in their study that the most important attribute leading to a purchase was the looks of the products, i.e., the visual appearance such as the size, color and shape (Abbott, 1999; Garitta et al., 2013; Spence et al., 2016). Furthermore, with the rise of smartphones, taking real-time images of the fresh produce would not necessarily be a high cost for the company. Cameras on today's phones are arguably of high quality and are used frequently by consumers to take pictures of their food (Gervis, 2019). Therefore, consumers are already familiar with seeing and evaluating images of food. Based on this, Park et al. (2021) conducted a study to test consumers ability to evaluate the quality of fresh food using real-time images. The study showed no significant differences in evaluating quality based on the images or in real life. This means that consumers can accurately evaluate quality through real-time images. This is congruent with previous research regarding similar testing (Brugiapaglia & Destefanis, 2009; Chan et al., 2013; Garitta et al., 2013). Thus, e-grocery retailers could implement this method in order to decrease the barriers that consumers are experiencing when purchasing perishable goods online. Real-time images could function as a trust building activity, where the consumer might have an increased level of trust when purchasing the product. In turn, this might lead to a higher purchase intent. To explore how real-time images could affect the existing barriers, the following research question was formulated.

RQ_4: *How will real-time images affect consumers' a) trust b) NFT and c) purchase intention for the fresh food product category?*

2.4.4 Physical touch

The final concept to be introduced is physical touch, as it could be argued that physical touch offers more advantages than the methods and strategies mentioned above when it comes to increasing purchase intention (Grohmann et al., 2007; Peck & Childers, 2003). The idea is to offer the consumer the ability to choose which product they want, by having baskets of several items they can choose from upon delivery. As the consumer can choose a product themselves using their physical senses, it can be argued that the confidence of receiving a high-quality product is increasing. This ability to choose might therefore increase consumers purchase intention of fresh foods. To explore if this is the case, the following research question was formulated.

RQ_5: *How will the ability to use physical touch affect consumers a) trust b) NFT and c) purchase intention for the fresh food product category?*

However, this concept would come with certain restrictions and possible complications that are hard to predict prior to trying the service offering. The employee delivering e-groceries would have to also bring baskets of different types of fresh produce. Although this option could pose some logistical complications, we believe that exploring this option would build a more thorough understanding of the necessity of touching the fresh foods before purchase. If the findings of the study shows that MBG is just as desirable for the consumer, this option of consumer choosing the product might not be the optimal investment, as MBG is arguably less complicated logistically.

2.4.5 Overall liking and perceived usefulness

As mentioned previously, in addition to trust and NFT, the variables overall liking and perceived usefulness were also added. This is to further explore which of the concepts that would be most liked and perceived as more helpful to consumers when purchasing fresh food online. Our assumption is that if most of the participants shows a low level of overall liking of one concept, the probability of the concept not being a success is larger, and the other way around. We further assume that the more useful the consumer feels the concept is, the more likely it is that the concept would have success – and vice versa. Thus, the following research questions are formulated as:

RQ_6: *Which of concept 1, 2a, 2b, 3 and 4 will receive the highest mean of overall liking?*
RQ_7: *Which of concept 1, 2a, 2b, 3 and 4 will receive the highest mean of perceived usefulness?*

2.4.5 Concepts overview

Based on findings from the literature review, five concepts were derived as potential solutions to overcome the barriers of online grocery shopping: (1) Money-back guarantee, (2a) Positive product reviews, (2b) Negative product reviews, (3) Real-time images and (4) Physical touch. These concepts represent different attributes of importance to the consumer when purchasing fresh food online. Comparing these concepts is a form of concept testing – a procedure that is an essential part of new product development, and widely used in marketing to assess the market potential for a new product or service (Peng & Finn, 2008; Friedman & Schillewaert, 2012). As introduced, this study will explore if these concepts have a significant effect on the consumers purchase intention, mediated through trust and NFT. The different concepts will from now on be referred to as MBG, product reviews (positive or negative), real-time images and physical touch. To understand which of the concepts would be preferred, the final research question is formulated as:

RQ_8: *Which of concept 1, 2a, 2b, 3 and 4 will be most favorable to the consumer?*

3.0 Research methodology

To find answers for our research questions, a randomized experiment was conducted using the online survey tool Qualtrics. Online surveys are considered an appropriate research approach as they have an advantage of being cost-effective, easy to use, as well as time efficient (Peng & Finn, 2008). In addition, respondents can typically complete the survey at their convenience (Malhotra, 2010, p. 359). Yet, online surveys have been found to potentially lead to uncertainty regarding validity of the data (Wright, 2005), thus, the following study will be developed based on scales and measures used in similar research papers. Before executing the main experiment, a prestudy was conducted to assess whether the barriers found in previous literature, also exist in the Norwegian online grocery market today.

3.1 Prestudy

The aim of the explorative prestudy was two-folded, as it sought to (1) establish existing barriers towards online grocery shopping for fresh food in the Norwegian market, and (2) establish whether consumers attribute low product quality to supplier or distributor. The latter question is interesting because it has implications for how the concepts should be framed. For example, if respondents place the quality assurance with the distributor, our concepts should be framed from the distributor's perspective, i.e., a webpage from Oda.no.

3.1.1 Study procedure

The prestudy was an online questionnaire sent out via the platform Qualtrics. The participants were asked about their current purchasing habits, whether they have experience with it or not, and their demographics such as age and gender. The respondents were also asked an open-ended question regarding their thoughts and perspective of shopping for fresh foods online. The purpose of this question was to collect data for a content analysis and gain a more in-depth understanding of the existing barriers in the Norwegian market. Lastly, to explore whether participants place the quality assurance with the distributor or producer, they were presented with a scenario of purchasing a banana. The question simply asked which of the producer and the distributor they would hold accountable if they received a banana of poor quality. The full questionnaire can be seen in Appendix, Exhibit 1.

3.1.2 Sample

The sample for the prestudy was a convenience sample, as the survey was distributed through the social media platforms LinkedIn, Facebook, and Instagram (Malhotra, 2010, p. 345). The convenience sample consisted of 44 participants, where 38.6% were male, and 61.4% were female. The age of the respondents ranged from 21 to 30, with an average age of 25.09 years.

3.1.3 Results

Initially, we conducted a content analysis based on participants' statements from the open-ended question about attitudes toward buying fresh food online. A content analysis contributes to reducing the volume of text collected, identifying and group categories together and seeking some understanding of potential barriers against online grocery shopping (Bengtsson, 2015). To secure reliable results, researchers should get the same results when applying the same technique to the same phenomena (Krippendorf, 2013, p. 24). Therefore, we individually placed respondent's statements into one of three categories, "Positive", "Negative" and "Neutral". We then created sub-categories within each category to further analyze the drivers (positive) or barriers (negative) of online grocery shopping. After we had coded the data individually, we looked at them collectively and agreed on which statements suited each category the best. After the categorization was finalized, we analyzed the frequency of "Positive", "Negative" and "Neutral" statements. The results from the content analysis can be seen in Table 1.

Categories	Number	Percentage
Positive		
Effortless	4	9
Time effective	2	5
Easy	7	16
Total Positive	**13**	**30**
Negative		
Hard to evaluate quality/freshness	7	16
No touching	2	5
Waiting time	2	5
Unnecessary	2	5
Expensive	1	2
Total Negative	**14**	**32**
Neutral		
Acknowledge benefits, prefer traditional stores	1	2
Unsure/no experience	16	36
Total Neutral	**17**	**39**
Grand Total	*100*	*100*

Table 1: Results from content analysis

The content analysis confirmed that there exist some barriers towards shopping for fresh food online in the Norwegian grocery market. The majority of the respondents were neutral ($n = 17$), followed by negative ($n = 14$), and positive ($n = 13$). The neutral respondents were either unsure about their attitudes towards online shopping or had no experience with it. Respondents with positive statements highlighted the benefits of it being effortless, time effective and easy. Most of the negative statements revolved around the difficulty of evaluating product quality and freshness, followed by limited ability to touch, long waiting time, unnecessary and expensive.

Further, the descriptive statistics presented in Table 2 shows that 89% respondents attribute low product quality towards the distributor (i.e., Oda), rather than the producer. Therefore, concepts in the main study will be framed from a distributor's perceptive, i.e., the distributor is responsible for product quality.

Descriptive Statistics

	Frequency	Percentage
Producer	5	11.4
Distributor	39	88.6
Total	44	100

Table 2: Results from scenario question

3.1.4 Conclusions

To conclude the prestudy, the content analysis revealed that there exist barriers towards shopping online for fresh food in the Norwegian market. The prestudy also confirmed that respondents attributed low product quality towards the distributor (i.e., Oda), rather than the producer. Thus, the concepts that will be used in the main experiment will be framed from the distributor’s point of view.

3.2 Main study

The main study was an experiment containing five levels of the independent variable (concept): (1) Money-back guarantee, (2a) Positive product reviews, (2b) Negative product reviews, (3) Real-time images and (4) Physical touch. Since the first concept, MBG, is currently used by the Norwegian online grocery retailers Oda and Meny, it served as a benchmark, or control group, for the other concepts. The selected research approach was a between-subjects factorial design (Gravetter & Forzano, 2016, p. 343), often referred to as a monadic test, where the respondents were randomly assigned to one of the five conditions (concepts) (Friedman & Schillewaert, 2012). The concepts were presented using visual and textual presentation, and the appearance of all concepts were somewhat similar across the five conditions in order to isolate the effect of the concept.

3.2.1 Questionnaire and measures

The experiment was forwarded using the online survey tool Qualtrics. Initially, respondents were asked descriptive questions about their general online shopping behavior, such as frequency and general satisfaction, followed by questions regarding their online grocery shopping behavior. The aim of the introduction questions was to use these as variables to group participants together based on purchasing habits.

After the opening questions, respondents were assigned to one of the five treatment conditions, and asked to evaluate a set of standardized questions regarding the concept they were shown. These questions were adopted from similar studies related to online shopping in order to increase construct validity (Malhotra, 2010, p. 320), and the scales were slightly modified to suit the context of fresh foods. The dependent variables were trust, instrumental NFT (NFT), purchase intention, overall liking, and perceived usefulness. Items measuring trust were adopted from Rose et al (2012), while items measuring NFT were adopted from Peck and Childers (2003), and items measuring purchase intention were adopted from Spears and Singh (2004). Further, items measuring overall liking were adopted from Kwon and Nayakankuppam (2015) and was be measured on a semantic differential scale, while perceived usefulness was adopted from Davis (1989). All items, except overall liking, were measured using a 1–5-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. This scale was chosen as it includes a neutral position for the respondents, while also not being too large, as some suggest that consumers show a tendency of not choosing the extreme values on large scales such as a 7-point scale (Jamieson, 2017). An overview of scales is presented be in Table 3.

Overview of scales			
Variables	Scale items	Adapted from	Scale
Trust	"Shopping online for fresh foods can be trusted, and there are no uncertainties." "In general, I can rely on online retailers of fresh foods keeping the promises they make." "Shopping online for fresh food is reliable." "Shopping online for fresh food is a trustworthy experience."	Rose et al., 20	Likert (1-5)
NFT (Instrumental)	I place more trust in products that can be touched before purchase I feel more comfortable purchasing a product after physically examining it I feel more confident making a purchase after touching a product If I cannot touch a product in the store, I am reluctant to purchase the product	Peck & Childers (2003)	Likert (1-5)
Purchase intention	I definitely intend to buy fresh food online from this retailer My purchase interest is high I will definitely buy fresh food online	Spears and Singh (2004)	Likert (1-5)
Overall liking	"Please evaluate the following statements about (The concept)" - Bad/good - Negative/positive - Unfavorable/favorable	Kwon and Nayakankuppam (2015)	Semantic differential (1-5)
Perceived usefulness	"(The concept) increase efficiency when shopping for fresh food online" "(The concept) increase my performance of evaluating the quality of the products more accurately" "I perceive (The concept) as useful"	Davis (1989)	Likert (1-5)

Table 3: Overview of scales

Lastly, respondents were asked demographic questions regarding their age and gender. The survey was conducted in Norwegian, as the target group for the survey were consumers in the Norwegian market. The full questionnaire can be seen in Appendix, Exhibit 2.

3.2.2 Concept presentation

In the experiment, all participants were shown a screenshot of a Norwegian online shopping site, inspired by the existing online retail distributor Oda.no. This was to make the experiment as realistic as possible and increase ecological validity, meaning that the experiment is close to real life (Malhotra, 2010, p. 223). However, some colors were adjusted, so that the participants did not immediately associate the screenshot with Oda.no. By doing so, the attempt was to avoid any brand-related associations affecting the results. The screenshot showed all participants the product-website of a banana and was kept as similar as possible across the different concepts in order to isolate the effect of what we intended to measure. As mentioned, each participant was randomly assigned to one of the concepts. Depending on which concept a participant was shown, the screenshot differed in symbols connected to that particular concept. For example, if the participant was shown the screenshot representing the concept of real-time photos, symbols like a camera depicting a button, in addition to a sentence shortly stating what time the photo was taken, was included (see Figure 1). To maximize the effect and make sure the participant understood the full extent of this service offering, a photo of a basket of bananas was included, representing how the service would be performed in reality. Further, as can be seen in the Figure 1, sentences explaining the participant what their assignment is, as well as a short explanation of what the service offering is, was added. In this example, the sentences are translated to “Imagine the following scenario: you are purchasing a banana through an online grocery store. In the online grocery store, you get the following information:” and “The online grocery store offers to show updated product pictures in real-time. The photos are taken by the online grocery store the same day that you visit their website.”

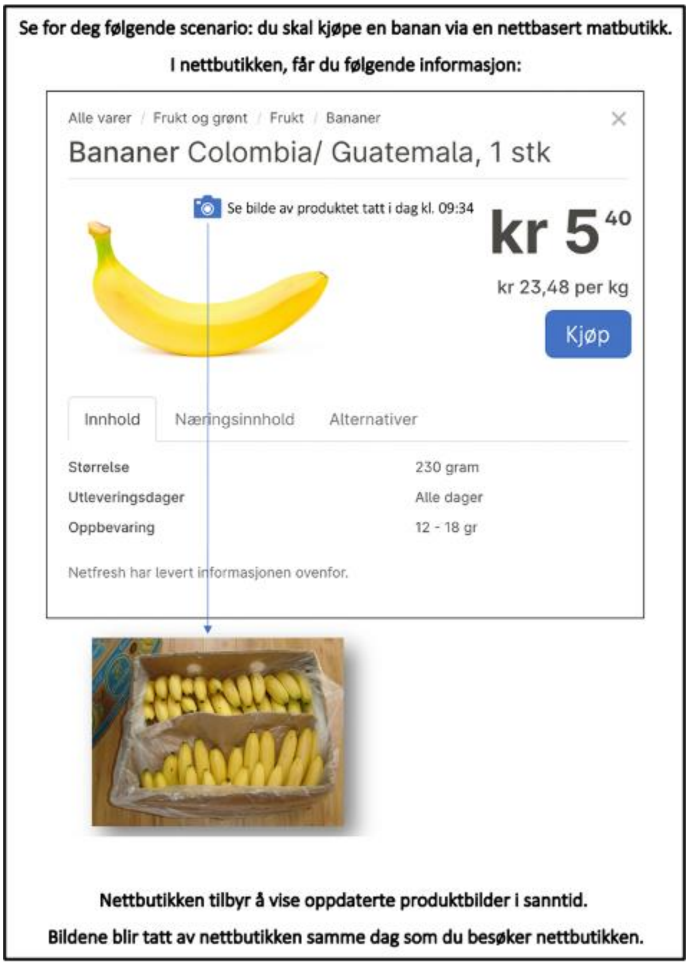

Figure 1: Real-time images concept

On the other hand, if the participant was shown the photo representing the concept of product reviews, the symbols was switched out with stars, representing the rating, as well as a review section, where participants could see comments made by previous "buyers". In the study, this particular concept was divided in two, to see the effect on the variables based on positive product reviews, as well as negative product reviews (as shown in Figure 2 below). An overview of all five concept presentations can be seen in Appendix, Exhibit 3.

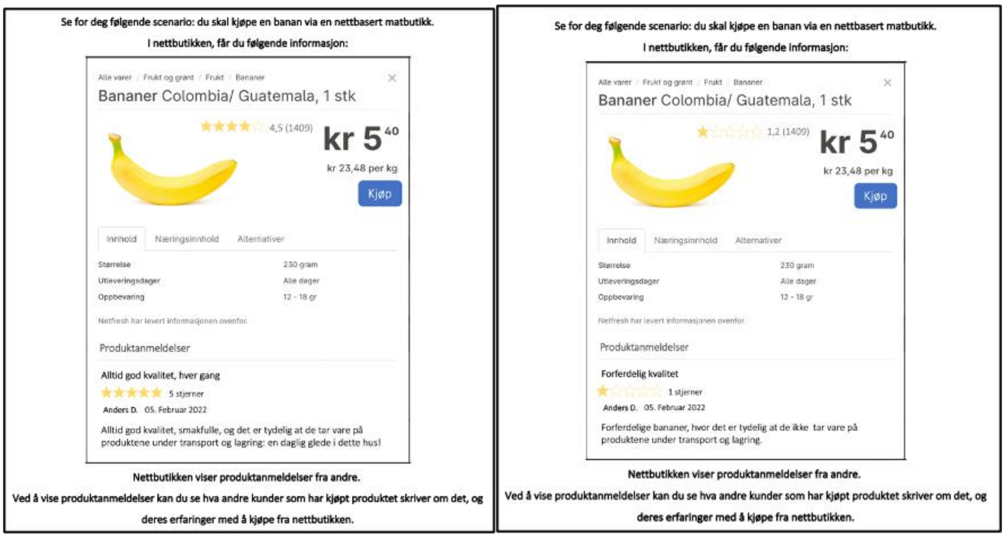

Figure 2: Positive (left) and negative product reviews concepts

3.2.2.1 Sequential monadic concept testing

As mentioned, the experiment had a between-subjects design, where each participant was randomly assigned to one of the five concepts and asked to evaluate a set of questions based on one concept. However, at the end of the questionnaire, all respondents were shown all concepts together, and asked to answer which seemed most favorable. This gave the study a mixed design, combining both within and between subjects' design (Gravetter & Forzano, 2016, p. 327). This is a form of sequential monadic testing, where respondents evaluate two or more concepts together (Friedman & Schillewaert, 2012). Benefits of having a within subjects' design is that it reduces the problems associated with individual differences, which can become confounders and increase the variance of the scores (Gravetter & Forzano, 2016, p. 326). In addition, it is a productive way to understand how one concept compares against each other in the eyes of the customers. To control for the possibility that participants only choose the first option, the concepts were presented together in a randomized order. Participants were shown four concepts: MBG, product reviews (positive), real-time images and physical touch. Negative product reviews were excluded from this question because this concept is the same as positive product reviews per se, where both offer a rating and a comment section of the same product. Thus, this similarity might be confusing to the consumer. An example of the visual presentation of the question can be seen in Appendix, Exhibit 4.

3.2.3 Sampling

Participants in the experiment were recruited using a convenience sample, as they were recruited using online social media platforms such as Facebook, LinkedIn, and Instagram (Malhotra, 2010, p. 345). Convenience sampling is a time-efficient and convenient sampling technique; however, the sample can often be non-representative (Malhotra, 2010, p. 356). Thus, the aim was to collect at least 250 responses, which equals around 50 respondents per concept. It was important to collect responses from several age groups, making the sample more representative. We attempted to do this by receiving help to distribute the survey from people in different age groups.

3.2.4 Reliability analysis

A reliability analysis was used to assess the reliability of the scales measuring the scale items (NFT, trust, purchase intention, overall liking, and perceived usefulness). With the alpha coefficients (α) being $\alpha_{Trust} = .893$, $\alpha_{NFT} = .833$, $\alpha_{Purchase\ Intention} = .877$, $\alpha_{Overall\ Liking} = .927$, $\alpha_{Perceived\ Usefulness} = .749$, all items have a score above 0.7. Thus, the score from the reliability analysis had a satisfactory internal consistency reliability, and the different items measured the intended construct (Malhotra, 2010, p. 287). The reliability analysis for each scale can be seen in Appendix, Exhibit 5.

3.2.5 Data collection

The data collection did not include collecting data such as name, address etc., as it was completely anonymous. This was conveyed before the respondents were presented with the questions in the survey, and they were informed that the response they provide would be deleted within 30 days. Due to the anonymity, the project was not subject to filling out the form regarding personal information (NDS, n.d.). The respondents were also informed that it was possible to withdraw from participating in the study, where they only needed to exit the survey, and their responses would be deleted. If the respondents had questions regarding the survey, they were invited to send an email to the authors.

4.0 Data analysis and results

After the data collection ended, the dataset was transferred from Qualtrics to SPSS. All statistical analysis in this paper was conducted using the software

SPSS. Initially, we started with data screening and cleared the dataset from missing variables. 264 respondents were in the dataset, however, after controlling for missing values, i.e., respondents that did not complete the full questionnaire, the final number of respondents were 203. Each condition group had over 30 respondents, thus, it can be assumed that the analysis and results are based upon a normal distribution (Ghasemi & Zahediasl, 2012). The distribution frequency of each concept is presented in Table 4.

Concept Distribution

Concept	Frequency (n)	Percentage (%)
Money-back guarantee	54	26.6
Product reviews (positive)	34	16.8
Product reviews (negative)	41	20.2
Real time images	39	19.2
Physical touch	35	17.2
Total	203	100

Table 4: Concept frequency

4.1 Sample demographics

203 participants partook in the survey, where 31.5% were male and 68.5% were female. The age ranged from 16 to 72, with a mean of 40.3. Table 5 presents an overview of the sample demographics in the main experiment.

Sample Demographics

		Frequency (n)		Percentage (%)
Gender	Male	64		31.5
	Female	139		68.5
Age	<18	1		0.4
	18-24	37		18.3
	25-34	55		27.1
	35-44	19		9.4
	45-54	43		21.2
	55-64	40		19.7
	65-74	8		3.9
Total		203		100
Age	*Min*	*Max*	*Mean*	*SD*
	16	72	40.3	15.7

Table 5: Sample demographics

As seen in Table 6, the majority of the respondents (40.4%) purchase online every other month, while 33.5% purchase online once a month or more frequently.

Purchase Frequency		
	Respondents (n)	Percentage (%)
Several times a week	2	1.0
Once a week	13	6.4
Several times a month	53	26.1
Once a month	34	16.7
Every other month	82	40.4
Once a year	18	8.9
Never	1	0.5
Total	203	100

Table 6: Respondents online purchase frequency

Further, 38.4% of the respondents are active online grocery shoppers $(n = 78)$, (active shoppers purchased food online at least once during the last 12 months), while 61.6% are inactive online grocery shoppers $(n = 125)$, presented in Table 7. When comparing inactive online shoppers to active online shoppers, descriptive statistics show that the mean age is higher for the inactive shoppers than for active shoppers ($M_{Inactive} = 43.00\ vs. M_{Active} = 35.97$) (Appendix, Exhibit 6).

Online grocery shopping frequency			
	Respondents (n)	Percentage (%)	Mean age
Active online grocery shoppers	78	38.4	35.97
Inactive online grocery shoppers	125	38.4	43.00
Total	203	100	

Table 7: Respondents online grocery shopping frequency with age

4.2 Relationship between mediators and purchase intention

A Pearson Correlation Coefficient test was conducted to explore if purchase intention had a positive linear relationship with dependent variables; trust, overall liking and perceived usefulness, and a negative linear relationship with NFT. Our overall research questions assume that these mediate the relationship of each concept on purchase intention. Pearson's r varies between +1 (perfect positive correlation) and -1 (perfect negative correlation), and 0 indicating no linear correlation at all (Malhotra, 2010, p. 531). The Correlation Matrix in Table 8 confirmed that purchase intention has a positive linear relationship with trust $(r = .579, p - value < .001)$, overall liking $(r = .384, p - value < .001)$ and perceived usefulness $(r = .353, p - value < .001)$, and a negative linear relationship with NFT $(r = -.382, p - value =< .001)$, congruent with findings in previous research (Peck & Childers, 2003; Grohmann et al., 2007; Sam &

Tahir, 2009). Thus, trust, NFT, overall liking and perceived usefulness does seem to affect purchase intention in this study.

Correlations

		Purchase Intention	Trust	NFT	Overall Liking	Perceived Usefulness
Purchase Intention	Pearson Correlation	1	.579**	-.382**	.384**	.353**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001
	N	203	203	203	203	203
Trust	Pearson Correlation	.579**	1	-.405**	.466**	.398**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001
	N	203	203	203	203	203
NFT	Pearson Correlation	-.382**	-.405**	1	-.254**	-.135
	Sig. (2-tailed)	<.001	<.001		<.001	.055
	N	203	203	203	203	203
Overall Liking	Pearson Correlation	384**	.466**	-.254**	1	.607**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001
	N	203	203	203	203	203
Perceived Usefulness	Pearson Correlation	.353**	.398**	-.135	.607**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	
	N	203	203	203	203	203

**. Correlation is significant at the 0.01 level (2-tailed)

Table 8: Correlation matrix

4.3 Trust

To examine the difference in level of respondents' trust across the five concepts, a One-Way Analysis of Variance (ANOVA) was conducted (see Appendix, Exhibit 7 for all conducted ANOVAs). The descriptive statistics presented in Table 9 show a slightly higher mean level of trust for concept 2b: product reviews (negative) and concept 4: physical touch, compared to the three other concepts. However, the results from the ANOVA did not indicate significant differences on level of trust across concept 1, 2a, 2b, 3 or 4 ($F\ (4, 1.067), p = 0.374, n^2\ = 0.021$).

Descriptives Trust

	N	Mean	Std. dev	Min.	Max.
1: Money back guarantee	54	2.9815	.72660	1.00	5.00
2a: Product reviews (positive)	34	2.7868	.84864	1.00	5.00
2b: Product reviews (negative)	41	3.0732	.55970	2.00	4.25
3: Real-time images	39	2.8846	.80264	1.50	4.00
4: Physical touch	35	3.0571	.53236	2.00	4.25
Total	203	2.9618	.70541	1.00	5.00

Table 9: Descriptive statistics – respondents' level of trust

Further, to analyze differences between each concept, a Bonferroni correction test was conducted (See Appendix, Exhibit 7 for all Bonferroni corrections). The results from the pairwise comparison showed no significant differences between concepts with $all\ p - values = 1.00$, except concept 2a: Product reviews (positive) and 2b: Product reviews (negative), which had a $p - value = .814$. These concepts differed the most in respondents' level of trust, where respondents showed negative product reviews had the highest level of trust, and positive product reviews had the lowest level of trust. Yet, the results from the ANOVA and Bonferroni correction test were not significant. Thus, we cannot conclude that offering MBG, product reviews (positive or negative), real-time images or physical touch are significantly different in affecting customer's level of trust in the distributor.

4.3 Need for touch

To examine if there was a difference in NFT across concepts, another ANOVA was conducted. A concept should *decrease* the customers NFT to increase purchase intention. The mean NFT level for each concept is presented in Table 10, and the concept with the lowest mean level of NFT is 2a: Product reviews (positive). However, the results from the ANOVA did not indicate significant differences on level of NFT across concept 1, 2a, 2b, 3 or 4 ($F\ (4, 0.439), p = 0.780, n^2\ =\ 0.009$).

Descriptives NFT

	N	Mean	Std. dev	Min.	Max.
1: Money back guarantee	54	3.8333	.56843	2.50	4.75
2a: Product reviews (positive)	34	3.6838	.69170	2.00	5.00
2b: Product reviews (negative)	41	3.8415	.47023	2.75	4.75
3: Real-time images	39	3.7436	.67005	2.00	4.75
4: Physical touch	35	3.7517	.75363	1.75	5.00
Total	203	3.7796	.62467	1.75	5.00

Table 10: Descriptive statistics – respondents' level of need for touch

Further, a Bonferroni multiple comparisons test showed no significant differences between the five concepts ($all\ p = 1.00$). Thus, we cannot conclude that one or more concepts leads to a significantly lower (or higher) NFT.

4.4 Purchase intention

A one-way ANOVA was also used to understand the differences in purchase intention between the concepts. The result of this analysis is presented in Table 11, and it shows a slightly higher mean of purchase intention for the MBG-concept and surprisingly the negative product review concept. However, the results were not significant ($F\ (4, 0.880), p = 0.477, n^2 =\ 0.017$). To further examine if any of the concepts differed from each other, a Bonferroni correction was conducted. The pairwise comparison showed no significant evidence for differences between any of the concepts ($p\ =\ 1.00\ between\ all$), but the results leaned towards that the MBG-concept was the one with the highest purchase intention ($M = 3.0093$). Yet, as the results were not significant, we have no statistical evidence to conclude that any of the concepts have a larger direct effect on purchase intention, compared to the others.

Descriptives Purchase Intention

	N	Mean	Std. dev	Min.	Max.
1: Money back guarantee	54	3.0093	.93411	1.00	5.00
2a: Product reviews (positive)	34	2.8235	1.23633	1.00	5.00
2b: Product reviews (negative)	41	2.9878	1.08102	1.00	5.00
3: Real-time images	39	2.6923	1.04261	1.00	5.00
4: Physical touch	35	2.7143	.88522	1.00	5.00
Total	203	2.8621	1.03201	1.00	5.00

Table 11: Descriptive statistics – respondents' level of purchase intention

4.5 Overall liking

Further, a one-way ANOVA was conducted to analyze differences in means on overall liking of the different concepts. The results of the ANOVA showed a slightly higher mean in overall liking for the concept of real-time images ($M = 3.7009$) and MBG ($M = 3.6481$)(Table 12), yet the results were not significant ($F\ (4, 0.510), p = 0.729, n^2 =\ 0.010$). A Bonferroni correction was used to examine the concepts compared to each other. Again, the results showed no significant evidence for differences between any of the concepts ($p\ =\ 1.00\ between\ all$). The concept of real-time images was leaning towards being the one with the highest overall liking. Still, since the results were not significant, we cannot conclude that overall liking is significantly higher or lower for any of the concepts.

Descriptives Overall Liking					
	N	Mean	Std. dev	Min.	Max.
1: Money back guarantee	54	3.6481	.92579	1.67	5.00
2a: Product reviews (positive)	34	3.4608	.97792	1.00	5.00
2b: Product reviews (negative)	41	3.5691	.81050	2.33	5.00
3: Real-time images	39	3.7009	1.09160	1.00	5.00
4: Physical touch	35	3.4571	.93615	1.67	5.00
Total	203	3.5780	.94445	1.00	5.00

Table 12: Descriptive statistics – respondents' level of overall liking

4.6 Perceived usefulness

To examine the differences in perceived usefulness between the five concepts, an ANOVA was conducted. The descriptive statistics presented in Table 13 shows that concept 2b: negative product reviews had a slightly higher mean of perceived usefulness, compared to the other four concepts. Yet, the ANOVA showed no significant evidence of differences $F\ (4{,}1.495), p = 0.205, n2\ =\ 0.029)$. Furthermore, a Bonferroni correction was used for a pairwise comparison between the five concepts. The results show that the concept of negative product reviews was perceived as most useful of the concepts, however the results were not significant ($p\ =\ 1.00$ for all except 2b: Product review vs. 4: Physical touch: $p\ =\ 0.253$). The result indicate that respondents perceived concept 4: physical touch as least useful, however, it was not significantly different. Based on these findings, there is no statistical evidence that any of the concepts has a higher or lower level of perceived usefulness, compared to the other concepts.

Demographics Perceived Usefulness					
	N	Mean	Std. dev	Min.	Max.
1: Money back guarantee	54	3.3580	.73787	1.00	4.67
2a: Product reviews (positive)	34	3.4510	.97401	1.00	5.00
2b: Product reviews (negative)	41	3.6098	.61420	2.33	5.00
3: Real-time images	39	3.5043	.68770	2.00	4.33
4: Physical touch	35	3.2190	.74948	1.00	4.67
Total	203	3.4286	.75686	1.00	5.00

Table 13: Descriptive statistics – respondents' level of perceived usefulness

4.7 Concept choice

To explore which of the concepts that was most preferred, the respondents were presented with all concepts together at the end of the questionnaire and asked which seemed most favorable. Table 14 shows the choice-frequency of each concept, and concept 1: MBG was chosen most frequently ($n = 65, 32\%\ of\ respondents$), followed by concept 2: Product reviews ($n = 51$), concept 3: Real-time images ($n = 47$) and concept 4: Physical touch ($n = 40$).

Frequency Concept Choice

Concept	Frequency (n)	Percentage (%)
Money-back guarantee	65	32.0
Product reviews	51	25.1
Real time images	47	23.2
Physical touch	40	19.7
Total	203	100

Table 14: Frequency of concept choice

Further, descriptive analyses of age groups revealed interesting findings when comparing the youngest age group (age 18-24) to the oldest age group (age 55<). As displayed in Figure 3, concept 4: Physical touch was chosen the least by the young age group ($n = 4$), while for the oldest group, physical touch was the second most preferred concept ($n = 18$), after money-back guarantee ($n = 20$). In addition, concept 3: Real-time images were the most preferred concept among the young respondents ($n = 13$), and the least preferred by the older age group ($n = 2$). The age groups between these (age 25-34, 35-44 and 45-54) had a similar pattern of preferred concepts, without any large outliers. The full descriptive analysis of age groups and preferred concepts can be seen in Appendix, Exhibit 8.

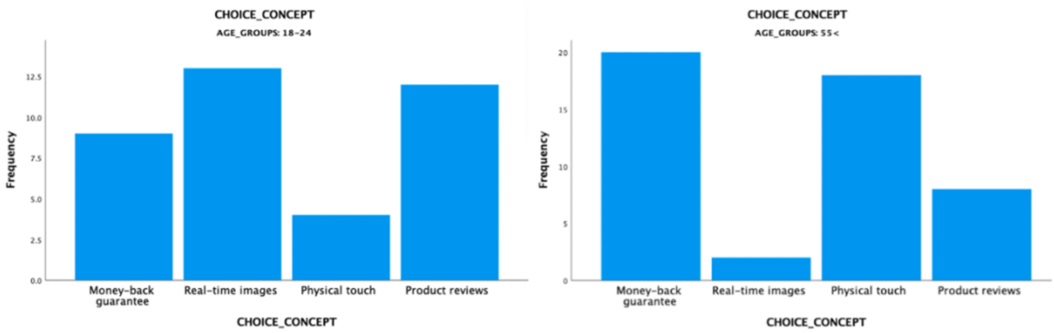

Figure 3: Concept choice for age groups

To further explore whether the differences in age were significantly different across concepts, a multinomial logistic regression was conducted as the dependent variable “concept choice” had more than two categories (MBG, Real-time images, Physical touch, and Product reviews) (Malhotra, 2010, p. 592). The independent variables were age group, gender, and online shoppers (active vs. inactive). The parameter estimates are displayed in Table 15, with concept 4: Physical touch serving as the reference category. The first set of coefficients compare physical touch (coded as 0) to MBG (coded as 1), and none of the predictors were significant (age group, gender, or online shopper).

Further, comparing Physical touch to Real-time images, the results show that age group is the only significant predictor in the model ($\beta = -.481, p = .003$). This means that respondents scoring higher on this variable (age), are less likely to choose Real-time images. The odds ratio is $.618$, indicating that for every one unit increase in age group, the odds of a person choosing Real-time images as their preferred concept change by a factor of $.618$, which is a decrease.

The last set of coefficients compare Physical touch to Product reviews, and again, age group is the only significant predictor ($\beta = -.346, p = .024$). The negative β coefficient indicates that respondents scoring higher on age are less likely to choose Product reviews, than Physical touch. The odds ratio is $.708$, indicating that for every one unit increase in age group, the odds of a person choosing product reviews change by a factor of $.708$.

Lastly, Table 15 indicates that the independent variables gender and online shoppers (active vs. inactive) had no statistically significant effect on which concept was preferred, when comparing Physical touch to the others. See the full multinominal logistic regression in Appendix, Exhibit 9.

Parameter Estimates

Concept choice		B	df	Sig.	Exp(B)
Money-back guarantee	Intercept	1.500	1	.140	
	Age groups	-.109	1	.455	.897
	Gender	-.315	1	.489	.730
	Online shoppers	-.277	1	.516	.758
Real-time images	Intercept	2.979	1	.005	
	Age groups	-.481	1	.003	.618
	Gender	-.737	1	.130	.479
	Online shoppers	-.315	1	.497	.730
Product reviews	Intercept	2.114	1	.046	
	Age groups	-.346	1	.024	.708
	Gender	-.395	1	.411	.647
	Online shoppers	-.266	1	.554	.554

The reference category is: Physical touch.

Table 15: Multinomial logistic regression

4.8 Additional analyses

The ANOVA analyses did not indicate any significant differences between the concepts on either of the dependent variables (trust, NFT, purchase intention, overall liking, and perceived usefulness). To further explore whether other factors could indicate differences between the concepts, we conducted additional exploratory analyses. To explore whether the variation in the dependent variables can be explained by independent variables such as concept stimulation, respondent’s age, gender or whether they were active vs. inactive online shoppers, linear regression was used. A regression model was conducted for each of the dependent variables; trust, NFT, purchase intention, overall liking, and perceived usefulness. We created dummy variables for each concept, with concept 1: MGB serving as the reference category. The categorical variable *online shoppers* take the value 0 for inactive online grocery shoppers, and 1 for active grocery shoppers. As an example, the regression model for the dependent variable trust becomes:

$$Trust = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 Online\ Shoppers + \beta_6 Age + \beta_7 Gender + \varepsilon$$

The regression model is similar across all dependent variables, except for a change of dependent variable (trust, NFT, purchase intention, overall liking, and perceived usefulness).

4.8.1 Trust

After running a linear regression for trust, we get the results that are displayed in Table 16. The model explains $14{,}6\%$ of the variation in trust ($R^2 = 0{,}146$) (see all regression analyses in Appendix, Exhibit 10). With no independent variables considered, respondents’ level of trust is estimated to be 2.862 (on a scale from 1-5). Online shoppers are the only coefficient that is significant $(p - value < .001)$, with all the other coefficients having a p-value above .005. Since active shoppers take the value 1 in the regression line, active shoppers have an increase in trust of .488, compared to inactive shoppers. Thus, the average level of trust is significantly higher ($\beta = .488$) for active than for inactive online grocery shoppers.

Coefficients		
	Unstandardized β	Sig.
(Constant)	2.863	<.001
D1 – Product reviews (Positive)	-.160	.276
D2 – Product reviews (Negative)	.109	.436
D3 – Real-time images	-.085	.552
D4 – Physical touch	.112	.441
Online Shoppers (Active vs. Inactive)	.488	<.001
Age	-.003	.421
Gender	.009	.931

Table 16: Variables in regression model – Trust

This difference in trust between active and inactive shoppers is also illustrated in the profile plot in Figure 4. The plot also illustrates how the mean level of trust is similar across each concept for both groups. For active shoppers, mean trust is ranging from around 3.18-3.45, while for inactive shoppers, mean level of trust ranges from around 2.50-2.90.

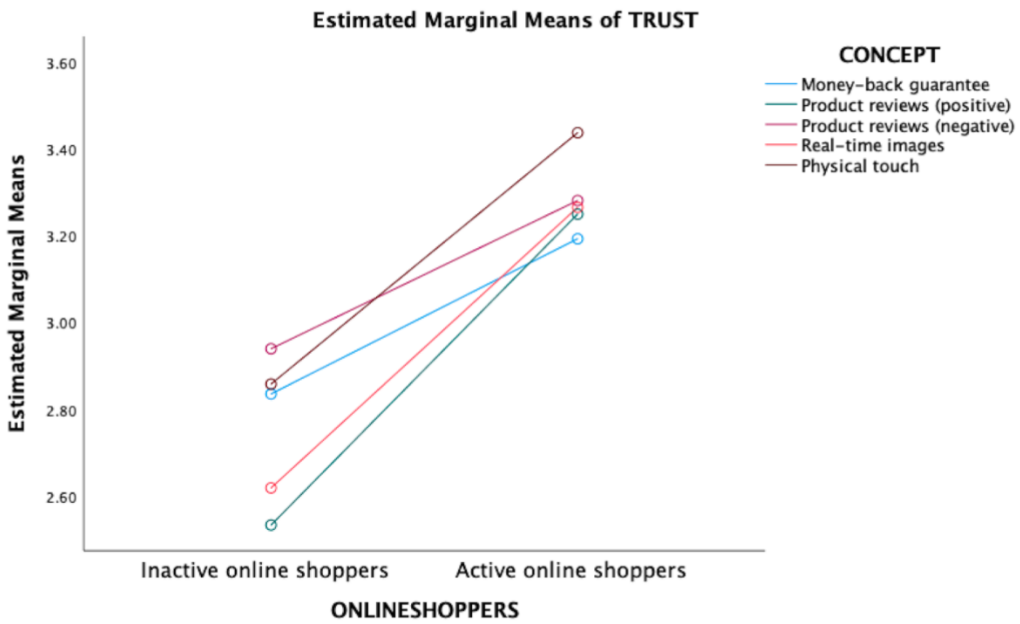

Figure 4: Level of trust differences between active and inactive online shoppers

4.8.2 NFT

The estimated coefficients for NFT are displayed in Table 17, and the model explains 5,4% of the variation in NFT ($R^2 = .054$). Without independent variables, the average level of NFT is 4.104. Similar to trust, online shoppers are the only significant coefficient ($p - value = .003$). Furthermore, active online grocery shoppers have a significantly lower level of NFT (-.272) compared to inactive shoppers.

Coefficients		
	Unstandardized β	Sig.
(Constant)	4.104	<.001
D1 – Product reviews (Positive)	-.156	.255
D2 – Product reviews (Negative)	.012	.926
D3 – Real-time images	-.074	.580
D4 – Physical touch	-.090	.607
Online Shoppers (Active vs. Inactive)	-.272	.003
Age	-.004	.193
Gender	-.008	.939

Table 17: Variables in regression model – NFT

Figure 5 illustrates the difference in level of NFT between active and inactive users across the five concepts. The figure shows that the mean level of NFT is lower for active users across all concepts, except concept 1: MBG, which is the same for inactive and active users.

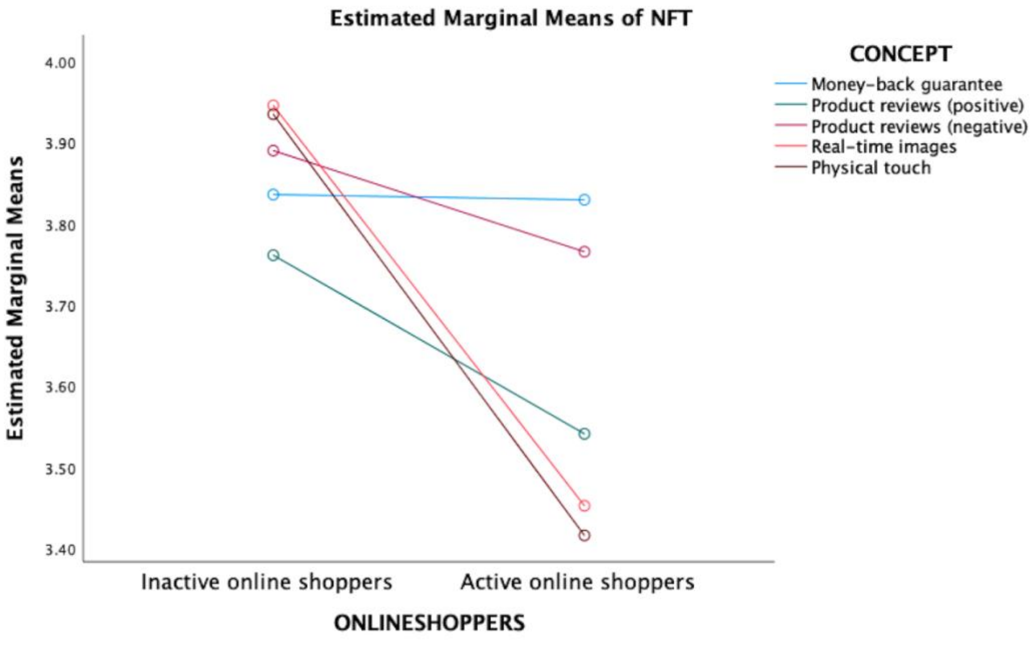

Figure 5: Level of NFT between active and inactive online shoppers

4.8.3 Purchase intention

The estimated regression coefficients for purchase intention can be seen in Table 18, and the regression line explains 24.2% of the variation in purchase intention ($R^2 = .242$). The linear regression reveals two independent variables that have a significant effect on purchase intention. Age has a significant negative effect on purchase intention ($\beta = -.016,\ p < 0.001$), meaning that a one unit increase in age will decrease purchase intention with -.016. Further, shopping frequency (active vs. inactive shoppers) also has an effect on purchase intention ($\beta = .767, p < .001$). Thus, active shoppers have a significantly higher purchase intention than inactive shoppers.

Coefficients

	Unstandardized β	Sig.
(Constant)	3.201	<.001
D1 – Product reviews (Positive)	-.094	.642
D2 – Product reviews (Negative)	.049	.798
D3 – Real-time images	-.233	.235
D4 – Physical touch	-.217	.277
Online Shoppers (Active vs. Inactive)	.767	<.001
Age	-.016	<.001
Gender	.057	.687

Table 18: Variables in regression model – Purchase intention

A profile plot was also made to illustrate the differences in purchase intentions, between active and inactive online shoppers. As can be seen in Figure 6, active shoppers have a higher purchase intention, across all concepts.

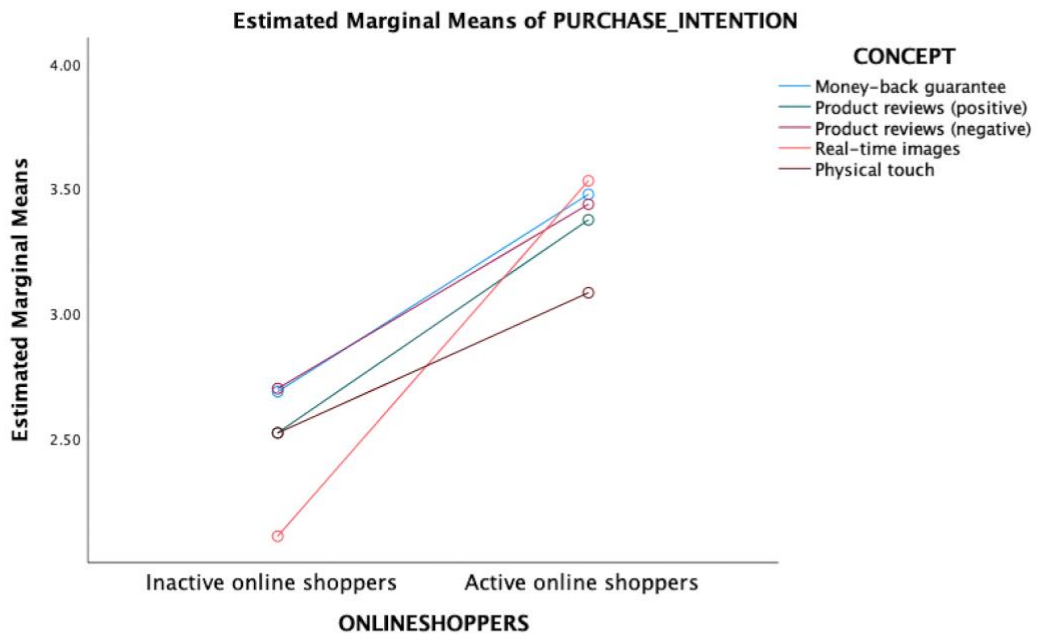

Figure 6: Level of purchase intention between active and inactive online shoppers

4.8.4 Overall liking

The results from the linear regression for overall liking are displayed in Table 19, and the regression line explains 13.7% of the variation in overall liking ($R^2 = .137$). Without accounting for the independent variables, respondents have an average level of overall liking of 4.193. Similar to the results of purchase intention, the linear regression reveals that age and active online shoppers has a significant effect on overall liking of the five different concepts. Age has a significant negative effect ($\beta = -0.015, p < 0.001$), while active online shoppers have a significant positive effect ($\beta = 0.408, p = 0.002$). This means that the older the consumer is, the lower their overall liking are, and active online shoppers have on average a higher overall liking for the different concepts.

Coefficients

	Unstandardized β	Sig.
(Constant)	4.193	<.001
D1 – Product reviews (Positive)	-.143	.469
D2 – Product reviews (Negative)	-.051	.787
D3 – Real-time images	.099	.605
D4 – Physical touch	-.154	.429
Online Shoppers (Active vs. Inactive)	.408	.002
Age	-.015	<.001
Gender	-.079	.571

Table 19: Variables in regression model – Overall liking

The same profile plot was made to illustrate the differences in mean on overall liking for all the different concepts, which revealed a visible difference between active online shoppers and inactive shoppers, illustrated in Figure 7. It is evident that the concept with the most visual difference is concept 3 and 4 – Real-time images and Physical touch. These concepts are ranked the least liked by the inactive shoppers, and the most liked by active shoppers.

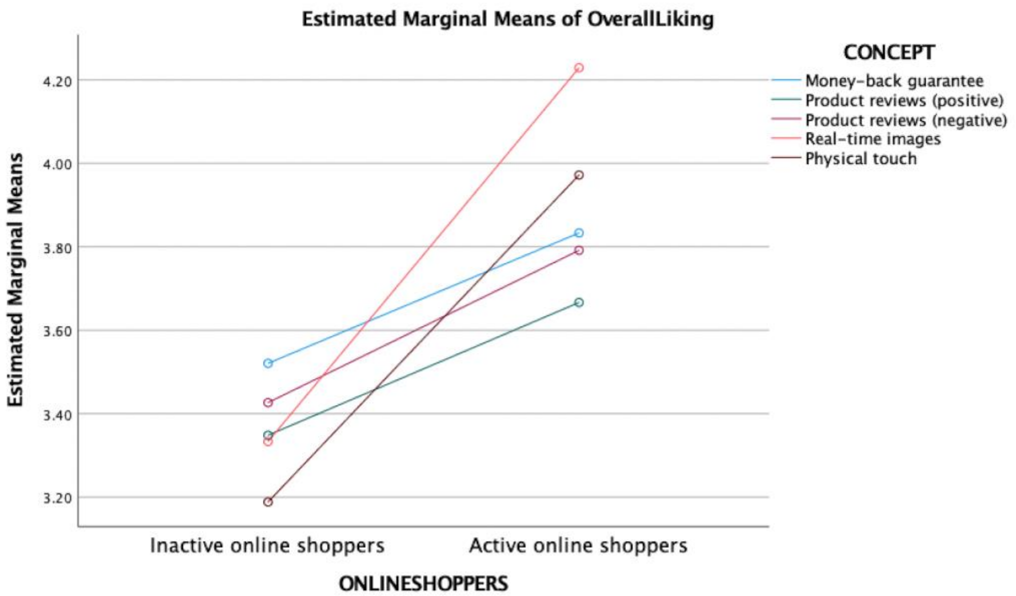

Figure 7: Level of overall liking between active and inactive online shoppers

4.8.5 Perceived usefulness

The estimated model coefficients for perceived usefulness are displayed in Table 20. The estimated regression line explained 12,1% of the variation in perceived usefulness ($R^2 = .121$). As with the results of purchase intention and overall liking, both age and active online shoppers both have a significant effect on respondents perceived usefulness. Similar to the previous dependent variables, age has a significant negative effect on perceived usefulness ($\beta = -0.010, p < 0.001$), while active online shoppers show a significant positive effect on perceived usefulness ($\beta = 0.269, p = 0.013$). Thus, the older the consumer is, the less they would perceive one of the concepts as useful, while the more of an active online shopper they are, the more they perceive the concepts as more useful.

Coefficients

	Unstandardized β	Sig.
(Constant)	3.547	<.001
D1 – Product reviews (Positive)	.143	.371
D2 – Product reviews (Negative)	.298	.052
D3 – Real-time images	.206	.186
D4 – Physical touch	-.101	.521
Online Shoppers (Active vs. Inactive)	.269	.013
Age	-.010	.003
Gender	.054	.627

Table 20: Variables in regression model – Perceived usefulness

Lastly, as can be seen in Figure 8, a profile plot was made to illustrate the differences in mean on perceived usefulness for each concept divided into inactive and active online shoppers. The visual difference in mean is less clear for one of the concepts, MBG, than for the rest.

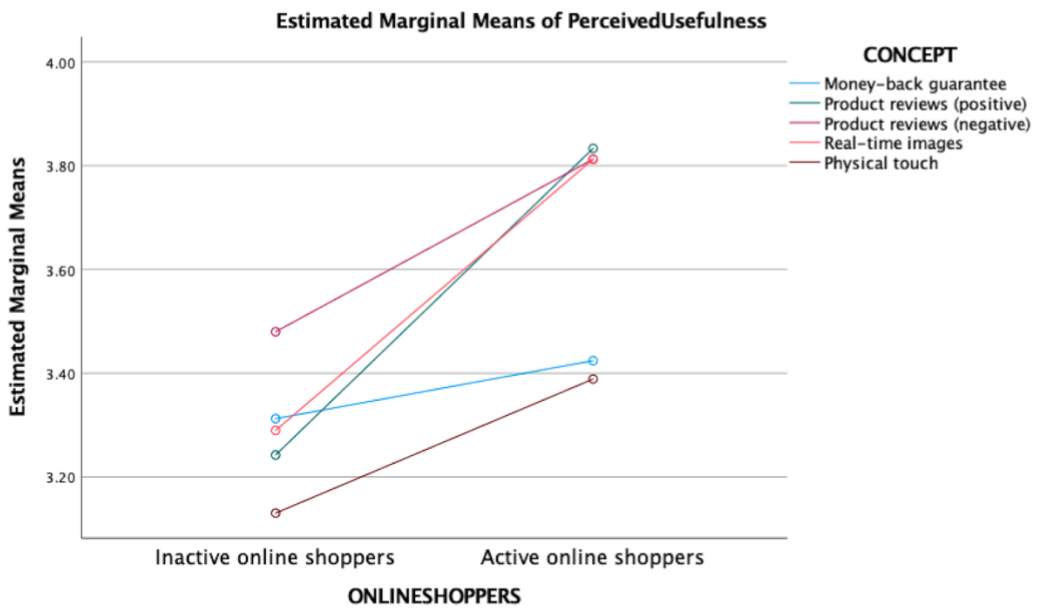

Figure 8: Level of perceived usefulness between active and inactive online shoppers

4.8.6 Explained variance

In the estimated linear regression models, R^2 was ranging 5.4% to 24.2% at the highest. R^2 indicates how much of the variation in the dependent variable is explained by the independent variables, and in our study, R^2 is relatively low. This is expected as our dependent variables such as trust and purchase intention are complex constructs, and our experiment did not capture all the variation in these variables.

4.9 Results overview

In conclusion, the results from the conducted ANOVA analyses indicted no significant differences across concepts on the dependent variables. As presented in Table 21, none of our research questions had statistically significant answers except for RQ_8, where we could conclude that concept 1: MBG was most preferred, based on the frequency table (Table 14).

Number	Formulated research question	Results
RQ_1	How does the existing concept, MBG, affect consumers' a) trust, b) NFT and c) purchase intention for the fresh food product category?	No statistical evidence to conclude
RQ_2	How will product reviews affect consumers' a) trust, b) NFT and c) purchase intention for the fresh food product category comparing to the other concepts?	No statistical evidence to conclude
RQ_3	How will positive and negative product reviews differ with regards to affecting a) trust, b) NFT and c) purchase intention?	No statistical evidence to conclude
RQ_4	How will real-time images affect consumers' a) trust, b) NFT and c) purchase intention for the fresh food product category comparing to the other concepts?	No statistical evidence to conclude
RQ_5	How will physical touch affect consumers' a) trust, b) NFT and c) purchase intention for the fresh food product category comparing to the other concepts?	No statistical evidence to conclude
RQ_6	Which of concept 1, 2a, 2b, 3 and 4 will receive the highest mean of overall liking?	No statistical evidence to conclude
RQ_7	Which of concept 1, 2a, 2b, 3 and 4 will receive the highest mean of perceived usefulness?	No statistical evidence to conclude
RQ_8	Which of concept 1, 2a, 2b, 3 and 4 will be most favorable	Money-back guarantee

Table 21: Summary of research questions and results

Further, the results from a multinominal logistic regression indicated that different age groups preferred different concepts, with the youngest respondents (age 18-24) and the oldest respondents (55<) preferring the opposite (Table 15).

Additional analysis was conducted to further explore the data from the main experiment. Findings from the linear regression models revealed that active online grocery shoppers in general had a higher level of trust, purchase intention, overall liking and perceived usefulness across the five concepts, compared to inactive shoppers. NFT was lower for active shoppers compared to inactive. Thus, this showed that active online shoppers consider all concepts more favorable than inactive shoppers (based on the dependent variables). However, based on the Bonferroni correction with pairwise comparison between the concepts, we cannot conclude which of the concepts have a significantly higher or lower level of trust, NFT, purchase intention, overall liking, or perceived usefulness.

Moreover, for purchase intention, overall liking and perceived usefulness, higher age led on average to a decrease in the dependent variable, which was statistically significant in the linear regression model (Table 18, 19 and 20). Gender had no statistically significant effect on explaining the variation in the dependent variables, which was also the case for the five concepts. Thus, the variation in trust, NFT, purchase intention, overall liking and perceived usefulness can be explained by purchase frequency (active vs. inactive) and age.

5.0 Discussion

The primary aim of this study was to explore if different concepts could overcome the barriers of purchasing fresh foods online. Although the outbreak of Covid-19 led to an increase in online grocery shopping, recent research shows that consumers still have concerns about purchasing fresh food online (Mintel, 2021). Researchers have identified several barriers that stunts the adoption of these services, such as the lack of touch which prevents quality assurance of the product (Peck & Wiggins, 2011; Jin & Phua, 2015), delivery fees (Huang & Oppewal, 2006) as well as security and privacy concerns (Miyazaki, 2001). Concepts were developed based on previous theory and identified barriers in the online grocery shopping market, mainly focusing on consumers' need for touch to evaluate product quality before purchase.

The results from our analysis showed no statistical difference between the concepts on any of the dependent variables. Thus, it could not be concluded if any of the concepts are more effective than others, to increase purchase intention. This could indicate that there is no purpose of investing in complicated logistical strategies (such as the concept with physical touch) as it does not evidently result in a higher purchase intention compared to existing concepts (MBG). However, this could also mean that there are other aspects that need to be included, in order to affect the consumer's purchase intentions. Previous studies show that elements such as website design, its ease of use and information quality does influence online purchase intention (Barnes & Vidgen, 2006; Sam & Tahir, 2009; Aull, 2021). As these elements were constant in this study, it might have generated different results if consumers had all their needs met with regards to the other elements. In other words, if the information quality, the website layout or its ease of use had met the participants' needs, the concepts themselves might have differed more in terms of the trust, need for touch, overall liking and perceived usefulness.

On the other hand, the estimates might also be a result of the sample used. It was evident that there were significant differences between inactive shoppers and active shoppers, across all concepts on the dependent variables. This finding highlights the importance of previous experience on the different variables. Active shoppers showed a significantly higher trust, overall liking, perceived usefulness, and purchase intention, compared to inactive shoppers (Table 16, 18, 19 and 20). It can be argued that this would be quite intuitive. Active shoppers are already familiar with the process of shopping online, which makes them more prone to score higher on the different variables, due to the familiarity effect. This effect, often referred to as the mere exposure effect, explains how people tend to like things they are already familiar with (Fang et al., 2007). Familiarity can build trust as it provides a framework for future expectations (Gefen, 2000), and in the case of online grocery shopping, familiarity might reduce the perceived complexity of purchasing fresh foods online. This effect might also explain why inactive shoppers do not score higher on any of the variables – they solely lack the familiarity of the shopping process. The finding of these differences underlines the importance of using different strategies for the two different customer segments. To showcase the difference, we can look at how the two groups had the highest mean of overall liking on opposite concepts (Figure 8). Active shoppers had the highest mean of overall liking for concept 3 and 4 – Real-time images and Physical touch, while these concepts received the lowest mean of overall liking from the inactive shoppers.

It is interesting that negative product reviews did not have any significant differences on the dependent variables. Based on previous research, it could be argued that negative product reviews would have a lower level of trust, higher level of NFT and a lower level of purchase intention, compared to positive product reviews (Chevalier and Mayzlin, 2006; Yin et al., 2016; Filieri et al., 2021). In contrast, although not significant, negative product reviews had the highest level of trust $(M = 3.0732)$, while positive product reviews had the lowest level of trust $(M = 2.7868)$(Table 9). This might be explained by how the sample had mostly inactive shoppers $(n_{Inactive} = 125\ vs. n_{Active} = 78)$. Research suggests that people tend to like information that confirms their initial beliefs – the confirmation bias (Klayman and Ha, 1987; Yin et al., 2016). It can be argued that inactive shoppers already had negative beliefs regarding online shoppers, as they choose not to shop online. As such, negative product reviews would confirm their beliefs and perception of online grocery shopping.

Another interesting finding was the significant effect of age on some of the different variables. The older the consumer is, the lower they scored on overall liking, perceived usefulness, and purchase intention towards the concepts (Table 19, 20 and 18). This might be explained by the difference in upbringing for the different age groups, where the familiarity effect again becomes relevant. The younger generation grew up with the internet all around them, while the older generation grew up with only traditional stores. As the concept of online shopping is rather new, the younger generation would be more used to it, and thus have a higher liking of the experience of online shopping. The older generation had to learn a new shopping method later in life, which might lower their purchase intentions as they are not familiar with it in their upbringing. This is also congruent with the fact that the mean age of active online shoppers is lower than the inactive shoppers (Table 7). Further, another fascinating finding related to age, was from the monadic testing, where the youngest (18-24) and oldest (55<) preferred opposite concepts (Figure 3). Participants that were 18-24 years old were more likely to choose concept 2: Product reviews and concept 3: Real-time images. On the other hand, respondents that were 55< years old's were most likely to choose concept 4: Physical touch, and the least likely to choose concept 2 and 3. This difference was confirmed significant in a multinomial logistic regression (Table 15). This again indicates customer heterogeneity and underlines the importance of adapting different strategies to different customer segments.

It could be argued that concept 4: Physical touch would positively affect the different dependent variables the most. This is because the concept resembles traditional online shopping, where consumers use their senses to evaluate product quality. However, the results were inconsistent, as they did not indicate that this concept was most preferred. Similarly, it could be argued that MBG would have the least effect on the different variables, as this is the currently used service offering. Yet, MBG received high scores on purchase intention and overall liking (Table 11 and 12). Although not significantly different from the other concepts, this could indicate that the current concept is sufficient. In contrast to MBG, it is important to mention that concept 3: Real-time images and concept 4: Physical touch are not being used in today’s online market, and it is therefore uncertain how consumers evaluated them. This could affect the results we received by (1) not being familiar and (2) not perceived as realistic. MBG is already a widely used strategy to assure customers in a purchasing situation and thus likely familiar to the respondents. This can explain why MBG received no significant different results. The familiarity effect might have increased the concept’s performance on the different variables, or the respondents may be satisfied with the current MBG-solution of online distributors of fresh foods.

Lastly, the primary aim of this study was to explore how to overcome the existing barriers to shop fresh foods online, to increase purchase intention, which was reflected in our overall research question:

“How to overcome the barriers to shop fresh foods online in order to increase purchase intention in the Norwegian market?”

The study did not reveal which of the proposed concepts that would be most effective in decreasing the existing barriers for shopping fresh food online, as none of the concepts were significantly different on the dependent variables. Yet, this is a finding of its own, as it can indicate that the concepts are all equally viable options. On the other hand, MBG was the most frequently chosen concept, which can indicate that this service offering already fulfills the barriers that we tried to overcome with the other concepts. It is possible that there are other barriers that we did not capture in this study, that affect consumer purchase intention of fresh food online.

5.1 Managerial implications

The results from our study have some implications for online retailers, as there are several opportunities that online distributors of fresh foods can pursue. One of the most important findings was regarding customer heterogeneity, which implies that online retailers should adapt their strategies accordingly. Depending on if the retailers want to acquire new active shoppers, gain loyal active shoppers, or focus more on different age groups in their marketing strategy – different concepts should be applied. For example, the results showed that older respondents preferred concept 4: Physical touch in comparison to the other concepts. This can imply that this customer segment value NFT more than the other segments. As there were no other significant results, it cannot be concluded which of the different concepts that would generate a higher purchase intention for fresh foods online. More so, all concepts are viable options for the different online retailers. Yet, the currently used strategy, MBG, might be sufficient, and there is no immediate need to invest in more complex solutions, such as real-time images and physical touch.

5.2 Limitations

A limitation in this study is the use of nonprobability sampling. This method does not use chance selection procedures, and the estimates are thus not statistically projectable to the population (Malhotra, 2010, p. 344). Convenience sampling, the nonprobability sampling used in this study, has some advantages of being easy to measure, accessible and non-expensive. However, this method contains selection bias, as proper randomization is not achieved (Malhotra, 2010, p. 245). The experiment was posted on the authors' social media platforms, which limits the participants to being in virtually close social proximity to the authors. Members outside this social "bubble" would not be represented. The same goes for consumers that are not on any online social platforms at all, or only visit on rare occasions. The method was chosen due to limited time and resources, and it is recognized that this threatens the external and internal validity of the experiment (van Oest, 2021). Furthermore, when dividing the sample into different demographics such as age and gender, the sample size becomes smaller, and less generalizable to the population. Additionally, almost 70% of the sample were female, which can make the results less representative to the population.

Another limitation to our study is other potential barriers that were not included, such as delivery fees (Huang & Oppewal, 2006) as well as security and privacy concerns (Miyazaki, 2001). Previous research has established that these can affect purchase intention online, yet these were not accounted for in our study.

Lastly, as mentioned in the discussion section, a limitation in this study was the use of concepts that do not exist today in any online shopping category (based on the lack of such findings by the authors). MBG and product reviews both exist today, which makes it easier to imagine in an e-grocery setting. However, real-time images and the ability to choose the product you want at home, is not offered in any online shopping market. This might make it hard for the consumer to envision these scenarios into real life, which in turn might affect the results. It is possible that the results would be different if these services existed.

5.3 Further research

As mentioned prior, previous research stated that fresh foods were one of the slowest growing categories in online shopping, however, e-grocery itself has grown tremendously the last few years (Redman, 2020a). The conducted research in this paper tested the barriers of buying fresh foods online for both buyers with e-grocery experience and buyers without any experience. However, future research should explore dividing between these two, focusing solely on people with prior experience. It could be argued that converting these consumers into fresh-food buyers online is easier than converting the non-experienced buyers. This latter group may have barriers to shopping online at all, such as privacy concerns and security, or lack of motivation to understand the online shopping world. However, the experienced buyers are likely to have other reasons for not buying fresh food online, such as the barriers tested in this research. Thus, isolating the research to this segment, might give more significant results between the concepts. Furthermore, understanding the barriers of non-online shoppers could also induce helpful information and implications for the marketing as to why they stick to the physical stores. Future research could also explore and test concepts that fulfills the other existing barriers, such as privacy concerns and security. These barriers might be more impactful on consumers' purchase intention for fresh food online.

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7.0 Appendix

Exhibit 1: Questionnaire for Pretest

Construct	**Measurement Items**

Descriptive and demographic questions	*Descriptive*: Purchasing habits today and previous experience with fresh foods.
	• How often do you purchase goods online?
	    ○ Several times a week
	    ○ Once a week
	    ○ A few times a week
	    ○ Once a month
	    ○ Once every few month
	    ○ Once a year
	    ○ Never
	• Which of the following items have you purchased online in the past 12 months?
	    ○ Fashion and accessories
	    ○ Electronics and technology
	    ○ Groceries, food and drink
	    ○ Home and furniture
	    ○ Toys / Hobbies
	    ○ Personal care (beauty, health)
	    ○ Flowers and gifts
	    ○ Books
	    ○ None of the above
	Demographics: Age, gender.

Open-ended question	What are your thoughts about shopping for fresh food online? (Fruits, vegetables, meat, etc.)
Scenario	Imagine the following scenario: You are going to buy a banana online. Which of the following parties do you consider more responsible for the quality of the banana you are going to get? • The producer (the banana farm in f.ex. Spain)

	• The distributor (the online store in which you purchase from)

Exhibit 2: Questionnaire for Main Experiment

Construct	**Measurement Items**	**Based on**
Descriptive and demographic questions	Demographics: Age, gender. Descriptive: Purchasing habits today and previous experience with fresh foods.	
Instrumental NFT	I place more trust in products that can be touched before purchase I feel more comfortable purchasing a product after physically examining it I feel more confident making a purchase after touching a product If I cannot touch a product in the store, I am reluctant to purchase the product	Peck & Childers (2003)
Trust	Shopping online for fresh foods can be trusted, and there are no uncertainties. In general, I can rely on online retailers of fresh foods keeping the promises they make. Shopping online for fresh food is reliable. Shopping online for fresh food is a trustworthy experience.	Rose et al (2012)
Purchase intention	I definitely intend to buy fresh food online from this retailer My purchase interest is high I will definitely buy fresh food online	Spears and Singh (2004)

Overall liking	Please evaluate the following statements about (The concept)): - Bad/good - Negative/positive - Unfavorable/favorable (on a 5-point semantic differentiation scale)	Kwon and Nayakankuppam (2015)
Perceived usefulness	- (The concept) increase efficiency when shopping for fresh food online - (The concept) increase my performance of evaluating the quality of the products more accurately - I perceive (The concept) as useful	Davis (1989)

Exhibit 3: Visual presentation of concepts

Concept 1: Money-back guarantee

Se for deg følgende scenario: du skal kjøpe en banan via en nettbasert matbutikk.

I nettbutikken, får du følgende informasjon:

Nettbutikken tilbyr en fornøydhetsgaranti.

Med denne garantien kan du returnere produktet og få tilbake pengene, dersom produktet ikke tilfredsstiller dine behov.

Concept 2a: Product reviews (positive)

Se for deg følgende scenario: du skal kjøpe en banan via en nettbasert matbutikk.

I nettbutikken, får du følgende informasjon:

Nettbutikken viser produktanmeldelser fra andre.

Ved å vise produktanmeldelser kan du se hva andre kunder som har kjøpt produktet skriver om det, og deres erfaringer med å kjøpe fra nettbutikken.

Concept 2b: Product reviews (negative)

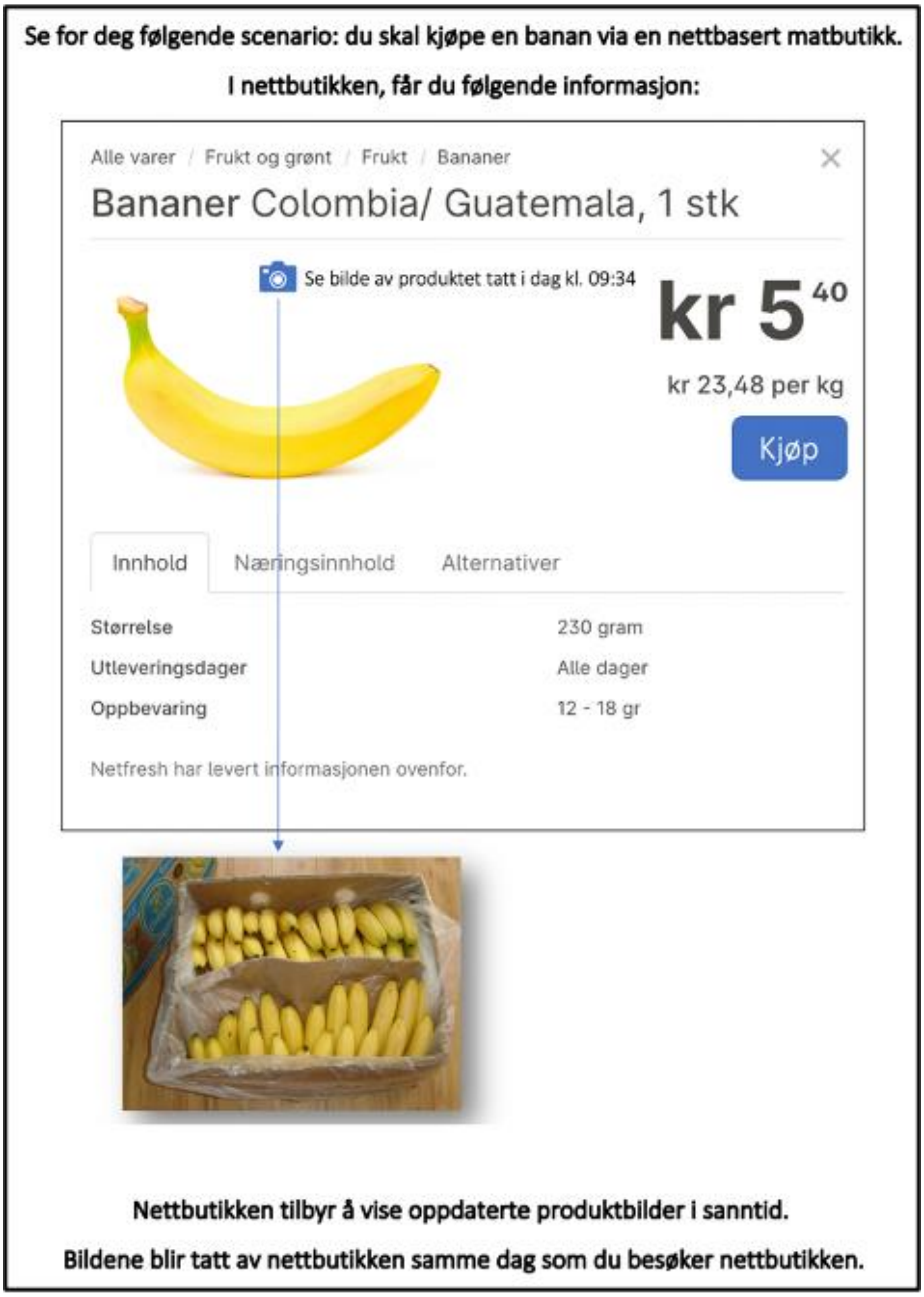
Se for deg følgende scenario: du skal kjøpe en banan via en nettbasert matbutikk.

I nettbutikken, får du følgende informasjon:

Nettbutikken viser produktanmeldelser fra andre.

Ved å vise produktanmeldelser kan du se hva andre kunder som har kjøpt produktet skriver om det, og deres erfaringer med å kjøpe fra nettbutikken.

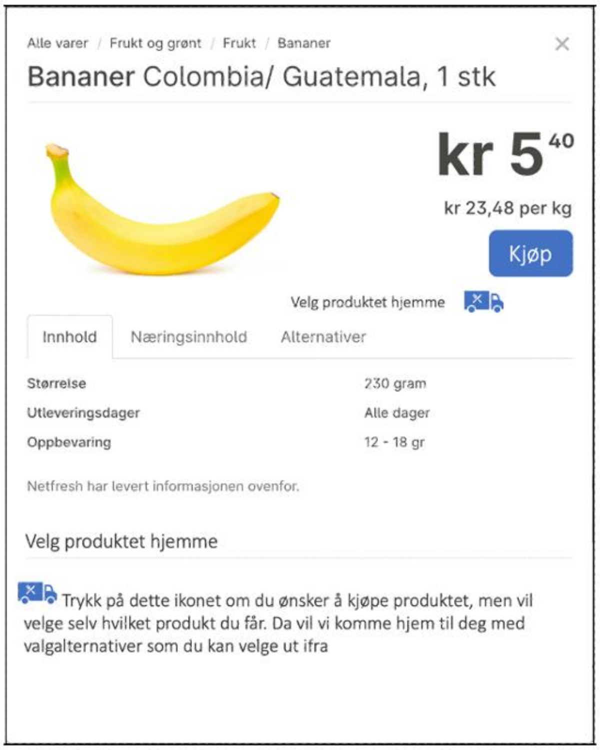
Concept 3: Real-time images



Concept 4: Physical touch

Se for deg følgende scenario: du skal kjøpe en banan via en nettbasert matbutikk.

I nettbutikken, får du følgende informasjon:



Nettbutikken tilbyr å ta med flere produkter hjem til deg, slik at du kan velge akkurat hvilket produkt du vil ha når varene blir levert.

Exhibit 4: Visual presentation of all concepts together

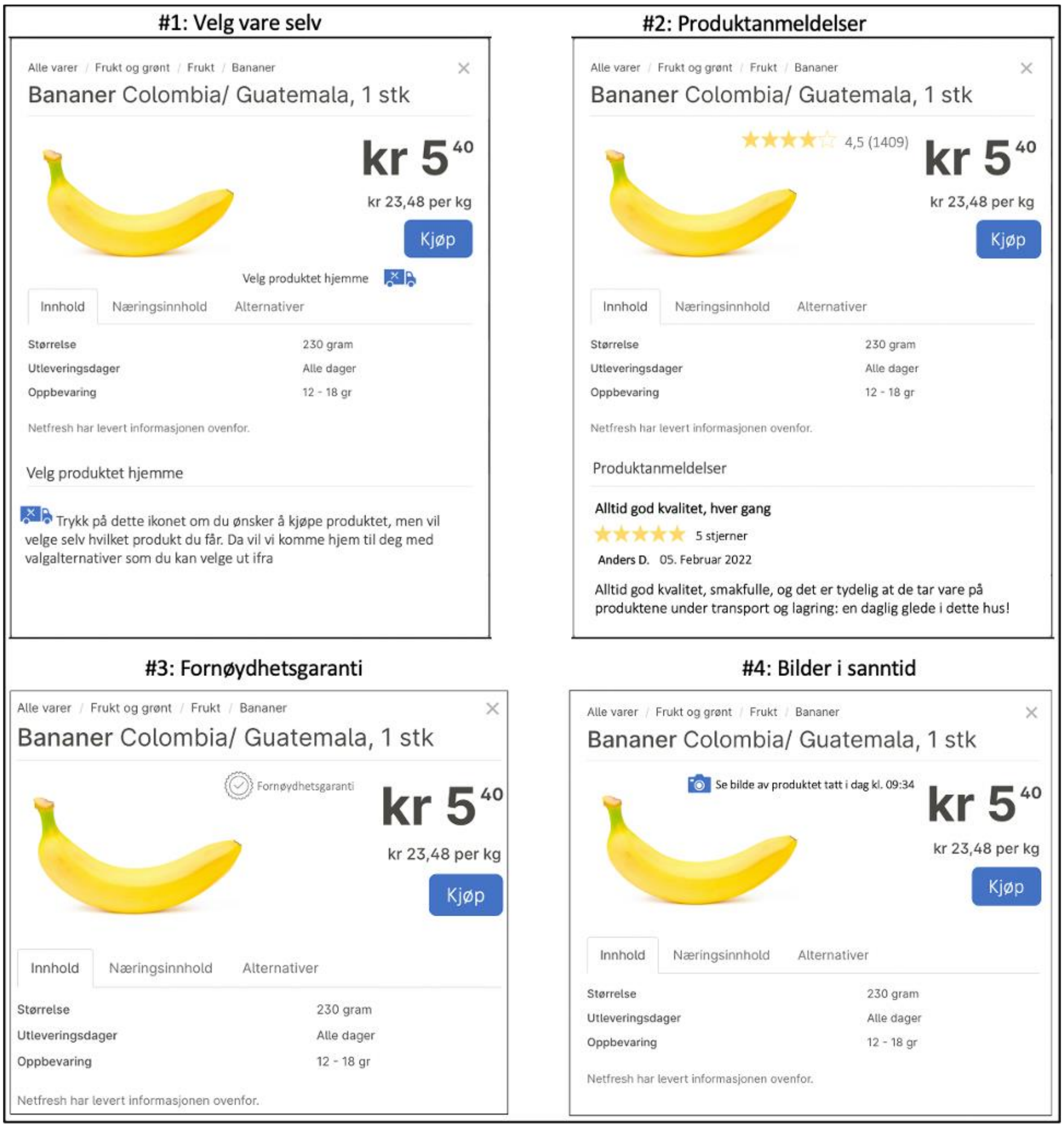


Exhibit 5: Reliability analysis

Trust

Reliability Analysis – *Trust*

Cronbach's alpha	N of items
.893	4

NFT

Reliability Analysis – *NFT*

Cronbach's alpha	N of items
.833	4

Purchase intention

Reliability Analysis – *Purchase intention*

Cronbach's alpha	N of items
.877	2

Overall liking

Reliability Analysis – *Overall liking*

Cronbach's alpha	N of items
.927	3

Perceived usefulness

Reliability Analysis – *Perceived usefulness*

Cronbach's alpha	N of items
.749	3

Exhibit 6: Age difference between active vs. inactive shoppers

Descriptives

ONLINESHOPPERS = Inactive online shoppers

Descriptive Statistics[a]

	N	Minimum	Maximum	Mean	Std. Deviation
AGE	125	23.00	72.00	43.0000	16.12902
Valid N (listwise)	125				

a. ONLINESHOPPERS = Inactive online shoppers

ONLINESHOPPERS = Active online shoppers

Descriptive Statistics[a]

	N	Minimum	Maximum	Mean	Std. Deviation
AGE	78	16.00	68.00	35.9744	13.02941
Valid N (listwise)	78				

a. ONLINESHOPPERS = Active online shoppers

Exhibit 7: ANOVA

Trust

Oneway

Descriptives

TRUST_SAMLET

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1.00	54	2.9815	.72660	.09888	2.7832	3.1798	1.00	5.00
2.00	34	2.7868	.84864	.14554	2.4907	3.0829	1.00	5.00
3.00	41	3.0732	.55970	.08741	2.8965	3.2498	2.00	4.25
4.00	39	2.8846	.80264	.12853	2.6244	3.1448	1.50	4.00
5.00	35	3.0571	.53236	.08998	2.8743	3.2400	2.00	4.25
Total	203	2.9618	.70541	.04951	2.8642	3.0594	1.00	5.00

ANOVA

TRUST_SAMLET

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.122	4	.530	1.067	.374
Within Groups	98.395	198	.497		
Total	100.517	202			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
TRUST_SAMLET	Eta-squared	.021	.000	.056
	Epsilon-squared	.001	-.020	.037
	Omega-squared Fixed-effect	.001	-.020	.037
	Omega-squared Random-effect	.000	-.005	.009

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Post Hoc Tests

Multiple Comparisons

Dependent Variable: TRUST_SAMLET
Bonferroni

(I) Gruppe_konsept	(J) Gruppe_konsept	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.00	2.00	.19472	.15433	1.000	-.2434	.6328
	3.00	-.09169	.14602	1.000	-.5062	.3229
	4.00	.09687	.14814	1.000	-.3237	.5174
	5.00	-.07566	.15297	1.000	-.5099	.3586
2.00	1.00	-.19472	.15433	1.000	-.6328	.2434
	3.00	-.28641	.16351	.814	-.7506	.1778
	4.00	-.09785	.16540	1.000	-.5674	.3717
	5.00	-.27038	.16975	1.000	-.7523	.2115
3.00	1.00	.09169	.14602	1.000	-.3229	.5062
	2.00	.28641	.16351	.814	-.1778	.7506
	4.00	.18856	.15768	1.000	-.2591	.6362
	5.00	.01603	.16223	1.000	-.4445	.4766
4.00	1.00	-.09687	.14814	1.000	-.5174	.3237
	2.00	.09785	.16540	1.000	-.3717	.5674
	3.00	-.18856	.15768	1.000	-.6362	.2591
	5.00	-.17253	.16414	1.000	-.6385	.2934
5.00	1.00	.07566	.15297	1.000	-.3586	.5099
	2.00	.27038	.16975	1.000	-.2115	.7523
	3.00	-.01603	.16223	1.000	-.4766	.4445
	4.00	.17253	.16414	1.000	-.2934	.6385

NFT

Oneway

Descriptives

NFT_SAMLET

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1.00	54	3.8333	.56843	.07735	3.6782	3.9885	2.50	4.75
2.00	34	3.6838	.69170	.11862	3.4425	3.9252	2.00	5.00
3.00	41	3.8415	.47023	.07344	3.6930	3.9899	2.75	4.75
4.00	39	3.7436	.67005	.10729	3.5264	3.9608	2.00	4.75
5.00	35	3.7571	.75363	.12739	3.4983	4.0160	1.75	5.00
Total	203	3.7796	.62467	.04384	3.6931	3.8660	1.75	5.00

ANOVA

NFT_SAMLET

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.693	4	.173	.439	.780
Within Groups	78.130	198	.395		
Total	78.823	202			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
NFT_SAMLET	Eta-squared	.009	.000	.028
	Epsilon-squared	-.011	-.020	.008
	Omega-squared Fixed-effect	-.011	-.020	.008
	Omega-squared Random-effect	-.003	-.005	.002

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Post Hoc Tests

Multiple Comparisons

Dependent Variable: NFT_SAMLET
Bonferroni

(I) Gruppe_konsept	(J) Gruppe_konsept	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.00	2.00	.14951	.13752	1.000	-.2409	.5399
	3.00	-.00813	.13012	1.000	-.3775	.3613
	4.00	.08974	.13200	1.000	-.2850	.4645
	5.00	.07619	.13631	1.000	-.3108	.4632
2.00	1.00	-.14951	.13752	1.000	-.5399	.2409
	3.00	-.15764	.14571	1.000	-.5713	.2560
	4.00	-.05977	.14739	1.000	-.4782	.3586
	5.00	-.07332	.15126	1.000	-.5027	.3561
3.00	1.00	.00813	.13012	1.000	-.3613	.3775
	2.00	.15764	.14571	1.000	-.2560	.5713
	4.00	.09787	.14051	1.000	-.3010	.4967
	5.00	.08432	.14456	1.000	-.3261	.4947
4.00	1.00	-.08974	.13200	1.000	-.4645	.2850
	2.00	.05977	.14739	1.000	-.3586	.4782
	3.00	-.09787	.14051	1.000	-.4967	.3010
	5.00	-.01355	.14626	1.000	-.4288	.4017
5.00	1.00	-.07619	.13631	1.000	-.4632	.3108
	2.00	.07332	.15126	1.000	-.3561	.5027
	3.00	-.08432	.14456	1.000	-.4947	.3261
	4.00	.01355	.14626	1.000	-.4017	.4288

Purchase intention

Oneway

Descriptives

PI_SAMLET

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
1.00	54	3.0093	.93411	.12712	2.7543	3.2642	1.00	5.00
2.00	34	2.8235	1.23633	.21203	2.3922	3.2549	1.00	5.00
3.00	41	2.9878	1.08102	.16883	2.6466	3.3290	1.00	5.00
4.00	39	2.6923	1.04261	.16695	2.3543	3.0303	1.00	5.00
5.00	35	2.7143	.88522	.14963	2.4102	3.0184	1.00	5.00
Total	203	2.8621	1.03201	.07243	2.7192	3.0049	1.00	5.00

ANOVA

PI_SAMLET

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.757	4	.939	.880	.477
Within Groups	211.381	198	1.068		
Total	215.138	202			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
PI_SAMLET	Eta-squared	.017	.000	.049
	Epsilon-squared	-.002	-.020	.029
	Omega-squared Fixed-effect	-.002	-.020	.029
	Omega-squared Random-effect	-.001	-.005	.007

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Post Hoc Tests

Multiple Comparisons

Dependent Variable: PI_SAMLET
Bonferroni

(I) Gruppe_konsept	(J) Gruppe_konsept	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1.00	2.00	.18573	.22621	1.000	-.4564	.8279
	3.00	.02145	.21403	1.000	-.5861	.6290
	4.00	.31695	.21713	1.000	-.2994	.9333
	5.00	.29497	.22421	1.000	-.3415	.9315
2.00	1.00	-.18573	.22621	1.000	-.8279	.4564
	3.00	-.16428	.23966	1.000	-.8446	.5161
	4.00	.13122	.24243	1.000	-.5570	.8194
	5.00	.10924	.24880	1.000	-.5971	.8155
3.00	1.00	-.02145	.21403	1.000	-.6290	.5861
	2.00	.16428	.23966	1.000	-.5161	.8446
	4.00	.29550	.23111	1.000	-.3606	.9516
	5.00	.27352	.23778	1.000	-.4015	.9485
4.00	1.00	-.31695	.21713	1.000	-.9333	.2994
	2.00	-.13122	.24243	1.000	-.8194	.5570
	3.00	-.29550	.23111	1.000	-.9516	.3606
	5.00	-.02198	.24057	1.000	-.7049	.6610
5.00	1.00	-.29497	.22421	1.000	-.9315	.3415
	2.00	-.10924	.24880	1.000	-.8155	.5971
	3.00	-.27352	.23778	1.000	-.9485	.4015
	4.00	.02198	.24057	1.000	-.6610	.7049

Overall liking

Oneway

Descriptives

OverallLiking

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1.00	54	3.6481	.92579	.12598	3.3955	3.9008	1.67	5.00
2.00	34	3.4608	.97792	.16771	3.1196	3.8020	1.00	5.00
3.00	41	3.5691	.81050	.12658	3.3133	3.8249	2.33	5.00
4.00	39	3.7009	1.09169	.17481	3.3470	4.0547	1.00	5.00
5.00	35	3.4571	.93615	.15824	3.1356	3.7787	1.67	5.00
Total	203	3.5780	.94445	.06629	3.4473	3.7087	1.00	5.00

ANOVA

OverallLiking

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.836	4	.459	.510	.729
Within Groups	178.346	198	.901		
Total	180.182	202			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
OverallLiking	Eta-squared	.010	.000	.032
	Epsilon-squared	-.010	-.020	.012
	Omega-squared Fixed-effect	-.010	-.020	.012
	Omega-squared Random-effect	-.002	-.005	.003

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Post Hoc Tests

Multiple Comparisons

Dependent Variable: OverallLiking
Bonferroni

(I) Gruppe_konsept	(J) Gruppe_konsept	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.00	2.00	.18736	.20778	1.000	-.4025	.7772
	3.00	.07904	.19659	1.000	-.4791	.6371
	4.00	-.05271	.19944	1.000	-.6189	.5135
	5.00	.19101	.20595	1.000	-.3937	.7757
2.00	1.00	-.18736	.20778	1.000	-.7772	.4025
	3.00	-.10832	.22014	1.000	-.7333	.5166
	4.00	-.24007	.22268	1.000	-.8722	.3921
	5.00	.00364	.22853	1.000	-.6451	.6524
3.00	1.00	-.07904	.19659	1.000	-.6371	.4791
	2.00	.10832	.22014	1.000	-.5166	.7333
	4.00	-.13175	.21229	1.000	-.7344	.4709
	5.00	.11196	.21841	1.000	-.5081	.7320
4.00	1.00	.05271	.19944	1.000	-.5135	.6189
	2.00	.24007	.22268	1.000	-.3921	.8722
	3.00	.13175	.21229	1.000	-.4709	.7344
	5.00	.24371	.22098	1.000	-.3836	.8710
5.00	1.00	-.19101	.20595	1.000	-.7757	.3937
	2.00	-.00364	.22853	1.000	-.6524	.6451
	3.00	-.11196	.21841	1.000	-.7320	.5081
	4.00	-.24371	.22098	1.000	-.8710	.3836

Perceived usefulness

Oneway

Descriptives

PerceivedUsefulness

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1.00	54	3.3580	.73787	.10041	3.1566	3.5594	1.00	4.67
2.00	34	3.4510	.97401	.16704	3.1111	3.7908	1.00	5.00
3.00	41	3.6098	.61420	.09592	3.4159	3.8036	2.33	5.00
4.00	39	3.5043	.68770	.11012	3.2813	3.7272	2.00	4.33
5.00	35	3.2190	.74948	.12668	2.9616	3.4765	1.00	4.67
Total	203	3.4286	.75686	.05312	3.3238	3.5333	1.00	5.00

ANOVA

PerceivedUsefulness

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.392	4	.848	1.495	.205
Within Groups	112.323	198	.567		
Total	115.714	202			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
PerceivedUsefulness	Eta-squared	.029	.000	.071
	Epsilon-squared	.010	-.020	.052
	Omega-squared Fixed-effect	.010	-.020	.052
	Omega-squared Random-effect	.002	-.005	.013

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

Post Hoc Tests

Multiple Comparisons

Dependent Variable: PerceivedUsefulness

Bonferroni

(I) Gruppe_konsept	(J) Gruppe_konsept	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.00	2.00	-.09296	.16489	1.000	-.5611	.3752
	3.00	-.25173	.15602	1.000	-.6946	.1912
	4.00	-.14625	.15828	1.000	-.5956	.3031
	5.00	.13898	.16344	1.000	-.3250	.6030
2.00	1.00	.09296	.16489	1.000	-.3752	.5611
	3.00	-.15878	.17470	1.000	-.6547	.3372
	4.00	-.05329	.17672	1.000	-.5550	.4484
	5.00	.23193	.18136	1.000	-.2829	.7468
3.00	1.00	.25173	.15602	1.000	-.1912	.6946
	2.00	.15878	.17470	1.000	-.3372	.6547
	4.00	.10548	.16847	1.000	-.3728	.5837
	5.00	.39071	.17333	.253	-.1014	.8828
4.00	1.00	.14625	.15828	1.000	-.3031	.5956
	2.00	.05329	.17672	1.000	-.4484	.5550
	3.00	-.10548	.16847	1.000	-.5837	.3728
	5.00	.28523	.17537	1.000	-.2126	.7831
5.00	1.00	-.13898	.16344	1.000	-.6030	.3250
	2.00	-.23193	.18136	1.000	-.7468	.2829
	3.00	-.39071	.17333	.253	-.8828	.1014
	4.00	-.28523	.17537	1.000	-.7831	.2126

Exhibit 8: Concept choice age

Age group 18-24

Frequencies

AGE_GROUPS = 18-24

Statistics[a]

CHOICE_CONCEPT

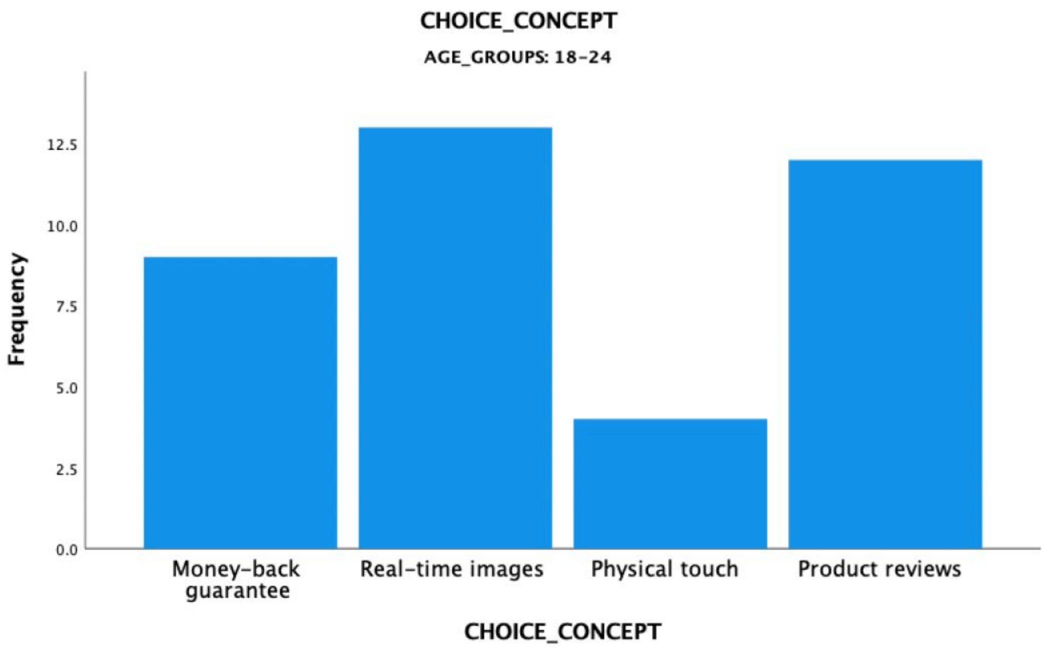
N	Valid	38
	Missing	0

a. AGE_GROUPS = 18-24

CHOICE_CONCEPT[a]

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Money-back guarantee	9	23.7	23.7	23.7
	Real-time images	13	34.2	34.2	57.9
	Physical touch	4	10.5	10.5	68.4
	Product reviews	12	31.6	31.6	100.0
	Total	38	100.0	100.0	

a. AGE_GROUPS = 18-24



Age group 25-34

AGE_GROUPS = 25-34

Statistics[a]

CHOICE_CONCEPT

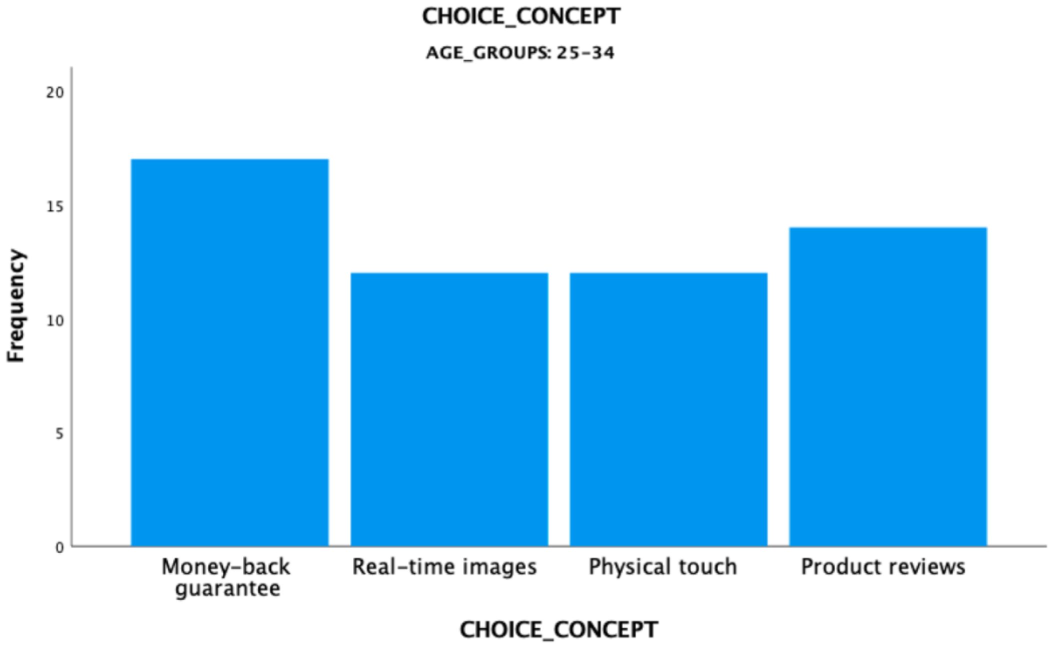
N	Valid	55
	Missing	0

a. AGE_GROUPS = 25-34

CHOICE_CONCEPT[a]

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Money-back guarantee	17	30.9	30.9	30.9
	Real-time images	12	21.8	21.8	52.7
	Physical touch	12	21.8	21.8	74.5
	Product reviews	14	25.5	25.5	100.0
	Total	55	100.0	100.0	

a. AGE_GROUPS = 25-34



Age group 35-44

AGE_GROUPS = 35-44

Statistics[a]

CHOICE_CONCEPT

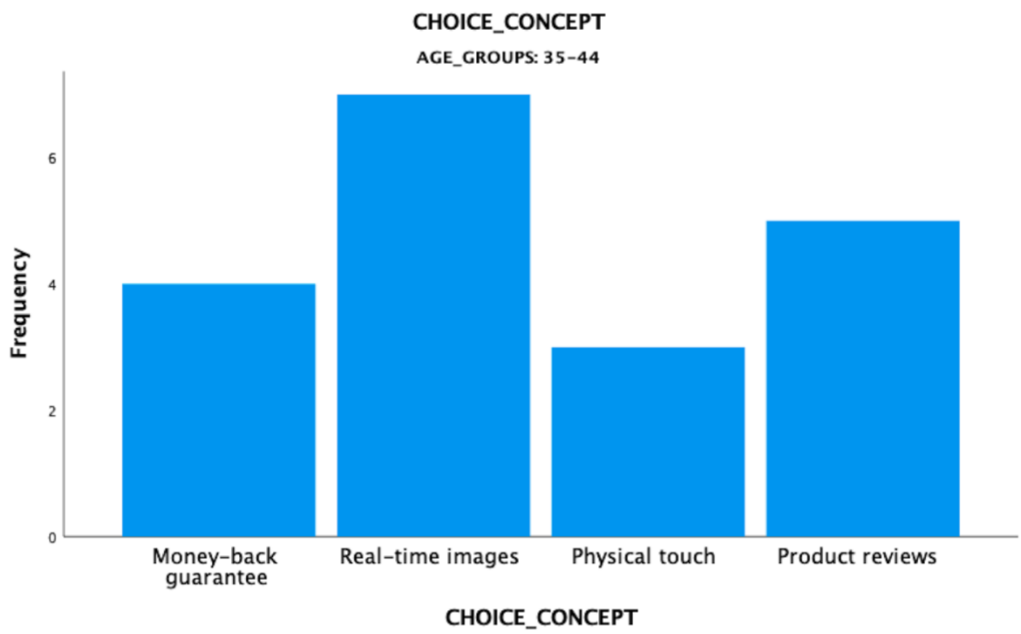
N	Valid	19
	Missing	0

a. AGE_GROUPS = 35-44

CHOICE_CONCEPT[a]

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Money-back guarantee	4	21.1	21.1	21.1
	Real-time images	7	36.8	36.8	57.9
	Physical touch	3	15.8	15.8	73.7
	Product reviews	5	26.3	26.3	100.0
	Total	19	100.0	100.0	

a. AGE_GROUPS = 35-44



Age group 45-54

AGE_GROUPS = 45-54

Statistics[a]

CHOICE_CONCEPT

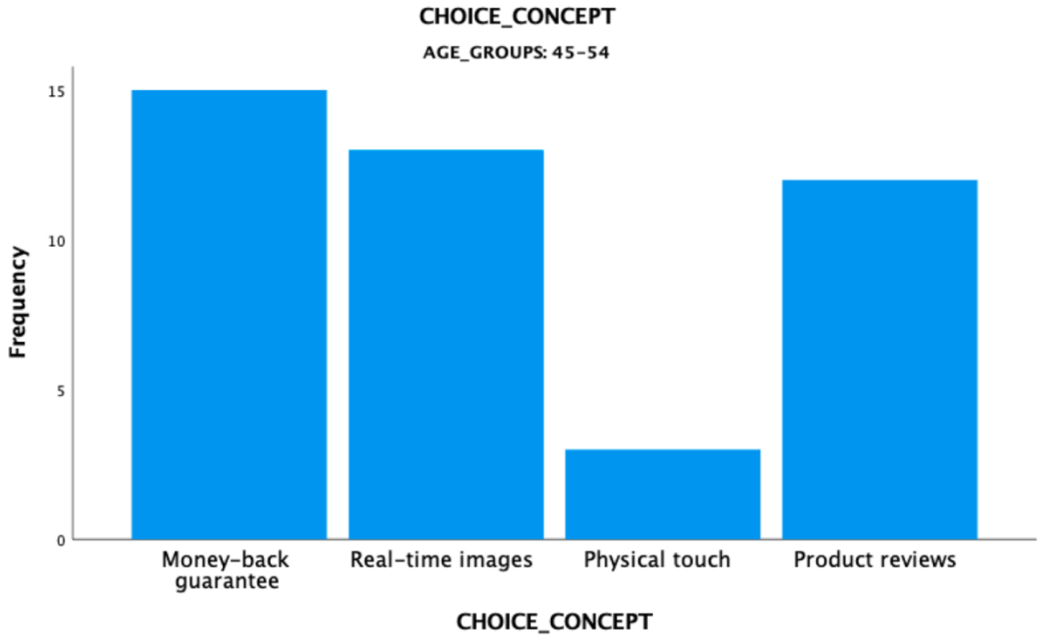
N	Valid	43
	Missing	0

a. AGE_GROUPS = 45-54

CHOICE_CONCEPT[a]

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Money-back guarantee	15	34.9	34.9	34.9
	Real-time images	13	30.2	30.2	65.1
	Physical touch	3	7.0	7.0	72.1
	Product reviews	12	27.9	27.9	100.0
	Total	43	100.0	100.0	

a. AGE_GROUPS = 45-54



Age group 55<

AGE_GROUPS = 55<

Statistics[a]

CHOICE_CONCEPT

N	Valid	48
	Missing	0

a. AGE_GROUPS = 55<

CHOICE_CONCEPT[a]

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Money-back guarantee	20	41.7	41.7	41.7
	Real-time images	2	4.2	4.2	45.8
	Physical touch	18	37.5	37.5	83.3
	Product reviews	8	16.7	16.7	100.0
	Total	48	100.0	100.0	

a. AGE_GROUPS = 55<

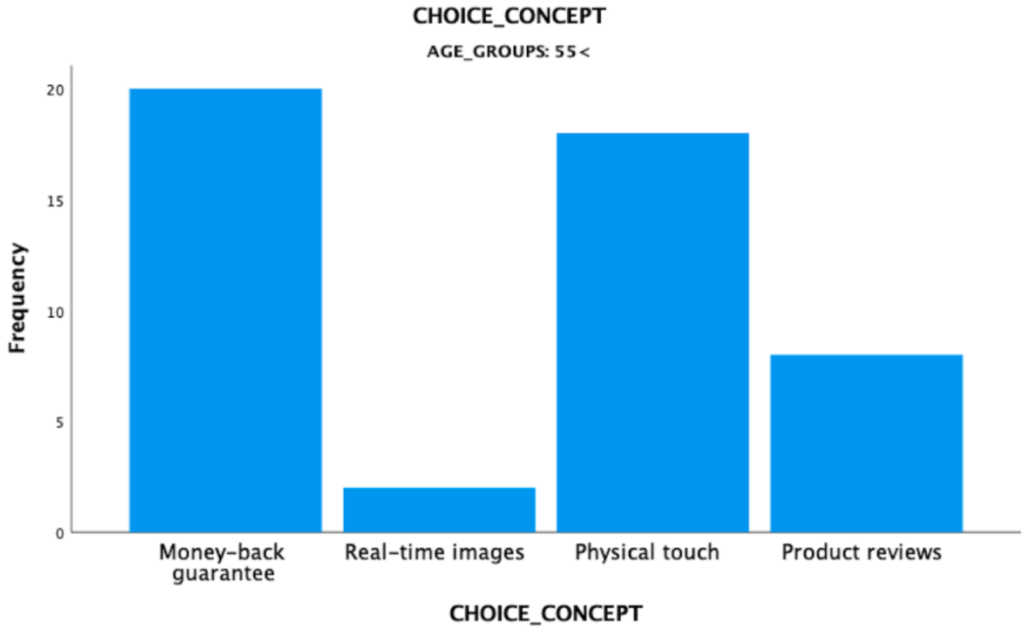


Exhibit 9: Multinomial logistic regression

Reference group: physical touch

Nominal Regression

Warnings

There are 15 (18.8%) cells (i.e., dependent variable levels by subpopulations) with zero frequencies.

Case Processing Summary

		N	Marginal Percentage
CHOICE_CONCEPT	Money-back guarantee	65	32.0%
	Real-time images	47	23.2%
	Physical touch	40	19.7%
	Product reviews	51	25.1%
Valid		203	100.0%
Missing		0	
Total		203	
Subpopulation		20	

Model Fitting Information

	Model Fitting Criteria			Likelihood Ratio Tests		
Model	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	202.338	212.278	196.338			
Final	205.155	244.913	181.155	15.184	9	.086

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	61.858	48	.086
Deviance	77.494	48	.004

Pseudo R-Square

Cox and Snell	.072
Nagelkerke	.077
McFadden	.027

Likelihood Ratio Tests

	Model Fitting Criteria			Likelihood Ratio Tests		
Effect	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	208.014	237.832	190.014	8.859	3	.031
AGE_GROUPS	212.152	241.971	194.152	12.997	3	.005
GENDER	201.577	231.396	183.577	2.422	3	.490
ONLINESHOPPERS	199.732	229.551	181.732	.577	3	.902

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Parameter Estimates

CHOICE_CONCEPT[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
Money-back guarantee	Intercept	1.500	1.015	2.183	1	.140			
	AGE_GROUPS	-.109	.145	.558	1	.455	.897	.675	1.193
	GENDER	-.315	.455	.478	1	.489	.730	.299	1.782
	ONLINESHOPPERS	-.277	.427	.421	1	.516	.758	.328	1.751
Real-time images	Intercept	2.979	1.067	7.792	1	.005			
	AGE_GROUPS	-.481	.160	9.025	1	.003	.618	.451	.846
	GENDER	-.737	.486	2.296	1	.130	.479	.185	1.241
	ONLINESHOPPERS	-.315	.464	.462	1	.497	.730	.294	1.811
Product reviews	Intercept	2.114	1.058	3.990	1	.046			
	AGE_GROUPS	-.346	.153	5.086	1	.024	.708	.524	.956
	GENDER	-.395	.481	.675	1	.411	.674	.262	1.729
	ONLINESHOPPERS	-.266	.450	.350	1	.554	.766	.317	1.851

a. The reference category is: Physical touch.

Classification

Observed	Predicted Money-back guarantee	Real-time images	Physical touch	Product reviews	Percent Correct
Money-back guarantee	50	13	0	2	76.9%
Real-time images	27	19	0	1	40.4%
Physical touch	34	4	0	2	0.0%
Product reviews	37	8	0	6	11.8%
Overall Percentage	72.9%	21.7%	0.0%	5.4%	36.9%

Exhibit 10: Linear regression

Trust

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2[b]	.	Enter

a. Dependent Variable: TRUST

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.382[a]	.146	.115	.66358

a. Predictors: (Constant), GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14.651	7	2.093	4.753	<.001[b]
	Residual	85.866	195	.440		
	Total	100.517	202			

a. Dependent Variable: TRUST

b. Predictors: (Constant), GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.863	.254		11.280	<.001
	D1	-.160	.147	-.085	-1.092	.276
	D2	.109	.140	.062	.780	.436
	D3	-.085	.142	-.047	-.595	.552
	D4	.112	.145	.060	.771	.441
	ONLINESHOPPERS	.488	.099	.337	4.951	<.001
	AGE	-.003	.003	-.055	-.806	.421
	GENDER	.009	.103	.006	.087	.931

a. Dependent Variable: TRUST

NFT

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2[b]	.	Enter

a. Dependent Variable: NFT

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.231[a]	.054	.020	.61852

a. Predictors: (Constant), GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.222	7	.603	1.577	.144[b]
	Residual	74.600	195	.383		
	Total	78.823	202			

a. Dependent Variable: NFT

b. Predictors: (Constant), GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.104	.237		17.348	<.001
	D1	-.156	.137	-.094	-1.143	.255
	D2	.012	.131	.008	.092	.926
	D3	-.074	.133	-.047	-.555	.580
	D4	-.090	.135	-.054	-.664	.507
	ONLINESHOPPERS	-.272	.092	-.213	-2.964	.003
	AGE	-.004	.003	-.094	-1.306	.193
	GENDER	-.007	.096	-.006	-.077	.939

a. Dependent Variable: NFT

Purchase intention

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2[b]	.	Enter

a. Dependent Variable: PURCHASE_INTENTION

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.492[a]	.242	.215	.91432

a. Predictors: (Constant), GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	52.122	7	7.446	8.907	<.001[b]
	Residual	163.016	195	.836		
	Total	215.138	202			

a. Dependent Variable: PURCHASE_INTENTION

b. Predictors: (Constant), GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.201	.350		9.153	<.001
	D1	-.094	.202	-.034	-.465	.642
	D2	.049	.193	.019	.256	.798
	D3	-.233	.196	-.089	-1.191	.235
	D4	-.217	.199	-.080	-1.091	.277
	ONLINESHOPPERS	.767	.136	.362	5.644	<.001
	AGE	-.016	.004	-.237	-3.685	<.001
	GENDER	.057	.142	.026	.404	.687

a. Dependent Variable: PURCHASE_INTENTION

Overall liking

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2[b]	.	Enter

a. Dependent Variable: OverallLiking

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.370[a]	.137	.106	.89321

a. Predictors: (Constant), GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24.607	7	3.515	4.406	<.001[b]
	Residual	155.575	195	.798		
	Total	180.182	202			

a. Dependent Variable: OverallLiking

b. Predictors: (Constant), GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.193	.342		12.273	<.001
	D1	-.143	.198	-.057	-.725	.469
	D2	-.051	.188	-.022	-.271	.787
	D3	.099	.192	.041	.518	.605
	D4	-.154	.195	-.062	-.792	.429
	ONLINESHOPPERS	.408	.133	.211	3.074	.002
	AGE	-.015	.004	-.241	-3.510	<.001
	GENDER	-.079	.138	-.039	-.567	.571

a. Dependent Variable: OverallLiking

Perceived usefulness

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2[b]	.	Enter

a. Dependent Variable: PerceivedUsefulness

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.347[a]	.121	.089	.72239

a. Predictors: (Constant), GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.953	7	1.993	3.820	<.001[b]
	Residual	101.761	195	.522		
	Total	115.714	202			

a. Dependent Variable: PerceivedUsefulness

b. Predictors: (Constant), GENDER, D4, AGE, D1, ONLINESHOPPERS, D3, D2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.547	.276		12.838	<.001
	D1	.143	.160	.071	.898	.371
	D2	.298	.152	.159	1.957	.052
	D3	.206	.155	.107	1.328	.186
	D4	-.101	.158	-.051	-.643	.521
	ONLINESHOPPERS	.269	.107	.173	2.504	.013
	AGE	-.010	.003	-.212	-3.051	.003
	GENDER	.054	.112	.034	.486	.627

a. Dependent Variable: PerceivedUsefulness