

# UNDERSTANDING PRODUCT ATTRIBUTES ASSOCIATED WITH FOOD SALES: SENSORY ATTRIBUTES FOR ONLINE VERSUS OFFLINE OPTIONS OF A MULTI-CHANNEL RETAILER<sup>1</sup>

Eunsoo Choi

Department of Agricultural Economics & Rural Development  
Food Biz Lab, Seoul National University  
1 Gwanak-ro, Gwanak-gu, Seoul, 08826, Republic of Korea  
[ivces0@snu.ac.kr](mailto:ivces0@snu.ac.kr)

Haram Eom

Department of Agricultural Economics & Rural Development  
Food Biz Lab, Seoul National University  
1 Gwanak-ro, Gwanak-gu, Seoul, 08826, Republic of Korea  
[eomharam@snu.ac.kr](mailto:eomharam@snu.ac.kr)

Junghoon Moon

Department of Agricultural Economics & Rural Development  
Food Biz Lab, Seoul National University  
1 Gwanak-ro, Gwanak-gu, Seoul, 08826, Republic of Korea  
[moonj@snu.ac.kr](mailto:moonj@snu.ac.kr)

## ABSTRACT

Given the explosive growth of the online food market since the COVID-19 outbreak, this study aimed to examine search attributes affecting food sales in online channels compared to offline channels, focusing on a sensory attribute – visibility of the package. The results affirm a difference in the food sales model of on/offline channels before and after adding a sensory attribute. This study utilized POS (point of sale) data from a multi-channel retailer in the Republic of Korea. All products were classified according to five search attributes, and the effect of each attribute on sales in a channel was analyzed. Compared to the model that included only non-sensory attributes, the model that added a sensory attribute was more sophisticated in the online channel, while the offline channel did not have a significant change after adding a sensory attribute. Comparing on and offline channels with attribute effects, product category (frozen food, ambient food, vs. produce), brand type (private vs. national), and visibility of package (non-sensory vs. sensory line) showed significant differences. This study provides evidence that perceived invisible risk, which is a barrier to online purchase intentions, can be affected by package visibility based on empirical sales data. The study presents theoretical and practical insights for the multi-channel retailer and consumer research literature.

Keywords: Sensory attributes; Multi-channel retailer; Online grocery shopping; Visibility of package; Temperature of preservation

## 1. Introduction

“Groceries” has been widely accepted as a category not popular with online shopping customers because they mainly rely on offline supermarket shopping where they can personally observe and compare products (Campo & Breugelmans, 2015; Huang et al., 2004; Nepomuceno et al., 2014). However, delivery infrastructure improvements and product preservation technology have alleviated some consumer concerns, prompting high growth of online grocery shopping (Lee et al., 2020). The increase in food demand due to the COVID-19 outbreak (Chen et al., 2021; Güney & Sangün, 2021; Lu et al., 2022) and consumer aversion to personal visits to stores further accelerated the growth of online grocery shopping (Chang & Meyerhoefer, 2021). COVID-19 also brought other changes to consumer food purchasing and consumption. Concerns about social distance and price inflation have reduced grocery shopping

---

<sup>1</sup>Cite: Choi, E., Eom, H., & Moon, J., (2024, Feb.) Understanding Product Attributes Associated with Food Sales: Sensory Attributes for Online Versus Offline Options of a Multi-Channel Retailer, *Journal of Electronic Commerce Research*, 25(1).

frequency and increased consumption of foods such as frozen and canned products (Güney & Sangün, 2021; Janssen et al., 2021). Additionally, demands for healthy and local products have increased along with a growing awareness of food safety (e.g., Filimo nau et al., 2021; Shamim et al., 2021).

However, most studies have examined the increasing or decreasing tendencies of sales or the changes of purchase rate in certain categories (e.g., Bartók et al., 2021; Chen et al., 2021; Güney & Sangün, 2021). Only a few researchers have studied changes in the food market from the perspective of product attributes and category characteristics (e.g., brand name, price) (e.g., Valaskova et al., 2021; Verstraeten et al., 2023). This implies that it is difficult to identify the main factors and determinants of such changes. Until COVID-19, researchers gained significant insights from the characteristic effects of product attributes and category characteristics on consumer purchase outcomes, emphasizing the role of product properties as quality cues for purchase decision making (e.g., Andrews & Currim, 2004; Chu et al., 2008; Danaher et al., 2003). Quality cues are used to evaluate the performance of the product with respect to consumer demands (Steenkamp, 1997). Furthermore, previous empirical findings were skewed to how extrinsic product attributes were associated with consumers' purchases. Especially in studies about online shopping, many researchers have placed a greater importance on extrinsic (mainly non-sensory) attributes due to the unavailable sensory properties when shopping online (e.g., Degeratu et al., 2000; Huang et al., 2004). However, consumer decision making for food choices is determined based on the interactive perception between extrinsic and intrinsic product cues (i.e., sensory and non-sensory) rather than relying on just a few specific attributes (e.g., Milosavljevic et al., 2012; Symmank, 2019). In particular, among sensory attributes, visual intrinsic cues have been emphasized as critical with a decisive role in food buying decision making (Kosslyn, 1994; Posner et al., 1976).

Therefore, we applied the sensory characteristic of transparent packaging, which allows consumers to visually assess the intrinsic quality of the food contents, as the "visibility of package" variable in our research model. The food package is a messenger that delivers extrinsic cues (e.g., brand name, product information) to consumers or serves as a window that allows users to assess the visual intrinsic characteristics (e.g., appearance, color, size) of products before purchase (Simmonds & Spence, 2017). Our study addressed this issue using POS data of 4,563 items (73 categories accounting for 33.8% of all food sales) sold both online and offline from a major Korean multi-channel retailer. All items were categorized into five attributes: product category, brand type, visibility of package, unit of sales, and unit of pack. Seven attributes (including price and amount of loss) were used to compare the differences between groups within the same attribute and channel. Finally, the main objectives of this study were as follows.

1. Investigate product attributes that affect food sales through on/offline channels in terms of sensory/non-sensory attributes and
2. Identify the significant effects of the sensory attribute (visibility of package) in online compared to offline channel.

This study makes three unique contributions concerning changes in the food market following COVID-19 and addressing flaws (restricted food category, focused on common attributes) in previous research. First, we scrutinize the representative factors of overall food consumption patterns in the aftermath of the COVID-19 outbreak from the perspective of product attributes and category characteristics. Second, this study confirms the substantial impact of package visibility (a sensory attribute) on food sales models and identifies variations in effects depending on channel. Third, we derive essential food attributes specific to the online channel by comparing effects between channels. This study proceeds in the following order: (a) hypotheses are formed based on a literature review, (b) a research model for each channel is presented based on the hypotheses, (c) the data and methods of analysis used in this study are described, and (d) the results and the practical and academic implications are discussed.

## 2. Literature review

### 2.1. Multi-channel grocery shopping

Most online grocery consumers are multi-channel shoppers who shop both online and offline (Alba et al., 1997; Chu et al., 2008; Venkatesan et al., 2007). Although they use both channels, multi-channel consumers show differing sensitivity to marketing tools and purchase tendencies in specific categories depending on channel (Levin et al., 2003; Levin et al., 2005; Campo & Breugelmans, 2015). For instance, in the sensory category, where consumers mostly tend to compare and evaluate product quality and make purchase decisions based on personal experience, the online purchase rate is low (Chu et al., 2008; Degeratu et al., 2000). In contrast, large or heavy products show a high online purchase rate (Andrews & Currim, 2004; Chintagunta et al., 2012). Because of this, researchers have mainly studied the shopping behaviors of multi-channel retailer consumers to learn more about product characteristics that affect consumer buying behaviors between online and offline channels.

However, most studies were analyzed based on only a few specific categories or used purchase data from obtained consumer panels. Thus, there are some limitations to understanding and explaining the overall food buying behaviors of multi-channel retailer consumers. Studies on multi-channel retailers have mainly examined differences between channels in terms of search attributes and economic factors (e.g., transaction costs, shopping frequency). Such studies have examined differences in brand loyalty by channel (e.g., Chu et al., 2010; Danaher et al., 2003; Pozzi 2012), the influence of price on consumer purchasing behavior and price sensitivity by channel (e.g., Chu et al., 2008; Chu et al., 2010; Degeratu et al., 2000), and transaction costs that affect channel selection (e.g., Campo & Breugelmans, 2015; Chintagunta et al., 2012; Pozzi, 2012). Based on the purchase data of the breakfast cereals category by 11,640 households from a US large national supermarket chain, Pozzi (2012) found that consumers more often performed a brand search (use of brand products they had not tried before) offline than online due to the difficulty of a brand search online. Chintagunta et al. (2012) demonstrated that transaction costs (e.g., travel time, quality inspection costs, and inconvenience costs) differed and showed opposing correlations between heavy items and perishable items such as fresh food between channels based on the shopping records of 3,556 households from a major Spanish grocery chain. As such, shoppers can use online and offline channels differently depending on their circumstances or the characteristics of the product. Thus, even if the same consumer purchases in the same product category, different shopping behaviors may appear between shopping channels.

Furthermore, after the COVID-19 outbreak, fresh food purchases in the online channel increased and the variety of grocery items sold expanded (Chang & Meyerhoefer, 2021), diversifying consumers' online buying behavior. Thus, these shopping environments complicated retailers' operational decisions, requiring a deeper understanding of and insight into consumer behaviors across both channels and product categories. However, few recent studies have been conducted on the factors behind these changes or the attributes related to them (i.e., in terms of product attributes and category characteristics). Güney and Sangün (2021) showed that changes in food consumption behaviors and habits due to the pandemic were related to stockpiling, food safety, natural/organic food preferences, and packaging of foods. Thus, the authors suggested that consumers mainly consumed fresh vegetables and fruits, animal-based products, and popular food. Janssen et al. (2021) studied food consumption changes during the COVID-19 pandemic in Denmark, Germany, and Slovenia, and showed the highest rate of change in frozen and canned products and cake and biscuits categories, while bread, alcoholic beverages, and dairy products showed the lowest rate.

In addition, most of the studies just researched changes in eating habits and purchase patterns in terms of social environments and consumer's psychological changes (e.g., Chenarides et al., 2021; Filimonau et al., 2021). Thus, the practical insights from these studies are very limited. Therefore, we empirically investigated changes in food consumption after the COVID-19 outbreak (using annual data of 73 food categories across all food divisions) from a large multi-channel nationwide retailer. Furthermore, our study differs from extant studies in that it focused on the characteristics of the products themselves and practical attributes of the food retail industry (e.g., brand type, package type, unit of sales, unit of pack).

## 2.2. Product characteristics and attributes of online shopping

The intangibility (i.e., not being able to be seen, felt, tasted, smelled, or heard) of online shopping channels causes consumers anxiety in making purchasing decisions (Huang et al., 2004; Nepomuceno et al., 2014). For grocery items in particular, online shoppers must accept perceived risks due to quality uncertainty due to inconsistent intrinsic item properties (e.g., appearance, color, size) and limited shelf life (Chu et al., 2010). However, online consumer reluctance to purchase in certain categories (e.g., fresh food, perishable categories) is showing a rapid change since the COVID-19 outbreak (e.g., Chang & Meyerhoefer, 2021; Chen et al., 2021; Lu et al., 2022). Lu et al. (2022) suggested that purchasing frequency and amount of fresh food purchased online increased after the COVID-19 outbreak, and that consumers were willing to purchase fresh food online even after the pandemic. In addition, Taiwan's largest agri-food e-commerce platform provided evidence that the variety of items sold also increased during the COVID-19 period, along with increased sales and number of customers (Chang & Meyerhoefer, 2021). However, despite these positive signals, the invisible drawbacks of online shopping are still recognized as the biggest barriers to its use (Bartók et al., 2021; Brüggemann & Olbrich, 2022). Even in an online environment, consumers are mainly making product purchasing decisions based on the visual cues obtained from product imagery and photos rather than information attributes such as brand name, origin of country, or ingredients (Benn et al., 2015).

On the other hand, most of the online buying behavior studies so far have focused on non-sensory attributes (e.g., brand name, price, label information), which are considered to have higher usefulness and importance online (vs. offline). Degeratu et al. (2000) classified product search attributes into four categories: brand name, price, sensory attributes, and non-sensory attributes. Sensory attributes are product characteristics recognized and evaluated via human sensory organs, and non-sensory attributes are nutritional or product-related information that can be delivered in writing. The authors showed that consumers weigh sensory attributes more heavily offline than online. Conversely, greater importance is placed on non-sensory attributes in online shopping because they are more readily available than

in the offline channel. Among the non-sensory attributes, brand name (type) has been actively studied in marketing and consumer research and was an important quality attribute to replace sensory attributes in the online channel (e.g., Arce-Urriza & Cebollada, 2018; Danaher et al., 2003; Dawes & Nenycz-Thiel, 2013). Consumers tend to rely on brand names to reduce quality uncertainty (Png & Reitman, 1995). In an offline environment where products can be personally observed and compared, the dependence on brand names is relatively lower than in online channels (Dawar & Parker, 1994; Huang et al., 2004). Additionally, the latest study by Verstraeten et al. (2023) explained that the demand difference between brand groups (private vs. national brand) online is based on the differences in the degree of consumer dependence on product cue heuristics for inferring product quality. The authors demonstrated that online consumers rely less on heuristics based on external product cues (price, brand name, and packaging) to infer product quality, which leads them to perceive a smaller quality gap between private brands and national brands in online grocery shopping. As such, differences in dependence and preference of consumers for product brands are founded on the differences of the on/offline shopping environments, which are consequently based on the perceived quality. DelVecchio (2001) found that differences in perceived quality are based on the perceived risk from product category characteristics (complexity, price level, average inter-purchase time, and quality variance of the product category).

Consequently, a study of online buying behavior should first be based on the product's nature and non-sensory attributes in combination with sensory attributes. Therefore, we adopted a classification method according to the transparency of the package (used in the study of Chu et al. [2010] for sensory categories) and applied the visual package attributes (i.e., visibility of package) as the sensory variable to the research model. Chu et al. (2010) defined these classifications as follows. A sensory line is one in which buyers can evaluate the actual appearance of the product before purchasing in a physical store. When buyers are unable to inspect a product due to opaque packaging, that product is said to be a non-sensory line. They found that households are more brand loyal, more size loyal but less price sensitive in the online channel than in the offline channel, and the channel differences in brand loyalty, size loyalty, and price sensitivity are larger for sensory lines. Thus, along with package visibility (non-sensory vs. sensory line), product categories (5 dummy variables in 6 food departments), and brand type (generic brand, private brand vs. national brand) were applied together to the research models as independent variables for this study.

### 2.3. Quality attributes and cues for food choice

Product quality can be examined from two perspectives (e.g., Bernués et al., 2003; Espejel et al., 2007): measurable objective quality and perceived quality based on consumer perception. However, the objective product characteristics are not the center of interest, rather the subjectively perceived product attributes (Steenkamp, 1997). Olson and Jacoby (1972) explained perceived quality from two types of quality cues (intrinsic and extrinsic). Intrinsic cues are associated with physical characteristics (e.g., shape, appearance, visible fat), while extrinsic cues relate to non-physical characteristics (e.g., place of origin, brand name, production history, product information). The quality expectations of consumers are based on the intrinsic and extrinsic cues of products. That is, quality perceptions are integrated outcomes of perceived intrinsic and extrinsic cues (Steenkamp, 1990). Nevertheless, due to shopping conditions, consumers unwillingly decide whether to purchase products based mainly on perceived quality, which depends on the package and brand (Simmonds & Spence, 2017). Thus, as general indicators of product valuation, extrinsic variables in Table 1 have been addressed as essential determinants of product purchase in previous studies.

Table 1: Extrinsic Cues for Food Quality Perception

Variables	Studies
Price	Chu et al., 2008; Chu et al., 2010; Degeratu et al., 2000; Lange et al., 2000; Steenkamp & Van Trijp, 1989
Brand name	Arce-Urriza & Cebollada, 2012; Arce-Urriza & Cebollada, 2018; Danaher et al., 2003; Dawes & Nenycz-Thiel, 2013; Roe et al., 2021
Product information (e.g., origin, organic)	Brata et al., 2022; Lee et al., 2019; Lee & Yun, 2015; Schleenbecker & Hamm, 2013; Singh & Sharma, 2013; Wang et al., 2022; Zheng et al., 2020
Label & Package	Reinoso-Carvalho et al., 2021; Simmonds et al., 2018; Simmonds & Spence, 2017; Vilnai-Yavetz & Koren, 2013

Packaging can provide a means of customer communication beyond simply preventing damage and facilitating distribution (Spence, 2016) and has long been an important technique of branding and marketing (Rundh, 2005). In

addition, consumer demand for packaging that allows personal inspection of contents before purchase is motivating the use of transparent material packaging (Simmonds et al., 2018). Based on this background, many studies have researched the effects of transparent packaging (vs. opaque or imagery) on perceived quality and purchase intentions (e.g., Al-Samarraie et al., 2019; Simmonds et al., 2018; Vilnai-Yavetz & Koren, 2013). The results of these studies have shown that transparent packaging increases trust in products, leading to higher consumer preferences and higher purchase intentions (Billeter et al., 2012; Simmonds et al., 2019). However, most of these studies were conducted in an experimental lab or as a simulation. Thus, it is difficult to conclude the applicability of these results. Despite the defects of these experimental studies, their results suggest that packaging type is organically correlated with other properties (brand type and category characteristics) and plays an important role in consumer quality perception and purchase intentions.

In an efficiency evaluation study of transparent packages (vs. product imagery), Simmonds et al. (2018) showed that the positive effects (better taste, more innovative, and higher preference) of transparent packaging vary depending on the evaluated product category characteristics. Sabri et al. (2020) argued that these effects vary depending on the perceived quality of each product category. That is, transparent packaging improves the product perceived quality, and the effect of packaging (transparent vs. opaque) on purchase intention will be more strongly mediated through product quality perception when the participants are exposed to perishable products with a high level of product quality risk. Additionally, Chandran et al. (2009) showed that the perceived quality effects of transparent packaging are moderated by product (brand) trust and familiarity. Participants in the study evaluated unfamiliar brand products with transparent packages as having higher quality and trustworthiness and familiar brand products with transparent packages as having lower quality. Therefore, based on the results of previous studies, we intended to verify whether these influences are significant in actual food sales data. Furthermore, this study can be assumed to be a unique analysis of the visibility of packages as a sensory attribute variable in the product attribute research.

### 3. Hypotheses development

Peterson et al. (1997) defined the characteristic product dimensions in internet marketing as their differentiation potential, purchase frequency, and tangibility. Jahng et al. (2000) suggested that the suitability of the shopping channel for a particular product could be evaluated by the fit between the degree of need for the product and the degree to which the product can be evaluated to address that need through the shopping medium. Thus, the authors argued that the category characteristics of a product can have different effects on purchase intention based on the sales channel. For instance, due to the intangible characteristics of the online channel, the lack of sensory information leads to greater uncertainty and product quality risk, which can increase the transaction costs for purchases of sensory categories in the online channel (Gupta & Kim, 2010). These higher transaction costs result in a relatively lower purchase rate than products in non-sensory categories (Campo & Breugelmans, 2015; Chintagunta et al., 2012). This is even more true of fresh produce due to its heterogeneous characteristics, of which buyers cannot determine the quality easily in an online setting (Chung et al., 2006). Furthermore, in the online channel, the expansion of product variety and accumulated consumer shopping experiences suggest that consumers' buying behavior may be further subdivided according to specific characteristics (Campo & Breugelmans, 2015; Chang & Meyerhoefer, 2021). Therefore, we first confirmed the correlation between on/off channel sales and the characteristic differences of product categories, from which we derived H1. Accordingly, the first hypotheses are as follows.

*H1a: Product categories (meat & seafood ~ ambient food vs. produce) will influence offline sales.*

*H1b: Product categories (meat & seafood ~ ambient food vs. produce) will influence online sales.*

The correlation between brand attributes and consumer purchase behavior has been studied by numerous researchers and provides consistent implications for higher brand dependence and loyalty in online channels compared to offline channels (e.g., Arce-Urriza & Cebollada, 2012; Danaher et al., 2003). Degeratu et al. (2000) argued that consumer brand dependence decreases in the presence of a large volume of useful information about product attributes (i.e., offline channels). Arce-Urriza and Cebollada (2012) showed that all brands exhibited increased loyalty online as opposed to offline, and only private brands showed an increase in market share and dominance online. Furthermore, consumers' increased awareness of food safety and healthy diets after the COVID-19 outbreak has led to greater preferences for brand products (Shamim et al., 2021; Charm et al., 2020). Consumers tried new brands or products they had not previously purchased and increased consumption of affordable private brands for functional values (Knowles et al., 2020). As such, significant differences in brand influence between channels and consumer attitude changes toward brand products (greater dependence and lower loyalty) suggest that brand effects on on/offline channel sales may be further divided and strengthened. Therefore, based on the implications of previous studies, we confirmed the correlation between on/off channel sales and differences between brand attributes, from which we derived H2.

*H2a: Brand type (generic, private vs. national brand) will influence offline sales.*

*H2b: Brand type (generic, private vs. national brand) will influence online sales.*

Quality expectations are outcomes of visual impressions based on perceived intrinsic and extrinsic cues (Acebron & Dopico, 2000). Consequently, visual cues are important determinants of perceived quality at the point of purchase (e.g., Huang & Lu, 2016; Hurling & Shepherd, 2003). Therefore, based on the positive correlation between the transparent effects of packages and consumers' purchase intentions proven by the extant studies (e.g., Al-Samarraie et al., 2019; Simmonds et al., 2018), the following third set of hypotheses is presented.

*H3a: Visibility of package (non-sensory vs. sensory line) will influence offline sales.*

*H3b: Visibility of package (non-sensory vs. sensory line) will influence online sales.*

Additionally, the fourth set of hypotheses is presented as follows based on the correlation between the visibility effects of the package and the brand attributes and product category characteristics, which were presented in the literature review above (e.g., Chandran et al., 2009; Sabri et al., 2020).

*H4a: Depending on the control of the sensory attribute (visibility of package), the influence will differ for offline sales.*

*H4b: Depending on the control of the sensory attribute (visibility of package), the influence will differ for online sales.*

Finally, based on the differences in consumer buying behaviors according to product categories, brand attributes, and visibility of package, which were proven in extant studies (e.g., Danaher et al., 2003; Gupta & Kim, 2010; Ma et al., 2020), we derived H5 to identify the differential attributes between channels as follows.

*H5: The product attributes that influence food sales will differ between online and offline channels.*

In sum, the research model tested five hypotheses, as shown in Figure 1. Hypotheses H1 (H1a for offline, H1b for online) to H4 (H4a, H4b) verify the influence of the respective product attributes on each channel (level 2), and H5 compares the influence of attributes between channels (level 1). The dependent variable is the total annual sales of foods in 2020, and the independent variables are product category, brand type, and visibility of the package. Additionally, four control variables that may affect food sales were applied to the research model: unit of sales, unit of pack, price per unit, and amount of food loss. The reason why control variables are included is explained below in the empirical analytic equation.

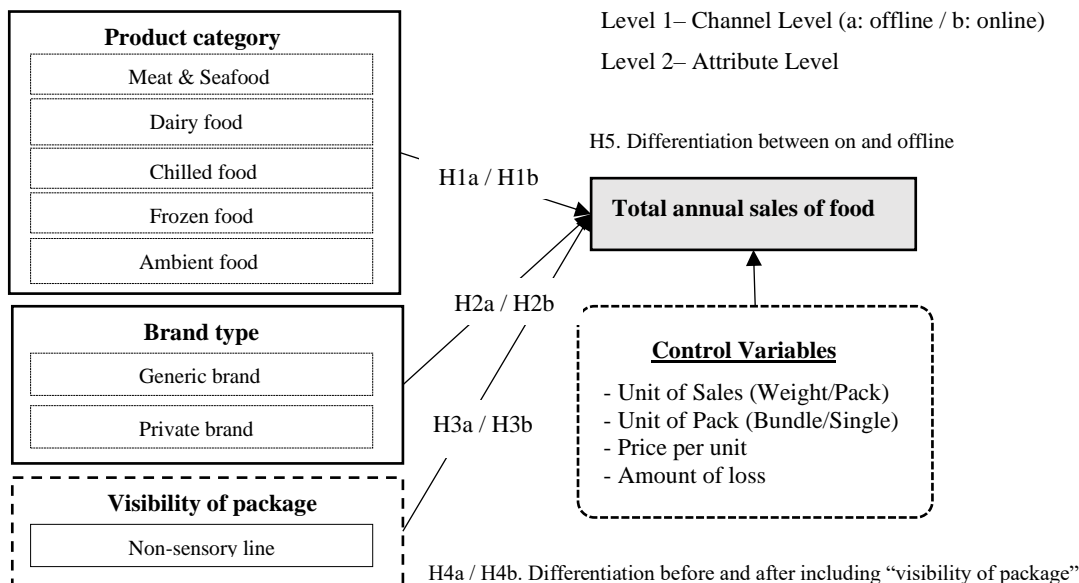


Figure 1: Research Model of Food Sales

#### 4. Research methodology

##### 4.1. Sample and data collection

We investigated one of the leading multi-channel retailers operating in the Republic of Korea, H-Mart, and used the POS sales data by item, aggregated over the 12 months from January to December 2020. H-Mart is one of the top three retail chains in the hypermarket setting and food-focused merchandising nationally across 139 large stores. H-Mart has private brand (PB) products in categories with a national market share. About 2,000 of approximately 26,000 food items sold by H-Mart each year are PBs, which represents a sales share of 8.0%. H-Mart went online in 2002, and online sales make up 21.6% of the business (2020). Their online strategy is to provide the same range of products at the same pricing both online and offline. Additionally, marketing activity (e.g., promotions, price discounts) is nearly the same in both channels. However, free delivery is offered only for orders greater than 40,000 KRW.

We adopted three criteria to select the categories representing food division: (a) the category should include primary subclasses in terms of sales and volume (top 20 subclasses by 6 food departments), (b) non-meal foods such as confectionaries and alcoholic drinks were excluded to focus on foods for meal preparation, and (c) seasonal categories based on a sales commission were excluded. Finally, we selected 73 food categories consisting of 4,563 items sold both online and offline. The sales data were extracted through the product management system (PMS, internal system of H-mart) with their permission, and all items were classified and re-organized by product attributes (i.e., product category, brand type, unit of sales, unit of pack) and on/off channel. The product hierarchy (department, section, class, subclass) and item information (e.g., store format, item description, unit price, *uda\_pb*, *value\_rtc\_waste*) were obtained from extracted raw data. The visibility of the package (non-sensory vs. sensory) was first categorized based on product photos (imagery) on the website, and then the uncertain items were approved and corrected through a random sampling check. A wide range of products of retailers was generally classified and managed either by industry-wide standards or by an individual retailer according to their operation strategy (related to ordering, delivering, sales, and review). Thus, the product category variables were analyzed by 6 food departments (5 dummy variables) based on the H-Mart category classification. The other attribute variables were measured as dichotomous for comparison between groups: coded as 0 or 1. A detailed description of variables for product categories and attributes is attached as Appendix 1. Table 2 shows the descriptive statistics by sensory variable.

Table 2: Descriptive Statistics

Variable		Frequency			Percentage (%)		
		Sensory	Non-sensory	Total	Sensory	Non-sensory	Total
Product category	Produce	383	208	591	8.4%	4.6%	13.0%
	Meat & Seafood	598	84	682	13.1%	1.8%	14.9%
	Dairy food	0	615	615	0.0%	13.5%	13.5%
	Chilled food	424	228	652	9.3%	5.0%	14.3%
	Frozen food	0	422	422	0.0%	9.2%	9.2%
	Ambient food	198	1403	1,601	4.3%	30.7%	35.1%
Brand type	Generic brand	760	37	797	16.7%	0.8%	17.5%
	National brand	706	2,656	3,362	15.5%	58.2%	73.7%
	Private brand	137	267	404	3.0%	5.9%	8.9%
Unit of sales	Weight	289	0	289	6.3%	0.0%	6.3%
	Pack	1314	2,960	4,274	28.8%	64.9%	93.7%
Unit of pack	Bundle pack	76	863	939	1.7%	18.9%	20.6%
	Single pack	1,527	2,097	3,624	33.5%	46.0%	79.4%
Total		1,603	2,960	4,563	35.1%	64.9%	100.0%

##### 4.2. Empirical analytic models

The dependent variable is  $\ln(\text{total annual sales})$ , for which we calculated the log value of total annual sales. The following independent variables were used in our models: product category (PC2~ PC6), brand type (GB, PB), and visibility of package (NSL). The four control variables were unit of sales, unit of pack,  $\ln(\text{price})$ , and  $\ln(\text{loss})$ . The reason why control variables are included is as follows. As “price” is a very important determinant in consumers'

purchase decisions, many previous studies have shown a significant relationship between this attribute and consumer purchase intentions (e.g., Dawar & Parker, 1994; Lange et al., 2000; Steenkamp & Van Trijp, 1989). In retailing, bundle packs are mainly designed to provide better value to consumers for promotion purposes. Thus, “unit of pack” was also applied as a control variable. Additionally, “unit of sales,” which is the criteria for pricing, and “amount of loss,” for considering individual item characteristics (e.g., perishable, period of shelf life) within the same category, were applied through log transformations to the models. The purpose of the logarithm transformations for the three variables (i.e., total annual sales, price, amount of loss) was to eliminate the error that occurred due to extreme values. Due to the function of the log values, extreme values and outliers that produced errors were minimized (Leydesdorff & Bensman, 2006). In addition, the log transformation changed the high fluctuation of distribution into a smaller distribution, resulting in standardization. Also, these three variables have only a positive number, and the relative sales size between variables or attributes should be considered. Therefore, logarithmic transformation was applied to these variables in the process of constructing the analytic models.

First, the independent variables (product category, brand type) and the control variables (unit of sales, unit of pack,  $\ln(\text{price})$ ,  $\ln(\text{loss})$ ) were introduced to Model 1 for verifying H1 (H1a, H1b) and H2 (H2a, H2b) without considering the “visibility of package” variable. By entering an additional variable (visibility of package), Model 2 was used to verify H1 (H1a, H1b), H2 (H2a, H2b), and H3 (H3a, H3b) while considering the “visibility of the package.” Next, H4 (H4a, H4b) was verified through changes in the influence of attributes on food sales between models (Model 1, Model 2) by on/off channel, and H5 was affirmed through a comparison of influences between channels based on Model 2.

The equation for Model 1 is

$$\begin{aligned} \ln(\text{Total annual sales}) \\ = a_1 + b_1PC2 + b_2PC3 + b_3PC4 + b_4PC5 + b_5PC6 + b_6GB + b_7PB + b_8PK + b_9SP \\ + b_{10}\ln(\text{Price}) + b_{11}\ln(\text{Loss}) + e_1 \end{aligned}$$

In comparison, that of Model 2 is

$$\begin{aligned} \ln(\text{Total annual sales}) \\ = a_2 + b_1PC2 + b_2PC3 + b_3PC4 + b_4PC5 + b_5PC6 + b_6GB + b_7PB + b_8PK + b_9SP \\ + b_{10}\ln(\text{Price}) + b_{11}\ln(\text{Loss}) + b_{12}NSL + e_2 \end{aligned}$$

where, PC denotes product category (meat & seafood, dairy, chilled, frozen, ambient food vs. produce, respectively PC2 ~ PC6); GB is a generic brand (vs. NB); PB means private brand (vs. NB); PK is pack (vs. weight); SP denotes single pack (vs. bundle pack); and NSL means non-sensory line (vs. sensory line).

#### 4.3. Methods for hypotheses tests

The hypotheses tests consisted of three stages. First, we estimated food sales models (Model 1, Model 2) simultaneously according to the difference of attributes in product category, brand type, and visibility of package by channel (for H1 ~ H3). Secondly, we confirmed the coefficients between the respective attribute variables and  $\ln(\text{total annual sales})$ , comparing between Model 1 and Model 2 (for H4). Finally, we compared the influences of attributes between channels (for H5) based on Model 2. We used hierarchical linear modeling (HLM) for the first and second stages. In studies that connect organizations and members, it is common for members to be affected by different variables according to the organization level due to their structural characteristics. However, HLM could minimize the mutual influences between levels of channel and food attribute (Raudenbush & Bryk, 2002). Additionally, HLM estimation was conducted with nested regression function within the Stata program. Nested regression involves sequential estimation by adding a bundle of independent variables to the basic model. In this adding procedure, the measurement errors are adjusted to make sure all regressions are comparable (StataCorp, 2021). Consequently, HLM simultaneously executes 2 models (Model 1, Model 2), considering the associated covariance to minimize the measurement error (Matsuyama, 2013). Then, the changes of F-values and  $R^2$  (Wald test results derived from HLM analysis) between the step-by-step models were used for the robustness of the HLM estimations. That is, a significant F-value between models means the model became more accurate and precise. Then, to compare the attribute effects between on/off channels (H5), we analyzed the linear regression analysis with seemingly unrelated estimation (SUE) based on Model 2 (including “visibility of package”). SUE is known to be effective in comparing the marginal effects from separate linear estimations (Weesie, 2000). Specifically, while SUE is performed, 2 or more separate linear regressions are simultaneously estimated with error terms, which enables comparison across separate linear estimations. We utilized the statistical software Stata 17.0 SE to perform HLM and SUE analyses. Finally, the differences between online and offline channels were confirmed through the Chi-square test.



**5. Results**

5.1. Offline channel analysis

We demonstrate the parameter estimates for the offline model in Table 3. The result derived 3 attributes with a significant effect on food sales in offline Model 1a: PC6 ( $\beta = 0.63, p < 0.01$ ), SP ( $\beta = -0.31, p < 0.05$ ), ln(loss) ( $\beta = 0.36, p < 0.001$ ). This result means that the influence on the dependent variable of PC6 (ambient food) is +0.63 compared to PC1 (produce). In Model 2a with the sensory attribute, we could not find any more significant variables from Model 1. This result partially supports the statement of H1a regarding the influence of product category. However, H2a regarding the influence of brand type, and H3a regarding the influence of visibility of package are rejected. As shown in Table 4, the respective R<sup>2</sup> and F values were 20.79% and 46.77 ( $p < 0.001$ ) in Model 1a and 20.8% and 42.87 ( $p < 0.001$ ) in Model 2a. The F-value differences were not significant between models. This means that the sensory attribute of “visibility of package” does not significantly affect the offline model. Thus, H4a (difference after adding “visibility of package”) also was rejected. However, we presented the significant negative effect of SP and the positive effect of ln(loss) on food sales.

Table 3: Hierarchy Linear Model Results of an Offline Model

		Model 1a		Model 2a	
		Coefficient	SE	Coefficient	SE
Product category	PC2	0.05	0.20	0.07	0.21
	PC3	0.12	0.21	0.10	0.22
	PC4	0.14	0.21	0.15	0.21
	PC5	0.45	0.24	0.44	0.24
	PC6	0.63**	0.20	0.63**	0.20
Brand type	GB	0.29	0.18	0.31	0.20
	PB	0.29	0.17	0.29	0.17
Visibility of package	NSL			0.05	0.15
Control variables	PK	-0.46	0.26	-0.46	0.26
	SP	-0.31*	0.12	-0.3*	0.12
	ln(Price)	0.02	0.07	0.02	0.07
	ln(Loss)	0.36***	0.02	0.36***	0.02
	Constant	14.36***	1.00	14.32***	1.01

Notes. \*\*\* $p < .001$ , \*\* $p < .01$ , \* $p < .05$

Table 4: Wald Test of the Offline Model

Block	F	Block df	Residual Df	R <sup>2</sup>	Change in $\Delta R^2$	$\Delta F$
Model 1a	46.77***	11	1960	20.79	20.79	46.77***
Model 2a	42.87***	1	1959	20.8	0	0.1

Notes. \*\*\* $p < .001$ , \*\* $p < .01$ , \* $p < .05$

5.2. Online channel analysis

Table 5 presents the results of the online channel. We derived all 11 variables with a significant effect on food sales in online Model 1b: PC2, PC3, PC4, PC5, PC6, GB, PB, PK, SP, ln(Price), and ln(Loss). In Model 2b with an additional sensory attribute (i.e., visibility of package), we confirmed significant changes from Model 1b. PC4 and GB did not show significant effects in Model 2b. However, all variables except PC4 and GB showed a significant influence on online food sales. In the product category, PC5 ( $\beta = 1.23, p < 0.001$ ) and PC6 ( $\beta = 1.26, p < 0.001$ ) had

significantly greater effects versus PC1. In brand type, PB ( $\beta = 0.9, p < 0.001$ ) had a significant positive effect on online sales versus NB. Additionally, NSL ( $\beta = -0.47, p < 0.01$ ) had a significant negative effect on online food sales. Consequently, NSL received a lower product evaluation than SL, leading to negative sales effects in the online channel. Finally, these results support H1b (influence of product category), 2b (influence of brand type), and 3b (influence of visibility of package). As shown in Table 6, the respective  $R^2$  and F values were 12.01% and 21.77 ( $p < 0.001$ ) in Model 1b and 12.37% and 20.61 ( $p < 0.001$ ) in Model 2b. The significant F-value change between Model 1b and Model 2b (7.1,  $p < 0.01$ ) means that Model 2b is more accurate and precise than Model 1b. Thus, we also proved H4b (differentiation before and after including “visibility of package”) and additionally confirmed significant effects of PK, SP,  $\ln(\text{price})$ , and  $\ln(\text{loss})$ . These results mean that the online channel is sensitive to differences depending on the product categories and attributes compared to offline sales. Additionally, when the sensory attribute (i.e., visibility of package) was considered also, the attribute effects became clearer, and the explanatory power increased in the online model.

Table 5: Hierarchy Linear Model Results of Online Model

		Model 1b		Model 2b	
		Coefficient	SE	Coefficient	SE
Product category	PC2	0.67**	0.24	0.53*	0.25
	PC3	0.53*	0.25	0.65*	0.25
	PC4	0.53*	0.24	0.37	0.25
	PC5	1.13***	0.28	1.23***	0.28
	PC6	1.12***	0.23	1.26***	0.23
Brand type	GB	0.53*	0.22	0.31	0.23
	PB	0.89***	0.20	0.9***	0.20
Visibility of package	NSL			-0.47**	0.18
Control variables	PK	0.82*	0.33	0.88**	0.33
	SP	-0.53***	0.15	-0.6***	0.15
	$\ln(\text{Price})$	0.3***	0.08	0.3***	0.08
	$\ln(\text{Loss})$	0.26***	0.02	0.25***	0.02
	Constant	9.16***	1.24	9.53***	1.25

Notes. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

Table 6: Wald Test of the Online Model

Block	F	Block Df	Residual df	$R^2$	Change in	
					$\Delta R^2$	$\Delta F$
Model 1b	21.77***	11	1754	12.01	12.01	21.77***
Model 2b	20.61***	1	1753	12.37	0.35	7.1**

Notes. \*\*\* $p < .001$ , \*\* $p < .01$ , \* $p < .05$

### 5.3. Comparison between on/offline channels

Table 7 presents the coefficients between online and offline channels. We found 4 variables with significant differences between channels: PC5 ( $\beta = 4.25, p < 0.05$ ) and PC6 ( $\beta = 4.49, p < 0.05$ ) in the product category, PB ( $\beta = 9.13, p < 0.01$ ) in brand type, and NSL ( $\beta = 5.71, p < 0.05$ ) in visibility of package. Additionally, we confirmed significant attributes between channels to be PK,  $\ln(\text{price})$ , and  $\ln(\text{loss})$ . Consequently, this result supports H5 (differentiation between on/off channels) and helps us understand the characteristic differences between online and offline channels.

Table 7: Comparison Between Online and Offline Models

		Off		On		Chi <sup>2</sup>
		Coefficient	Robust SE	Coefficient	Robust SE	
Product category	PC2	0.07	0.21	0.53	0.25	1.78
	PC3	0.10	0.19	0.65**	0.25	3.04
	PC4	0.15	0.18	0.37	0.25	0.49
	PC5	0.44	0.24	1.23***	0.30	4.25*
	PC6	0.63**	0.19	1.26***	0.23	4.49*
	Brand type	GB	0.31	0.20	0.31	0.25
	PB	0.29*	0.15	0.9***	0.14	9.13**
Visibility of package	NSL	0.05	0.14	-0.47**	0.16	5.71*
Control variables	PK	-0.46	0.26	0.88*	0.33	8.4**
	SP	-0.3*	0.13	-0.6***	0.14	2.5
	ln(Price)	0.02	0.06	0.3***	0.08	7.55**
	ln(Loss)	0.36***	0.02	0.25***	0.03	10.82***
	Constant	14.32***	1.01	9.53***	1.31	
	R <sup>2</sup>	20.8		12.37		
	F	42.87***		20.61***		

Notes. \*\*\* $p < .001$ , \*\* $p < .01$ , \* $p < .05$

The significant attributes of the online model, differentiated from the offline model, support the results of extant research while providing new important implications. In the product category, the greater influence of PC6 confirmed the higher preferences of standardized products with smaller quality variance rather than fresh foods in the online channel, as shown conventionally (e.g., Chung et al., 2006). On the other hand, the significant positive effects of PC5 presented interesting and conflicting results against the negative perception toward frozen foods online. In brand type, PBs showed significantly more competitive effects online compared to offline. This supports previous studies (e.g., Dawes & Nenycz-Thiel, 2013) showing that PBs improve the market share and have higher purchase intentions online than offline. In addition, the negative influence of NSL supports the positive effects of transparent packages shown in previous studies (e.g., Sabri et al., 2020; Simmonds & Spence, 2017; Simmonds et al., 2018). Above all, it is very interesting that the negative effect of NSL is derived as a characteristic difference of online distinct from offline. Additionally, the significant relationships of other variables, such as PK and ln(price), are supported by the findings indicating a greater preference for pre-packaged products (e.g., Bartók et al., 2021; Ramus & Asger Nielsen, 2005) and reduced-price sensitivity among consumers in the online channel (e.g., Chu et al., 2008; Degeratu et al., 2000), as documented in prior research. The significant result of ln(Loss) is inferred by a more positive correlation between offline sales and ln(Loss) due to the perishable characteristics of fresh foods that mainly lead food sales in the offline channel. As such, this study proved that product category characteristics and attributes affect food sales differently according to the channel and that the sensory attribute visibility of package plays a critical role online. The characteristic variables that were confirmed only in the online model will be addressed in detail in the discussion section.

## 6. Discussion and implications

### 6.1. General discussion

The most important contribution of this study is that marketers and researchers, whose attention is more focused on non-sensory attributes (e.g., brand, price), need greater understanding and consideration of sensory attributes for the online channel rather than the offline channel. The structural defects of the online channel for sensory attributes and the higher weighted importance on non-sensory attributes (than sensory attributes) have resulted in the neglect of studies about sensory attributes of online grocery buying. However, the negative correlation between opaque packaging and online food sales shown in this study provides an interesting implication that visual cues online may be more crucial than offline. The assumed reason for this result is that insufficient visual cues may cause significant

differences according to “visibility of package” in the online channel, while the offline channel provides more sufficient intrinsic information (e.g., tasting, seeing, and touching).

Second, this study newly indicated the significant influence of category characteristics according to the preservation temperature of processed foods in the online channel, providing more competitive category characteristics (ambient and frozen foods) online than offline. Ambient foods with relatively lower quality risk and smaller quality variation are generally considered the most appropriate grocery items for online shopping (e.g., Jahng et al., 2000; Peterson et al., 1997). However, online consumers have been reluctant to buy frozen foods because of the thawing problem and quality concerns during delivery (Ramus & Asger Nielsen, 2005; Zatz et al., 2021). Furthermore, it is not easy to find related studies that can confirm significant correlations between frozen products and purchase intentions in the online channel. Nevertheless, this preference is inferred to be due to consumers' lower perceived quality risk for frozen foods and accumulated positive shopping experiences based on the technological advancement of the cold chain system and the elaborated last-mile services (Meng et al., 2022).

Finally, these interesting and significant results have been supported empirically based on actual on/off channel sales after COVID-19. For instance, the greater influence of PBs in the online channel proved online consumers' need for more beneficial and functional brands (rather than conspicuous brands) that exist even after COVID-19. Additionally, the implications from the practical product attributes (such as PK, SP) will be greater and more useful for industry practitioners and academia in the food retail industry.

### 6.2. Practical and academic implications

This study contributed to a theoretical expansion of online grocery shopping and food attribute studies. First, we provided evidence that a study on “visibility of package” (NSL vs. SL) can be significant both from a consumer preference perspective and from a consumer behavior perspective between channels. Additionally, we identified that the visibility of package attribute is a theoretically valuable quality in the online channel, presenting evidence that the influences of this attribute vary according to model (Model 1, Model 2) and channel. Furthermore, this study newly suggested a meaningful processed food attribute (i.e., temperature of preservation), proving significant effects online according to the categories (ambient, frozen, chilled).

The practical implications for food marketers and retail buyers in the food retail industry are as follows. A new marketing approach toward visual cues of food products is required in the online environment. Despite significant efforts by online marketers to lower product quality risks (providing detailed information, technological services, and improving image quality), consumers still showed their need to visually check the product contents inside the package in this study. Since most products (photos) shown on the web are images of packaged products, opaque packaging increases the quality risk for consumers who want to assess the contents of products visually. Therefore, intrinsic visual information, such as imagery of product contents inside the package (only for visually attractive foods [Billeter et al., 2012]) or zoom functions and 360 spin, should be complementary. Additionally, the communication tools (e.g., online review, chatting service, quality evaluation of consumers) with customers should be reinforced to allow them to easily evaluate the physical product characteristics (e.g., appearance, texture, taste) based on other consumers' opinions. This study also has some useful implications for retailers to consider in establishing marketing and operation strategies. In terms of operation, it is necessary to consider the brand type (PB) and preservation temperature of products in building the product searching path and category classification (to make it easier for consumers to access and identify) online. For convenience and to increase purchase frequency, the minimum number of products, sold in units of 100 g, should be decreased and the variety of pre-packed items should be increased. Additionally, from a marketing perspective, category-specific promotional communications (e.g., cold chain system for frozen foods, the cost-effectiveness of PBs) are needed online.

### 6.3. Conclusions

This study confirmed the characteristic effects of product-oriented attributes on food sales by channel after the COVID-19 outbreak. Above all, the crucial effects of the “visibility of package” attribute online have been clearly identified through comparison between models (before and after adding “visibility of package”) and channels (online and offline). These results demonstrated that the sensory attribute (visibility of package) is a critical quality attribute for online consumers to lower perceived quality risk, even though the website may provide only product photos, and provided evidence that it is an essential product attribute to be considered in future grocery buying studies. However, this study has several limitations. The sample used in this study was suitable for the purpose in terms of food attributes between channels under the same conditions (such as product range, price, and promotion) of the same retailer. However, a fundamental limitation is that consumers are not equivalent across channels. Additionally, as this study focused on attributes of the product itself, it could not consider the related variables in terms of consumer consumption style. Therefore, future research is expected to be able to derive more practical and useful insights through a panel study (including significant food attributes newly proven in this study) on consumers' consumption tendencies or lifestyles.

## REFERENCES

- Acebron, L. B., & Dopico, D. C. (2000). The importance of intrinsic and extrinsic cues to expected and experienced quality: An empirical application for beef. *Food Quality and Preference*, *11*(3), 229-238.
- Alba, J., Lynch, J., Weitz, B., Janiszewski, C., Lutz, R., Sawyer, A., & Wood, S. (1997). Interactive home shopping: Consumer, retailer, and manufacturer incentives to participate in electronic marketplaces. *Journal of Marketing*, *61*(3), 38-53.
- Al-Samarraie, H., Eldenfria, A., Doodoo, J. E., Alzahrani, A. I., & Alalwan, N. (2019). Packaging design elements and consumers' decision to buy from the Web: A cause and effect decision-making model. *Color Research & Application*, *44*(6), 993-1005.
- Andrews, R. L., & Currim, I. S. (2004). Behavioural differences between consumers attracted to shopping online versus traditional supermarkets: Implications for enterprise design and marketing strategy. *International Journal of Internet Marketing and Advertising*, *1*(1), 38-61.
- Arce-Urriza, M., & Cebollada, J. (2012). Private labels and national brands across online and offline channels. *Management Decision*, *50*(10), 1772-1789.
- Arce-Urriza, M., & Cebollada, J. (2018). Assessing the success of private labels online: Differences across categories in the grocery industry. *Electronic Commerce Research*, *18*(4), 719-753.
- Bartók, O., Kozák, V., & Bauerová, R. (2021). Online grocery shopping: The customers' perspective in the Czech Republic. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *16*(3), 679-695.
- Benn, Y., Webb, T. L., Chang, B. P. I., & Reidy, J. (2015). What information do consumers consider, and how do they look for it, when shopping for groceries online? *Appetite*, *89*, 265-273.
- Bernués, A., Olaizola, A., & Corcoran, K. (2003). Extrinsic attributes of red meat as indicators of quality in Europe: An application for market segmentation. *Food Quality and Preference*, *14*(4), 265-276.
- Billeter, D., Zhu, M., & Inman, J. J. (2012). Transparent packaging and consumer purchase decisions. *Advances in Consumer Research*, *40*, 308-312.
- Brata, A. M., Chereji, A. I., Brata, V. D., Morna, A. A., Tirpe, O. P., Popa, A., ... & Muresan, I. C. (2022). Consumers' perception towards organic products before and after the COVID-19 pandemic: A case study in Bihor County, Romania. *International Journal of Environmental Research and Public Health*, *19*(19), 12712.
- Brüggemann, P., & Olbrich, R. (2022). The impact of COVID-19 pandemic restrictions on offline and online grocery shopping: New normal or old habits? *Electronic Commerce Research*, 1-22.
- Campo, K., & Breugelmans, E. (2015). Buying groceries in brick and click stores: category allocation decisions and the moderating effect of online buying experience. *Journal of Interactive Marketing*, *31*, 63-78.
- Chandran, S., Batra, R. K., & Lawrence, B. (2009). Is seeing believing? Consumer responses to opacity of product packaging. *ACR North American Advances*, *36*, 970-971.
- Chang, H. H., & Meyerhoefer, C. D. (2021). COVID-19 and the demand for online food shopping services: Empirical evidence from Taiwan. *American Journal of Agricultural Economics*, *103*(2), 448-465.
- Charm, T., Coggins, B., Robinson, K., & Wilkie, J. (2020, August 4). *The great consumer shift: Ten charts that show how US shopping behavior is changing*. McKinsey & Company. Retrieved from <https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/the-great-consumer-shift-ten-charts-that-show-how-us-shopping-behavior-is-changing>
- Chen, J., Zhang, Y., Zhu, S., & Liu, L. (2021). Does COVID-19 affect the behavior of buying fresh food? Evidence from Wuhan, China. *International Journal of Environmental Research and Public Health*, *18*(9), 4469.
- Chenarides, L., Grebitus, C., Lusk, J. L., & Printezis, I. (2021). Food consumption behavior during the COVID-19 pandemic. *Agribusiness*, *37*(1), 44-81.
- Chintagunta, P. K., Chu, J., & Cebollada, J. (2012). Quantifying transaction costs in online/off-line grocery channel choice. *Marketing Science*, *31*(1), 96-114.
- Chu, J., Arce-Urriza, M., Cebollada-Calvo, J.-J., & Chintagunta, P. K. (2010). An empirical analysis of shopping behavior across online and offline channels for grocery products: The moderating effects of household and product characteristics. *Journal of Interactive Marketing*, *24*(4), 251-268.
- Chu, J., Chintagunta, P., & Cebollada, J. (2008). A comparison of within-household price sensitivity across online and offline channels. *Marketing Science*, *27*(2), 282-299.
- Chung, M., Moon, J., Yoo, B., & Choe, Y. (2006). Paradox of information quality: Do consumers pay more for premium product information on e-commerce sites? In *Proceedings of the Americas Conference on Information Systems* (pp. 418-424). Mexico.
- Danaher, P. J., Wilson, I. W., & Davis, R. A. (2003) A comparison of online and offline consumer brand loyalty. *Marketing Science*, *22*(4), 461-476.
- Dawar, N., & Parker, P. (1994). Marketing universals: Consumers' use of brand name, price, physical appearance,

- and retailer reputation as signals of product quality. *Journal of Marketing*, 58(2), 81-95.
- Dawes, J., & Nencyz-Thiel, M. (2013). Comparing retailer purchase patterns and brand metrics for in-store and online grocery purchasing. *Journal of Marketing Management*, 30(3-4), 364-382.
- Degeratu, A. M., Rangaswamy, A., & Wu, J. (2000). Consumer choice behavior in online and traditional supermarkets: The effects of brand name, price, and other search attributes. *International Journal of Research in Marketing*, 17(1), 55-78.
- DelVecchio, D. (2001). Consumer perceptions of private label quality: The role of product category characteristics and consumer use of heuristics. *Journal of Retailing and Consumer Services*, 8(5), 239-249.
- Espejel, J., Fandos, C., & Flavian, C. (2007). The role of intrinsic and extrinsic quality attributes on consumer behaviour for traditional food products. *Managing Service Quality: An International Journal*, 17(6), 681-701.
- Filimonau, V., Beer, S., & Ermolaev, V. A. (2021). The Covid-19 pandemic and food consumption at home and away: An exploratory study of English households. *Socio-Economic Planning Sciences*, 101125.
- Güney, O. I., & Sangün, L. (2021). How COVID-19 affects individuals' food consumption behaviour: A consumer survey on attitudes and habits in Turkey. *British Food Journal*, 123(7), 2307-2320.
- Gupta, S., & Kim, H. W. (2010). Value-driven Internet shopping: The mental accounting theory perspective. *Psychology & Marketing*, 27(1), 13-35.
- Huang, L., & Lu, J. (2016). The impact of package color and the nutrition content labels on the perception of food healthiness and purchase intention. *Journal of food products marketing*, 22(2), 191-218.
- Huang, W. Y., Schrank, H., & Dubinsky, A. J. (2004). Effect of brand name on consumers' risk perceptions of online shopping. *Journal of Consumer Behaviour: An International Research Review*, 4(1), 40-50.
- Hurling, R., & Shepherd, R. (2003). Eating with your eyes: Effect of appearance on expectations of liking. *Appetite*, 41, 167-174.
- Jahng, J., Jain, H., & Ramamurthy, K. (2000). Effective design of electronic commerce environments: A proposed theory of congruence and an illustration. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 30(4), 456-471.
- Janssen, M., Chang, B. P., Hristov, H., Pravst, I., Profeta, A., & Millard, J. (2021). Changes in food consumption during the COVID-19 pandemic: Analysis of consumer survey data from the first lockdown period in Denmark, Germany, and Slovenia. *Frontiers in Nutrition*, 8, 635859.
- Knowles, J., Ettenson, R., Lynch, P., & Dollens, J. (2020). Growth opportunities for brands during the COVID-19 crisis. *MIT Sloan Management Review*, 61(4), 2-6.
- Kosslyn, S. (1994). *Image and brain: The resolution of the imagery debate*. MIT Press.
- Lange, C., Issanchou, S., & Combris, P. (2000). Expected versus experienced quality: Trade-off with price. *Food Quality and Preference*, 11(4), 289-297.
- Lee, D., Moon, J., & Ryu, M. H. (2019). The effects of extrinsic cues on online sales of fresh produce: A focus on geographical indications. *Cahiers Agricultures*, 28, 13.
- Lee, H. J., & Yun, Z. S. (2015). Consumers' perceptions of organic food attributes and cognitive and affective attitudes as determinants of their purchase intentions toward organic food. *Food Quality and Preference*, 39, 259-267.
- Lee, S. H., Kwak, M. K., & Cha, S. S. (2020). Consumers' choice for fresh food at online shopping in the time of Covid-19. *The Journal of Distribution Science*, 18(9), 45-53.
- Levin, A. M., Levin, I. P., & Heath, C. E. (2003). Product category dependent consumer preferences for online and offline shopping features and their influence on multi-channel retail alliances. *Journal of Electronic Commerce Research*, 4(3), 85-93.
- Levin, A. M., Levin, I. P., & Weller, J. A. (2005). A multi-attribute analysis of preferences for online and offline shopping: Differences across products, consumers, and shopping stages. *Journal of Electronic Commerce Research*, 6(4), 281.
- Leydesdorff, L., & Bensman, S. (2006). Classification and powerlaws: The logarithmic transformation. *Journal of the American Society for Information Science and Technology*, 57(11), 1470-1486.
- Lu, M., Wang, R., & Li, P. (2022). Comparative analysis of online fresh food shopping behavior during normal and COVID-19 crisis periods. *British Food Journal*, 124(3), 968-986.
- Ma, X., Zhuang, X., & Ma, G. (2020). Transparent windows on food packaging do not always capture attention and increase purchase intention. *Frontiers in Psychology*, 11, 593690.
- Matsuyama, Y. (2013). *Hierarchical linear modeling (HLM)*. Springer, New York.
- Meng, B., Zhang, X., Hua, W., Liu, L., & Ma, K. (2022). Development and application of phase change material in fresh e-commerce cold chain logistics: A review. *Journal of Energy Storage*, 55, 105373.
- Milosavljevic, M., Navalpakkam, V., Koch, C., & Rangel, A. (2012). Relative visual saliency differences induce sizable bias in consumer choice. *Journal of Consumer Psychology*, 22(1), 67-74.

- Nepomuceno, M. V., Laroche, M., & Richard, M. (2014). How to reduce perceived risk when buying online: The interactions between intangibility, product knowledge, brand familiarity, privacy and security concerns. *Journal of Retailing and Consumer Services*, 21(4), 619-629.
- Olson, J. C., & Jacoby, J. (1972). *Cue utilization in the quality perception process*, In *Proceedings of the Third Annual Conference of the Association for Consumer Research* (pp. 167-179). Chicago.
- Peterson, R. A., Balasubramanian, S., & Bronnenberg, B. J. (1997). Exploring the implications of the Internet for consumer marketing. *Journal of the Academy of Marketing Science*, 25, 329-346.
- Png, I., & Reitman, D. (1995). Why are some products branded and others not? *The Journal of Law & Economics*, 38(1), 207-224.
- Posner, M. I., Nissen, M. J., & Klein, R. M. (1976). Visual dominance: An information processing account of its origins and significance. *Psychological Review*, 83, 157-171.
- Pozzi, A. (2012). Shopping cost and brand exploration in online grocery. *American Economic Journal: Microeconomics*, 4(3), 96-120.
- Ramus, K., & Asger Nielsen, N. (2005). Online grocery retailing: What do consumers think? *Internet Research*, 15(3), 335-352.
- Raudenbush, S.W., & Bryk, A.S. (2002), *Hierarchical Linear Models, Applications and Data Analysis Methods*. Sage London.
- Reinoso-Carvalho, F., Campo, R., De Luca, M., & Velasco, C. (2021). Toward healthier cookie habits: Assessing the role of packaging visual appearance in the expectations for dietary cookies in digital environments. *Frontiers in Psychology*, 12, 679443.
- Roe, B. E., Bender, K., & Qi, D. (2021). The impact of COVID-19 on consumer food waste. *Applied Economic Perspectives and Policy*, 43(1), 401-411.
- Rundh, B. (2005). The multi-faceted dimension of packaging: Marketing logistic or marketing tool? *British Food Journal*, 107(9), 670-684.
- Sabri, O., Doan, H. V., Malek, F., & Bachouche, H. (2020). When is transparent packaging beneficial? *International Journal of Retail & Distribution Management*, 48(8), 781-801.
- Schleenbecker, R., & Hamm, U. (2013). Consumers' perception of organic product characteristics. A review. *Appetite*, 71, 420-429.
- Shamim, K., Ahmad, S., & Alam, M. A. (2021). COVID-19 health safety practices: Influence on grocery shopping behavior. *Journal of Public Affairs*, 21(4), e2624.
- Simmonds, G., & Spence, C. (2017). Thinking inside the box: How seeing products on, or through, the packaging influences consumer perceptions and purchase behaviour. *Food Quality and Preference*, 62, 340-351.
- Simmonds, G., Woods, A. T., & Spence, C. (2018). "Show me the goods": Assessing the effectiveness of transparent packaging vs. product imagery on product evaluation. *Food Quality and Preference*, 63, 18-27.
- Simmonds, G., Woods, A. T., & Spence, C. (2019). "Shaping perceptions": Exploring how the shape of transparent windows in packaging designs affects product evaluation. *Food Quality and Preference*, 75, 15-22.
- Singh, H., & Sharma, H. (2013). Consumer perception towards the quality marks of products. *International Journal of Management and Social Sciences Research*, 2(9), 50-53.
- Spence, C. (2016). Multisensory packaging design: Color, shape, texture, sound, and smell. *Integrating the Packaging and Product Experience in Food and Beverages*, 1-22.
- StataCorp, L (2021). *Stata statistical software: Release 17*. StataCorp LLC.
- Steenkamp, J. B. E., & Van Trijp, H. C. (1989). A methodology for estimating the maximum price consumers are willing to pay in relation to perceived quality and consumer characteristics. *Journal of International Food & Agribusiness Marketing*, 1(2), 7-24.
- Steenkamp, J.-B. E. M. (1990). Conceptual model of the quality perception process. *Journal of Business Research*, 21, 309-333.
- Steenkamp, J.-B. E. M. (1997). Dynamics in consumer behavior with respect to agricultural and food products. In *Agricultural marketing and consumer behaviour in a changing world* (pp. 143-188). Boston, Springer.
- Symmank, C. (2019). Extrinsic and intrinsic food product attributes in consumer and sensory research: Literature review and quantification of the findings. *Management Review Quarterly*, 69(1), 39-74.
- Valaskova, K., Durana, P., & Adamko, P. (2021). Changes in consumers' purchase patterns as a consequence of the COVID-19 pandemic. *Mathematics*, 9(15), 1788.
- Venkatesan, R., Kumar, V., & Ravishanker, N. (2007). Multichannel shopping: Causes and consequences. *Journal of Marketing*, 71(2), 114-132.
- Verstraeten, J., Heeremans, E., Geuens, M., & Vermeir, I. (2023). How online grocery shopping drives private label food purchases. *Journal of Business Research*, 167, 114057.

- Vilnai-Yavetz, I., & Koren, R. (2013). Cutting through the clutter: Purchase intentions as a function of packaging instrumentality, aesthetics, and symbolism. *The International Review of Retail, Distribution and Consumer Research*, 23(4), 394-417.
- Wang, H. H., Han, X., Jiang, Y., & Wu, G. (2022). Revealed consumers' preferences for fresh produce attributes in Chinese online markets: A case of domestic and imported apples. *Plos One*, 17(6), e0270257.
- Weesie, J. (2000). Seemingly unrelated estimation and the cluster-adjusted sandwich estimator. *Stata Technical Bulletin*, 9(52), 34-47.
- Zatz, L. Y., Moran, A. J., Franckle, R. L., Block, J. P., Hou, T., Blue, D., ... & Rimm, E. B. (2021). Comparing online and in-store grocery purchases. *Journal of Nutrition Education and Behavior*, 53(6), 471-479.
- Zheng, Q., Chen, J., Zhang, R., & Wang, H. H. (2020). What factors affect Chinese consumers' online grocery shopping? Product attributes, e-vendor characteristics and consumer perceptions. *China Agricultural Economic Review*, 12(2), 193-213.



## APPENDIXES

**Appendix 1. Description of Variables for Product Categories and Attributes**

Attributes	Variables	Descriptions
Product Category	Produce (PC1) Meat & Seafood (PC2) Dairy food (PC3) Chilled food (PC4) Frozen food (PC5) Ambient food (PC6)	PC2 (PC1=0, PC2=1) PC3(PC1=0, PC3=1) PC4 (PC1=0, PC4=1) PC5 (PC1=0, PC5=1) PC6 (PC1=0, PC6=1) - PC1 (fresh veg., fruits and dried agri-foods) - PC2 (fresh pork, beef, fish, and shellfish) - PC3 (milk, cheese and butter) - PC4 (chilled tofu, ham, and pickled veg.) - PC5 (frozen dumplings and fried rice) - PC6 (pasta, wheat flour and seasonings)
Brand Type	Generic Brand (GB) National Brand (NB) Private Brand (PB)	GB (NB=0, GB=1) PB (NB=0, PB=1) - GB (no specific company label) - NB (distributed nationally by a producer) - PB (owned by a retailer)
Visibility of Package	Sensory Line (SL) Non-Sensory Line (NSL)	NSL (SL=0, NSL=1) - SL (transparent package including semi-style) - NSL (opaque package)
Unit of Sales	Weight (WT) Pack (PK)	PK (WT=0, PK=1) - Be sold per 100g(weight) or pack
Unit of Pack	Bundle Pack (BP) Single Pack (SP)	SP (BP=0, SP=1) - A bundle pack is a product made by grouping several single products for the promotion.
Price per Unit	ln(Price)	- Price on Dec. 31 <sup>st</sup> , 2020
Amount of Loss	ln(Loss)	- Reduced to clear and wasted ("Reduced to Clear" means discount sale prices for nearly expired or damaged stock)
Annual sales of Food	ln(Total annual sales)	- Total annual sales of items (2020)