

**UNIVERSIDAD ESAN**



**PURCHASING FOOD  
BECOMES OMNICHANNEL**

**UNDERSTANDING FOOD SHOPPER SEGMENTS AND LIFESTYLES**

**In collaboration with:**



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IÉSEG School of Management – Paris, France

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**Christian Anthony Gamero Jorge**

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**IÉSEG**  
SCHOOL OF MANAGEMENT

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ESAN Graduate School of Business  
1652 Alonso de Molina, Santiago de Surco - Lima, Peru

IÉSEG School of Management  
1 parvis de La Défense – 92044 Paris - La Défense, France

**Name and Surname**  
Christian Anthony Gamero Jorge

**Academic Director:**  
Nathalie Demoulin

**Paris, France**

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## ABSTRACT

Global consumption trends and technological disruption is creating the path towards an omnichannel approach in marketing strategies, that is reshaping how customers buy products and interact with companies. Food-related companies have seen an unprecedented evolution in this context representing a challenge to remain competitive, to attract customers, and improve their purchase experience.

This thesis tackles this problem by developing a segmentation study, employing Latent Class Analysis, based on the use of multiple touchpoints across the food purchase process, aiming to identify customer profiles, their channel allocation, and psychographic characteristics related to food consumption.

Three segments were identified: Early Omnichannel Adopters, Curious Conservatives, and Uninterested Traditional shoppers. The findings reveal key differences in their adoption of online and mobile touchpoints across the purchase stages, in their expertise purchasing food online, and the impact of the COVID-19 pandemic in channel allocation. A Multinomial logistic regression was then performed to determine psycho-demographic differences between the segments and allowing to characterize their food-related lifestyles.

The insights developed in this research contributes to the literature and to the business world by confirming the utility of LCA analysis to segment customers considering different food purchase phases and multiple touchpoints, using the most recent programming language software and integrating specific covariates relevant to food shoppers. Food marketers can find valuable to implement a similar approach to reinvent strategies in times of uncertainty and change.

## **Christian Anthony Gamero Jorge**

Profesional trilingüe, analítico, entusiasta y líder. Con experiencia en Perú y Europa en inteligencia comercial y operaciones de ventas internacionales B2B en el sector de alimentos y fragancias. Actualmente realizo actividades de coordinación de ventas para impulsar el desarrollo comercial internacional y proyectos de desarrollo de fragancias para la división de fragancias finas para Europa de Symrise.

MBA - MSc. in Management & Marketing y Licenciado en Administración y Negocios Internacionales. Responsable, Perseverante y un team player comunicativo y proactivo. He desarrollado capacidades polivalentes tanto en operaciones de ventas y usando software para la gestión de información y herramientas de investigación para realizar análisis de mercado, ventas e insights.

### **1 EXPERIENCIA PROFESIONAL**

#### **Symrise – Paris, Francia**

Empresa alemana líder en el desarrollo, producción y comercialización de fragancias, activos cosméticos e ingredientes para alimentos. 4to proveedor global de la industria de perfumes y cosméticos – \$3.8b facturados en 2021 a nivel mundial.

#### **2 Coordinador Comercial y de Proyectos – Fragancias Finas para Europa**

**Abril 2022 - Actualidad**

- Coordinación global de proyectos de desarrollo de fragancias para perfumería fina en Europa.
- Análisis del performance y proyecciones de venta para la división europea.
- Participación en actividades de planificación comercial.

#### **3 Coordinador Comercial y de Proyectos Globales para L'Oréal Marzo 2021 – Abril 2022**

- Coordinación global de proyectos de desarrollo de fragancias para productos de cuidado personal de L'Oréal
- Coordinación interna y logística para estudios de consumidor en Francia, África y Asia.
- Participación en actividades de marketing B2B y de planificación estratégica.
- Análisis del performance de la cuenta en todas las categorías y regiones.
- Participación y colaboración con L'Oréal en la implementación de nuevas plataformas online para la venta y pricing.

#### **4 Gandules INC – Lima, Perú**

Empresa agroindustrial líder en la producción y comercialización de conservas, congelados y frescos de frutas y hortalizas. \$80M de facturación anual en promedio.

#### **5 Coordinador de Inteligencia Comercial**

**Febrero 2018 – Diciembre 2019**

- Gestión de actividades de inteligencia de mercados para 3 líneas de negocio:
  - Contacto con agencias de información, estudio de mercado y ferias.
  - Gestión de información y monitoreo de reportes de mercado.
  - Participación en iniciativas de innovación
- Evaluación, análisis y monitoreo de los KPI comerciales, rentabilidad y presupuesto de ventas.
- Coordinación interna para asegurar el flujo de información comercial interno (stocks, SKUs, etc.)
- Implementación de un nuevo equipo de marketing e inteligencia comercial.

#### **6 Analista Comercial**

**Febrero 2017 – Enero 2018**

- Análisis de mercado y exportaciones de alimentos en conserva, congelados y granos. (extracción, tratamiento de datos y actualización de reportes).

- Optimización de las herramientas de análisis comercial (presentaciones, performance, lanzamiento de productos, etc.)
- Gestión del proyecto de renovación de la página web corporativa.

## 7 Vínculos Agrícolas – Lima, Perú

Empresa agroindustrial de acopio y comercialización de quinua y derivados. \$10M de facturación anual en promedio.

## 8 Analista Comercial

Marzo 2016 – Enero 2017

- Creación y actualización de reportes de monitoreo de mercado y exportaciones (granos andinos).
- Soporte en la evaluación de propuestas comerciales y plan de ventas
- Análisis del performance de ventas de la empresa.

## 9 Asistente Comercial

Julio 2015 – Febrero 2015

- Registro en el ERP y seguimiento de órdenes de compra, contratos y despachos.
- Soporte en las actividades de promoción y ventas internacionales (EE. UU. & Europa).
- Soporte a clientes internacionales en atención postventa.

## 10 FORMACIÓN PROFESIONAL

IESEG SCHOOL OF MANAGEMENT - Francia 2020 - 2021  
MSc. in Management

ESAN GRADUATE SCHOOL OF BUSINESS - Perú 2018 - 2019  
MBA Maestría en Administración

UNIVERSIDAD PRIVADA DEL NORTE - Perú 2008 - 2013  
Administración y Negocios Internacionales

ESCE - Francia 2012 - 2013  
International Business – Intercambio

## 11 OTROS ESTUDIOS

ESAN Graduate School of Business *Diploma en Gestión de Proyectos* 2015  
POSGRADO UPC: *Curso Especializado en Business Analytics* 2017  
El Cultural: **Inglés Avanzado** 2004 – 2007  
ALIANZA FRANCESA: **Francés Avanzado** 2010 - 2015

## EXECUTIVE SUMMARY

### Summary:

Food-related companies are facing disrupting changes in sales and distribution solutions due to the rise of digital and hybrid channels. They will need to engage in an omnichannel approach to remain competitive as customers demand lifestyle-driven and customized experiences. New challenges in the market such as the impact of the COVID-19 Pandemic in 2020 and environmental concerns are also shaping how customers buy food and interact with brands and companies both online and offline. In this context, this research started highlighting the need to segment food shoppers within the omnichannel shopping process based on the customers interaction with multiple touchpoints, aiming to identify their purchase profiles and to unveil relevant food-related lifestyle characteristics.

Five purchase process stages were evaluated from the perspective of the consumer, according to the touchpoint usage frequency across the food shopping process. Several multichannel segmentation studies provided the main touchpoints and the segmentation method (LCA) that was implemented in this research based on survey data. Previous food-shopper research unveiled the psychographic lifestyle dimensions and demographic measures that were used to characterize and to identify differences among the food shopper segments.

The segmentation results unveiled the existence of three food shopper segments: The Early Omnichannel Adopters (38.3% of customers), Curious Conservatives (51.5%) , and Uninterested Traditional shoppers (10.1%). The first segment, The Early Omnichannel Adopters, manifested using offline, online, and mobile touchpoints for purchase like multichannel customers found in previous studies. Despite using physical touchpoints more frequently, digital touchpoints are used as a secondary channel to search for information, to purchase, to pay or to receive their food courses, in a higher frequency compared to the other two segments. The impact of COVID-19 was moderate, pushing online (+5.15%) and mobile (+2.43) purchases upward. These customers are also younger, more savvy buying food online, time-pressured, do not give too much importance to product information and quality aspects, but enjoys food shopping and cooking.

Secondly, Curious Conservatives shoppers allocated physical touchpoints to buy food at a higher average (89%) than the Early Omnichannel Adopters (60.8%) and use online touchpoints less. Some manifested using search engines rarely or buying on mobile applications. These shoppers are young as the Early Omnichannel Adopters, but are less-time pressured, not too experienced buying foods online, they enjoy food shopping less. They scored similar in shopping convenience but higher to the uninterested traditional shopper. The COVID pandemic impacted less their channels allocation than the first segment, increasing food courses mainly online (+3.63%).

In contrast, the Uninterested Traditional shoppers are the less enthusiastic segment to use digital channels to purchase food. Indeed, they scored the highest average of channel allocation on physical touchpoints even after the pandemic (98.8%). This segment visits physical stores sometimes to look for information and purchases sometimes in specialty or convenience stores apart from supermarkets. Compared to the first two segments, they give significant importance to food quality aspects, they are the least time-pressured and pay more attention to product information than early omnichannel adopters. They tend to be older than the previous segments and to live in smaller households.

It is noteworthy that the segments have a uniform interest in food and their experience since no significant differences were found in terms of enjoying eating in company, passion for cooking, pleasure, and interest in food. All showed similar and high scores in environmental concerns and quality aspects in line with current market trends and challenges. These challenges in line with all the findings exposed previously, represent new opportunities that companies in the food industry should analyze to plan, reinvent, or adapt their marketing strategies.

The integration of online, mobile touchpoints and physical stores is becoming a new trend in France and worldwide, in which marketers need to tailor digital marketing strategies to meet the customer's need for coherent product information, safe transactions, and practical purchase and delivery within the omnichannel experience. Aligning communication practices, optimal customer service, in-store solutions, and customized offers could boost profits, share-of-wallet, and market share.

Companies can implement the segmentation methodology performed in programming language software in this thesis to identify shopper segments tailored to the industry in which they operate, combining psychographic covariates and touchpoints to the products and markets they analyze. Future academic research efforts can be directed to that end, using real transactional data, monitoring customers across time or unveiling hidden relationships between inner motivations and omnichannel behavior.

# I. INTRODUCTION

## 11.1 Context and Research Questions

The technological revolution in the 21<sup>st</sup> century has transformed different social and economic aspects of our daily lives. Citizens around the world live now in a hyperconnected society, exchanging information and knowledge in unprecedented volumes and accelerating the speed at which the digital evolution impacts both companies and customers. Different companies and retailers have also realized how customers reach and interact across different devices, websites, platforms that different authors refer to as touchpoints (Grewal et al., 2016; Verhoef et al., 2015).

In order to match new consumer lifestyles and their shopping experiences, companies across different sectors have developed more sophisticated channels and technologies to address customer's expectations for contextual, consistent, and relevant interactions (McKinsey, 2016). This is also the case in the food industry, in which technology has also been a disruptor (Howard et al., 2017). These technologies, and a larger universe of online platforms, offer customers the possibility to use diverse sources of product information when shopping, including in-store displays, retailer websites, online review sites, virtual marketplaces (Ernst & Young, 2014), mobile apps, thus, offering more choices of how and where to shop food and letting customers embrace an integrated in & out-of-store purchase experience (Howard et al., 2017).

This integration of all multiple touchpoints between customers and organizations that enable different means for coordinated information, communication, and purchase phases, is what has introduced the concept of omnichannels (Manser Payne et al., 2017), omnichannel systems (Saghiri et al. 2017) and omnichannel management strategy that seeks to enable a seamless purchase experience whether the customer buys online or in a physical store (Deloitte, 2014).

Companies around the globe will increasingly engage in an omnichannel strategy as customers explore the market and get in contact with a brand or service by different means and moments. Food shopping specifically will encounter different touchpoints that will allow customers to use vast options to choose where, when, how, and why their food needs will be satisfied (Howard et al., 2017). For instance, initiatives like the *click and collect* or *drive* in France have also boosted food e-commerce, integrating a digital purchase, and a physical pick up (Bertrand, 2019).

Moreover, the outbreak of the COVID-19 Pandemic in 2020, has boosted customers globally to select online and offline touchpoints alongside each other, proving how important the omnichannel purchase has become (Nielsen, 2020). In addition to growing environmental and health concerns by customers for food choice (Honkanen et al., 2006; JLL, 2018; Lindeman & Vaananen, 2000; Lockie et al., 2010; Nie & Zepeda, 2011), food retailers and foodservice providers must compete, present, and maintain their value propositions in this challenging scenario. Their marketing strategies should indeed be tailored accordingly, and operational tactics should be aligned to the customer's behavior during the purchase process online and offline, understanding their lifestyles, as they will influence the omnichannel food shopping experience in the future (Howard et al., 2017).

Aiming to improve the overall experience for customers, the challenge of analyzing customer behavior using multiple touchpoints has been addressed before employing multichannel segmentation, and it has been considered vital to design multichannel strategies (Neslin et al., 2006). However, most of the previous segmentation studies have studied the potential of multiple touchpoints in the retail sector in general, but not in the food industry with specific psychographics and the impact of new coming trends such as omnichannel shopping, lifestyle-driven consumption, customization, and a digitally integrated experience end to end (Howard et al., 2017).

Therefore, this thesis seeks to solve the following research question: *What are the profiles of food shopper segments in France by their use of specific touchpoints throughout the purchase process?* More specifically: What is the relative role of these touchpoints across the stages of the omnichannel food shopping process? Do omnichannel food shopping segments have different food-related lifestyle characteristics?

The research performed to answer these questions followed the structure of previous academic efforts in multichannel segmentation, but widens their perspective towards an omnichannel purchase system, where different agents and touchpoints are used among the purchase stages. The frequency in which consumers use those touchpoints in each stage is evaluated to assess and to identify customer segments. Additionally, specific psychographic covariates to analyze food-related lifestyles are measured to further characterize and identify significant differences between the segments, including the impact of the COVID-19 Pandemic in channel allocation for food purchase and several demographic aspects such as income, family size, or monthly budgets.

## 11.2 Objectives and Contributions

This thesis performs a segmentation study of food shoppers in France, based on multiple touchpoints used during their food procurement process, unveiling lifestyle psychographics in each segment to describe their attitudes, needs, or motivations within their food consumption. The academic marketing research addressing customer segmentation has been flourishing around the globe, starting with Konuş et al. (2008) who proposed a Latent-Class Cluster Analysis based on the use of multiple channels, and their method has been implemented among other different studies.

For instance, Nakano & Kondo (2018) investigated multichannel segments based on source panel data in Japan, using LCA on a transactional database. Sands et al., (2016) segmented customers across the three stages of purchase as Nakano & Kondo, complementing Konuş et al. approach. Lazaris et al. (2014) analyzed omnichannel shopper segments based on online and offline retailing usage intensity and behavior, and Park & Kim (2018) introduced a country comparison based on multichannel segments in US and Korea to identify key differences and similarities in their adoption of several channels in the buying process.

Extending these preceding efforts, the first objective of this research is to investigate the existence of consumer segments based on the usage frequency of the touchpoints used to search for information, to purchase, to request delivery solutions, to pay, and to provide after-purchase feedback about their food-related courses. A segmentation methodology using open-source data mining software, to implement LCA analysis, is applied within an omnichannel perspective, specifically designed for food shopping, and evaluating physical, online, and mobile channels.

Previous research has explored demographic and psychographic variables to explain the needs and behavior of multichannel segments. However, it is necessary to address the omnichannel management for food consumption with a specific approach to understand different attitudes and behaviors specifically related to food shopping. To this end, different methods have been used to segment food customers, such as Benefit segmentation presented by Haley (1968), Means-end chains (MEC) proposed by Gutman (1982). Then, Chetthamrongchai & Davies (2000) segmenting according to attitudes to shopping and time, and the Food Related Lifestyles (FRL), introduced by Brunsø (1997).

The Food-Related Lifestyles method (Brunso et al., 1996; Brunsø & Grunert, 1998) proposes specific psychographic variables for food shopping and it has been widely used as a validated instrument because it not only measures how customers react to products but how they interact with food-related marketing efforts (Grunert, 2019). Consequently, this research also aims to combine the segmentation results with a psychographic descriptive analysis, using the most relevant covariates related to food consumption to

unveil the food-related customer lifestyles and demographics for each segment. Several studies, using the same approach in food purchase related studies, are used to select the final lifestyles dimensions in line with current food consumption trends and challenging events such as the COVID-19 Pandemic.

### **11.3 Managerial Relevance**

As previously presented, the business literature has embraced customer segmentation generally on general retail shopping, and few are category or industry-specific. The food sector represents an important role in the French economy as the first employer in the manufacturing industry, and it is the second-largest food sector in Europe (Ministère de l'Agriculture et de l'Alimentation, 2018). The rise of online channels for food purchases in France since 2012 has also been remarked, where new distribution formats and solutions have been introduced (Bertrand, 2019; France Agrimer, 2018).

Furthermore, if food companies need to target and create consistent marketing activities, it is vital to identify market segments in which specific channels could appeal more to a specific customer lifestyle in order to improve its purchase experience and satisfaction. Therefore, it is necessary to introduce a new approach to identify market segments specifically for this industry, focusing on how customers have embraced multiple touchpoints throughout their omnichannel food purchase process and describing the different food-related lifestyle characteristics that each segment exposes.

This thesis would be useful both for food retailers or companies that plan to develop or improve an omnichannel strategy in the French market, providing an insight of how these customers behave and interact with different touchpoints when they search for information about meals or groceries, when they purchase and receive their orders and how they interact with different companies marketing efforts.

### **11.4 Structure**

This study starts with a literature review outlining the main concepts related to the omnichannel theory to establish the framework in which the purchase process will be analyzed. Then, relevant multichannel segmentation studies will be discussed to unveil the main findings, methods, and limitations, allowing to select the relevant touchpoints and the first covariates to be covered. Finally, the food-related studies and trends will be evaluated to construct the set of final psychographic and demographic covariates that will be measured to characterize the segments.

The research methodology will describe the research model in which the touchpoints usage within the omnichannel food purchase will be evaluated, and the final food-related lifestyle dimensions that will be considered. It also includes the data collection and

analysis plan to carry out the segmentation technique and the covariates probability analysis for each segment.

The data analysis section will describe the segmentation process implemented on survey data, distributed through Qualtrics to residents in France online. The information gathered is later analyzed in R Studio to identify the segments, and later in SPSS to run statistical tests, factor analysis, and a multinomial regression to analyze the covariates. The results are presented and discussed, providing the main academic contributions, managerial implications, limitations, and recommendations for further research. The study closes with a conclusion section that summarizes the research process, main findings, and final thoughts.

## **II. LITERATURE REVIEW**

### **2.1. Omnichannel Segmentation**

#### **2.1.1. Omnichannel Theory**

The disruptive evolution and implementation of new information and communication technologies during the 21st century have transformed both business processes and strategies. Retailers around the globe have seen how the internet and the mobile technologies have generated important changes in the customer purchase behaviors enabling them to research and buy every time and everywhere, making the shopping experience a sophisticated experience and creating new ways for top retailers to target their customers (Deloitte, 2014). The new experiences that they face nowadays include having a wide range of purchase channels and options such as retail stores, collection, and delivery points or digitally accessible items (Saghiri et al., 2017), and has affected the business models and retail mix for many companies (Sorescu et al., 2011).

As new channels and means for purchase are available for customers due to the disruption of new technologies, companies have adapted its marketing strategies and have been implementing ways to continue to offer an appealing and integrated experience to customers. Indeed, customers now expect to use omnichannel means as an easy and quick way to cope with purchase difficulties with a minimal effort, creating also an omnichannel environment thanks to the integration of digital innovations (McKinsey, 2016).

From that perspective, the business literature has seen an evolution towards the management of multiple channels by companies. Different authors referred to this new marketing practice as multichannel retailing or multichannel

management. But it is important to state that multichannel is not the same as omnichannel which is the focus in this thesis, and discussing its difference is relevant to formally present a proper theoretical framework for the omnichannel concept.

Verhoef et al. (2015) discussed in their paper how the conceptual dimensions between multichannel and omnichannel have been addressed in the business literature. After their exhaustive revision and analysis, the main aspects in which both concepts differ can be seen in **Table 1**. Even if these aspects are shared between both perspectives, the focus and the scope differ from the business and the customer's perspective.

**Table 1 : MULTICHANNEL VERSUS OMNICHANNEL MANAGEMENT**

	MULTI-CHANNEL MANAGEMENT	OMNI-CHANNEL MANAGEMENT
Channel Focus	Interactive channels only	Interactive and mass-communication channels
Channel Scope	Retail channels: store, online website, and direct marketing (catalog)	Retail channels: store, online website, and direct marketing. Mobile channels: Smart phones, tablets, apps. Social media Customer Touchpoints: (incl. mass communication channels: TV, Radio, Print, C2C, etc.).
Separation of Channels	Separate channels with no overlap	Integrated channels providing seamless retail experiences.
Brand vs. Channel Customer Relationship focus	Customer – Retail channel focus	Customer – Retail channel – Brand focus
Channel Management	Per channel	Cross-channel
Objectives	Channel objectives (i.e., sales per channel; experience per channel)	Cross-channel objectives (i.e., overall retail customer experience, total sales over channels)

Source : (Verhoef et al., 2015)

The first point to note is that the channel focus and scope in multichannel management is based only on the channels that are interactive and that belong to the retailer (store, website, catalog), whereas, in the omnichannel management, companies have to be aware of the channels in which the customers can perceive the brand and that could escape from their direct control, such mass communication channels and social media, as these touchpoints are getting more integrated with interactive channels (Verhoef et al., 2015).

Secondly, in the multichannel perspective, the channels tend to be managed separately with their own objectives and measures. In the multichannel system, channels still work autonomously and are detached (Balasubramanian et al., 2005); (Wilding, 2013). Furthermore, the integration of all touchpoints is important and should be managed to create a seamless experience for the customer as the limits of the different channels begin to fade during search and purchase (Verhoef et al., 2015).

The table also shows that mobile channels (branded apps, tablets, smartphones, laptops) are considered in omnichannel management. These technologies are important as they have been adopted to create a change in offline and online retailing, and form part of the omnichannel experience of the customer (Verhoef et al., 2015). It has been already studied that the mobile channel use is changing shopping behavior (Verhoef et al., 2015) and touchpoint interactions, influencing brand preferences (Macdonald et al., 2012).

Moreover, customer relationship covers not only the customer itself and its preferred channels but also the brand, focusing on cross channel objectives that evaluates the overall customer experience and the revenues generated across the multiple touchpoints. The cross channel systems try to provide customers with easier and different means to get information and to make decisions (Saghiri et al., 2017). This could be a challenge for the supply chain as there is not a central knowledge point about a product, synced among all channels (Saghiri et al., 2017), which introduces the notion of omnichannel where a complete view of all channels is given to the customer and the supply chain participants (Cunnane, 2012).

All the dynamics mentioned above have also created new concepts such as webrooming, in which customers gather information online to shop offline (Verhoef et al., 2015) complementing the famous concept of showrooming, in which customers browse in physical stores. However, now they are empowered with internet and mobile devices and thus it makes it a relevant issue in omnichannel management (Verhoef et al., 2015). Consequently, consumers can change from one channel or touchpoint to another in their purchase experience (search, order placement, and delivery) (Saghiri et al., 2017).

It is important to note that Verhoef et al. (2015, p. 3) also concludes defining omnichannel management as:

The synergetic management of the numerous available channels and customer touchpoints, in such a way that the customer experience across channels and the performance over the channels is optimized. ... [They] thereby acknowledge that the different channels interact with each other and are used simultaneously.

Implicitly, it can be stated that the omnichannel purchase refers to the use of different touchpoints across the customer buying experience, that generates an interaction between the company, intermediaries, and the customer. The integration of multiple touchpoints enables different means for coordinated

information, communication, and purchase phases (Manser Payne et al., 2017) and enables a seamless purchase experience online or offline (Deloitte, 2014).

The study performed by Verhoef et al. (2015) established an important academic effort to gather and propose a formal definition of omnichannel management among different marketing and retail-related papers across the world. It provided a clear reference to differentiate it from the multichannel concept which has been extensively researched. However, it is important to mention that the concept was developed basically from an extensive literature review of several research streams, but still lacks an empirical and managerial validation that could be implemented for customer segmentation.

A conceptual framework with managerial validation is needed to measure purchase phases, channels, and members of the omnichannel purchase where customers interact and experience an integrated flow of information, and the means to satisfy their buying needs. For this mission, Saghiri et al. (2017) developed a conceptual framework in which they identified and validated the key elements that form an omnichannel system and its enablers.

Saghiri et al. (2017) stated that the omnichannel can be identified as a complex adaptive system, and they proved it by the validation and identification of its agents, channels, schema (stages and enablers), connectivity, interactions, autonomy, and control. All the parties interact continuously, but its adaptative property enables to rewire itself in different points of data and resources across several channels (Saghiri et al., 2017) .

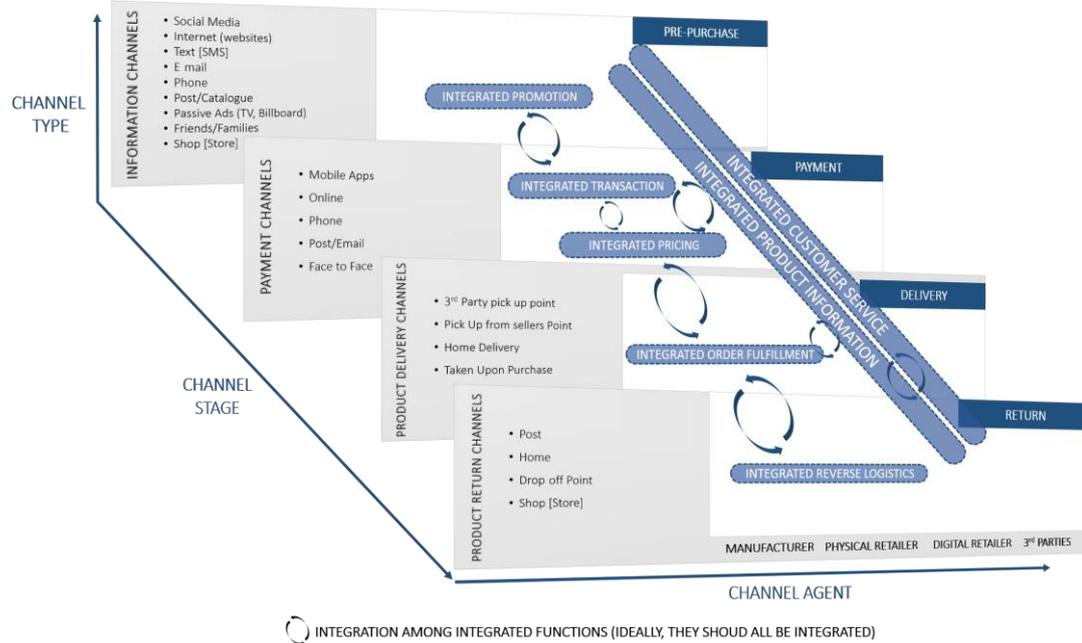
The conceptual framework scheme developed by Saghiri et al. (2017) visible in **Figure 1** distinguishes 3 dimensions in the omnichannel system: the channel stage, the channel type, and channel agent; and 2 enablers: integration and visibility.

First of all, the channel stage represents the buying process, or the value-adding journey according to Wilding (2003), which stars before the purchase point and covers the return phase. Four clear stages are identified: Pre-Purchase, payment, delivery, and return, in which different agents and channel types are identified as well.

The channel type illustrates the different means that the customer, the company or a third party have at their disposal in each stage of the purchase process, or at each omnichannel stage, to give information and access to the product or service. The channel types are not the same for all the stages of the system, but

some of them are used more than once such as e-mail, phone, or websites. They are identified in **Figure 1**.

**Figure 1: A THREE-DIMENSIONAL CONCEPTUAL FRAMEWORK OF OMNI-CHANNEL SYSTEMS**



Source: (Saghiri et al., 2017)

The authors validated the cited framework after the study of several business cases. Moreover, they implemented a second phase in order to identify the enablers that make the system operational, implementing interviews with different business leaders and professionals. Saghiri et al. (2017) concluded that in the omnichannel systems, customers should be able to change between channels flawlessly, and that integration and visibility build or enable an omnichannel system.

These enablers are defined by Saghiri et al. (2017) as follows: integration, visible in **Figure 1**, is the omnichannel effort to coordinate its member’s activities and decisions (in 3 dimensions, among the stages, the channels and the agents). Visibility refers to the customer expectation of the services and products they need and that are provided by the omnichannel system. The functions and dimensions of the channel integration and the visibility needed across the system are described in **Table 2**. Both integration and visibility form and support a synced and self-organized omnichannel system, and reaffirms how this conceptual framework explains that the system “is capable of adjusting its resources and processes to meet the market and supply fluctuations” (Saghiri et al., 2017, p. 63).

**Table 2 : ENABLERS OF THE OMNICHANNEL SYSTEM**

INTEGRATION		VISIBILITY	
Integrated promotion	Linking and synchronizing the sources, channels and interfaces of market data and promotions.	Product visibility	Implies keeping and sharing product data, including the product's technical, physical, component, and ingredient data.
Integrated transaction	Involves payment tools and linking them with authorization mechanisms.	Demand visibility	Market trends, demand size, consumer taste, consumer behavior, and similar demand data, as well as accessibility to them by relevant omni-channel parties.
Integrated pricing	Synchronizes the products' prices and makes changes in them, visible for consumers and other members of the omni-channel system.	Order/payment visibility	Includes the availability of payment data of individual consumers to relevant parts of the omni-channel system and can apply to consumers and other omni-channel parties.
Integrated order fulfillment	Addresses traceability, tractability, and changeability of product, consumer, stock keeping point(s), delivery point(s), and transport mode(s) across all channels.	Stock visibility	Inventory status and location information, which should be accessible and retrievable across the omnichannel system.
Integrated reverse logistics	Implies links among different stages of reverse logistics and different channels, return points and products involved.	Shipment/delivery visibility	Transparency in delivery conditions, status of the delivery, location of the shipped items, and proof of delivery.
Integrated product information	Implies that providers, organizers, and distributors of product information in all channels should make sure that the same information about the product is distributed to all members of the omni-channel system as well as the consumer.	Supply visibility	Awareness of consumers and different parties of the omni-channel system of the origin and supply process of the products.
Integrated customer service	Implies the same or compatible service standards which are delivered by all members of the omni-channel across all the omnichannel stages.		
Proper links among the above-mentioned integrated functions will enhance the omni-channel system toward total integration, where all are fully coordinated throughout channel stages, types, and agents.		Channel visibility refers to the capacity of supply chain members to provide, share, or retrieve the required timely information (Goh et al., 2009). Given the omni-channel framework, the information can be about products, consumers, inventories, deliveries, returns, and so on.	

Source : (Saghiri et al., 2017) and one argument from (Goh et al., 2009)

Their research is relevant for this thesis as it has provided a conceptual framework that illustrates the omnichannel dimensions (channels, agents, and stages) and highlights the key functions and aspects that should be integrated and visible to support its connectivity and implementation (Saghiri et al., 2017). The enablers proposed for the omnichannel systems are aligned with another study performed by Peltola et al. (2015) in which they identified the key factors that create a unified omnichannel experience such as unified product information and pricing, integrated systems and logistics, unified customer communications and organizational unity. Jimenez Barreto et al. (2019) also concluded that the sense of omnichannel coherence (SCO) is formed by perceived congruence, the coordination among channels that influences brand loyalty, perceived consistency, and sensibility to the context.

Hence, the conceptual framework proposed by Saghiri et al. (2017) was validated by the study of several cases from the UK from retail (physical and digital) and manufacturing companies. Additionally, the system's enablers were supported by companies from the grocery, non-grocery, and food sectors (Saghiri et al., 2017). Nonetheless, the research still requires to be proved from the perspective of the consumer (Saghiri et al., 2017) and its actual behavior in the omnichannel system. One important aspect that the authors proposed was channel choice, the agents involved, its enablers and channel switch decisions (Saghiri et al., 2017). There is where this thesis will fill a managerial and

academic gap, as it will implement this framework, adapted to a specific sector (food), segmenting customers according to their touchpoint use across the food shopping process.

### **2.1.2. Multichannel and Omnichannel Segmentation**

The business literature has seen an evolution across different academic efforts to explain and identify customer decisions, behavior, and channel choice drivers (Verhoef et al., 2015) in multiple or specific categories. To that end, several researchers have addressed this mission implementing segmentation studies that has attracted a notorious interest. Omnichannel shopping segmentation has been recently studied (Lazaris et al., 2014; Herhausen et al., 2019), but most of the previous literature has been focused on multichannel segmentation with the goal to study the selection behavior across different channels or touchpoints (Verhoef et al., 2015).

With the objective to settle the building blocks to segment the market in this thesis, an overview and analysis of previous research addressing market segmentation will be provided, focusing on the phases or channel stages (Saghiri et al., 2017), the touchpoints or channel types (Saghiri et al., 2017), the segments identified and categories covered. The covariates and methodology will be mentioned by will be extensively discussed the next two sections of this chapter of the literature review. A summary of the main aspects of the studies analyzed can be seen in **Table 3**.

**Table 3 : PREVIOUS MULTICHANNEL AND OMNICHANNEL SEGMENTATION STUDIES**

Study	Phases/Stages	Touchpoints/Channel Type	Covariates	Sample and Categories	Methodology	Identified Segments
(Herhausen et al., 2019)	Search Purchase.	Physical store Online store Catalog, Competitor physical store, online store and catalog Search engine, Brand website, Comparison portal. Social media community, News portal. Word of mouth.	<b>Psychographic:</b> Price Consciousness, Involvement, Time Pressure. <b>Sociodemographic:</b> Age, Education, Household size, Income, Urbanization. <b>Others:</b> Duration of journey, online and physical channel experience, use of mobile device, buying frequency, spending level, touchpoints sequence.	<ul style="list-style-type: none"> <li>Sample 1 (2013): 2,443 customers*</li> <li>Sample 2 (2016): 2,649 **</li> <li>From Germany, Switzerland and Austria in Apparel, Electronic, Entertainment, Cosmetics</li> </ul>	Latent Class Cluster Analysis (LCA).  Akaike Information Criterion (AIC and AIC3), Bayesian Information Criterion (BIC) for model selection.	<ul style="list-style-type: none"> <li>Store-focused shoppers (22%* - 24%**)</li> <li>Pragmatic online shoppers (23%* - 22%**)</li> <li>Extensive online shoppers (21%* - 13%**)</li> <li>Multiple touchpoint shoppers (13%* - 14%**)</li> <li>Online-to-offline shoppers (20%* - 26%**)</li> </ul>
(Nakano & Kondo, 2018)	Search, Purchase	Physical Store Online Store Mobile PC Social Media	<b>Psychographic:</b> Price Consciousness, Loyalty, Shopping Enjoyment, Time Pressure, Motivation to Conform, Innovativeness. <b>Sociodemographic:</b> Gender, Household members, Age, Education, Marital Status, Income.	<ul style="list-style-type: none"> <li>2595 customers in Japan</li> <li>Categories: Groceries, Beverages, sundries, cosmetics and drugs.</li> </ul>	Latent Class Cluster Analysis (LCA).  Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and the Consistent Akaike Information Criterion (CAIC) for model selection.	<ul style="list-style-type: none"> <li>Store-focused/anti-digital customers (21.3%)</li> <li>Store-focused light/anti-digital customers (19.0%).</li> <li>Store-focused light/multimedia social customers (15.7%).</li> <li>Store-focused/multimedia social customers (15.7%).</li> <li>Uninvolved shoppers (15.4%)</li> <li>Online-favored multichannel enthusiasts/PC customers (6.5%)</li> <li>Store-favored multichannel enthusiasts/ multimedia social customers (6.4%)</li> </ul>
(Park & Kim, 2018)	Search, purchase, payment, delivery	Physical Store Online Store Mobile Payment Cash/Credit Payment	<b>Psychographic:</b> Not used. Study focused on the relative importance given to Shopping factors and channels. <b>Sociodemographic:</b> Gender, Age, Education, Income.	<ul style="list-style-type: none"> <li>445 surveys in Korea and 130 in US.</li> <li>Categories: Not specified</li> </ul>	K-means clustering and Ward's for segmentation.  Association Rule Mining (ARM) and Social Network Analysis (SNA) for characterization.	<ul style="list-style-type: none"> <li>Korea: Indecisive shoppers, versatile-convenience shopper, Traditional consumers, Innovative consumers, Early Adopter.</li> <li>US: Multi-channel shopper, Web-roomers, Online shopper, Reverse-show roomers</li> </ul>
(Sands et al., 2016)	Search, purchase, after-sales	Internet Store Mobile Social Media	<b>Psychographic:</b> Shopping Enjoyment, Innovativeness Price Consciousness, Loyalty, Time Pressure. <b>Sociodemographic:</b> Gender, Age, Income, smartphone ownership,	<ul style="list-style-type: none"> <li>930 consumers in Australia.</li> <li>Categories: Consumer electronics, Clothing, Holiday travel</li> </ul>	Latent Class Cluster Analysis (LCA)  Bayesian Information Criterion (BIC) and AWE (Averaged Weighted Evidence) for model and cluster selection.	<ul style="list-style-type: none"> <li>Research online –purchase offline anti-mobile/social media (36%).</li> <li>Research online –purchase offline Multichannel Enthusiasts (22%).</li> <li>Research online –purchase offline social media enthusiasts (16%).</li> <li>Internet-focused, anti-mobile (14%).</li> <li>Internet-focused, multichannel enthusiasts (12%).</li> </ul>
(Keyser et al., 2015)	Search, purchase, after-sales	Internet Store Call Center	<b>Psychographic:</b> Innovativeness, Perceived Risk, Product Complexity, Perceived Price, Involvement. <b>Sociodemographic:</b> Age, Loyalty, Average revenue	<ul style="list-style-type: none"> <li>314 customers in the Netherlands.</li> <li>Category: Telecom (mobile solutions)</li> </ul>	Latent Class Cluster Analysis (LCA) & Akaike Information Criterion (AIC3) for model selection.	<ul style="list-style-type: none"> <li>Research shoppers –aftersales: store (34%)</li> <li>Web-focused shoppers (22%)</li> <li>Store-focused Shoppers (18%)</li> <li>Research shoppers – After sales Internet/store (11%)</li> <li>Web-focused shoppers – after sales: store/call Center (9%)</li> <li>Call center-prone shoppers (6%)</li> </ul>
(Lazaris et al., 2014)	Search Purchase	Physical Store Call Center Online Store Catalogs In-Store Technologies Social Media Store Mobile Web Version Mobile Apps	<b>Psychographic:</b> Not used <b>Sociodemographic:</b> Gender, Age, Internet access, Mobile device access.	<ul style="list-style-type: none"> <li>894 online surveys in Greece.</li> <li>Category: not specified.</li> </ul>	Independent-Samples Kruskal-Wallisnon-parametric test.	<ul style="list-style-type: none"> <li>Full Omnishoppers (23%)</li> <li>Partial Omnishoppers (21%)</li> <li>In-Store Internet Users and Potential Omnishoppers (10%)</li> <li>In-Store Internet Users but Omnishopping Avoiders (26%)</li> <li>Non In-Store Internet Users but Potential Omnishoppers (6%)</li> <li>Omnishopping Avoiders (14%)</li> </ul>
(Konus et al., 2008)	Search Purchase	Store, Internet, Catalog	<b>Psychographic:</b> Price Consciousness, Loyalty, Shopping Enjoyment, Time Pressure, Motivation to Conform, Innovativeness. <b>Sociodemographic:</b> Household, Age, Education, Welfare, Urbanization, income.	<ul style="list-style-type: none"> <li>364 Customers in the Netherlands.</li> <li>Category: Electronics, computers, mortgage, health insurance, holidays, books.</li> </ul>	Latent Class Cluster Analysis (LCA) Bayesian Information Criterion (BIC) for model selection.	<ul style="list-style-type: none"> <li>Uninvolved shoppers (40% over all categories).</li> <li>Multichannel enthusiasts (37% over all categories).</li> <li>Store Focused (23% over all categories).</li> </ul>
(Keen et al., 2004)	Purchase	Physical store, online store, catalog.	<b>Psychographic:</b> Attributes of Customer channel choice. <b>Sociodemographic:</b> Gender, Age, Income, Education, Marital Status.	<ul style="list-style-type: none"> <li>281 Customers in the US.</li> <li>Category: Electronics (PC and CDs)</li> </ul>	Hierarchical and K-means Clustering.	<ul style="list-style-type: none"> <li>Generalists (35% CDs – 33% PCs)</li> <li>Formatters (15% CDs – 17% PCs)</li> <li>Price Sensitiveness (29% CDs – 24% PCs)</li> <li>Experiencers (22% CDs – 27% PCs)</li> </ul>

Source : (Herhausen et al., 2019); (Nakano & Kondo, 2018) ; (Park & Kim, 2018); (Sands et al., 2016) ; (Keyser et al., 2015) ; (Lazaris et al., 2014); (Konus et al., 2008) ; (Keen et al., 2004)

Among the segmentation studies, all of them have shared the objective of studying the customer preferences, attitudes, and behaviors in touchpoint choice among the purchase stages, describing them, in most of the cases, based on both psychographics and sociodemographic covariates. While most of them used a Multichannel perspective, Lazaris et al. (2014) and Herhausen et al. (2019) took an omnichannel approach for segmentation. The main difference between these two was that Lazaris et al. (2014) focused on describing the segments based on the usage intensity of channels in the purchase and search phases, and Herhausen et al. (2019) implemented their research using specific psychographic and demographic covariates, similar to the approach initiated by Konuş et al., (2008), but taking an omnichannel perspective and revealing key loyalty drivers.

Overall, different service and product categories were covered, being the electronics and mobile related items the most popular. The research samples have been diverse but the study of Nakano & Kondo (2018) was the sole to use actual transactional data and not surveys, basically to address the discrepancy between real behavior and intention (Nakano & Kondo, 2018). The main purchase phases analyzed in previous segmentation studies have been search and purchase. Keyser et al., (2015), Sands et al., (2016), and Park & Kim (2018) included an aftersales phase, but Park & Kim (2018) was the first to split this phase and considered payment and delivery as separate steps, which is in line with the omnichannel theory of Saghir et al. (2017). This aspect is important to this thesis as food-related purchases are becoming an omnichannel experience (Howard et al., 2017). Keyser et al., (2015) also commented that using 3 stages generates a better interpretation of the customer segments.

As mentioned before, most of the studies have had a multichannel approach, with some nuances in terms of the phases covered. Within each purchase phase, several touchpoints have been analyzed, and they can be grouped in 5 types: physical touchpoints, online stores & websites, social media, mobile touchpoints for purchase and payment, and support touchpoints. Physical touchpoints mainly covered brick and mortar stores, online stores and websites that were studied mainly from the retailer. However, Herhausen et al., (2019) was the first to amplify the scope of both the physical and online stores of the competitor, finding that they were relevant in the customer journey.

They also considered important to evaluate different websites and platforms such as comparison sites and search engines to describe how several digital channels can be used in an omnichannel purchase experience. Following (Nakano & Kondo, 2018) recommendation to evaluate specific digital channels

if a category is analyzed, this thesis should consider digital platforms not only from the store, but also those that the consumer finds relevant to search and purchase food, including those from a competitor. Social media platforms were analyzed as touchpoints with methodological differences in the purchase phases where it was considered. Most of them mainly considered them at the search phase, expect Sands et al., (2016) who included it in the purchase phase. Although social commerce will be a trend in the future (Howard et al., 2017), purchasing food stills be concentrated in online stores, delivery apps, physical stores or foodservice.

It is noteworthy that the increasing use of mobile technologies has enabled customers with tools to search, purchase, and pay. In this regard, mobile sites were considered in most of the studies, but a few have considered mobile applications as critical touchpoints. (Park & Kim, 2018) highlighted the use of apps for payment which is the path to follow in this thesis as payment is a critical step in the omnichannel purchase and an activity that can be easily performed nowadays. Other support touchpoints such as call centers and in-store technologies have been considered, and they also can have a role in food shopping especially for customer service or purchase convenience.

Regarding the customers segments identified, 4 important macro-segments can be mentioned across the studies analyzed. First, previous research has found *uninvolved customers* who are less loyal (Konus et al., 2008; Nakano & Kondo, 2018), indecisive (Park & Kim, 2018), less involved and interested in shopping (Nakano & Kondo, 2018) or are not prone to use several channels for purchase (Lazaris et al., 2014). However, even if they do not have preferences towards specific channels, Keyser et al. (2015), Sands et al. (2016) and (Herhausen et al., 2019) did not identify these customers, which might suggest that they can be switching their behaviors according to certain circumstances and that multiple touchpoints are still important (Herhausen et al., 2019).

Secondly, *store-oriented customers* evidently have shown strong favoritism towards brick and mortar stores and tend to be more traditional (Park & Kim, 2018). Nonetheless, (Nakano & Kondo, 2018) also found that these customers can still use social networks. Then, a third macro-segment of *Pure Online-oriented customers* have been found by Keyser et al., (2015), Sands et al., (2016), Park & Kim (2018) and (Herhausen et al., 2019). They use at least two online touchpoints for information search and always buy online (Herhausen et al., 2019), showing an innovative attitude towards shopping in virtual channels. These two opposite segments illustrate clear orientations among several product categories. Even if (Nakano & Kondo, 2018), who included groceries as a

subcategory, did not find pure online customers, this thesis will reveal if a segment of food shoppers only uses the internet in the purchase journey or if they have a more versatile behavior.

The fourth macro-segment can be labeled as *the multi-omnishoppers*. Across all the studies, this segment has been identified with specific characteristics that explain their behavior both online and offline. First, there are full multi-omni shoppers who have a notorious explorative and innovative orientation (Konus et al., 2008), who purchase both online and offline, have frequent use of mobile internet especially for comparing prices and to search for product information (Herhausen et al., 2019; Lazaris et al., 2014) and a positive journey satisfaction was key to gain their loyalty (Herhausen et al., 2019). (Nakano & Kondo, 2018) also found that they are loyal basically due to the nature of categories studied, contradicting the arguments of Konuş et al. (2008). Nakano & Kondo, (2018) covered categories of frequent purchase, such as groceries and beverages, and may also led to think that food shoppers can also be loyal even if they use several touchpoints for shopping and search, an attribute that this thesis will confirm.

Webroomers and showroomers have been identified as well as key multi-omnishopper subsegments (Herhausen et al., 2019; Lazaris et al., 2014; Nakano & Kondo, 2018; Sands et al., 2016). Webroomers prefer to search online and purchase offline, while showroomers explore their options in the store and then will purchase online. Even if there are some customers that tend to prefer the store or the web for purchase, they will use several touchpoints along their journey to decide for the best option (Lazaris et al., 2014; Nakano & Kondo, 2018; Sands et al., 2016). In this regard, this thesis will confirm whether customers have a preference to engage on this type of behavior or if they still are traditionalists, given that food shopping will increasingly be surrounded by different touchpoints and solutions for purchase, search and delivery by 2025, according to Howard et al. (2017).

The main limitations that can be highlighted across all previous research analyzed are the limited number of online and mobile touchpoints despite the fact that mobile internet represents 52% of all web traffic nowadays (Clement, 2020). Keen et al., (2004) performed the first attempt, but considered that retail store had a bigger advantage over the internet. (Konus et al., 2008). (Sands et al., 2016) (Sands et al., 2016) included the internet as a broad channel without being specific, while (Park & Kim, 2018) (Nakano & Kondo, 2018) and (Herhausen et al., 2019) used the online store as touchpoint.

Herhausen et al., (2019) were the first one to integrate more than one online touchpoint, apart from social media, to provide better insights. Moreover, as proposed by (Saghiri et al., 2017), the payment and delivery steps are critical, and these aspects were only analyzed by Park & Kim (2018). However, they considered the only mobile payment but not mobile purchase as Herhausen et al. (2019) given the importance of these channels in omnichannel and multichannel shopping (Saghiri et al., 2017; Verhoef et al., 2015). Given the rise of mobile applications for shopping and to have food and groceries delivered, these touchpoints, along with more than one online channel, will be considered for purchase, payment, and delivery.

It is also important to mention that the covariates used to describe or to predict customer segments, did not have a homogenous degree of significance in the previous segmentation studies, showing mixed results among all the product categories covered. This suggests a clear need to evaluate and propose covariates that can be tailored to the specific product category to study, aiming to identify clear behavioral patterns. This thesis will analyze specific covariates from segmentation studies and food-related studies in the coming sections, to select the ones that can enhance description, actionability and relevance for food consumption

Nevertheless, the relevance of all these segmentation studies for this thesis lays first, on the validation of the LCA technique for clustering not only with survey data but also larger volumes of information. It has been found as proper method to use both data related to channel preferences and psychographic and demographic variables. Secondly, it was found useful to switch the psychographic and innovate when the covariates are included, to expand the purchase phases and to include several touchpoints, differentiated or reused in each phase, to enrich the analysis of the customer segments and aiming to find the “moments of truth” (Herhausen et al., 2019, p. 7) for the food shopping in this thesis.

Finally, considering mobile technologies, applications and social media is critical in the omnichannel context as it was described by (Park & Kim, 2018) and supported by (Herhausen et al., 2019) and (Nakano & Kondo, 2018). These thesis will consider these touchpoints in line with the omnichannel framework (Saghiri et al., 2017).

### 2.1.3. Covariates in Multichannel and Omnichannel Segmentation

Among all the previous studies analyzed, sociodemographic and psychographic covariates have been used to explain different multichannel choices in different categories and countries. These covariates will be discussed to evaluate the accuracy and significance that they may have for this thesis, their limitations, and possible improvements.

It is important to note that the psychographic covariates have been an essential element in multichannel and omnichannel segmentation, and previous findings have confirmed that consumer behavior is influenced mainly by psychographics than sociodemographics (Ailawadi et al., 2001; Konuş et al., 2008). Nonetheless, not all the covariates employed in segmentation research have been significant exploring behavior as a whole, or by category, suggesting that it might result useful and necessary to adapt, build or use variables adjusted to the category and the perspective used (number of phases, agents and touchpoints).

As it was described in the previous section, the first attempt to introduce variables to explain a particular channel choice for purchase was done by Keen et al., (2004). In their study, the preference of a specific format (i.e. store, internet), price, and the attitude from previous positive experiences were important attributes identified for the segments. It should be noted though that they did not use scales in their measures as the subsequent studies where it was the preferred method. The fact that they proposed specific linked to the type of products covered in the study, highlights the importance of applying the same practice to segment customer for specific categories.

The importance of having a specific retail format to purchase products and their price preferences indicates that they are also important to explain customer behavior in several multichannel segments. For that reason, related covariates such as price consciousness or perceived price were also used in segmentation studies (see **Table 3**). Almost all studies have included it using specific scales labeled *price consciousness* and *perceived price*. The former is defined as the degree in which individuals pay attention to low prices (Lichtenstein et al., 1990) looking to save money during their purchases (Konuş et al., 2008). The latter refers to customer's perception of the product's price in a determined channel (Verhoef et al., 2007).

In the omnichannel setting, as customers visit a store and use their mobile phones simultaneously to check prices and better deals (Verhoef et al., 2015),

including this covariate to predict their preference in a determined segment is important. As price consciousness was significant in 4 of the 6 studies explored, it would be expected to detect customers with an omnichannel behavior also when s/he buys food, motivated by their need to reduce their personal or family budget.

Then, *shopping enjoyment* was another covariate included in segmentation studies. It is related to the entertainment (Babin et al., 1994) and pleasure (Ailawadi et al., 2001) found in shopping. Although it has been found to influence channel choice positively for purchase and search (Verhoef et al., 2007) and has been significant in most of the studies analyzed, Verhoef & Langerak (2001) did not identify an association between enjoyment and the advantage of groceries sold online. Evaluating this covariate, or a related scale for shopping in this thesis will confirm if such behavior applies to the whole food shopping experience.

*Innovativeness* is defined as the pleasure (Ailawadi et al., 2001) and preference to explore new experiences and products (Midgley & Dowling, 1978). This covariate might be linked to the degree to which customers use different channels (Konus et al., 2008) to look for innovative items online or offline. It has been used in 4 of the studies analyzed and has been significant in 3 of them. For food shopping, looking for new recipes or different ingredients derived from an innovative orientation in people could also motivate to use different channels, without necessarily buying in only one channel. It would be useful to include it in this thesis, using the same scale or adapting it.

Seeking for the opinion of others to decide is known as the *motivation to conform* (Ailawadi et al., 2001). As mentioned previously, Keen et al. (2004) used it in their research to evaluate if it influenced channel choice in line with Verhoef et al., (2007) who stated that people's reference group could also influence the channels they use. However, none of the studies analyzed unveiled that it was a significant covariate for cluster membership prediction. In the food shopping setting, individuals can receive opinions to purchase in a certain channel, but their final decision might be linked to other variables related to their health, diet preferences, or budget, so it won't be used in this thesis.

The implementation of *retailer or brand loyalty* in segmentation studies has had different outcomes and methods for its measurement. Konuş et al., (2008), Nakano & Kondo (2018) and Sands et al., (2016) used the same scale<sup>1</sup>. The

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<sup>1</sup> (Keyser et al., 2015) did not use it as a psychographic scale but found it significant and important for the store focused segment.

results between the first two were contradictory<sup>2</sup>, while Sands et al., (2016) did not find it significant. From the customer perspective, having a favorite brand or store might lead them to stay in one single channel (Konus et al., 2008).

However, Nakano & Kondo (2018) suggested that multichannel oriented customers can remain being loyal. Given that customers have now access to a larger number of digital touchpoints, and mixed retail models are being implemented, such as *click-and-collect* (Bertrand, 2019), it may be expected that individuals who use several touchpoints to buy foods can remain loyal if their favorite brand or store (whether digital or physical) offers them the chance to do so. In fact, it was found that customers with experience using shopping groceries online tend to be loyal to the online store, and the alignment of the assortment with the offline store is important to reduce perceived risk (Melis et al., 2015). That is aligned with the concept of integration in the omnichannel theory (Saghiri et al., 2017) and should be a covariate to consider in this thesis.

Similarly, *time pressure* has had mixed results in segmentation studies. It is related to the tendency of considering time as a limited resource (Kleijnen et al., 2007). While Verhoef & Langerak (2001) found a positive relationship between the relative advantage of online channels and time pressure, Konuş et al., (2008) could not prove that it was significant in any segment. It was included by Herhausen et al. (2019), stating that customers with less time might prefer to consider few touchpoints, but it resulted partially significant in two segments in their second database. In this thesis, it will be confirmed if customers with an orientation to save time opt to use mainly digital channels to search or purchase food, in line with some findings that revealed that customers had a positive attitude towards online food delivery services when they allowed them to save time (Yeo et al., 2017). Consequently, this covariate will also be included using the same scale or adapting it for this thesis.

Customer *involvement* was used by Herhausen et al., (2019)<sup>3</sup> and Keyser et al., (2015) arguing that involved consumers would find beneficial to shop in different channels (Herhausen et al., 2019). Indeed, it was found that customers in multiple touchpoints and webroomer (online to offline) segments were more involved than other segments (Herhausen et al., 2019). Categories such as groceries have been labeled as products of low-involvement (Nakano & Kondo, 2018), but, as customers are now better informed and seek for personalized experiences (Howard et al., 2017), they could find their food purchasing

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<sup>2</sup> It is important to highlight that (Nakano & Kondo, 2018) studied other product categories than the ones covered by (Konus et al., 2008). They included categories of lower involvement and higher rotation (Groceries, Beverages, sundries, cosmetics and drugs) See **Table 3**

<sup>3</sup> They did not use the same involvement scale (Srinivasan & Ratchford, 1991) as (Keyser et al., 2015). They only asked how important the product purchased was for the customers.

experiences more appealing if they explore more channels. This could depend on other specific covariates as well, so related scales specific for food shopping will be included.

Herhausen et al., (2019) also found purchase *journey duration* as a significant covariate in multichannel and webroomer segments. Evidently, this may be related to a long time invested looking for products in different channels. As this thesis will cover food purchasing as an activity both for groceries and prepared meals, the time invested in this activity may depend on the type of meal or the context, so it will not be considered as other covariates might have a higher significance.

The *experience using online* and *physical channels* were measured by Herhausen et al., (2019) and both were found significant among most the segments. It will be confirmed in this thesis if customers with a longer experience using online channels might also be motivated to use digital channels to purchase foods, thus belonging to segments that prefer these channels. On the other hand, customers that have more experience buying in physical stores might prefer staying on that channel (Gensler et al., 2012). To better understand this behavior in the omnichannel food shopping setting, these covariates will be used.

*Customer duration* and *buying frequency* were also used by Herhausen et al., (2019) and none of them were significant. It is already known that purchasing food tends to be a regular activity so it will not be used in this thesis, along with *customer duration*. However, the *spending level* of customers was found significant in their research, and it would be useful to use it to describe if a segment has a certain budget average for their food needs. This scale should be used as a demographic variable. In another research, Keyser et al., (2015) introduced risk aversion and product complexity as covariates, but none of them were significant in their 3-stage purchase model. This thesis will not cover products of high complexity, but the environmental concern could be a variable to include in this thesis.

Regarding sociodemographic covariates, Konuş et al. (2008) was the first one to propose and identified certain relationships revealing evidence of demographics and channel behavior. Several variables have been used in the segmentation studies analyzed, but not all of them have been significant. From the variables used in past segments, gender, age, household size, income, spending level (in food shopping) and gender will be used in this thesis as it is expected to

influence segment membership at some degree as previous studies. It will be found whether younger consumers have a dynamic omnichannel food shopping behavior depending on their needs or budgets. Income and spend levels might differentiate some characteristics in each segment. Individuals living in big families or as a couple, might prefer a channel to purchase but several for searching food, so household size is an important variable to consider.

#### 2.1.4. Multichannel and Omnichannel Segmentation Methods

The first critical step in strategic marketing is segmentation. This task is performed by companies to better understand the main characteristics of their customers and their behavior, to allow targeting their preferred segments and execute more efficient operational marketing tactics. It has been discussed previously that customer behavior has changed as new technologies are available to shop online and offline and segmenting the market has allowed identifying several multichannel customer profiles in different countries or categories.

Researchers have implemented different segmentation methodologies as can be seen in **Table 3**. The method that has been widely used has been the Latent Class Cluster Analysis, followed by K-means cluster analysis in two studies. In this section, both segmentation methodologies will be discussed and analyzed to select the best approach for this thesis, beginning with Hierarchical and K-means Clustering, and then Latent Class Cluster Analysis.

Performing a segmentation study using k-means clustering normally consists of two steps. Keen et al., (2004) and Park & Kim, (2018) documented this approach in their study, using hierarchical clustering to determine the number of clusters and then using non-hierarchical clustering (k-means) to adjust their results. This practice has also been analyzed by Charry et al. (2016) who suggested that among all the hierarchical clustering methods available, the Wards Minimum Variance method is used to set the number of clusters, then k-means clustering is performed using the number of clusters previously set, to assign the final cluster membership to the observations.

As the main non-hierarchical method used in marketing, employing Ward's allows to reduce the variance in each cluster, comparing the mean of the variables with the observations (Charry et al., 2016) and can work with quantitative, count or binary information (Charry et al., 2016). The number of clusters selected by the researcher should find a proper balance between a proper number of segments (for analysis) and its size (Charry et al., 2016). In the K-method, a random number of observations are chosen and are used as "centroids...so that the squared distance between each individual and the individual is minimized" (Charry et al., 2016, p. 36).

K-means tend to be faster than hierarchical methods for larger samples (Charry et al., 2016) and it allowed Keen et al., (2004) and Park & Kim (2018) to find an appropriate number of segments in their studies. However, it also carries some limitations such as the need to set the number of clusters and to standardize the variables before the analysis is performed (Magidson & Vermunt, 2002a). Moreover, it works mainly with interval quantitative variables (Magidson & Vermunt, 2002a), it does not perform properly with outliers and may give different results in separate clustering attempts (Singh et al., 2011).

Given the mentioned drawbacks for k-means clustering, it has been observed in the previous section that the segmentation tasks involved a complex combination of variables in different purchase stages to understand customer behavior oriented to their usage of several touchpoints. Consequently, the Latent Class Cluster Analysis (LCA) has been the preferred method for customer segmentation, as it has been considered as an effective instrument, including behavioral-based clustering (Magidson & Vermunt, 2002b).

One of the main advantages of this method is that it is probabilistic, meaning that it uses the estimation of maximum likelihood methods to create models that will assign probabilities for clustering membership reducing the error of classification compared to the k-means clustering (Magidson & Vermunt, 2002a). Additionally, it allows to use of variables in different scales (Magidson & Vermunt, 2002b) and the inclusion of several covariates, that could be

demographical, improving the segment's description (Magidson & Vermunt, 2002a). In practical terms, it allows to identify hidden linked patterns in data that k-means analysis do not observe.

Since this thesis aims to identify customer segments based on their usage of different touchpoints in the omnichannel food purchase process, including several covariates that explain its behavior for this specific category will enrich customer profiling. This approach is similar to the studies previously analyzed, which was first implemented by Konuş et al., (2008) who identified the clustering structure based on channel usage and the impact of potential covariates. Keyser et al., (2015), Sands et al., (2016) and Nakano & Kondo, (2018) followed their steps adding one stage to the purchase journey, resulting in also being a useful tool. Herhausen et al., (2019) implemented the same methodology, alongside with k-means cluster analysis as a complement to confirm the findings. In the case of Park & Kim (2018), it should be noted that their clustering research design was based on the importance given to retail factors, using ranked ordered data, and not behavioral and sociodemographic covariates, leading them to use other complementary methods such as Association Rule Mining and Network visualization.

Performing a segmentation study based on behavioral data will provide a better insight of customers, and given that this thesis seeks to uncover this patterns for omnichannel food purchasing, LCA is the best method to use, as it has proved to be better than K-means clustering (Magidson & Vermunt, 2002a) and it has been widely used in multichannel and omnichannel segmentation studies.

## **2.2. Consumer's Food Shopping Behavior**

### **2.2.1. Food Related Lifestyles**

The first chapter of the literature revealed key theoretical aspects and research initiatives that highlighted the importance of segmenting to identify different customer's behavioral patterns based on their use of different channels. Most of the segmentation studies revised in the previous section have covered multiple categories, and just a few were focused on a specific category (Keen et al., 2004) (Keyser et al., 2015). Some covered groceries as a subcategory in a broad

perspective but they did not analyze the category with behavioral covariates linked to food products.

With the emergence of new technologies that are affecting how customers purchase and consume, companies must observe these patterns to generate more sales, increase loyalty, and attract new customer segments (Deloitte, 2014). Among the main imperatives for the food industry, (Howard et al., 2017) stated that to ensure their importance in the purchase journey, companies should identify customer segments, their needs, motivators, and several factors that affect purchase behavior in each channel.

As customers have now more options to fulfill their food shopping needs through new digital disruptions, they will expect to have an integrated experience in both physical and digital channels (Howard et al., 2017). Given that the food shopping experience will be omnichannel, guided by lifestyles and customization by 2025 (Howard et al., 2017), it is necessary to approach this segmentation thesis using the appropriate set of variables that will enable a better comprehension of the customer that uses several (or some) touchpoints to purchase food and interact in their omnichannel experience.

From that perspective, customer segmentation in the food domain has been widely addressed, but most of them have been focused on the aspects that drive food choice based on product benefits, customer's attitude, or life values, in different markets, using several demographic or psychographic variables as segmentation bases. Grunert (2019) analyzed extensively this topic in the food domain, suggesting that the segmentation process should be based on concepts founded on "previous theoretical reasoning linking them to how customers react to marketing stimuli ...and to their food purchasing behavior" (Grunert, 2019, p. 314).

Several segmentation approaches were analyzed by Grunert (2019), and his main findings and comments have been summarized in **Table 4**. Even though the Product benefits, food-choice, and MEC methods have solid theoretical bases, most of them are focused on the motives that drive the customer to select a product and not the factors around the shopping purchase experience itself. These can be driven by inner personal beliefs, behavioral or social motives, attitudes, or psychographic orientations. In contrast, since the process of food purchasing is becoming a "lifestyle choice" (Howard et al., 2017, p. 19), the Food Related Lifestyles (FRL) methodology is a powerful tool to complement the segmentation base for this thesis, applying it in a novel perspective based on the omnichannel purchase process discussed in the previous chapter.

**Table 4 : SEGMENTATION BASES IN THE FOOD DOMAIN**

Segmentation Base	Advantage	Disadvantage
Product Benefits (Haley, 1968)	<ul style="list-style-type: none"> <li>Theoretically supported and intuitively linked with buying behavior</li> </ul>	<ul style="list-style-type: none"> <li>Segmentation is mainly product focused.</li> <li>Segments do not provide enough information about actual customer behavior.</li> <li>No motivational factors are considered.</li> <li>Cultural bias can affect the scale.</li> </ul>
Means-end Chains MEC (Gutman, 1982)	<ul style="list-style-type: none"> <li>Links product attributes with life values satisfaction.</li> <li>Good theoretical basis</li> </ul>	<ul style="list-style-type: none"> <li>Demanding in qualitative preparation, analysis and data collection.</li> <li>Preferably for segmentation in a country-group study.</li> <li>Product Focused.</li> </ul>
Food Related Lifestyles (Brunso, 1997).	<ul style="list-style-type: none"> <li>Based on what people consider important about foods and their shopping habits, meal patterns, food related motives.</li> <li>Designed to be used in several languages and contexts</li> <li>Well reported results.</li> <li>Has been proved to explain the relationship between life value and food related behavior.</li> <li>Effective in Western countries.</li> </ul>	<ul style="list-style-type: none"> <li>Complexity and length of factors</li> <li>Some dimensions may be out-of-date</li> <li>Does not include ethical or environmental concerns</li> </ul>
Food Choice (Step toe et al., 1995)	<ul style="list-style-type: none"> <li>Evaluates food choice based on several motives</li> <li>Includes ethical concern as dimensions.</li> </ul>	<ul style="list-style-type: none"> <li>Problems with reliabilities and factor invariance</li> <li>Limited use in segmentation</li> </ul>

Source : Based on (Grunert, 2019).

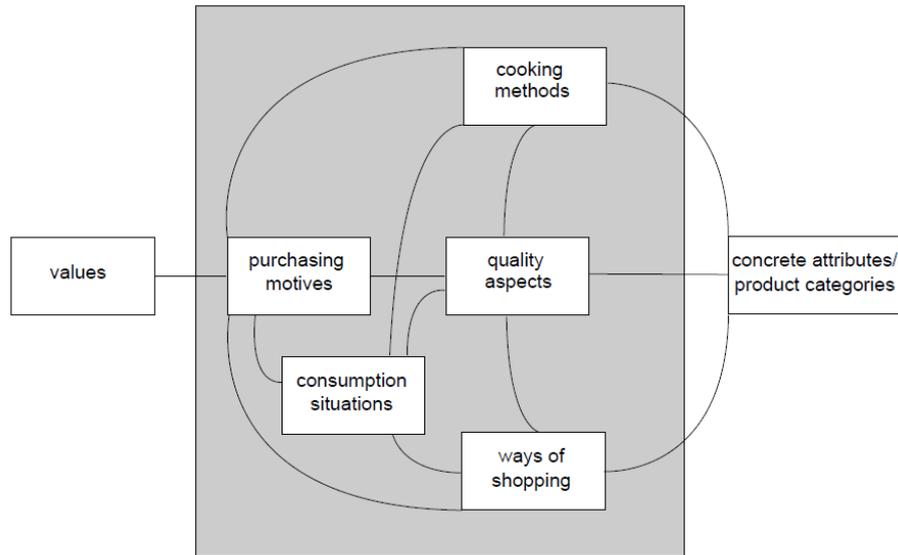
The FRL has been implemented in several studies (Grunert, 2019). It has less critical disadvantages compared to the other methodologies, and different segmentation studies have solved the disadvantage related to the off-date factors and the lack of others, combining the original FRL items with other covariates and aligning them to the research objective, as it will be discussed in the following section.

Grunert (2019) stated that the FRL is a segmentation tool that can provide the insight of customers not only based on their attitudes towards food products but also on how they “react to food-related marketing efforts in general” (p. 316). This method was introduced, developed and implemented across Europe (Brunso, 1997; Brunso et al., 1996), and following revisions and validations (Brunso & Grunert, 1998; Scholderer et al., 2004) were performed concluding that the tool provided powerful measures to evaluate food-related lifestyles in western Europe.

The authors define the lifestyle approach as “the system of cognitive categories, scripts, and their associations which relate a set of products to a set of values” (Brunso et al., 1996, p. 5). This suggests three main conceptual notions: lifestyle relates products with personal consequences derived from actual behavior, it overpasses a particular product or brand and plays a role “between values and product/brand (...) attitudes” (Brunso & Grunert, 1998, p. 146). Built with a strong cognitive basis, the FRL provides an insight on how certain activities related to specific aspects of food purchase, consumption and quality can unveil a behavioral profile of consumers which can be used as a base for segmentation. In fact, this tool showed that people are different in their

enthusiasm, innovativeness, and the rational-emotional approach for food and eating (Grunert, 2019).

**Figure 2 : FRL COGNITIVE STRUCTURE MODEL**



Source: (Brunsø et al., 1996)

**Figure 2** illustrates the cognitive structure model of the FRL, showing how it mediates the values with concrete attributes related to a product category (food) among 5 areas: ways of shopping, cooking methods, importance of quality aspects, consumption situations and purchase motives. Each one has its own set of dimensions, which in total provide 69 items or statements that are answered using a 7 point scale from agree to disagree. The meaning of each area and the dimensions in its revised version<sup>4</sup> (Scholderer et al., 2004) can be found in **Table 5**

<sup>4</sup> The wording in seven statements were changed to enhance reliability (Scholderer et al., 2004)

**Table 5 : FOOD-RELATED LIFESTYLES AND COGNITIVE ASPECTS DEFINITIONS**

Cognitive Structure Aspects	Meaning	Dimensions
Ways of Shopping	<p>“How do people shop for food products? Is their decision-making characterized by impulse buying or by extensive deliberation? Do they read labels and other product information, or do they rely on the advice of experts, such as friends or sales personnel? In which shops—one-stop versus specialty food shops?”</p> <p>(Brunsø et al., 1996, p.5)</p>	Importance to Product Information
		Attitudes to Advertising
		Enjoyment from Shopping
		Specialty Shops
		Price Criteria
Quality Aspects	<p>“This refers not to concrete attributes of individual products, but to attributes which may apply to food products in general. Examples may be healthy, natural, fresh, and tasty”.</p> <p>(Brunsø et al., 1996, p.6)</p>	Shopping List
		Health
		Price/quality relation
		Novelty
		Organic Products
Cooking Methods	<p>“How are the products purchased transformed into meals? How much time is used for preparation? Is preparation characterized by efficiency, or by indulgence? Is it a social activity, or one characterized by family division of labor? To which extent is it planned or spontaneous?”</p> <p>(Brunsø et al., 1996, p.5-6)</p>	Taste
		Freshness
		Interest in cooking
		Looking for new ways
		Convenience
Consumption situations	<p>“How are meals spread over the day? How important is eating out?”</p> <p>(Brunsø et al., 1996, p.6)</p>	Whole family Planning
		Woman’s Task
Purchasing motives	<p>“What is expected from a meal, and what is the relative importance of these various consequences? How important are social aspects, hedonism, tradition and security?”</p> <p>(Brunsø et al., 1996, p.6)</p>	Snack vs Meals
		Social event
		Self-fulfilment in food
		Security
		Social relationships

Source : (Brunsø et al., 1996); (Scholderer et al., 2004)

As the consumption of food is becoming an experience and an expression of lifestyle (Howard et al., 2017), the FRL provides a set of dimensions that can allow understanding how consumers behave in their food shopping journey and will enhance the analysis of their behavior and preferences towards a specific or several touchpoints to fulfill their needs. In the previous chapter, some covariates were found to be relevant in this experience, but the FRL covariates give a tailored framework specific to food shopping that will be relevant to this thesis.

In terms of the *Ways of shopping*, price consciousness and shopping enjoyment find an important place in this aspect, as it was for omnichannel shopping. Customers may navigate among different touchpoints (or prefer a few) according to their price sensitiveness, the importance they give to product information and may respond in different ways to advertising. The specialty shops scale will be omitted as several touchpoints will be evaluated in this thesis.

The *Quality aspects* play a central role in food consumption, and the advantages or disadvantages perceived by customers towards digital or hybrid channels could be influenced by the importance they give to aspects such as health,

freshness, or price/quality relation. As it was seen in omnichannel segmentation, novelty can be related to the innovativeness covariate used in previous studies, and it can unveil whether customers with such orientation in their food purchases tend to use or give more importance to certain touchpoints.

Howard et al. (2017) highlight that the shopping experience is truly developed during the preparation, sharing, and consumption of food in a social context. They also found that 84% of customers prefer to cook using “premade ingredients... or from the scratch” (Howard et al., 2017, p. 22). As new business models are disrupting the way people purchase food, making easier to prepare, for example, a fancy restaurant recipe at home using digital channels (Howard et al., 2017) understanding the inner motives in *cooking methods* such as the interest in cooking, looking for new ways to do it, and meal planning would reveal if such profiles have preferences to a touchpoint before the purchase, the delivery or for sharing the experience. These dimensions are related to the innovativeness and involvement covariates found before in omnichannel segmentation.

Similarly, identifying the motivations behind food consumption such as the purchasing motives and situations for self-fulfillment, social life, or security (contrary to novelty) can also complement the analysis of omnichannel food shoppers and see if a specific profile opts to use only physical channels or specific methods for delivery. Most of these covariates, along with the dimensions revised before can be complemented with other psychographic variables such as price consciousness, innovativeness, loyalty, and time pressure, that were found important in omnichannel and multichannel segmentations.

Nonetheless, the cognitive aspects have covered slightly some dimensions related to environmental, safety, and health concerns such as the importance to product information, healthy food, and preferences for organic foods. As customers are more environmentally aware (JLL, 2018) is important to consider covariates linked to these concerns to evaluate if they can trigger the preference of certain channels for food shopping. The following section will expose and analyse how several segmentation studies, that used the FRL covariates as a base for segmentation, have combined or adapted covariates to achieve their research objectives. (Grunert, 2019) suggested that new aspects could be added for food shopping styles, cooking, or product-specific items according to each segmentation approach.

### 2.2.2. Prior Segmentation Research on Food Shopping and Lifestyles

Brunsnø et al. (1996) concluded that the FRL had a reasonable level of cross-cultural validity that allowed identifying segments with similar food-related consumer's lifestyles, with certain singularities in some of them. Although it has been used in the food domain with acceptable levels of efficiency and depth, its implementation should be tailored to the objective of a segmentation study. In this section, the main findings, importance, and limitations across five relevant studies that segmented customers based on lifestyles and attitudes to shopping will be analyzed to verify and evaluate if adapting and combining the FRL with other scales is a methodological procedure that this thesis could also follow.

While three studies used the segmentation studies to evaluate consumer lifestyles for specific food products (Björnsson, 2015; Nie & Zepeda, 2011; Shim et al., 2001), two studies analyzed customer shopping attitudes and behavior as a whole (Chetthamrongchai & Davies, 2000; Gunarathne et al., 2017), using food-related lifestyles as a base for segmentation. In order to provide an efficient analysis of the food-related lifestyles dimensions covered in all the studies, all of them have been grouped in nine *Lifestyle Aspects* (see detailed list in **Annex 1**). As it can be seen in **Table 6**, five aspects are clearly related to the original FRL methodology and have been used in most of the studies, both adapted or borrowed from the original tool. Food as an experience, Environmental awareness, healthy lifestyles, and Time Concerns were added by the researchers using their own proposed scales or borrowing from other sources.

**Table 7** illustrates in larger detail which lifestyles aspects have been covered in each study, the number of dimensions used, and the sources from which they gathered those scales or dimensions for their analysis. It is noteworthy that food quality & safety and food shopping enjoyment are the most frequent aspects that have been evaluated in these studies. In this thesis, they can reveal if customers, who put certain importance on those aspects, are inclined to use diverse touchpoints for purchase and information, or if they tend to be more traditional.

**Table 6 : LIFESTYLES, RELATED ASPECTS, STUDIES AND NUMBER RELATED DIMENSIONS**

Lifestyle Aspects Covered	FRL (1997) Related Aspects	Studies	Dimensions
Food Quality & Safety	Quality Aspects	(B)(C)(D)(E)	15
Food Shopping Enjoyment	Ways of Shopping	(A)(B)(C)(D)(E)	10
Cooking Enjoyment	Cooking Methods	(B)(C)(D)(E)	9
Novelty	Purchasing Motives Quality Aspects	(C)(D)(E)	4
Food Shopping Convenience	Consumption Situations Purchasing Motives	(A)(C)(D)	1
Food as an Experience	-	(B)(E)	6
Environmental Awareness	-	(C)(D)	6
Healthy Lifestyle	-	(C)(D)	6
Time Concerns	-	(A)	1

(A) Chetthamrongchai & Davies (2000) (D) Björnsson (2015)  
 (B) Shim et al. (2001) (E) Gunarathne et al. (2017)  
 (C) Nie & Zepeda (2011)

**Table 7 : PREVIOUS FOOD SHOPPING SEGMENTATION STUDIES**

Study	Lifestyle Aspects Covered	# Dimensions Used	Dimension/Scale Sources	Segments
(Chetthamrongchai & Davies, 2000)	Food Shopping Enjoyment	4	<ul style="list-style-type: none"> <li>• (Buttle and Coates, 1984)</li> <li>• (Herrmann and Warland, 1990)</li> <li>• 4 scales Proposed by the Authors</li> </ul>	<ul style="list-style-type: none"> <li>• Hedonists (20%),</li> <li>• Apathetic but regular (23%)</li> <li>• Convenience seekers (29%)</li> <li>• Time pressured (28%)</li> </ul>
	Time Concerns	1		
	Food Shopping Convenience	1		
(Shim et al., 2001)	Food Quality & Safety	7	<ul style="list-style-type: none"> <li>• 9 scales Adapted from Food Related Lifestyles</li> <li>• 4 scales Proposed by the Authors</li> </ul>	<ul style="list-style-type: none"> <li>• Creative/highly involved (50%)</li> <li>• Practical/moderately involved (30%)</li> <li>• Aesthetic/uninvolved (20%)</li> </ul>
	Food as an Experience	3		
	Food Shopping Enjoyment	2		
	Cooking Enjoyment	1		
(Nie & Zepeda, 2011)*	Food Quality & Safety	8	<ul style="list-style-type: none"> <li>• 7 Adapted from Food Related Lifestyles*</li> <li>• 3 Adapted from Guagano et al. 1995</li> <li>• 12 Proposed by the Authors*</li> </ul>	<ul style="list-style-type: none"> <li>• Rational consumers (29%)</li> <li>• Adventurous consumers (24%)</li> <li>• Careless customers (18%)</li> <li>• Conservative uninvolved (29%)</li> </ul>
	Environmental Awareness	5		
	Healthy Lifestyle	4		
	Cooking Enjoyment	2		
	Novelty	1		
	Food Shopping Enjoyment	1		
(Björnsson , 2015)	Food Shopping Enjoyment	5	<ul style="list-style-type: none"> <li>• 9 from Food Related Lifestyles (1997)</li> <li>• Lindeman &amp; Väänänen (2000)</li> <li>• Pliner and Hobden (1992); Ritchey et al. (2003)</li> <li>• Roininen et al. (1999)</li> <li>• Steptoe et al. (1995)</li> <li>• 3 scales Proposed by the Author</li> </ul>	<ul style="list-style-type: none"> <li>• Health oriented disbelievers (30.2%)</li> <li>• Health oriented believers (20.4%)</li> <li>• Careless (17.2%)</li> <li>• Habitual skeptics (19.6%)</li> <li>• Average disbelievers (12.6%)</li> </ul>
	Food Quality & Safety	4		
	Healthy Lifestyle	2		
	Novelty	3		
	Environmental Awareness	1		
	Food Shopping Convenience	1		
(Gunarathne et al., 2017)	Cooking Enjoyment	7	<ul style="list-style-type: none"> <li>• 8 from Food Related Lifestyles (1997)</li> <li>• 4 Adapted from Food Related Lifestyles</li> <li>• 7 scales Proposed by the Authors</li> </ul>	<ul style="list-style-type: none"> <li>• Average Nutrition Enthusiast (21.7%)</li> <li>• Light Foodies (21.5%), %)</li> <li>• Uninvolved (18.2%)</li> <li>• Traditionalist (17.1%)</li> <li>• Uninterested (9.5%)</li> <li>• Foodies (12%)</li> </ul>
	Food as an Experience	5		
	Food Quality & Safety	4		
	Novelty	2		
	Food Shopping Enjoyment	1		

Source: Own analysis. \*This research did not used the original scales but direct statements (Yes/No) adapted from the FRL tool.

Cooking Enjoyment, seeking novelty and Food as an Experience are also important aspects to be considered as they can provide insights about how customers fulfill these needs and the touchpoints that are relevant for different customer segments. For instance, (Björnsson, 2015) unveiled a segment of *Foodies* who had an important orientation towards the involvement and the

enjoyment of cooking and sharing food with friends and family. They are passionate and curious about food and put attention to their well-being (Baumann & Johnston, 2010). Therefore, using this tool can provide behavioral information about this kind of food shoppers in this thesis, as it has been mentioned that not only food purchasing, but cooking is also becoming a social, health-oriented and lifestyle expression.

Surprisingly, as reviewed in the previous chapter of this literature review, convenience is a covariate that was not covered in omnichannel segmentation studies. In the food domain, Food Shopping Convenience has not been widely used. It may be explained by the nature of most of the segmentation studies that were focused on product development and market research. Even if they included behavioral or attitudinal aspects of food purchase, most of them considered only physical stores as touchpoints and did not analyzed the influence of other types of channels for shopping or for information search.

Additionally, as it has been revised before, the original dimensions of the FRL do not include aspects regarding environmental convenience and healthy lifestyles. These are aspects of higher relevance in the food industry as customers are more environmentally aware (JLL, 2018) as well as more healthy-conscious (Euromonitor International, 2019b). These are important aspects to be considered in this thesis, along with time concerns that have been found relevant for omnichannel segmentation studies.

Concerning the sources of the dimensions and methods used, note that while most of the studies used scales from the FRL, Nie & Zepeda, (2011) adapted 7 dimensions as direct statements, for instance, asking whether convenience or healthiness was important or not. , without using scales. The rest complemented their analysis using new proposed dimensions, such as Gunarathne et al. (2017) who adapted them for the country and the research or using scales from other authors. These aspects analyzed are important for this thesis as it shows that the FRL has been the main methodological source to evaluate behavioral and attitudinal covariates in food segmentations studies, and adapting or using several segmentation bases can complement each other to generate improved results (Kamakura & Wedel, 2000).

While exploring all the segments identified by previous research on food shopping, they can be grouped into 3 main customer macro profiles. In general, *Uninvolved* consumers tend to be less involved in food shopping activities or do not see it as a hedonist activity. They are time-pressured (Chetthamrongchai & Davies, 2000), convenience seekers (Chetthamrongchai & Davies, 2000; Nie &

Zepeda, 2011) and less concerned about healthiness or environmental issues (Björnsson, 2015; Gunarathne et al., 2017; Nie & Zepeda, 2011), thus do not consume organic foods and demand an acceptable quality for the price they pay (Gunarathne et al., 2017; Nie & Zepeda, 2011). This thesis will reveal whether these customers, if identified, tend to be store-focused or uninvolved in omnichannel shopping.

The *Conservative/Rational* consumers seek to find a balance between price (Björnsson, 2015; Gunarathne et al., 2017; Nie & Zepeda, 2011), convenience (Chetthamrongchai & Davies, 2000; Shim et al., 2001) and are more focused on quality aspects such as healthiness and environmental issues (Björnsson, 2015; Gunarathne et al., 2017; Nie & Zepeda, 2011), than the uninvolved consumers. Then, the *Food Enthusiasts* are consumers who see food shopping (Chetthamrongchai & Davies, 2000; Nie & Zepeda, 2011; Shim et al., 2001) and cooking (Gunarathne et al., 2017; Nie & Zepeda, 2011) as a pleasant experience, they attend to food events (Gunarathne et al., 2017), seek quality, organic foods, novelty and are concerned about their health and the environmental impact of their consumption (Björnsson, 2015; Gunarathne et al., 2017; Nie & Zepeda, 2011). Similarly, this thesis will unveil if similar segments seek a versatile use of several touchpoints for shopping or information search, or if they still prefer only physical channels.

Some limitations have been observed across all the studies such as the lack of inclusion of digital or hybrid channels for product search, purchase, or after-sales service. The sample sizes and profiles for representability, and the need to use the local languages when implementing the data collection tools have been a general aspect emphasized by the authors. Nonetheless, the studies analyzed have provided potential behavioral scales than can be used to describe omnichannel food shopping attitudes and behavior, as they have shown to be effective using the lifestyle approach to segment customers in the food domain, integrating psychographic and demographic variables.

In conclusion, it can be observed that all studies have mixed certain dimensions of the original FRL with scales developed for each study or borrowed from other segmentation bases such as Food Choice or Attitudes to Time. The environmental and health concerns that the FRL does not evaluate can be addressed using new covariates from other sources. It is clear the shopping enjoyment, using scales tailored for food shopping, should be included as well as the convenience seek while shopping, and not from the food itself. Olsen et al., (2007) and Onwezen et al. (2012) have designed scales for convenience orientation, which is an important covariate to measure in the omnichannel food

purchase context as it has become a need fulfilled nowadays with online shopping or home delivery (Howard et al., 2017).

## **2.3. Food Shopping Trends**

### **2.3.1. New Shopping Channels and Touchpoints**

With the emergence of new technologies, food consumption trends, and unprecedented information interchange between customers and brands, food shopping has evolved from a being only accessed through physical channels to an increasing omnichannel experience that is continuously evolving. This has provided customers with new touchpoints for purchase and interaction in which companies must engage in all the stages of the buying process to generate value (Euromonitor International, 2019a).

As the limits between the digital and offline purchase fade, motivating stores to install digital devices and to have presence online, and online platforms offering offline solutions, customers are also seeking instant gratification, personalized experiences and are considering to purchase online in a larger number of categories (Euromonitor International, 2019a). In the food domain, new formats and platforms, enabled by a digital revolution, are increasingly appealing to customers such as online grocery, home delivery, and new business models (Howard et al., 2017). This applies to food purchase from retail companies or specialty shops with mixed or digitally-enabled touchpoints, and an increasing demand for experiencing the quality of a restaurant at home, seeking convenience and simplicity as an online grocery purchase (Hirschberg et al., 2016).

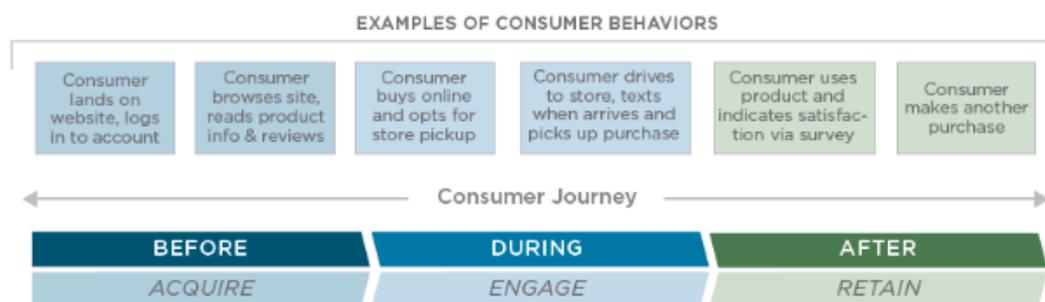
From the retail perspective, the number of channels for food purchase has been diversified, and even if the physical stores still attract most of customers, new mixed and digital formats are getting importance, and are placing challenges to retailers as consumers rely less in only one channel (Howard et al., 2017). Online delivery platforms are also a disruptor in the foodservice industry, allowing customers to order from restaurants conveniently from a wide offer, among websites and apps for comparison or purchase or online delivery platforms that can be used both for grocery shopping and meal delivery (Hirschberg et al., 2016). Some key figures reveal that 67% of consumers use online channels for grocery research and 25% order groceries online. (Howard et al., 2017), and for the non-frequent online shoppers, 59% are likely to use e-commerce websites and 35% would rely also on a delivery solution (Acosta, 2017). In France, 15% of

customers are using internet to buy organic foods, but the purchase at supermarkets (70%) and specialty shops (31%) remains important.

The use of mobile technologies is also imperative in the food industry especially due to the rise of purchase and delivery apps. As customers gain more experienced and find the use of technology more convenient, specialists consider that the food category might grow along with the use of smartphones (Hirschberg et al., 2016). 40% are already purchasing on their phones, being grocery a top category, reason why also 40% of buyers also use the mobile app of a retailer (Howard et al., 2017).

In terms of the purchase journey, studies performed by (Euromonitor International, 2019a) And (Deloitte, 2014) consider that the omnichannel purchase has an important phase after the pre-purchase and purchase stages. The post-purchase stage they have considered is in line with (Howard et al., 2017) who exposes that, for the food domain (See **Figure 3**), a customer can still offer feedback or seek a proper customer service using several channels, inviting food companies and retailers to retain those customers in this stage to stimulate another purchase afterward, or to generate loyalty (Deloitte, 2014). It is important to consider this aspect in this thesis due to the fact that Saghiri et al., (2017) only considers the return as the last stage of the omnichannel purchase and does not contemplate further customer engagement after the return stage. Considering an engagement or a post-purchase experience stage in food omnichannel shopping will be a key element of the purchase journey to be studied in this thesis.

**Figure 3 : FOOD SHOPPING CUSTOMER JOURNEY**



Source: (Howard et al., 2017)

According to Howard et al. (2017), companies should be able to predict customer's shopping behavior, embracing analytics, and understanding their customer's preferences. Using social touchpoints and other digital support will be critical. In the purchase stage, companies should offer customers the option to shop based on their profiles, integrating online and in-store, blended solutions such as pick-up in store (click and collect),

home delivery, or delivery at a specific point chosen by the customer (Howard et al., 2017), accompanied with digital and mobile payment technologies (Tussyadiah et al., 2017) for those purchases. Along with supermarkets or mass stores, specialty shops, convenience stores and click and drive, mobile apps and online grocery websites will also be considered in this thesis.

Embracing digital transformation with new delivery models in the food industry will increasingly be important to remain relevant in the market. As discussed above, multiple channels are accessible now to customers and the business world has seen the rise of Foodtech, that is creating a new whole ecosystem (See **Figure 4**) from production to distribution of food generating new ways for food consumption, marketing and production (DigitalFoodLab, 2020). Additionally, customers are also using apps to analyze products before buying. For instance, in France, the app *Yuka* enables customer to evaluate the product's nutritional values, in a market where they strongly seek product information to purchase foods. (OpinionWay, 2018).

**Figure 4 : FOODTECH ECOSYSTEM**



Source : (DigitalFoodLab, 2020)

Given the role that technology will play in the coming years with the emergence of the IoT, wearable gadgets (Howard et al., 2017) and 5g networks, customers will live undoubtedly in an omnichannel environment, being inspired from interactive cooking shows or health-tracking technologies (Howard et al., 2017). The sanitary crisis caused by the COVID-19 pandemic in 2020 has also enabled a greater success of online grocery businesses (DigitalFoodLab, 2020), including delivery apps, online food-service solutions which is creating a favorable environment for omnichannel food shopping.

### 2.3.2. Responsible and Healthy Consumption

Consumers around the globe are becoming increasingly aware of the impact of their activities and sustainable food consumption is growing concern (Verain et al., 2012). The responsible use of resources and the direct impact of the food industry in the planet is playing an important role in the food purchasing decisions. Kim (2017) commented that the proactive practices of corporate social responsibility beyond minimal requirements that are perceived by customers can lead to increase purchase intent. A global segment of green customers has also been identified, characterized by a favorable attitude towards the care of the environment (Verain, 2015).

As a response to this trend, food manufacturers and retailers have increased their offer of environmentally friendly products, which should complement their supply chains sustainable practices (Maloni & Brown, 2006). Consequently, customers have opted to purchase products that can assure that their consumption is both responsible for the planet and of their own wellbeing. Organic food has emerged as an important representation of this trend. For instance, in France, in a country where 88% consume this kind of food, the most important customer groups that purchase organic foods agree that these products preserve the environment, water resources and favors the biodiversity (Agence Bio, 2019). Consequently, it is visible that customers are opting to have sustainable consumption behaviors that are aligned with their lifestyles, looking also to engage with animal wellbeing and communitarian values, and buying products that are locally sourced or fair-trade labeled (Euromonitor International, 2019b).

Moreover, it is known that organic foods are valued by customers who search for safety, quality, nature, and health (Vega-Zamora et al., 2013). However, from a wider perspective, health is not only an exclusive feature of organic food consumers. Healthy lifestyles and consciousness are indeed gradually more important for the social responsibility programs in the food industry (Gunarathne et al., 2017; Maloni & Brown, 2006). Customers are demanding foods that can provide both good taste and high nutrition. Evidently, the healthy consumption patterns can vary among customers (Hollywood et al., 2013) due to a greater amount of information available (Euromonitor International, 2019b) and new food items that attract particular customer needs. Consumers also demand that balanced healthy foods (Euromonitor International, 2019b) and convenience, allowing to purchase or to prepare innovative and easy-to-cook meals (Hollywood et al., 2013).

These food shopping trends oriented to environmental sustainability and healthy food purchases confirm that using covariates related to these issues is important to portray food consumers in this thesis. In this thesis, it will be confirmed if customers with a higher concern about the environment tend to prefer channels that reduce the use of intermediaries or that can assure food quality and safety. The preference for healthy foods might also trigger the use of several touchpoints to find the right choice in terms of price and convenience. The blend of physical and digital channels can provide several clues about the omnichannel orientation of customers that prioritize health and/or environmental concerns in their food shopping. Due to the impact of the COVID-19 pandemic, aspects related to food safety, delivery hygiene and the origin of products will also important factors for buying decisions (Euromonitor International, 2020).

### **2.3.3. Food as an Experience**

Purchasing food and preparing meals is no longer a pure routine activity. Customers are involved in an ecosystem that has enabled them to access different sources of information for their coming dinner or lunch, they browse across several channels to purchase, to get their products delivered, and they are open to share their experiences with families and friends (JLL, 2018). This illustrates that food shopping is becoming an experience, where the consumer seeks for inspiration to cook healthy foods withing their knowledge (Hollywood et al., 2013) or demanding food retailers to be a supplier of curated meals (Howard et al., 2017).

This experience goes beyond the purchase and delivery, and customers are increasingly sharing what they do and consume. They want to make this experience an expression of their own life (Howard et al., 2017). In a world where foodies exist (Johnston and Baumann, 2010), social networks have become an important platform. For instance, it is known that people spent up to 5 hours looking at food on social media (JLL, 2018) and that the most active consumers of organic food in France, share their opinion about the products they eat on social networks (Agence Bio, 2019). For instance, a segment of “Foodies” in Germany was described as been passionate about cooking, innovative, conscious about freshness and quality, highly involved in creating meals and seeing the activity as a tool for realization (Gunarathne et al., 2017). Given that the food culture in France has as a clear orientation to seek conviviality and taste (Mathé et al., 2009), this

thesis will reveal if these customers have a particular attitude towards omnichannel shopping.

The importance of expending time cooking and sharing the experience of food consumption highlights the importance to consider covariates that can identify if customers with such orientation tend to use more digital channels or a combination of offline and online platforms. Covariates such as self-fulfillment from food, eating in company, involvement, or innovativeness can be evaluated to verify if there are differences among customer segments throughout their preferred touchpoints in purchase journey.

**Table 8 : CUSTOMER SEGMENT GROUPS IDENTIFIED IN OMNICHANNEL AND FOOD SHOPPING SEGMENTATIONS STUDIES**

OMNICHANNEL/MULTICHANNEL MACRO-SEGMENTS IDENTIFIED IN LITTERATURE	# RELATED SEGMENTS IDENTIFIED IN LITTERATURE	STUDIES	FOOD SHOPPER MACRO-SEGMENTS IDENTIFIED IN LITTERATURE	# RELATED SEGMENTS IDENTIFIED IN LITTERATURE	STUDIES
MULTI-OMNISHOPPERS	20	<ul style="list-style-type: none"> <li>• Konuş et al., (2008)</li> <li>• Lazaris et al. (2014)</li> <li>• Keyser et al., (2015)</li> <li>• Sands et al. (2016)</li> <li>• Park &amp; Kim (2018)</li> <li>• Nakano &amp; Kondo (2018)</li> <li>• Herhausen et al. (2019)</li> </ul>	FOOD ENTHUSIASTS	6	<ul style="list-style-type: none"> <li>• Chetthamrongchai &amp; Davies (2000)</li> <li>• Shim et al. (2001)</li> <li>• Björnsson (2015)</li> </ul>
PURE ONLINE-ORIENTED	8	<ul style="list-style-type: none"> <li>• Keyser et al., (2015)</li> <li>• Sands et al. (2016)</li> <li>• Park &amp; Kim (2018)</li> <li>• Herhausen et al. (2019)</li> </ul>	CONSERVATIVE/RATIONAL	8	<ul style="list-style-type: none"> <li>• Nie &amp; Zepeda (2011)</li> <li>• Gunarathne et al. (2017)</li> </ul>
STORE-ORIENTED CUSTOMERS	8	<ul style="list-style-type: none"> <li>• Konuş et al., (2008)</li> <li>• Keyser et al., (2015)</li> <li>• Nakano &amp; Kondo (2018)</li> <li>• Herhausen et al. (2019)</li> </ul>	UNINVOLVED	8	
UNINVOLVED CUSTOMERS	5	<ul style="list-style-type: none"> <li>• Konuş et al., (2008)</li> <li>• Lazaris et al. (2014)</li> <li>• Park &amp; Kim (2018)</li> <li>• Nakano &amp; Kondo (2018)</li> </ul>			

Source: Own analysis. The macro segments found in the literature have been grouped according to similar psychographic characteristics or channel preferences. See **Annex 2** and **Annex 3** to see the detailed segments lists.

The literature analyzed have provided relevant guidelines, methods, and an overview of segmentation research. Saghiri et al. (2017) have introduced a framework to study the purchase journey withing an omnichannel experience considering 4 stages and differentiated touchpoints and agents to consider in each stage. However, among the multichannel and omnichannel segmentation studies revised, only one study (Park & Kim, 2018) has been able to include 4 stages, while the others have focused only on two or three. As can be seen above in **Table 8**, four macro-segments have been derived from those studies providing some clues about the customer's profiles than have a preference to use a single or several channels.

Nonetheless, none of them have addressed the food industry or food shoppers as a category in their study, and most have preferred to cover several categories instead. In this regard, this thesis will identify specifically if food shoppers use several or specific touchpoints according to their behavior and attitudes to food-related activities. The

Food Related Lifestyles has been reviewed and confirmed to be a powerful tool for segmentation in the food domain and has been the base of several studies to identify 3 macro-segments in general (**Table 8**). The gap in those studies is their insufficient analysis of several touchpoints in their food shopping purchase or search. They have focused only on some physical retail formats but have not included digital or hybrid channels. Therefore, this thesis will fill this gap combining the most relevant covariates used in food segmentation, to unveil customer segments with their omnichannel food shopping experience, aligned with the latest global food shopping trends.

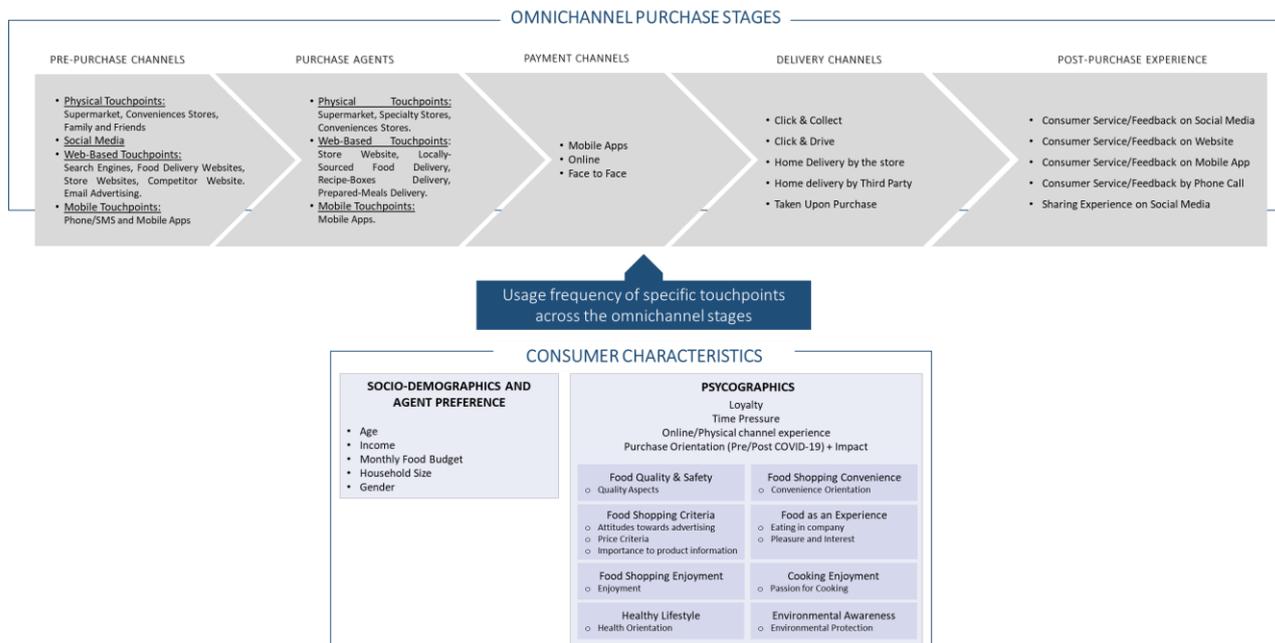
### III. RESEARCH METHODOLOGY

#### 3.1. Research Model

Following previous studies, the segments cannot be determined a priori, which does not require to propose a hypothesis (Konus et al., 2008; Sands et al., 2016). Consequently, the research model will expose the structure under which this thesis will implement a segmentation study to fill the gaps between food segmentation studies and omnichannel shopping using the methods and relevant covariates discussed in the literature.

Additionally to the stages considered by Saghiri et al. (2017), the purchase journey will be expanded to 5 stages, relabeling the last one as Post-Purchase Experience and including a specific stage of Purchase. Multiple touchpoints and purchase channels (i.e. agents for purchase) will be considered. Using sociodemographic covariates, some psychographic covariates from previous research, as well as relevant food related lifestyle aspects for this study will provide the characteristics of each segment. **Figure 5** illustrates an overview of the research model.

**Figure 5 : RESEARCH MODEL**



### **3.2. Purpose of Research**

The purpose of this thesis is to propose a novel segmentation approach for the food industry in which customers are segmented based on the usage frequency of several touchpoints among the purchase stages and the 10 food-related lifestyles and covariates that characterized each segment. It is expected that this analysis will unveil if different omnichannel segments have a certain pattern of food related lifestyles characteristics which can enable actionable insights later in the study. This thesis is different from previous segmentation studies in the fact that 5 stages are analyzed based on 4 stages of the omnichannel theory by (Saghiri et al., 2017) and (Howard et al., 2017) , and one purchase phase. A different number of touchpoints are considered in each stage but are somehow related in 3 general categories: Physical, Web-based, Social and Mobile.

It is assumed that the customer interacts with different touchpoints from search to his post-purchase experience, and this thesis will consider the purchase agents and touchpoints from the retailers, stores, websites and online delivery services and food delivery apps in general. Only the search phase will consider the frequency use given to the retailer's competitors website, similar to (Herhausen et al., 2019). The 5 purchase stages and the usage frequency of the touchpoints used in each stage will be used as the base of segmentation. The actual usage intensity of several channels for purchase, the lifestyles covariates and sociodemographic covariates will be used to characterize the segments. It is expected these psychographic and sociodemographic variables will influence the probability of the respondents that belong to each segment, enabling the identification of omnichannel food consumers in the market and their lifestyles profiles.

### **3.3. Data Collection and Measures**

#### **3.3.1. Measures**

##### **3.3.1.1. Segmentation Base: Purchase Stages and Touchpoints**

In this thesis the omnichannel purchase behavior of consumers will be evaluated based on the several touchpoints that they use in 5 purchase stages defined previously in the literature: Pre-Purchase, Purchase, Payment, Delivery and Post-purchase Experience. As (Howard et al., 2017) considered that new digital platforms are increasingly appealing to customers, such as online grocery, home delivery, and new business models, they will be considered in this thesis among the 5 purchase stages.

**Table 9** illustrates the touchpoints that will be evaluated in each purchase stage, showing some examples that will be used in the survey to illustrate its use. They have also been categorized as Physical, Web-based, Social and Mobile. Respondents will be asked about the frequency of use for each touchpoint in a 1 to 5 Likert scale, being 1 as “Never” and 5 “Always”. This will prevent the discrepancy between actual use and the attitude towards each touchpoint, which was studied by (Konus et al., 2008) and (Keyser et al., 2015). As Sands et al., (2016) exposed, the limitations in evaluating attitudes are that they do not reflect or foresee real behavior necessarily. Consequently, in this research, by asking directly how often these channels are used, consumers will evaluate less subjectively their omnichannel food shopping experience.

**Table 9 : TOUCHPOINTS CONSIDERED AMONG THE PURCHASE ANALYSIS AS THE BASIS FOR SEGMENTATION**

Stages	Touchpoints	Examples	Category
Pre-Purchase	Supermarket, Convenience Store, etc.	Visiting a Supermarket, Specialty Store or Kiosque	Physical
	Friends and Family	References or Recommendations from Families and Friends	Physical
	Social Media	Searching for information in Facebook, Instagram, YouTube, etc.	Social Media
	Search Engine	Searching for information in Google, Bing	Web-based
	Food Delivery Websites	Visiting Prepared-Meals, Recipe Boxes, or Locally Sourced Food Delivery Websites such us Hello Fresh, Epicery, etc.	Web-based
	Supermarket, Convenience Store Website	Visiting a Store or retailer website	Web-based
	Supermarket or Store's Competitor Website	Visiting the competitors store or retailer website	Web-based
	Email Ads	Ads received on your email from food companies or retailers	Web-based
	Phone/SMS	Push SMSs Received from food company or retailer	Mobile
	Search on Mobile Apps	Searching or Comparing prices on Delivery Apps (UberEats, JustEat, Deliveroo, etc.)	Mobile
Purchase	Supermarket or Mass Store	Buying in Auchan, Monoprix, Carrefour, LeClerc	Physical
	Specialty Store	Buying in Naturalia, Biocopp, Picard Surgelés, Etc.	Physical
	Convenience Store	Buying in Kiosques or local markets	Physical
	Supermarket Website or Online Retailer	Purchasing online on the Auchan.fr. Monoprix.fr or Amazon.fr	Web-based
	Online: Locally Sourced Food Delivery	Purchasing online on La ruche que di oui, Epicery, Vité mon marché, etc.	Web-based
	Online: Recipe-Boxes Delivery	Purchasing online on Hello Fresh, Quitoque, Foodette, etc.	Web-based
	Online: Prepared-Meals Delivery	Purchasing online on Seazon, FamileEat, Etc.	Web-based
	Mobile App from a Retailer	Purchasing through the Mobile Applications of Auchan, Monoprix Plus, etc.	Mobile
	Mobile App for Responsible Consumption	Purchasing to local markets or to reduce food waste using Phenix, Too good to go, etc.	Mobile
	Mobile App for Food Delivery	Purchasing through UberEats, JustEat, Deliveroo, etc.	Mobile
Payment	Mobile (App or Web's mobile Version)	Paying online using a mobile phone (Through an App or Website Mobile Verision)	Mobile
	Online (Website Desktop Version)	Paying online on the store or retailer Website on a Computer or Tablet	Web-based
	Face to Face (Card or Cash)	Paying in Cash or Card with a POS in the store or after delivery.	Physical
Delivery	Click & Collect	Order online, pick up on store	Web-based
	Click & Drive	Order online, pick up by car at the store	Web-based
	Home Delivery from Store	Delivered at home by the retailer or store after online purchase	Web-based
	Home Delivery by Delivery App	Delivered at home by the third-party App (Delivery, Uber Eats, etc.)	Mobile
	Taken Upon Purchase	Physical Purchase	Physical
Post-Purchase	Support and Feedback on Social Media	Being able to provide Feedback or request Customer Service on Facebook, Instagram, etc.	Social Media
	Support and Feedback on Website	Being able to provide Feedback or request Customer Service by sending a message through the Website	Web-based
	Support and Feedback on Mobile App	Being able to provide Feedback or request Customer Service through te Mobile App	Mobile
	Support and Feedback on by Phone	Being able to provide Feedback or request Customer Service by calling to the store or company	Mobile
	Experience Online	Sharing my food purchase and consumption experience on Social Media (Both Eating or Cooking)	Social Media

Source: Own analysis

The first stage, pre-purchase, will contemplate the frequency of using several touchpoints as references, or information sources as Saghiri et al., (2017) labeled them, that are used prior to perform the final purchase. The physical touchpoints to be evaluated in the first stage are the visit of physical stores such as Supermarkets, Hypermarkets, Mass Stores, Specialty Stores ,

Convenience Stores (such as *Kiosques*) and the recommendations or suggestions they gather from families and friends. Social Media, whether is Facebook, Instagram, or YouTube, is evaluated in this stage and in the last stage only, as part of the experience of food purchasing and sharing, described previously in the literature. Web-based touchpoints to be covered are the use of search engines to look for information about food items online. Moreover, visiting several food delivery related websites of any kind (prepared-meals, recipe-boxes, locally sourced food) along with retailer websites, their competitor's websites and receiving email ads from them will be evaluated. Mobile touchpoints consider the use any food delivery or marketplace's smartphone application to evaluate options before buying food.

The next stage, purchase, evaluates the frequency in which several touchpoints are used for the actual purchase. That is the reason why they will be more specific and differentiated to enable a proper sense of the current market preferences to several food online commerce and delivery models that have raised recently. The brick-and-mortar touchpoints to be measured are the purchase frequency on Super/Hypermarkets, Specialty Stores and Convenience Stores separately. The Web-based and mobile touchpoints chosen in this stage tend to cover the most presentative models of food purchase today enabled both by the internet.

Mixed formats and FoodTech (DigitalFoodLab, 2020; Howard et al., 2017; Jean, 2018) such as purchasing on a retailer's website or at an online retailer (such as Amazon), and purchasing online at a locally sourced food delivery service, in line with the responsible and environmental consciousness of today's customer (Verain et al., 2012). Then, evaluating the online food purchase for Recipe-Boxes and prepared-meals Delivery are also important as they have become new trending intermediaries and platforms, especially in countries like France (Conesa, 2017). Similarly, three main mobile channels to be measured will be the use of a retailer owned applications, food delivery apps and mobile apps that allow the purchase to local markets or to reduce food waste in line with today's environmental trends.

At the payment stage, three general items have been chosen from (Saghiri et al., 2017): Mobile (paying using an app or accessing online through the smartphone), Online (paying through a website on laptop computer) or paying face to face in cash or credit card. Next, at the 4<sup>th</sup> stage, delivery, relevant delivery or fulfillment methods have been taken from literature (Bertrand, 2019; Howard et al., 2017; Lelièvre, 2018) such as Click & Collect, Click & Drive, Home Delivery from Store, Home Delivery by Delivery App and the

actual pick up of courses after a physical purchase on a store. Finally, the aim of evaluating the post-purchase stage is to see if customers use a determined touchpoint for customer service or to provide feedback, and if they engage in social media to share their consumption experience both buying foods or cooking as part of the social experience that food has become (JLL, 2018).

### 3.3.1.2. Food Related Lifestyles Psychographics and Sociodemographic Covariates

As reviewed in the literature, demographic and psychographic covariates have illustrated several touchpoints choices and preferences (Sands et al., 2016). From (Konus et al., 2008) to (Herhausen et al., 2019), researchers have used these covariates to provide a deeper characterization of the segments unveiled in their studies. First, one starting measure will be related to the channel use orientation, which will aim to ask respondents to allocate a score (from 0 to 100) among the three general groups of touchpoints for food purchase: Physical, Web-based and Mobile. This will provide an additional support indicator to profile the segments profiling and the evaluation of the omnichannel agents. In addition, the impact of the COVID pandemic will be measured by asking if had an impact of the channels used for purchase before the lockdown. If respondents answer from “(2) a little” to “(5) very much” (in a 5 Likert scale) the same question will be asked again to scan their new purchase orientation post-lockdown.

Then, 14 variables will be used as psychographic covariates. The scales to measure the online and physical channel experience for purchase has been borrowed from (Herhausen et al., 2019), a loyalty scale used by Konuş et al., (2008), and one scale introduced by (Chetthamrongchai & Davies, 2000) to measure “Time Pressure”.

Additionally, the specific food related lifestyles characterization will come from the evaluation of 10 psychographic covariates linked to 8 main lifestyles aspects: Food Quality & Safety, Food Shopping Enjoyment, Food Shopping Criteria, Cooking Enjoyment, Food Shopping Convenience, Environmental Awareness, Food as an Experience and Healthy Lifestyle (See **Table 10**).

Most of the scales used for this thesis will be borrowed from (Gunaratne et al., 2017) who updated and adapted the food related lifestyles (FRL) scales in recent study in Europe, as discussed in the literature. The analysis of food shopping criteria will use 3 scales from the original FRL scale introduced by (Brunsø, 1997). For food shopping enjoyment, the scale from

(Chetthamrongchai & Davies, 2000) will be used as it evaluated enjoyment in shopping in their food related study.

A new covariate that was omitted in previous multichannel and omnichannel studies will be used in this research: convenience orientation (Olsen et al., 2007; Onwezen et al., 2012), given that it can motivate the use of specific channels such as mobile or web-based. Additionally, in line with environmental and responsible consumption concerns of customers, Environmental protection and Health orientation will be measured using the scales provided by (Lindeman & Vaananen, 2000) and (Onwezen et al., 2012).

**Table 10 : FOOD RELATED LIFESTYLES COVARIATES AND SOURCES**

Lifestyle Aspect	Dimensions (Covariates)	Source
Online Channel Experience	Online Experience	Herhausen et al. (2019)
Physical Channel Experience	Offline Experience	
Time Pressure	Time Concerns	(Chetthamrongchai & Davies, 2000)
Loyalty	Loyalty	Konuş et al. (2008)
Food Quality & Safety	Quality Aspects	(Gunarathne et al., 2017)
Food Shopping Enjoyment	Enjoyment	(Chetthamrongchai & Davies, 2000)
Food Shopping Criteria	Attitudes towards advertising	Food Related Lifestyles (1997)
	Price Criteria	Food Related Lifestyles (1997)
	Importance to product information	Food Related Lifestyles (1997)
Cooking Enjoyment	Passion for Cooking	(Gunarathne et al., 2017)
Food as an Experience	Eating in Company	(Gunarathne et al., 2017)
	Pleasure and Interest	(Gunarathne et al., 2017)
Food Shopping Convenience	Convenience Orientation	Olsen et al., (2007) and Onwezen et al. (2012)
Environmental Awareness	Environmental Protection	Lindeman & Väänänen (2000)
Healthy Lifestyle	Health Orientation	Onwezen et al. (2012)

As the socio demographic covariates have been proved to influence shopping behavior (Sands et al., 2016), gender, income and gender will be scanned in this research. Moreover, the household size and the budget allocated to food consumption will be included as they could reveal if the family size, used as covariate by (Herhausen et al., 2019; Konuş et al., 2008; Nakano & Kondo, 2018) and the amount of income spent (Herhausen et al., 2019) to purchase food or groceries, can also be a consumer trait in specific omnichannel segments.

The psychographic variables will be measured using several items (See **Annex 4**) with 5-point Likert scales from 1(Strongly agree) to 5 (Strongly agree).

Some of the questions have been rephrased for this thesis: How experienced are you in buying *food* online/in physical stores? (online/physical channels experience), The *place/platform* where I do my shopping is very important to me (loyalty), I generally do my *food shopping* in the same way (loyalty), I would like to pay more money for animal welfare *approved foods* (quality aspects), I like to go to several *stores/websites* to get the best value for money (enjoyment), I would like to eat only *organic foods* (healthy lifestyle).

The income and budget allocation for food consumption have been built based on economic data of the French government as it will be the market where the sample will be collected. The 10 levels of revenue observed by the (Insee, 2018) have been regrouped in 5 gross annual income levels:

**Table 11 : ADAPTED INCOME SCALE BASED ON REVENUE LEVES IN FRANCE**

Annual Revenue Levels in France in Euros (Insee, 2018)	Adapted Income Scale Gross Annual Income (in Euros)
13 630 – 17 470 (<D1)	<18 000
17470 - 21 120 (D1 – D2)	18 000 – 24 999
21 120 - 25 390 (D2 – D3)	
25 390 - 30 040 (D3 – D4)	25 000 – 40 999
30 040 - 35 060 (D4 – D5)	
35 060 - 41 290 (D5 – D6)	
41 290 - 49 350 (D7 – D8)	41 000 – 60 000
49 350 - 63 210 (D8 – D9)	
>63 120 (> D9)	>60 000

Source: Insee (2018) and Own analysis.

Similarly, the average expense allocation percentage of food (15.6%) according to (Ferret & Demoly, 2019) , is used as a proxy to build a 5 monthly budget level scale as a percentage from the income levels built on the previous income scale: (1) < 234 Euros (15.6% of 18 000 Euros / 12 months) (2) 234 – 325 Euros (15.6% of 25 000 Euros / 12 months for the upper limit) (3) 325 – 533 Euros (15.6% of 41 000 Euros / 12 months for the upper limit) (4) 533 to 780 Euros (15.6% of 60 000 Euros / 12 months for the upper limit) (5) >780 Euros. These calculations will be adapted to use the following scale:

- (1) < 240 €/Month
- (2) Between 240 to 329 €/Month
- (3) Between 330 to 529 €/Month
- (4) Between 530 to 780 €/Month
- (5) More than 780 €/Month

Finally, the household size will be measure from 1 (people living alone) to households having more than 5 members.

### 3.3.2. Data Collection

#### 3.3.2.1. Sampling and Survey Distribution

The sample has been defined to cover no less than 200 people and valid responses to meet a minimum statistical significance to this study. The participants will be residents currently living in France and older than 18 years old. An online survey was designed to gather the data using the web-based tool Qualtrics™. This tool can also optimize the survey for mobile responsive visualization allowing a comfortable use on smartphones and tablets. Moreover, the survey will be shared on social media, professional networks, e-mail, and personal contacts.

Due to the length of the survey, which will contain 56 questions and an approximate answer time of 17 minutes, a special prize draw will be used as an incentive after the full completion and validity (complete answers) of the survey. At the end the survey, respondents will be asked to complete any contact information to participate in a draw of 3 Amazon Gift Cards worth 30 Euros each. If they accept to participate, the contact information will be used in a virtual draw using My2lbox.com. Once the winners are identified and contacted, the prize (the physical card) will be mailed by Amazon.

#### 3.3.2.2. Survey

The online survey (**Annex 4**) has been structured in 3 parts and an introductory participant's permanent residency validation question. At the beginning, the participants will be asked if they are permanent residents in France living at least 6 months in French territory and if they regularly shop for groceries. If they do, they will be able to complete the survey.

The first section will gather information about the segmentation variables: the touchpoints frequency use among 5 purchase stages. The second part contains questions in which responders will evaluate their psychographic covariates, profiling variables and food related lifestyles aspects. The last part will gather sociodemographic data that will be used, along with the questions in part 2, to characterize the omnichannel segments. All questions will be translated to French and validated with local natives to assure the accuracy of the phrases and items. Additionally, the questions will also be

available in English and Spanish to increase the response rate to non-French speakers working or studying currently in France.

### 3.4. Data Analysis Methods

The data gathered from the surveys will be analyzed following the process illustrated in the following table:

**Table 12 : DATA ANALYSIS PLAN**

Step	Objective
<b>1. Data extraction and cleaning</b>	To remove uncomplete and invalid responses (R Studio).
<b>2. LCA Segmentation using R Studio</b>	To determine and evaluate the most appropriate number of classes or segments.
<b>3. Factor and Reliability Analysis using SPSS.</b>	To evaluate the psychographic factors and the scales reliability to allow a better segment's characterization.
<b>4. Multinomial Logistic regression and Descriptive Analysis (SPSS).</b>	To describe the segments characteristics.

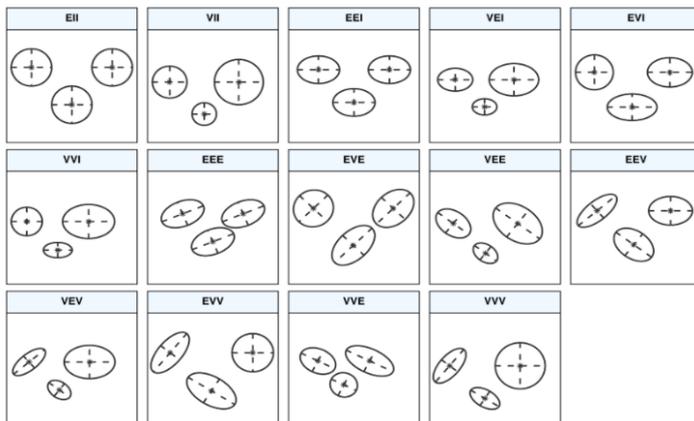
In the first step, the survey data will be revised to remove uncomplete answers or repeated answer patterns among the questions (i.e. all answers being the same for one respondent) which could be the result of unmotivated respondents. These poor responses will be considered outliers, and the software that will be used for this process will be R Studio, the open-source tool for data analysis and statistical computing based on the R programming language (R Studio, 2020) which will be also used for the segmentation process.

Secondly, the Latent Class Analysis segmentation process will be performed using R Studio Version 1.3.959. This open source software provides an interface to use the R programming language for data manipulation, statistical analysis, and graphical view (Haughton et al., 2009). As it allows to perform Latent Class Analysis (LCA) for segmentation purposes for free, compared to other software such as Latent Gold (Haughton et al., 2009), this tool has been chosen for this thesis due to its accessibility. Moreover, among other packages available in R for LCA, such as polLCA or polLPA, the MCLUST version 5.4.6 package (Scrucca et al., 2016) will be used in this thesis to determine the number of segments.

The MCLUST package allows to perform LCA (Haughton et al., 2009) and it has become a popular tool in R for model-based clustering and classification (Scrucca et al., 2016), estimating the best mixture models “according to different covariance structures and different number of clusters” (Haughton et al., 2009, pp. 88–89). One of main characteristics of MCLUST is that the model in which the clusters are formed is based on a Gaussian Mixture Model (GMM), where a multivariate distribution is assumed for each component or group (Scrucca et al., 2016). Consequently, the clusters have an ellipsoidal shape, and have geometric attributes such as volume, shape and orientation defined by the covariance pattern (Scrucca et al., 2016). **Figure 6** shows the 14 possible models in a multivariate perspective and the possible options obtained from the mentioned attributes, and whether if the covariances are equal or variable. The best possible model is the EII, as it illustrates homogeneous segments in distribution, form, and size, while the VVV is the less uniform model.

**Figure 6 : GAUSSIAN MODELS ANALYZED BY MCLUST**

Ellipses of isodensity for each of the 14 Gaussian models obtained by eigen-decomposition in case of three groups in two dimensions



Parameterizations of the within-group covariance matrix  $\Sigma_k$  for multidimensional data available in the **mclust** package, and the corresponding geometric characteristics.

Model	$\Sigma_k$	Distribution	Volume	Shape	Orientation
EII	$\lambda I$	Spherical	Equal	Equal	—
VII	$\lambda_k I$	Spherical	Variable	Equal	—
EEI	$\lambda A$	Diagonal	Equal	Equal	Coordinate axes
VEI	$\lambda_k A$	Diagonal	Variable	Equal	Coordinate axes
EVI	$\lambda A_k$	Diagonal	Equal	Variable	Coordinate axes
VVI	$\lambda_k A_k$	Diagonal	Variable	Variable	Coordinate axes
EEE	$\lambda D A D^T$	Ellipsoidal	Equal	Equal	Equal
EVE	$\lambda D_k A D^T$	Ellipsoidal	Equal	Variable	Equal
VEE	$\lambda_k D A D^T$	Ellipsoidal	Variable	Equal	Equal
VVE	$\lambda_k D_k A D^T$	Ellipsoidal	Variable	Variable	Equal
EEV	$\lambda D_k A D_k^T$	Ellipsoidal	Equal	Equal	Variable
VEV	$\lambda_k D_k A D_k^T$	Ellipsoidal	Variable	Equal	Variable
EVV	$\lambda D_k A_k D_k^T$	Ellipsoidal	Equal	Variable	Variable
VVV	$\lambda_k D_k A_k D_k^T$	Ellipsoidal	Variable	Variable	Variable

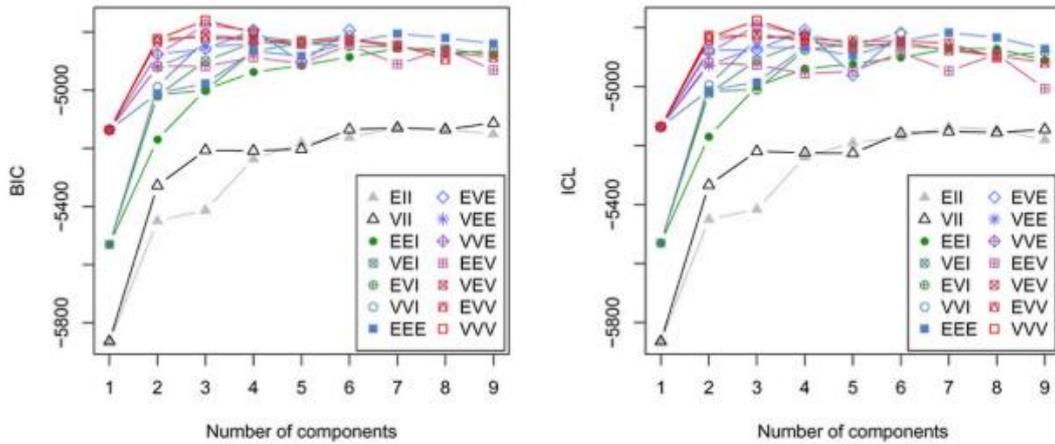
Source: (Scrucca et al., 2016)

As the segmentation bases for this thesis is based on multiple touchpoints across several purchase stages, a multivariate analysis that this tool will perform is suitable for this clustering task. Moreover, similarly to previous research (Keyser et al., 2015; Konuş et al., 2008; Nakano & Kondo, 2018; Sands et al., 2016) the Bayesian Information Criterion (BIC) and the Integrated Completed Likelihood criterion (ICL) will be the statistical indicators to decide on the proper number of clusters.

The first step will consist on obtaining the proposed number of segments using the BIC and ICL analysis functions integrated in the MCLUST package (Haughton et al., 2009; Scrucca et al., 2016) to obtain the top three proposed models among all the different configurations that is computed by the MCLUST codes. The models can also

be visualized graphically (See **Figure 7** below as an example). Then, model selection will be based on the criteria of interpretability and cluster size (Charry et al., 2016), analyzing first the BIC and secondly, the ICL as it has shown to be a better criteria to determine the number of clusters (Bertoletti et al., 2015; Biernacki & Celeux, 2006; Scrucca et al., 2016). The final model will be chosen considering the uniformity criteria described previously (**Figure 6**).

**Figure 7 : SCATTERPLOTS WITH SAMPLE DATA, WITH POINTS MARKED ACCORDING TO CLASSIFICATION USING BIC AND ICL CRITERIA IN R STUDIO AND THE MCLUST PACKAGE**



Source: (Scrucca et al., 2016)

The third step consist in the factor and reliability analysis that will be performed using the SPSS software to evaluate the structure of the psychographic covariates related to the 13 food related lifestyles dimensions. As these dimensions are measured using a multi-item 5 points Likert scale, it will be necessary to determine first, the items to be loaded per factor (in this case, the dimensions) based on the Keiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and the Bartlett's Test of Sphericity, using orthogonal factors with eigenvalues greater than 1 and items explaining at least 60% of variance (Charry et al., 2016). Then, the internal consistency of the statements that build the same construct (the dimensions) calculating the Cronbach's alpha coefficient (Charry et al., 2016). This coefficient should be superior to 0.7 (Charry et al., 2016) for each dimension in order to compute the summated scales (average from each valid statement) and that will be used as input for the next step.

Finally, once the clusters are assigned as categorical variables to each observation in the data, using the final psychographic factors calculated and the demographic variables, a multinomial logistic regression, performed in SPSS, will illustrate the probabilities that each covariate (psychographic and demographic) belongs to each segment, similar to (Konus et al., 2008; Nakano & Kondo, 2018; Sands et al., 2016). The Wald and p-value >0.05 parameters will be used to identify the weight and the significance of each covariate in the model, and the coefficients will illustrate how

each covariate behaves in each cluster. This process will enable the description and analysis of the clusters based on the omnichannel purchase of food and its related lifestyles and sociodemographic variables.

## IV. DATA ANALYSIS

Following the proposed Data Analysis plan, 347 from 401 responses collected using Qualtrics™ were extracted, filtered using the first two screening questions regarding the permanent residence in France and their regular food purchase behavior (See **Annex 4**). Then, invalid, and incomplete answers<sup>5</sup> were deleted resulting in 227 usable observations for data analysis. The final dataset was saved and loaded to R studio for the LCA segmentation procedure. The final segmentation solution was exported and used as input file for the multinomial logistic regression, done in SPSS, for the segment's final characterization based on psychographic and demographic variables.

### 4.1. Segmentation Analysis

#### 4.1.1. LCA Segmentation on R Studio

The complete code line to perform the analysis procedure in R Studio can be seen in **Annex 5**. The variables that were used as the segmentation base were selected in R to start the outlier's detection. In this thesis, the segmentation base was defined as the touchpoints used among the five food purchase stages.

Using the final 227 responses extracted from Qualtrics, 1 response, based on the segmentation variables questions, was detected by R as a *string*<sup>6</sup> (*string* = 33) or non-reliable response. The final 227 valid responses were used to implement the MCLUST package for LCA Segmentation in R (Scrucca et al., 2016). **Figure 8** below shows the generated results and evaluation of the 14 Gaussian Mixture Models based on the Bayesian Information Criterion (BIC). R proposed three top models in which 4, 3 and 2 segments were detected in the data.

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<sup>5</sup> The observations where respondents indicated ages below 18 years old were removed.

<sup>6</sup> 33 of the 33 questions related to the touchpoint's usage frequency were answered with the same score.

**Figure 8 : BIC EVALUATION BY NUMBER OF GAUSSIAN MIXTURE MODELS**

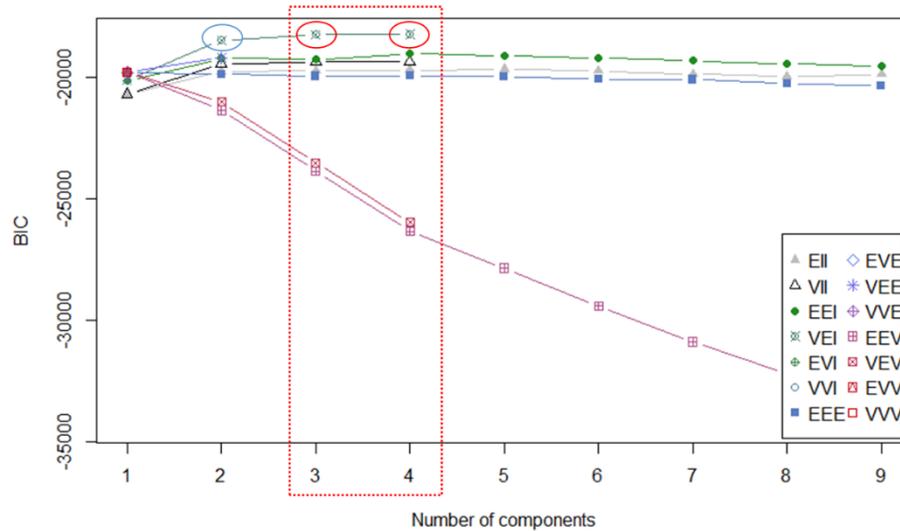
Bayesian Information Criterion (BIC):										
	EII	VII	EEI	VEI	EVI	VVI	EEE	EVE	VEE	VVE
1	-20716.20	-20716.20	-20145.71	-20145.71	-20145.71	-20145.71	-19805.55	-19805.55	-19805.55	-19805.55
2	-19776.80	-19438.67	-19231.68	-18485.06	NA	NA	-19877.28	NA	-19199.04	NA
3	-19751.33	-19378.96	-19282.03	-18250.69	NA	NA	-19965.87	NA	NA	NA
4	-19711.80	-19373.15	-19043.72	-18239.36	NA	NA	-19939.30	NA	NA	NA
5	-19686.33	NA	-19125.36	NA	NA	NA	-19989.20	NA	NA	NA
6	-19749.34	NA	-19205.63	NA	NA	NA	-20089.76	NA	NA	NA
7	-19881.77	NA	-19323.05	NA	NA	NA	-20104.63	NA	NA	NA
8	-19995.90	NA	-19463.23	NA	NA	NA	-20271.28	NA	NA	NA
9	-19887.43	NA	-19551.05	NA	NA	NA	-20356.72	NA	NA	NA
	EEV	VEV	EVV	VVV						
1	-19805.55	-19805.55	-19805.55	-19805.55						
2	-21370.28	-21032.51	NA	NA						
3	-23869.59	-23521.96	NA	NA						
4	-26344.81	-25979.31	NA	NA						
5	-27861.85	NA	NA	NA						
6	-29405.67	NA	NA	NA						
7	-30893.06	NA	NA	NA						
8	-32186.99	NA	NA	NA						
9	-34386.39	NA	NA	NA						

Top 3 models based on the BIC criterion:  
VEI,4    VEI,3    VEI,2  
-18239.36   -18250.69   -18485.06

Source: Outputs generated by R Studio

**Figure 9** illustrates below the plotted gaussian models by BIC, in which it can be seen that the first two proposed solutions, VEI diagonal, equal shape models containing 4-Segments, or components ( $BIC = -18\ 239.36$ ) and a 3-Segments solution ( $BIC = -18\ 250.68$ ) are vaguely different ( $-11.32$ ) compared to a 2 segment proposition ( $BIC -18\ 845.06$ ). The top two models containing 4 and 3 segments were also analyzed (See **Figure 10**) to compare their results in terms of segment size.

**Figure 9 : BIC EVALUATION BY NUMBER OF COMPONENTS AND SEGMENT**



Source: Outputs generated by R Studio

**Figure 10 : EVALUATION OF TWO PROPOSED SOLUTION BASED ON BIC**

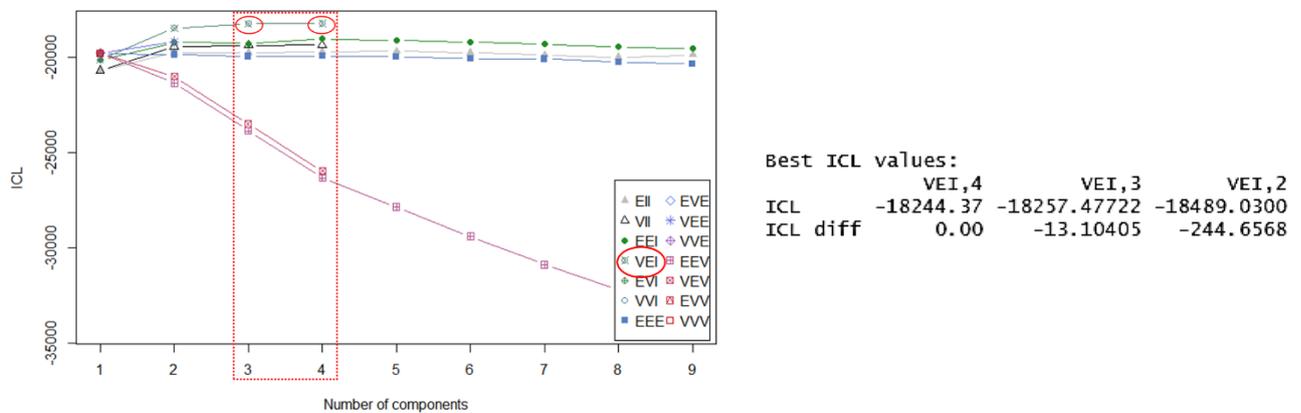
Gaussian finite mixture model fitted by EM algorithm					Gaussian finite mixture model fitted by EM algorithm				
Mclust VEI (diagonal, equal shape) model with 4 components:					Mclust VEI (diagonal, equal shape) model with 3 components:				
log-likelihood	n	df	BIC	ICL	log-likelihood	n	df	BIC	ICL
-8655.848	227	171	-18239.36	-18244.37	-8756.447	227	136	-18250.69	-18257.48
Clustering table:					Clustering table:				
1	2	3	4		1	2	3		
87	109	7	24		87	117	23		

Source: Outputs generated by R Studio

It can be observed that the 3-components model offers 3 relatively representative segments in terms of size compared to the 4-component solution that suggests an additional segment that is smaller and not representative (less than 3% of the observations). Consequently, an additional parameter to evaluate the proposed solutions and a graphical cluster analysis was performed to choose the final model.

As previous segmentation studies that implemented LCA, the Integrated Completed Likelihood (ICL) criterion was executed also to the data. The results seen in **Figure 11** below also confirmed the slight difference between a 3 and 4-Segment model.

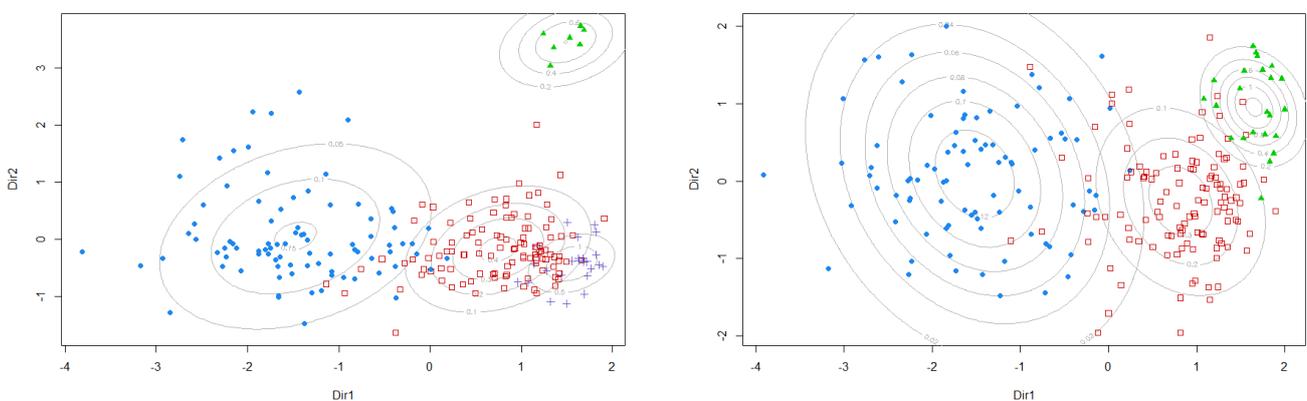
**Figure 11 : ICL EVALUATION BY NUMBER OF COMPONENTS**



Source: Outputs generated by R Studio

Finally, both segmentation models were graphed (**Figure 12**) in R to visually analyze if their relative difference in size and overlap supports the model selection.

**Figure 12 : SCATTERD PLOTS GENERATED BY R SHOWCASING TWO PROPOSED MODELS WITH 4 AND 3 SEGMENTS**



Source: Outputs generated by R Studio

The scattered plots in **Figure 12** shows the segments based on the observation's distances to each segment mean (Scrucca et al., 2016). The clusters are effectively VEI (equal form and diagonal). The graph at the left shows 4 segments where the

segment 2 (in red) and segment 4 (in purple) are too closed and highly overlapped. Additionally, the 3<sup>rd</sup> segment (in green) is seen as a small and isolated segment compared to the others. However, the 3-segments solution (graph at the right) clearly offers 3 distinct segments with lower overlap and representative sizes.

Subsequently, the final **3-segment solution** was finally chosen with (*BIC* = -18 250.68, *ICL* = -18 244.37 and a *LL* of -8756.447, and the results are illustrated in **Table 13** and **Figure 13** showing the segments profiles based on the means of touchpoint usage frequency. Segment 1 (S1) gathered 38.3% of participants with 87 observations, Segment 2 (S2) 51.54% of participants with 117 observations and Segment 3 (S3) with 23 observations (10.13%).

The significant differences between the segments were also tested through an ANOVA Analysis based on the means of touchpoint's usage frequency by segment. Differences are considered significant if  $p < .05$ . **Table 13** below summarizes the means representing each usage frequency level (measured from 1 to 5 in a Likert scale), and the ANOVA analysis results, including the Posthoc tests that were undertaken in each touchpoint. The detailed results of this analysis can be found in **Annex 8**, **Annex 9** and **Annex 10**.

**Table 13 : TOUCHPOINTS USED AMONG THE FOOD PURCHASE PROCESS BY USAGE FREQUENCY MEAN**

Stage	Touchpoint ID	TouchPoint	ANOVA			Segments			
			F	Sig.	PostHoc Test <sup>(a)</sup>	Sample Mean	S1: Early Omnichannel Adopters	S2: Curious Conservatives	S3: Uninterested Traditional
						n = 227	38.3% Mean S1	51.5% Mean S2	10.1% Mean S3
PrePurchase	S1PHMassStore	Supermarket, Convenience Store, etc. *S3	5.42	.005	Dunnett's C	<b>3.91</b>	3.99	4.00	<b>3.17</b>
	S1PHFriendsFam	Friends and Family. **	13.15	.000	Tukey HSD	<b>2.75</b>	<b>3.03</b>	<b>2.71</b>	<b>1.91</b>
	S1OLSocialMedia	Online: Social Media. **	19.65	.000		<b>1.91</b>	<b>2.26</b>	<b>1.82</b>	<b>1.00</b>
	S1OLSearchEng	Online: Search Engine. **	20.19	.000		<b>2.21</b>	<b>2.55</b>	<b>2.19</b>	<b>1.04</b>
	S1OLFoodDelWeb	Online: Food Delivery Websites. **	24.35	.000		<b>1.83</b>	<b>2.30</b>	<b>1.63</b>	<b>1.04</b>
	S1OLStoreWeb	Online: Supermarket, Convenience Store Website *S1	39.10	.000	Dunnett's C	<b>2.07</b>	<b>2.76</b>	1.69	1.39
	S1OLMassStoreCompWeb	Online: Supermarket or Store's Competitor Website *S1	17.86	.000		<b>1.72</b>	<b>2.17</b>	1.47	1.30
	S1OLEmailAd	Online: Email Ads **	18.54	.000		<b>1.56</b>	<b>1.98</b>	<b>1.37</b>	<b>1.00</b>
	S1MOBPhoneSMS	Mobile: Phone/SMS **	19.70	.000		<b>1.38</b>	<b>1.72</b>	<b>1.20</b>	<b>1.00</b>
S1MOBApps	Mobile: Search on Mobile Apps **	20.04	.000		<b>1.94</b>	<b>2.46</b>	<b>1.71</b>	<b>1.13</b>	
Purchase	S2PHMassStore	Supermarket or Mass Store *S2vsS1	5.40	.005		<b>4.15</b>	<b>3.94</b>	<b>4.32</b>	4.00
	S2PHSpecialtyStore	Specialty Store	0.73	.483	Tukey HSD	<b>2.85</b>	2.95	2.79	2.74
	S2PHConvenienceS	Convenience Store	0.02	.984		<b>2.66</b>	2.68	2.65	2.65
	S2OLStoreRetWeb	Online: Supermarket Website or Online Retailer **	68.37	.000		<b>1.94</b>	<b>2.84</b>	<b>1.43</b>	<b>1.17</b>
	S2OLLocalFoodDel	Online: Locally Sourced Food Delivery **	11.78	.000		<b>1.29</b>	<b>1.53</b>	<b>1.16</b>	<b>1.00</b>
	S2OLRecipeBox	Online: Recipe-Boxes Delivery *S1	12.26	.000		<b>1.18</b>	<b>1.41</b>	1.03	1.00
	S2OLPreparedMeal	Online: Prepared-Meals Delivery *S3	4.19	.016	Dunnett's C	<b>1.11</b>	1.21	1.05	<b>1.00</b>
	S2MOBStoreApp	Mobile App from a Retailer **	26.56	.000		<b>1.46</b>	<b>1.97</b>	<b>1.17</b>	<b>1.00</b>
	S2MOBAppResponsC	Mobile App for Responsible Consumption *S1	21.50	.000		<b>1.57</b>	2.03	1.32	1.09
S2MOBAppDelivery	Mobile App for Food Delivery **	28.42	.000		<b>2.31</b>	<b>2.92</b>	<b>2.08</b>	<b>1.22</b>	
Payment	S3MOB	Mobile (App or Web's mobile Version) **	61.20	.000		<b>1.90</b>	<b>2.69</b>	<b>1.49</b>	<b>1.00</b>
	S3OL	Online (Website Desktop Version) **	61.62	.000	Dunnett's C	<b>2.00</b>	<b>2.84</b>	<b>1.56</b>	<b>1.04</b>
	S3PH	Face to Face (Card or Cash) **	32.85	.000		<b>4.51</b>	<b>4.11</b>	<b>4.71</b>	<b>5.00</b>
Delivery	S4ClickCollect	Click & Collect **	20.53	.000		<b>1.69</b>	<b>2.15</b>	<b>1.46</b>	<b>1.13</b>
	S4ClickDrive	Click & Drive *S1	17.12	.000		<b>1.67</b>	<b>2.14</b>	1.40	1.26
	S4HomeDelivSt	Home Delivery from Store *S1	30.40	.000	Dunnett's C	<b>1.65</b>	<b>2.28</b>	1.29	1.13
	S4HomeDelivApp	Home Delivery by Delivery App **	24.63	.000		<b>2.15</b>	<b>2.75</b>	<b>1.88</b>	<b>1.22</b>
	S4TkonPurchase	Taken Upon Purchase **	15.94	.000		<b>4.24</b>	<b>3.79</b>	<b>4.43</b>	<b>4.96</b>
Post-Purchase	S5FeedbackSM	Support and Feedback on Social Media. **	37.97	.000		<b>1.39</b>	<b>1.87</b>	<b>1.11</b>	<b>1.00</b>
	S5FeedbackWebS	Support and Feedback on Website *S1	34.40	.000		<b>1.35</b>	<b>1.76</b>	1.10	1.04
	S5FeedbackMobApp	Support and Feedback on Mobile App **	32.14	.000	Dunnett's C	<b>1.33</b>	<b>1.74</b>	<b>1.10</b>	<b>1.00</b>
	S5FeedbackPhone	Support and Feedback on by Phone *S1	14.47	.000		<b>1.33</b>	<b>1.66</b>	1.15	1.04
	S5ShareExpSM	Sharing Experience Online **	19.23	.000		<b>1.37</b>	<b>1.72</b>	<b>1.18</b>	<b>1.00</b>

Source: Own analysis, Table extracted from Means generated after mclust segmentation in R Studio. ANOVA Analysis made in SPSS

Touchpoint usage frequency for food purchase rated on a 5-point Likert scale, being 1 (never used) to 5 (Always used)

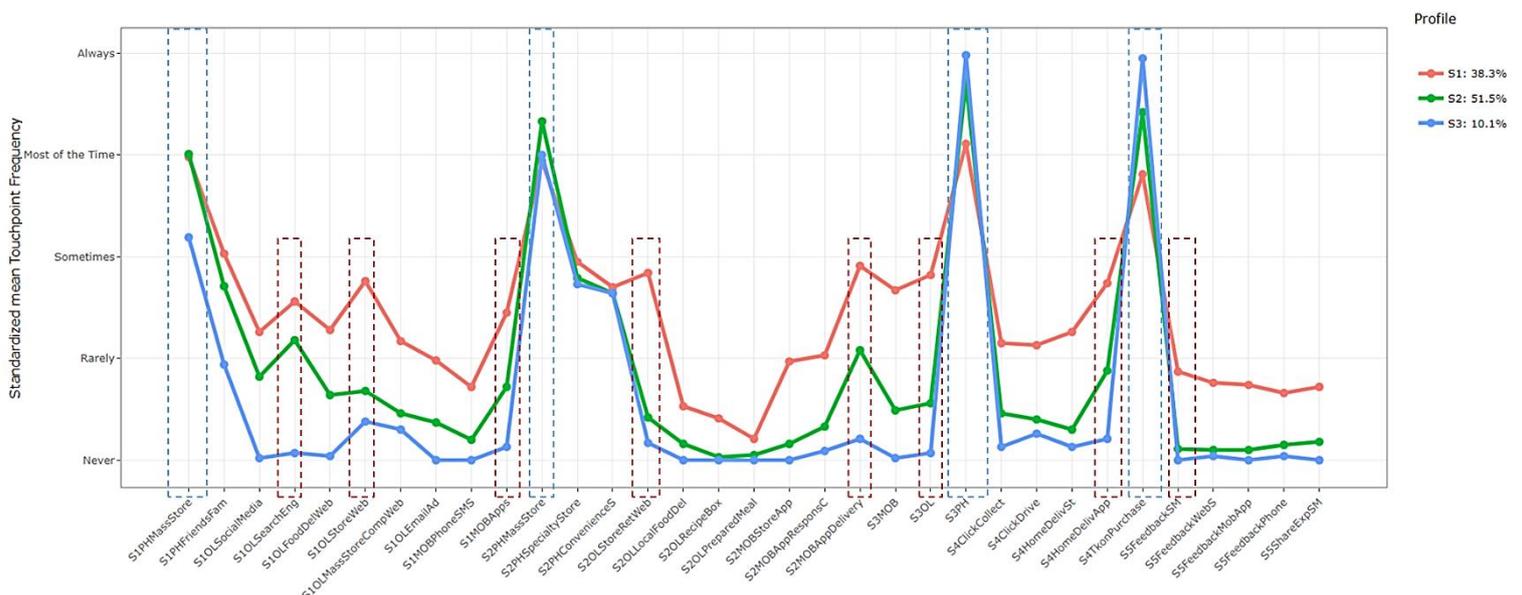
(a). Verify complete Posthoc tests in Annex 7

\* The mean difference is significant only between a given segment and the others: (\*S3 vs. S1&S2) or (\*S1 vs. S2&S3) or (\*S2 vs S1)

\*\* The mean difference is significant between all segments (S3 vs. S1, S3 vs. S2 and S1 vs. S2)

Digital Channels means highlighted in blue

**Figure 13 : TOUCHPOINTS USED AMONG THE FOOD PURCHASE PROCESS – GRAPHED BY USAGE FREQUENCY AVERAGE AND SEGMENT**



Source: Own analysis, Graph generated in R (ggplotly) from Means generated by segment in R Studio after mclust segmentation.

Touchpoint usage frequency for food purchase rated on a 5-point Likert scale, being 1 (never used) to 5 (Always used)

A score of 1 reveals the lowest usage frequency or touchpoint “Never” used, 2 reveals a rarely usage, 3 as occasional or a touchpoint used sometimes, 4 as a touchpoint used “most of the time” and 5 indicates the highest frequency or touchpoint “Always” used. Consequently, **Figure 13** translates **Table 13** showing graphically the usage frequency means, where the main differences and similarities between the 3 segments detected are visible, by touchpoint usage averaged score, throughout the purchase process, coded as S1 for Pre-Purchase to S5 for Post-Purchase.

The main differences (in red) and similarities (in blue) have been highlighted inside dotted areas, and it can be observed that the physical touchpoints (brick-and-mortar stores) are still being frequently used among the first 4 purchase stages (the peak points in **Figure 13**) by the three segments, most of time by Segment 1 and 2, and sometimes for Segment 3 (S3) in the first stage ( $M = 3.17$ ,  $SD = 1.47$ ), compared to online or mobile touchpoints. There was not a significant difference ( $p > .05$ ) between segment S1 ( $M=3.99$ ,  $SD=.92$ ) and S2 ( $M=4.0$ ,  $SD=1.20$ ) in the use brick-and-mortar stores during the prepurchase stage, and both still consider opinions from friends and family before food purchases, especially for Segment S1 in which it was significantly higher ( $M = 3.03$ ,  $SD = .970$ ,  $p = .001$ ) than S2 ( $M = 2.71$ ,  $SD = .947$ ) and S3 ( $M=1.91$ ,  $SD = .723$ ,  $p = .04$ ).

The Segment S1 uses Social Media ( $M=2.26$ ,  $SD=1.01$ ), Online Search Engines ( $M=2.55$ ,  $SD=1.11$ ), Food Delivery Websites such as Hello Fresh, Epicery, etc. ( $M=2.30$ ,  $SD=1.07$ ), Store Websites ( $M=2.76$ ,  $SD=1.12$ ), and Mobile Apps ( $M=2.46$ ,  $SD=1.27$ ) during the pre-purchase stage in a higher significant frequency (Rarely to Sometimes,  $p < .05$ ) compared to segment S3 and segment S2. Segment S2 scored significantly ( $p < .05$ ) higher using online search engines ( $M = 2.19$ ,  $SD=1.03$ ) than Segment 3 ( $M = 1.04$ ,  $SD=.21$ ) but significantly lower ( $p < .05$ ) than Segment 1 ( $M = 2.55$ ,  $SD=1.11$ ) which reveals that this online touchpoint is used by them, at least rarely, before considering food purchases, but not as much as the first segment.

In the second stage, food purchase, the second Segment uses Supermarket or Mass Stores Websites ( $M= 4.32$ ,  $SD=.81$ ) in a higher frequency (at least most of time) compared to segment S1 ( $M = 3.94$ ,  $SD=.87$ ) and statistically significant ( $p = .005$ ). However, no significant difference ( $p > .10$ ) was found in the use of alternative physical channels, such as specialty and convenience stores, between the three segments, during this stage.

Regarding the digital touchpoints, Segment 1 showed a significantly higher usage frequency ( $M=2.84$ ,  $SD=1.24$ ,  $p < .05$ ) of store websites or online retailers (rarely to

sometimes) than Segment 2 ( $M=1.43$ ,  $SD=.67$ ) and 3 ( $M=1.17$ ,  $SD=.39$ ) revealing a more digital inclination along with their use of store websites in the previous stage. Segment S2 showed a higher ( $M=2.08$ ,  $SD=1.052$ ) and significant difference ( $p<.05$ ) using mobile touchpoints more frequently than Segment S3 ( $M=1.22$ ,  $SD=0.52$ ), purchasing on mobile applications for food delivery, at least rarely. These touchpoints are significantly more frequently used by Segment 1 ( $M=2.92$ ,  $SD=1.21$ ,  $p<.05$ ) than S2 and S3, in line with previous findings. Additionally, Segment S1 was the only segment to buy on mobile apps for responsible consumption (i.e. *Too Good to Go*, *Phenix*, etc.) at least rarely ( $M=2.03$ ,  $SD=1.13$ ), and statistically significant ( $p<.05$ ) compared to Segment 2 ( $M=1.32$ ,  $SD=.64$ ) and 3 ( $M=1.09$ ,  $SD=.42$ )

Not surprisingly, the three segments scored high on paying face to face in cash or banking cards during their presential purchases (but with significant difference between them,  $p<.05$ ), showing that this touchpoint is used at least most of the time by Segment 1 ( $M=4.11$ ,  $SD=.754$ ) and Segment 2 ( $M=4.71$ ,  $SD=.526$ ), and always ( $M=5.0$ ,  $SD=.0$ ) by segment 3. Online payments (through websites) for food purchase is mainly used by Segment S1 at least rarely ( $M = 2.84$ ,  $SD=1.25$ ), along with mobile touchpoints payments ( $M = 2.69$ ,  $SD=1.10$ ), in line with the previous purchase touchpoints, and significantly higher ( $p<.05$ ) than segment S2 and S3.

At the 4<sup>th</sup> stage, clearly the segment 2 ( $M = 4.43$ ,  $SD=1.06$ ) and segment 3 ( $M = 4.96$ ,  $SD=.21$ ) scored high when taking their purchase upon purchase on presential courses, at least most of the time, compared to segment 1 ( $M=3.79$ ,  $SD=1.09$ ) with a small but significant difference ( $p<.05$ ). Among the online touchpoints, only the home delivery apps were found to be used more often (and significantly higher  $p<.05$ ) by Segment 1 ( $M = 2.75$ ,  $SD=1.26$ ) compared to segment 2 ( $M = 1.88$ ,  $SD=1.05$ ) and 3 ( $M = 1.22$ ,  $SD=.52$ ). Alternative delivery solutions were also detected to be used by Segment S1, at least rarely, such as Click&Collect ( $M = 2.15$ ,  $SD=1.12$ ), Click&Drive ( $M = 2.14$ ,  $SD=1.20$ ) and Home Delivery by a physical store ( $M = 2.28$ ,  $SD=1.29$ ) compared to segments S2 and S3 ( $p<0.05$ ).

Finally, the post-purchase stage did not show to be a critical stage where the consumers showed great involvement for food purchase. If some main differences can be highlighted, some members of segment S1 declared using rarely social media to give suggestions or feedback ( $M = 1.87$ ,  $SD=0.99$ ,  $p<.05$ ), but among all the touchpoints evaluated, the usage of additional touchpoints was weak in this stage. Sharing their consumption online was barely frequently done by some consumers belonging to the first segment ( $M=1.72$ ,  $SD=.97$ ), but with significant difference ( $p>.05$ ) against Segment 2 ( $M=1.18$ ,  $SD=.47$ ) and 3 ( $M=1.0$ ,  $SD=0$ ).

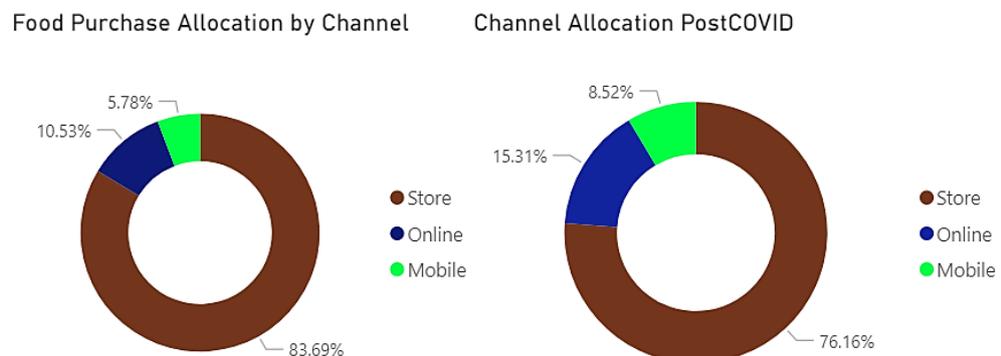
In conclusion, Segment 1 showed a higher usage frequency of online and mobile touchpoints, along with their use of physical touchpoints throughout the 4 food purchase stages, revealing an orientation towards an omnichannel behavior. This is why it was labeled as “*Early Omnichannel Adopters*” given that they did not registered high scores (over 4, most of time) on these digital channels but they are in an early stage of their versatile and regular adoption.

Segment 2 was labeled as “*Curious Conservatives*” as the frequency of physical touchpoints is higher than the “*Early Omnichannel Adopters*” but they are starting to explore on online search engines and mobiles apps for food delivery at least rarely. Segment 3 represents the most traditional segment showing no interest at all in digital touchpoints among the 5 purchase stages, exploring sometimes on brick and mortar stores, purchasing in them, paying and taking their courses once they finish, without engaging in any additional activity. This segment was labeled as “*Uninterested Traditional*” shoppers.

#### 4.1.2. Purchase Orientation and COVID-19 Impact

The evaluation of purchase orientation was used to confirm, first, the overall purchase profile of channel allocation for food purchase before and after the COVID-19 pandemic, and to be used as an additional indicator of the segment’s profiles generated in the first part of this segmentation study performed in R Studio. The relative channel change attitude due to COVID-19, measured in a 5-point Likert scale (from 1 = Never to 5 = A lot), was also tested using an ANOVA analysis to verify significant difference between the segments (See **Annex 11**)

**Figure 14 : FOOD PURCHASES CHANNEL ALLOCATION PREVIOUS AND AFTER COVID LOCKDOWN IN 2020**



Source: Own analysis

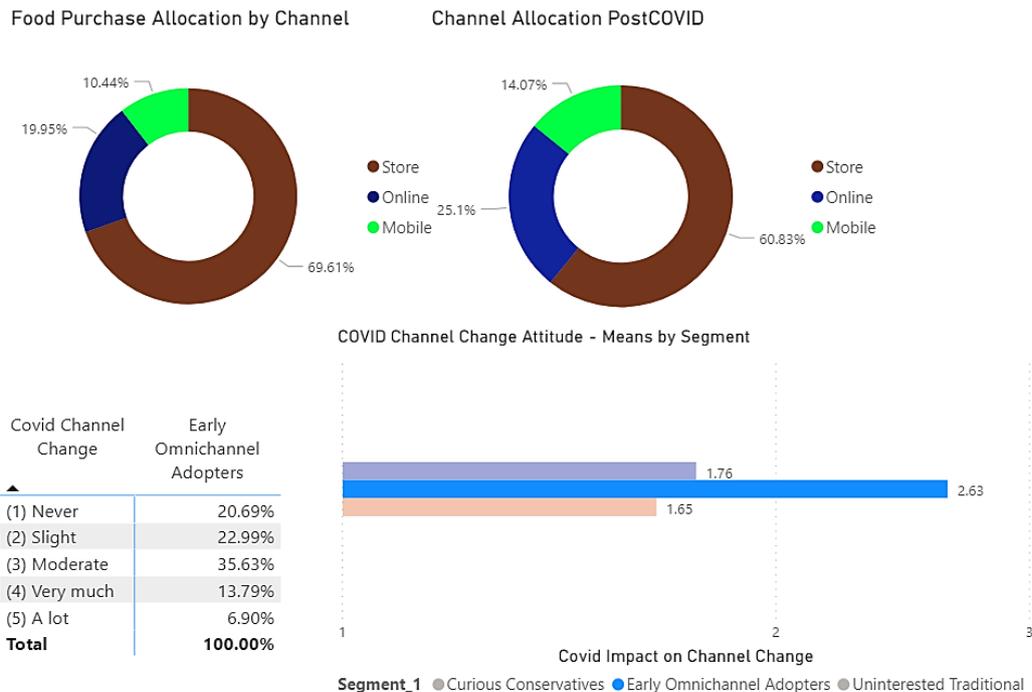
Overall (**Figure 14**), French residents have increased their allocation of food purchases on online and mobile channels after the COVID-19 pandemic by 4.78% and 2.74% respectively. They declared allocating, in average, 76.16% of

their food courses on physical stores after the pandemic, when it was 83.69% in average before the first lockdown.

Disaggregating the analysis by segment, it can be observed in **Figure 15** that the *Early Omnichannel Adopters* manifested the highest (moderate  $M = 2.63$ ,  $SD=1.16$ ) and most significant ( $p<.05$ ) impact in their channel allocation change due to the pandemic, where 56.32% of consumers declared having a moderate to high (“A lot”) channel switch.

The evidence is seen also in **Figure 15**, where the allocation of the online channels passed from 19.95% to 25.1% and 10.44% to 14.07% on mobile channels for food purchase. This is aligned with this segment’s usage frequency, particularly on digital touchpoints compared to the other segments.

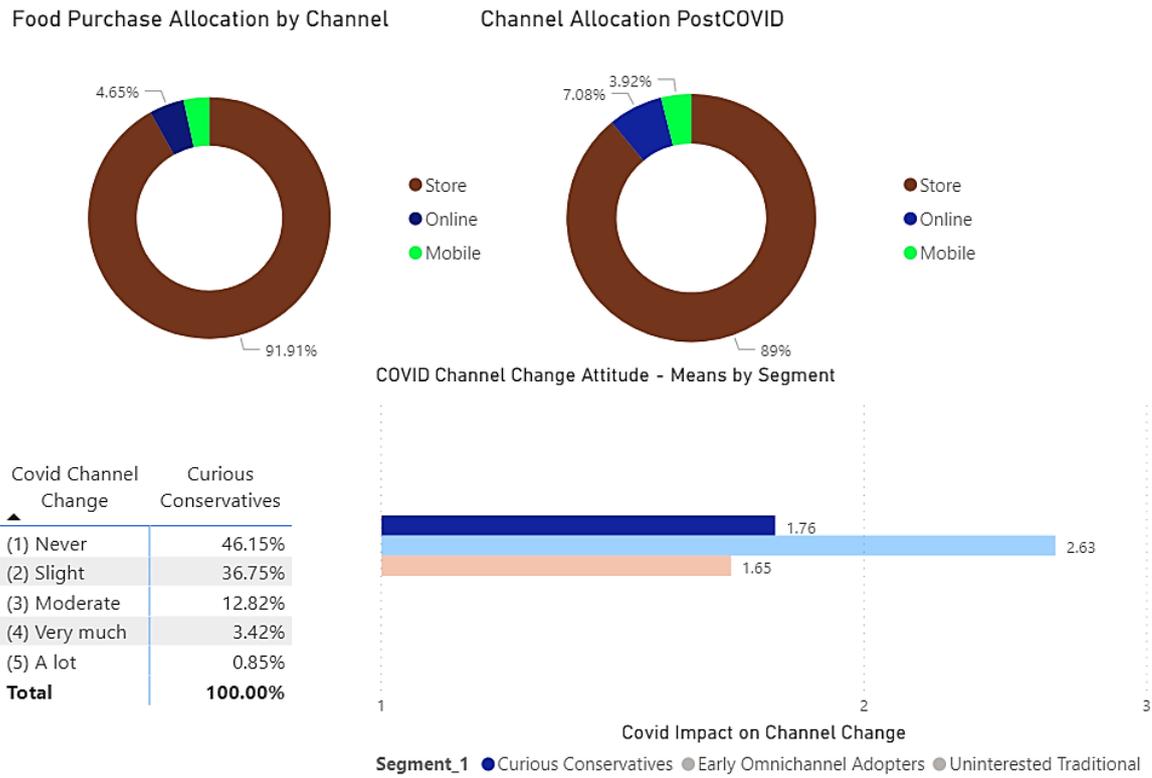
**Figure 15 : FOOD PURCHASES CHANNEL ALLOCATION AND COVID IMPACT TO EARLY OMNICHANNEL ADOPTERS**



Source: Own analysis

**Figure 16** below illustrates the purchase orientation of the *Curious Conservatives* who showed a slight increase in the allocation of online channels, from 4.65% to 7.08% after the first lockdown, and 3.44% to 3.92% in mobile channels. They keep a relatively similar behavior on their allocation of purchase on physical stores, even after the pandemic (89%). This segment manifested being somewhat affected by the impact in their channel allocation change due to the pandemic (low  $M= 1.76$ ,  $SD=.87$ ), where more than half of consumers (82.9%) declared that the pandemic never to slightly made them changed their channel choice.

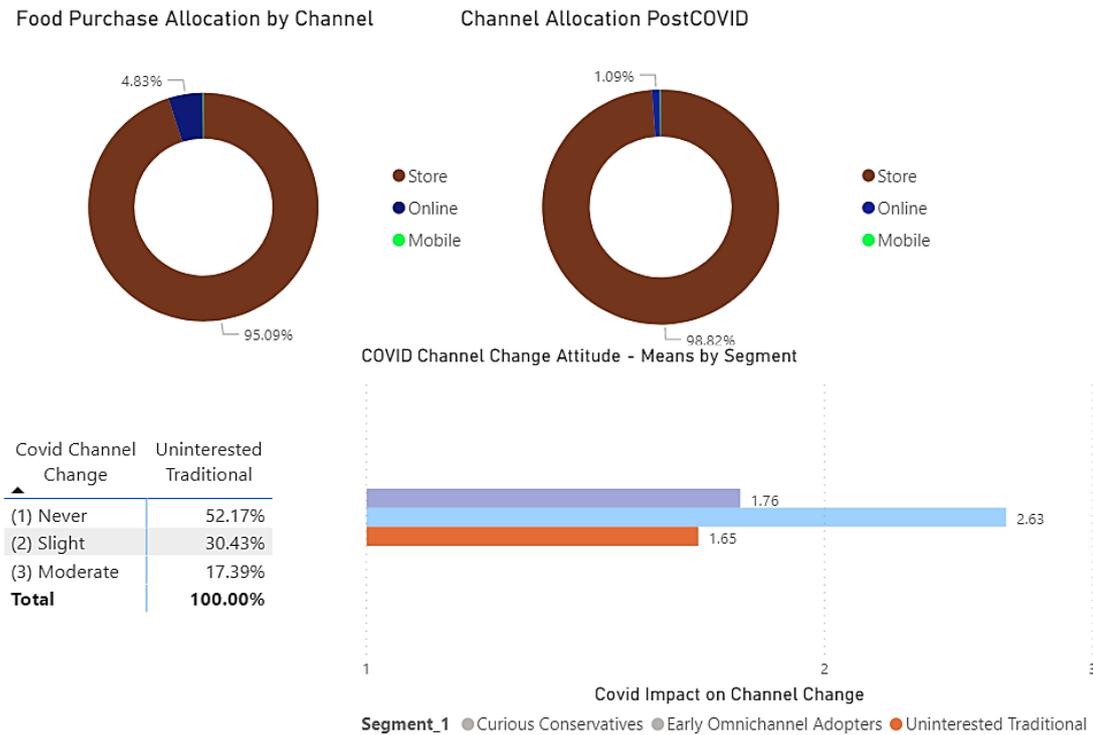
**Figure 16: FOOD PURCHASES CHANNEL ALLOCATION AND COVID IMPACT TO CURIOUS CONSERVATIVES**



Source: Own analysis

The *Uninterested Traditional shoppers* analyzed in **Figure 17** below manifested the lowest impact by the pandemic, allocating 98.82% of their food purchases in physical channels and decreasing their low allocation of online channels, if any, by 1%. More than half of these consumers (52.17%) declared that never changed their purchase channels after the lockdown, sticking to their presential courses as before, but the difference in channel change attitude ( $M=1.65$ ,  $SD=.78$ ) was not significant ( $p>.05$ ) compared to Curious Conservatives ( $M=1.76$ ,  $SD=.87$ ).

**Figure 17 : FOOD PURCHASES CHANNEL ALLOCATION AND COVID IMPACT TO UNINTERESTED TRADITIONAL**



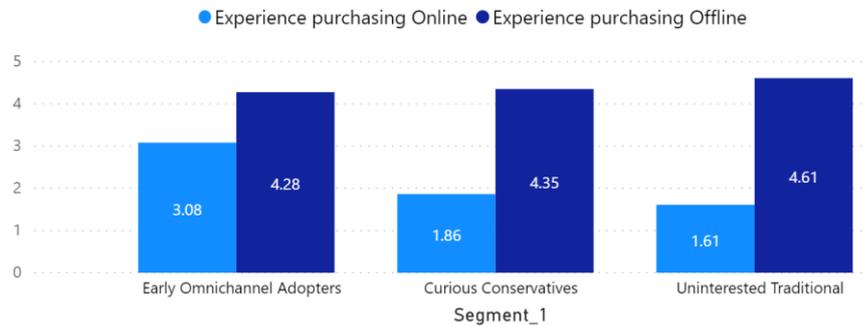
Source: Outputs generated by R Studio

These results revealed that the *Early Omnichannel Adopters* have registered the highest increase on the allocation of digital touchpoints for food purchase compared to the *Curious Conservatives* and the *Uninterested Traditional shoppers*. Using the scale borrowed from (Herhausen et al., 2019), it was found also, aligned with previous findings, that they also had a moderate ( $M = 3.08$ ,  $SD=1.01$ ,  $p=0.00$ ) and significantly<sup>7</sup> superior expertise buying food online compared to the *Curious Conservatives* ( $M=1.86$ ,  $SD=.086$ ) and the *Uninterested Traditional* ( $M=1.61$ ,  $SD=.941$ ) consumers.

As it can be seen below in **Figure 18** that the *Uninterested Traditional shoppers* showed the highest expertise buying food offline ( $M = 4.61$ ;  $SD=58$ ) among the 3, but it was not significantly different from the other two segments ( $p>0.05$ ). Evidently, as seen the segmentation analysis before, the three segments still allocate and have a relatively high frequency of purchase in physical touchpoints.

<sup>7</sup> See Annex 11

**Figure 18 : EXPERTISE PURCHASE FOOD ONLINE/OFFLINE BY SEGMENT MEAN SCORE**



Source: Own analysis

The statistical significance of this covariate was also included in the 3<sup>rd</sup> part of the study where a multinomial logistic regression was performed to assess the meaningful food related lifestyles and demographic differences between the segments.

#### 4.2. Food Related Lifestyles and Demographic Covariates

The evaluation of the covariates probabilities and impact by segment were calculated in SPSS using a multinomial logit model that identified the coefficients and statistical significance per covariate. Before loading the food related lifestyle dimensions, measured in multi-item questions, an Exploratory Factor Analysis was performed in SPSS to determine the proper number of items that loaded high in each construct, assessing their reliability using the Cronbach's Alfa test.

The final factor solution reduced the number of items from 66 to 44 items. The items were loaded considering that they explained at least (.60) of the variances per construct and eigenvalues >1 as the criteria to determine the 13 variables that measured the food related lifestyles dimensions. The final solution provided the 13 components (variables) that explained 75.432% of the total variance in the data set (See Table 14), a Kaiser-Meyer-Olkin Measure of Sampling Adequacy value of (.803) and significant ( $p > .05$ ) in the Bartlett's Test of Sphericity.

**Table 14 : EXPLORATORY FACTOR ANALYSIS – EIGEN VALUES**

Component	Total Variance Explained								
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.504	19.328	19.328	8.504	19.328	19.328	5.440	12.363	12.363
2	4.823	10.962	30.290	4.823	10.962	30.290	3.037	6.902	19.264
3	3.705	8.420	38.710	3.705	8.420	38.710	2.941	6.683	25.948
4	2.652	6.026	44.737	2.652	6.026	44.737	2.849	6.475	32.423
5	2.053	4.665	49.402	2.053	4.665	49.402	2.671	6.071	38.494
6	1.877	4.267	53.669	1.877	4.267	53.669	2.660	6.044	44.538
7	1.819	4.134	57.802	1.819	4.134	57.802	2.343	5.326	49.864
8	1.624	3.691	61.493	1.624	3.691	61.493	2.164	4.918	54.782
9	1.383	3.142	64.636	1.383	3.142	64.636	2.081	4.729	59.512
10	1.313	2.984	67.619	1.313	2.984	67.619	1.952	4.437	63.948
11	1.246	2.831	70.450	1.246	2.831	70.450	1.767	4.017	67.965
12	1.172	2.664	73.114	1.172	2.664	73.114	1.645	3.740	71.705
13	1.020	2.318	75.432	1.020	2.318	<b>75.432</b>	1.640	3.727	75.432
14	0.749	1.703	77.135						

Source: Outputs generated by SPSS

**Table 15** below summarizes the final Cronbach’s alfa evaluation (considering  $\alpha > .7$ ), the Pearson correlation for variables using only two items, the means (summated scales) by segment per construct. The final communalities, means and standard deviation of each item loaded can be verified in **Annex 13**.

**Table 15 : FOOD RELATED LIFESTYLES MEANS BY SEGMENT AND RELIABILITY ANALYSIS**

Food Related Lifestyles Covariates	SEGMENT			Sample Mean	Reliability	
	Early Omnichannel Adopters	Curious Conservatives	Uninterested Traditional		Cronbachs Alpha	Pearson
Time Pressure	3.66	3.46	3.19	<b>3.51</b>	.78	
Loyalty	3.76	3.77	3.67	<b>3.76</b>		.56
Quality Aspects	3.99	3.95	4.24	<b>3.99</b>	.84	
Enjoyment	2.82	2.50	2.37	<b>2.61</b>		.66
Price Criteria	3.59	3.57	3.45	<b>3.56</b>	.79	
Importance to Product Information	3.67	3.58	3.75	<b>3.63</b>	.83	
Passion for Cooking	3.52	3.37	3.38	<b>3.43</b>	.93	
Eating in Company	3.64	3.64	3.63	<b>3.64</b>		.60
Pleasure & Interest	4.11	4.12	4.12	<b>4.11</b>	.77	
Convenience	2.96	3.08	2.64	<b>2.99</b>	.89	
Environment Protection	3.87	3.91	3.88	<b>3.89</b>	.92	
Health Orientation	3.54	3.63	3.77	<b>3.61</b>	.81	
Attitudes to Advertisement	2.37	2.12	1.91	<b>2.19</b>		.71

Source: Own analysis

The items loaded per dimension were aggregated calculating their mean (Charry et al., 2016) to obtain the final factors used in the multinomial logistic regression. The model calculated, visible in **Table 16** below, passed the minimal significance test for Likelihood ( $p < .05$ ;  $BIC = 544.848$ ), Pearson ( $p > .05$ ) and Deviance ( $p > .05$ ) for model fit evaluation (See **Annex 7**). A strong *coefficient* ( $>1$ ) reveals that the participant who scored high in that covariate are more likely to belong to each segment and impacted negatively or positively by each dimension, compared to the reference category.

**Table 16 : SEGMENTS AND COVARIATE SIGNIFICANCE.**

	Early Omnichannel Adopters (a)			Curious Conservatives (a)			Early Omnichannel Adopters (c)			Model Test
		Wald	Sig.		Wald	Sig.		Wald	Sig.	Sig.
Intercept	0.89	0.02	0.878	7.36	1.99	0.158	-6.47	4.17	0.041	
<b>CovidCH</b>	<b>1.32</b>	7.79	<b>0.005</b>	0.42	0.95	0.329	<b>0.90</b>	12.22	<b>0.000</b>	<b>0.000</b>
<b>OnlineX</b>	<b>2.08</b>	20.92	<b>0.000</b>	0.35	0.85	0.356	<b>1.73</b>	35.19	<b>0.000</b>	<b>0.000</b>
OfflineX	-1.01	2.88	0.089	-0.92	2.92	0.087	-0.09	0.09	0.769	0.137
<b>Age</b>	<b>-0.07</b>	4.10	<b>0.043</b>	<b>-0.09</b>	9.49	<b>0.002</b>	0.03	1.18	0.277	<b>0.003</b>
<b>TimePressure</b>	<b>1.38</b>	9.24	<b>0.002</b>	<b>0.78</b>	3.99	<b>0.046</b>	<b>0.60</b>	4.95	<b>0.026</b>	<b>0.005</b>
Loyalty	-0.41	0.74	0.388	0.09	0.05	0.826	-0.50	2.19	0.139	0.329
<b>QualityAspects</b>	<b>-1.56</b>	4.09	<b>0.043</b>	<b>-1.35</b>	4.00	<b>0.046</b>	-0.20	0.26	0.611	0.081
<b>Enjoyment</b>	0.30	0.53	0.465	-0.26	0.49	0.484	<b>0.56</b>	5.82	<b>0.016</b>	<b>0.040</b>
Price Criteria	-0.11	0.05	0.821	-0.03	0.01	0.928	-0.07	0.05	0.818	0.968
<b>ProductInfo</b>	<b>-1.14</b>	4.74	<b>0.030</b>	-0.54	1.45	0.229	-0.60	3.71	0.054	<b>0.049</b>
Passion for Cooking	0.66	1.82	0.177	0.52	1.53	0.216	0.14	0.19	0.660	0.400
EatCompany	-0.07	0.03	0.866	-0.02	0.00	0.965	-0.06	0.04	0.837	0.977
Pleasure & Interest	-1.04	2.29	0.130	-0.64	1.12	0.291	-0.41	1.06	0.304	0.294
Convenience	0.45	0.99	0.320	0.65	2.87	0.090	-0.20	0.49	0.485	0.186
Environment	1.14	3.72	0.054	0.72	2.37	0.124	0.43	1.07	0.300	0.139
Health Orientation	1.01	3.21	0.073	0.70	2.04	0.154	0.31	0.81	0.369	0.202
AttitudeAds	-0.42	0.85	0.358	-0.37	0.83	0.362	-0.05	0.03	0.858	0.629
<b>Income</b>										0.084
<b>&lt; 24.9k €</b>	3.02	3.79	0.052	0.66	0.25	0.617	<b>2.362</b>	6.12	<b>0.013</b>	
<b>25k € - 60k €</b>	1.25	1.05	0.305	-0.26	0.06	0.801	<b>1.509</b>	3.92	<b>0.048</b>	
60k € +	0 <sup>b</sup>			0 <sup>b</sup>			0 <sup>b</sup>			
<b>FoodBudget</b>										<b>0.001</b>
<b>&lt; 240 €</b>	-1.51	0.40	0.526	-1.26	0.43	0.511	-0.248	0.02	0.879	
<b>240 € - 329 €</b>	3.86	3.07	0.080	2.11	1.42	0.234	1.75	1.36	0.243	
<b>330 € - 529 €</b>	2.33	1.56	0.211	-0.13	0.01	0.928	2.458	3.01	0.083	
<b>530 € - 780 €</b>	2.95	2.35	0.125	0.70	0.21	0.648	2.244	2.95	0.086	
<b>780 € +</b>	0 <sup>b</sup>			0 <sup>b</sup>			0 <sup>b</sup>			
<b>Household</b>										<b>0.012</b>
<b>1, living alone</b>	<b>-5.07</b>	4.35	<b>0.037</b>	-1.56	0.50	0.480	<b>-3.512</b>	8.83	<b>0.003</b>	
<b>2 people</b>	<b>-4.84</b>	4.66	<b>0.031</b>	-1.65	0.67	0.413	<b>-3.187</b>	8.11	<b>0.004</b>	
<b>3 people</b>	-1.40	0.33	0.564	1.05	0.23	0.631	<b>-2.45</b>	4.35	<b>0.037</b>	
<b>4 people</b>	-3.67	2.31	0.129	-0.34	0.02	0.878	<b>-3.336</b>	8.51	<b>0.004</b>	
4+ People	0 <sup>b</sup>			0 <sup>b</sup>			0 <sup>b</sup>			
<b>Gender</b>										<b>0.017</b>
<b>Female</b>	<b>2.23</b>	6.95	<b>0.008</b>	<b>1.86</b>	6.50	<b>0.011</b>	0.377	0.54	0.463	
Male	0 <sup>b</sup>			0 <sup>b</sup>			0 <sup>b</sup>			

a. The reference category is: **Uninterested Traditional**.

b. This parameter is set to zero because it is redundant.

c. The reference category is:

**Curious Conservatives**

In the aggregate model, the psychographic covariates that were found significant were, first, the relative channel change due to the pandemic ( $p < .01$ ) and the expertise buying food online ( $p < .01$ ). The covariates measuring the food related lifestyles (FRL) that were found significant were Time Pressure ( $p < .05$ ), Enjoyment ( $p < .05$ ) and Importance to Product information ( $p < .05$ ). Dimensions such as Quality Aspects were found significant ( $p < 0.05$ ) only when comparing segments.

Regarding the demographic covariates, Food Monthly Budget ( $p < .01$ ), Household size ( $p < .01$ ) and gender ( $p < .05$ ) were found significant. Some difference arose when the subcategories were analyzed between the segments, especially in Income, where some categories were found significant only when comparing Early Omnichannel Adopters and Curious Conservatives. Food Monthly budget was found significant only at the ( $p < .10$ ) level during the comparisons.

The results confirmed the previous findings regarding the COVID-19 relative impact on channel allocation change by segment, and the expertise buying food online or offline. The Early Omnichannel Adopters were more likely to change their channel for food purchase due to the pandemic compared to the Uninterested Traditional consumers (*CovidCH 1.32,  $p = .005$* ), and compared to the Curious Conservatives Shoppers (*CovidCH 0.90,  $p = .000$* ). Consumers belonging to the Early Omnichannel Adopters segment also revealed being more experienced buying food online than the Uninterested Traditional Shoppers (*OnlineX 2.08,  $p = 0.00$* ) and compared the Curious Conservatives (*OnlineX 1.73,  $p = .00$* ).

Concerning the food related lifestyles, the Early Omnichannel Adopters are more likely to feel more pressured and concerned about time (*TimePressure 1.38,  $p = .002$* ) than the Uninterested Traditional shoppers, and also compared to the Curious Conservative Shoppers (*TimePressure 0.60,  $p = .026$* ). The Curious Conservatives Shoppers were also found to feel more concerned about time than then the Uninterested Traditional shoppers (*TimePressure 0.7,  $p = .046$* ).

Hence, despite the fact that most of the segments scored high ( $M > 3.9$ ) on the importance they give to food quality aspects, the Early Omnichannel Adopters are less likely to be concerned about this dimension than the Uninterested Traditional shoppers (*QualityAspects -1.56,  $p = .043$* ) as the Curious Conservatives shoppers (*QualityAspects -1.35,  $p = .046$* ). The difference in this covariate was not significant between the Curious Conservatives and the Early Omnichannel Adopters.

Early Omnichannel Adopters showed a slightly superior enjoyment of food shopping compared to the Curious Conservatives Shoppers (*Enjoyment .56,  $p = .016$* ). These shoppers also give less importance to product information while shopping food compared to the Uninterested Traditional shoppers (*ProductInfo -1.14,  $p = .030$* ).

Regarding the covariates measured to evaluate the level of concerns about the environment during food purchases and the orientation to buy healthy foods, all the segments scored similar averages above  $M > 3.8$  (See **Table 15**), but the difference was not significant between them ( $p > 0.05$ ). Even though the orientation to consider acquiring healthy foods was higher in the Uninterested Traditional shoppers ( $M=3.77$ ), the difference was not significant ( $p > 0.05$ ) against the Early Omnichannel Adopters and Curious Conservatives Shoppers.

A demographic summary can be seen below by segment in **Table 17**. The regression model estimated that the Early Omnichannel Adopters are more likely to earn low and middle incomes rather than high incomes ( $>60k$  €) compared to Curious Conservatives (*Income < 25k€ 2.362 p=0.013; Income 25k-60k€ 1.51, p =.048*). Even though the proportion of Early Omnichannel Adopters earning below 25k € was higher (40.2%) compared to the Uninterested Traditional shoppers (30.4%) the difference was only significant at the  $p < .10$  level ( $p=0.052$ ). Not statistically significant difference was found among the food monthly budgets between the segments ( $p > .05$ ) despite the fact that the Curious conservative shoppers registered a higher proportion of respondents with lower budgets ( $<330€$ ) and Early Omnichannel Adopters having more respondents allocating budgets between 330€ and 780€.

Analyzing the household sizes, Early Omnichannel Adopters are more likely to live in larger households (over 2 people) compared to the uninterested traditional shoppers (**Living alone -5.07 p=0.037; 2 people -4.84 p=0.31**) and to the Curious conservative shoppers ( $p < 0.05$  for households with not less than 4 members). The latter showed the higher proportion of people living alone among the three segments (46.2%).

Finally, the, Early Omnichannel Adopters (*Age -.07, p= 0.043*) and curious conservative shoppers (*Age -.08, p= 0.002*) tend to be younger than the Uninterested traditional shoppers ( $M=39$ ) with an average age of 30 and 29 years old respectively.

**Table 17 : SOCIO-DEMOGRAPHIC CHARACTERISTICS BY SEGMENT**

		SEGMENT						Total	
		Early Omnichannel Adopters		Curious Conservatives		Uninterested Traditional			
		Count	%	Count	%	Count	%		
<b>Income</b>	Less than 24 999 €	35	40.2%	57	48.7%	7	30.4%	99	43.6%
	Between 25 000 € and 60 000 €	34	39.1%	30	25.6%	8	34.8%	72	31.7%
	More than 60 000 €	18	20.7%	30	25.6%	8	34.8%	56	24.7%
	<b>Total</b>	<b>87</b>	<b>100.0%</b>	<b>117</b>	<b>100.0%</b>	<b>23</b>	<b>100.0%</b>	<b>227</b>	<b>100.0%</b>
<b>FoodBudget</b>	< 240 €	11	12.6%	36	30.8%	7	30.4%	54	23.8%
	240 € - 329 €	27	31.0%	32	27.4%	2	8.7%	61	26.9%
	330 € - 529 €	32	36.8%	21	17.9%	7	30.4%	60	26.4%
	530 € - 780 €	14	16.1%	18	15.4%	2	8.7%	34	15.0%
	> 780 €	3	3.4%	10	8.5%	5	21.7%	18	7.9%
	<b>Total</b>	<b>87</b>	<b>100.0%</b>	<b>117</b>	<b>100.0%</b>	<b>23</b>	<b>100.0%</b>	<b>227</b>	<b>100.0%</b>
<b>Household</b>	Live Alone	20	23.0%	54	46.2%	9	39.1%	83	36.6%
	2 People	29	33.3%	25	21.4%	10	43.5%	64	28.2%
	3 People	14	16.1%	14	12.0%	1	4.3%	29	12.8%
	4 People	13	14.9%	20	17.1%	2	8.7%	35	15.4%
	>4 People	11	12.6%	4	3.4%	1	4.3%	16	7.0%
	<b>Total</b>	<b>87</b>	<b>100.0%</b>	<b>117</b>	<b>100.0%</b>	<b>23</b>	<b>100.0%</b>	<b>227</b>	<b>100.0%</b>
<b>Average Age</b>		30		29		39		30	
<b>Age Group</b>	<= 24	38	43.7%	61	52.1%	6	26.1%	105	46.3%
	25 - 34	24	27.6%	32	27.4%	5	21.7%	61	26.9%
	35 - 44	13	14.9%	8	6.8%	1	4.3%	22	9.7%
	45 - 54	9	10.3%	9	7.7%	6	26.1%	24	10.6%
	55 - 64	3	3.4%	4	3.4%	5	21.7%	12	5.3%
	65+	0	0.0%	3	2.6%	0	0.0%	3	1.3%
	<b>Total</b>	<b>87</b>	<b>100.0%</b>	<b>117</b>	<b>100.0%</b>	<b>23</b>	<b>100.0%</b>	<b>227</b>	<b>100.0%</b>
<b>Gender</b>	Female	62	71.3%	84	71.8%	13	56.5%	159	70.0%
	Male	25	28.7%	33	28.2%	10	43.5%	68	30.0%
	<b>Total</b>	<b>87</b>	<b>100.0%</b>	<b>117</b>	<b>100.0%</b>	<b>23</b>	<b>100.0%</b>	<b>227</b>	<b>100.0%</b>

## V. DISCUSSION AND CONTRIBUTIONS

### 5.1. Segments Analysis Overview

The summary **Table 18** below shows an overview of the main findings regarding the profiles of food shopper segments in France by their use of specific touchpoints throughout the omnichannel purchase process, and the relevant food related lifestyles characteristics and demographics.

**Table 18 : OMNICHANNEL FOOD PURCHASE SEGMENTATION IN FRANCE - OVERVIEW**

SEGMENT	EARLY OMNICHANNEL ADOPTERS – 38.3%	CURIOUS CONSERVATIVES – 51.5%	UNINTERESTED TRADITIONAL – 10.1%
<b>FOOD PURCHASE ORIENTATION AND COVID IMPACT</b>	<p><b>Moderately Experienced</b> Purchasing Food Online.</p> <p>Purchase Channel Allocation- Post COVID</p> <ul style="list-style-type: none"> <li>✓ 60.8% Physical Store</li> <li>✓ 25.1% Online</li> <li>✓ 14.1% Mobile</li> </ul> <p>Channel allocation was moderately to highly impacted by COVID, increasing purchases: <b>online (+5.15%)</b> and <b>mobile (+3.63%)</b></p>	<p><b>Slightly Experienced</b> Purchasing Food Online.</p> <p>Purchase Channel Allocation- Post COVID</p> <ul style="list-style-type: none"> <li>✓ 89% Physical Store</li> <li>✓ 7.1% Online</li> <li>✓ 3.9% Mobile</li> </ul> <p>Channel allocation was slightly impacted by COVID, increasing purchases. <b>online (+2.43%)</b> and <b>mobile (+.48%)</b></p>	<p><b>Slightly Experienced</b> Purchasing Food Online.</p> <p>Purchase Channel Allocation - Post COVID</p> <ul style="list-style-type: none"> <li>✓ 98.8% Physical Store</li> <li>✓ 1.1% Online</li> <li>✓ 0.1% Mobile</li> </ul> <p>Channel allocation was slightly impacted by COVID, increasing purchases mainly on physical stores <b>(+3.73%)</b>.</p>
<b>OMNICHANNEL FOOD PURCHASE BEHAVIOR BASED ON TOUCHPOINT USAGE FREQUENCY</b>	<p><b>PRE-PURCHASE (SEARCH):</b></p> <ul style="list-style-type: none"> <li>o Visits Physical Stores most of time.</li> <li>o Considers Friends &amp; Family opinions at least sometimes.</li> <li>o Rarely use of Social Media and Food Delivery Websites but they visit sometimes the Store Websites and uses Online Search Engines.</li> <li>o Mobile Apps are used at least rarely.</li> </ul> <p><b>FOOD PURCHASE:</b></p> <ul style="list-style-type: none"> <li>o Purchases in supermarkets and mass stores most of the time, and sometimes, in specialty and convenience stores</li> <li>o Highest frequency, rarely to sometimes, using store or supermarkets websites and food delivery mobile apps. Rarely use of mobile apps for responsible consumption.</li> </ul> <p><b>PAYMENT:</b></p> <ul style="list-style-type: none"> <li>o Presential payments are performed most of the time, but also uses online and mobile channels, rarely to sometimes, (more frequently) compared to other segments.</li> </ul> <p><b>DELIVERY:</b></p> <ul style="list-style-type: none"> <li>o Food purchases mainly are taken upon presential purchase but also considers having their food items delivered via Click &amp; Collect, Click and Drive and by home delivery, at least rarely. Mobile delivery apps (i.e. Uber eats, Deliveroo, etc.) is used rarely to sometimes.</li> </ul> <p><b>POST-PURCHASE:</b></p> <ul style="list-style-type: none"> <li>o Rarely use of Social Media and Websites to give feedback.</li> </ul>	<p><b>PRE-PURCHASE (SEARCH):</b></p> <ul style="list-style-type: none"> <li>o Visits Physical Stores most of the time.</li> <li>o Considers Friends &amp; Family opinions rarely to sometimes.</li> <li>o Rarely use of Online Search Engines.</li> </ul> <p><b>FOOD PURCHASE:</b></p> <ul style="list-style-type: none"> <li>o Purchases in supermarkets and mass stores at least most of the time, and in specialty and convenience stores sometimes.</li> <li>o Buys rarely on Mobile Apps for food delivery.</li> </ul> <p><b>PAYMENT:</b></p> <ul style="list-style-type: none"> <li>o Pays face to face upon purchase most of the time.</li> </ul> <p><b>DELIVERY:</b></p> <ul style="list-style-type: none"> <li>o Food purchases mainly taken upon presential purchase. Some consumers rarely consider home delivery while purchasing on a mobile app.</li> </ul> <p><b>POST-PURCHASE:</b></p> <ul style="list-style-type: none"> <li>o No touchpoints particularly used in this stage.</li> </ul>	<p><b>PRE-PURCHASE (SEARCH):</b></p> <ul style="list-style-type: none"> <li>o Visits Physical Stores sometimes</li> <li>o Rarely Considers Friends &amp; Family opinions.</li> </ul> <p><b>FOOD PURCHASE:</b></p> <ul style="list-style-type: none"> <li>o Purchases in supermarkets and mass stores most of the time, and sometimes in specialty and convenience stores.</li> </ul> <p><b>PAYMENT:</b></p> <ul style="list-style-type: none"> <li>o Always Pays face to face upon purchase.</li> </ul> <p><b>DELIVERY:</b></p> <ul style="list-style-type: none"> <li>o Food purchases are always taken upon presential purchase</li> </ul> <p><b>POST-PURCHASE:</b></p> <ul style="list-style-type: none"> <li>o No touchpoints used in this stage</li> </ul>
<b>FOOD RELATED LIFESTYLES</b>	Time pressured, do not give to much importance to product information but enjoys more doing food shopping than curious conservatives. Scored higher in Passion for Cooking and Enjoyment than other segments. Concerned about the environment as much as the other segments.	Less time pressured and less experienced buying food online than early omnichannel adopters. Concerned about the environment as much as the other segments	Gives more importance to food quality aspects compared to other segments, feels less time pressured, and pays more attention to product information than early omnichannel adopters. Concerned about the environment as much as the other segments.
<b>RELEVANT DEMOGRAPHICS</b>	Likely to earn from low to middle incomes compared to curious conservatives, live in larger households and are younger than the uninterested traditional shoppers in average.	Not significant differences among income levels with uninterested traditional shoppers but has highest proportion of monthly Budget allocation for food purchases below 330€ , live in smaller households and are as young as the early omnichannel adopters (30 y. in average).	Not significant differences among income levels or monthly Budget allocation for food. Tend to be older than the other segments and to live in small households up to 2 people.

## 5.2. Segments Comparisons with Previous Multichannel Segmentation Studies

This thesis has analyzed and segmented consumers residents in France using Latent Class Analysis, providing the profiles of three types of food shoppers based on the usage frequency of physical, online, and mobile touchpoints during the purchase process. Thus, relevant food-related lifestyles psychographics and demographic covariates were used to identify the main differences or similarities between the segments, and their approach towards their consumption and purchase of food.

From a methodological point of view, this research has contributed to confirm that the use of the latest programming language and open-source software, such as R, can also provide useful insights and LCA segmentation results efficiently and practically. Moreover, in addition to previous studies that considered the importance (Herhausen et al., 2019; Sands et al., 2016) or appropriateness (Keyser et al., 2015; Konuş et al., 2008) of the use of several channels as the basis for segmentation, this thesis showed that considering the usage frequency of those channels throughout the purchase journey, as a less subjective measurement with survey<sup>8</sup> data, can also be a valid approach to segment customers and analyze their touchpoints use for a given activity.

The conceptual perspective of (Saghiri et al., 2017) reviewed in the literature, provided a useful framework to this research regarding the analysis of consumer behavior in an omnichannel context from the perspective of the consumer. Consequently, the findings in this thesis proved that it was accurate to evaluate the food purchase process in several phases, or channel stages, given that the usage frequency of different touchpoints provided by several agents (retailers, third-party entities, etc.) in each stage was different between the three segments identified.

In contrast to studies that considered only two purchase stages (Herhausen et al., 2019; Keen et al., 2004; Konuş et al., 2008; Lazaris et al., 2014; Nakano & Kondo, 2018) or three stages (Keyser et al., 2015; Sands et al., 2016), this research evaluated five stages, considering payment and delivery as separate steps similar to (Park & Kim, 2018) and a post purchase phase, that even though it was expected to be relevant to food shopping as discussed by (Howard et al., 2017), only the Early omnichannel adopters manifested a bare involvement in this stage.

Additionally, key differences were found among the food shopper segments analyzed while considering different types of physical, online, and mobile touchpoints in line with the omnichannel systemic approach of (Saghiri et al., 2017), and following the

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<sup>8</sup> (Nakano & Kondo, 2018) used accumulated frequency information with actual transactional data, not surveys.

recommendation of (Nakano & Kondo, 2018) to evaluate specific digital touchpoints if a category is analyzed. The consideration of precise online (i.e. store's websites, search engines, social media, online payments) and mobile touchpoints (i.e. delivery apps, store apps, apps for responsible consumption, mobile payment, etc.) provided important insights to differentiate the Early omnichannel adopters with the other segments, and complemented the findings of (Park & Kim, 2018) who considered mobile touchpoints in their research in Korea and US. Thus, differentiating delivery channels such as Click&Collect, Home Delivery or Click&Drive for food shopping, served to identify that the Early omnichannel adopters have considered their use at least rarely, confirming the existing trend of new hybrid shopping models as (Park & Kim, 2018), (Howard et al., 2017) and (Acosta, 2017) exposed.

Concerning the results about the segmentation of food shoppers, this research contributes to the literature by providing a first outlook of their food purchase channels within an omnichannel context, supporting and complementing past studies in this domain. First, the Early Omnichannel Adopter segment identified in this thesis, can be classified within the *multi-omnishoppers* macro-segment found in the literature (See **Table 8<sup>9</sup>**). The Curious Conservatives and the Uninterested Traditional shoppers share some characteristics with the *store focused* macro-segment, with the main difference found in the lower, but existing usage of digital touchpoints in some stages by the Curious Conservatives, and significant and almost exclusive use of physical channels by the Uninterested Traditional shoppers.

Similarly to previous studies, the Early omnichannel adopters manifested using offline, online, and mobile touchpoints for purchase as multichannel enthusiasts (Konus et al., 2008) or to look for information as the full, partial or multi-touchpoint shoppers seen by (Herhausen et al., 2019) and (Lazaris et al., 2014). The main difference with the multi-touchpoint shoppers found by (Herhausen et al., 2019) was that the early omnichannel adopters do not use online touchpoints as their main channel, but as an additional or secondary touchpoint to search for information, to purchase, to pay, or to receive their food courses, rarely to sometimes.

Moreover, they still favor the purchase on physical stores as the multichannel enthusiasts (Konus et al., 2008) or Store-favored multichannel enthusiasts (Nakano & Kondo, 2018), but use digital channels in a higher frequency and are more savvy buying food online compared to the other two segments. This segment, and their use of supermarket websites, is also aligned with the findings in previous research pointing to France as a European leader in consumer goods' e-commerce (Nielsen, 2018).

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<sup>9</sup> Or Annex 2

While comparing the behavior in payment and delivery stages of the early omnichannel adopters, it was found that these customers also pay in cash or by credit card face to face most of the time, as the preference of the multichannel shoppers identified by (Park & Kim, 2018). However, early omnichannel adopters also consider paying online or through mobile apps as the online shoppers or reverse showroomers found in the US by (Park & Kim, 2018). Furthermore, apart from the fact that this segment prefers to take their food courses upon purchase, alternative delivery solutions (i.e. home delivery, click & collect, and click & drive) are used at least rarely, similar to the Korean versatile convenience shopper (Park & Kim, 2018).

As discussed before, the second and largest segment in this thesis, labeled as Curious Conservatives shoppers, manifested allocating physical touchpoints to purchase food in a higher average (89%) than the Early Omnichannel Adopters (60.8%) but a lower usage of online touchpoints (7.1% vs. 25.1%). Despite their focus on brick and mortar stores, they manifested using rarely search engines in the prepurchase phase or buying on mobile applications, similar to the store focused segment identified by (Konus et al., 2008) and the store focused light multimedia segment from (Nakano & Kondo, 2018) who also use some online touchpoints, though they were still attached to offline purchases.

It is noteworthy that no enough evidence was found of the existence of pure showroomers or webroomers, identified in previous studies (Herhausen et al., 2019; Keyser et al., 2015; Sands et al., 2016) as research shoppers. The three segments scored high on the frequency of using physical channels before and during the purchase, and consequently paying upon their presential activities or taking their purchases in their preferred stores. Moreover, the Uninterested Traditional shoppers found in this thesis are similar to the traditional and store-focused customers found by (Park & Kim, 2018) and (Keyser et al., 2015) respectively, due to their exclusive use of offline channels in terms of frequency and allocation.

Although all segments scored relatively high on physical channels usage frequency, the main difference between them, was the different frequency levels in the use of digital touchpoints as an additional touchpoint in the buying process. Indeed, it became a relevant behavior in the context of the COVID Pandemic in 2020<sup>10</sup>, that impacted their channel allocation, especially for Omnichannel Adopters and Curious Conservatives who increase their use of online (+5.15%, +2.43) and mobile touchpoints (+3.63%, +0.48%) to buy food, and thus pushing the adoption of omnichannel shopping in line with global trends (Nielsen, 2020).

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<sup>10</sup> First lockdown between March and May 2020

### 5.3. Segments Comparison with literature in terms of Food Related Lifestyles and Demographic covariates.

The segment's psychographic analysis in this thesis used variables that were different than other previous multichannel segmentation studies. The results discussed before are in line with the claim done by (Howard et al., 2017) in the fact that the food shopping experience will be omnichannel, as it was the case with the early omnichannel adopters who are more versatile and experienced using online tools to purchase food. (Howard et al., 2017) also mentioned that this experience will be guided by lifestyles and customization by 2025. For this reason, this study contributes to the literature by considering the measurement of food-related lifestyles to verify if each segment is effectively different in their approach to food, their consumption, and their omnichannel behavior.

First, it was found that the Early Omnichannel Adopters are significantly more time-pressured, do not give too much importance to product information and quality aspects, but more enjoy food shopping (exploring the best purchase options and prices) than the Curious Conservative and the Uninterested Traditional shoppers. They also scored a similar average in Loyalty and Price Criteria as the Curious conservatives, and both higher than the Uninterested Traditional shoppers, though it was not statistically significant.

Those characteristics are in line with the psychographic profiles found in multichannel enthusiasts shoppers found by (Lazaris et al., 2014), (Nakano & Kondo, 2018) and (Herhausen et al., 2019) who also are loyal, seek better prices, and are explorative. The fact that the Early Omnichannel Adopters are time-pressured, and savvy purchasing food online, may explain why they are more open to use digital touchpoints, as these technologies offer them more options to compare, pay and to have their courses delivered, in addition to physical means.

Additionally, this segment also shares some features with some segments (See **Table 8<sup>11</sup>**) found in the literature (Björnsson, 2015; Chetthamrongchai & Davies, 2000; Gunarathne et al., 2017; Nie & Zepeda, 2011; Shim et al., 2001). First, with conservative/rational consumers, especially in the search of better prices and relative convenience. Then, time pressured as the time-pressured segment found by (Chetthamrongchai & Davies, 2000) and third, with light food-enthusiasts (i.e. adventurous, foodies, etc.) as they also enjoy food shopping, compared to other segments, and scored the highest in passion for cooking though it was not statistically significant.

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<sup>11</sup> Or Annex 3

Overall, it can be stated that these consumers are relatively more involved with their food shopping experience, but as they feel pressured about time, they are open to explore more than one touchpoint to purchase food, allowing them to seek better prices, compare products or buy faster. It should be noted though that they do not put attention to quality aspects or product information as other segments, which may be explained by their assumption that all they buy is already safe thus taking from granted those aspects.

Secondly, the Curious Conservative shoppers identified in this thesis, despite being as young as the Early Omnichannel Adopters, are less time-pressured, less experienced buying foods online, enjoy food shopping less, and have a larger proportion of people earning high incomes. While not statistically significant, they also seek convenience while purchasing food as the early omnichannel adopters, due to a similar average in that dimension and higher than the uninterested traditional shoppers. These consumers are closer to the practical/moderately involved and convenience seekers described by (Shim et al., 2001) and (Chetthamrongchai & Davies, 2000) respectively, who were also not too concerned about time but prefer buying conveniently. This aspect might explain why this segment considers, at least rarely, buys in mobile apps for food delivery or looks for information on search engines before purchasing food.

As mentioned previously, consumers belonging to this segment are still store-focused, and have not embraced yet digital touchpoints as much as the first segment, but the evidence shows that the COVID-19 pandemic has slightly changed their channel allocation to purchase food online. Probably, this behavior might change as their experience buying online and their frequency using mobile touchpoints increases in the years to come, enabling a potential opportunity for hybrid and digital business models for food consumption in France.

Finally, the third segment, Uninterested Traditional, represents the classical store-focused non-digital customers, older in average and significantly more concerned about the quality aspects of food and the importance of product information. These consumers share these psychographic features with the traditionalists and foodies found by (Gunarathne et al., 2017) in Germany, who pay attention to food labels and good quality in foods. Although it was not statistically significant, they also scored the highest average in health orientation (buying healthy foods), explaining in part, their purchase behavior. It could be stated that these customers might prefer buying physical stores due to their inclination or concerns that doing it otherwise (i.e. online) could avoid them to verify if their food purchases meet their quality criteria, in addition to the fact that they are not experienced using those means for purchase and

even not being affected by the pandemic, prioritizing offline channels instead (98.82%).

In conclusion, it is noteworthy that customers completely uninvolved in food shopping were not detected in this study in contrast with previous literature from a psychographic perspective. Since all the segments did not evidence significant differences in terms of enjoying eating in company, having passion for cooking, and all scoring high ( $M > 4$ ) in pleasure and interest in food, the segments share a relative uniform interest in food and their experience, in line with other studies made in France showing that their food culture has as an orientation to pursue conviviality and taste (Mathé et al., 2009). Moreover, all showed similar scores in their concerns about the environment ( $M > 3.8$ ) and the quality aspects in food ( $M > 3.9$ ) in which one segment even had a significantly higher score (Uninterested traditionalists), confirming previous research about the trends towards healthy and responsible consumption (Agence Bio, 2019; Euromonitor International, 2019b; Hollywood et al., 2013; Verain, 2015).

#### **5.4. Managerial Implications**

This thesis has revealed substantial insights related to the adoption of several touchpoints in the context of omnichannel food shopping among three customer segments in the French market and their lifestyles, meaning both opportunities and challenges to companies and their marketing strategies in food-related industries. The COVID19 pandemic has also played an important role in some segments and should be a factor to be considered to plan and adapt current strategies.

First, it was observed the existence of a segment with early adoption of omnichannel behavior, experienced buying food online and who, to some extent, is already starting to use digital channels throughout the purchase process in addition to physical stores. This reconfirms that food-related businesses from retailers, food service companies to manufactures should consider the integration of online and mobile touchpoints in their delivery models and sale platforms, and develop digital marketing strategies accordingly, to reach a greater number of customers and to provide the necessary information for them to compare products or prices, and to make the purchase of food-related items, even more practical, and safe.

Previously, it was exposed in the literature that new formats and platforms for retailers, groceries, and restaurants has emerged due to a digital disruption (Hirschberg et al., 2016; Howard et al., 2017) and that consumers are already searching and purchasing food items online (Howard et al., 2017). This thesis reveals

to companies that consumers in the French market are also starting to embrace this trend and that the current sanitary crisis in 2020 has exacerbated the use of online channels in early omnichannel adopters and in curious conservative shoppers. At the rise of a second wave of the pandemic in which this research has been concluded, assuring sanitary protocols, aligning communication practices and optimal customer service will be vital for customer trust.

Secondly, the evidence shows that the purchase and exploration in physical touchpoints are still the most frequent channels in which customers buy food. Uninterested traditional customers, who prioritize quality aspects, product information, and that are not using digital channels due to their lack of online experience or high-quality concerns, represent for companies a segment that will likely prefer the interaction with in-store customer service, updated information, and strict sanitary protocols, to ensure that their experience is protected and well organized. For curious and early omnichannel adopters, integrating digital devices in the store to facilitate payment, such as portable scans, or developing mobile apps to anticipate orders based on purchase history can promote customer engagement, convenience, or even higher share-of-wallet. Moreover, the assortment of products and delivery solutions should also consider environmental impact, as all segments showed a high concern on this lifestyle dimension.

Besides, food companies and retailers must improve or redesigned their approach of e-mailing strategies, as all the segments declared being pushed by them never or rarely before purchase. Coordinating customized messages between mobile applications, websites, social media to push special discounts or to promote the brands could be options to consider. Hence, improving the appeal of digitally enabled delivery solutions for curious conservatives could also increase the adoption of online and mobile channels in the future, to boost sales for online recipe boxes delivery or groceries. Offering cost-free delivery to the top and loyal customers, based on recurrent or high-ticket purchases, can be a strategy to consider, as well as aligning the available stock information in real-time in mobile apps and websites.

Finally, this research has proved that using complex clustering techniques, such as LCA, in open-source software can provide useful and actionable insights that companies could implement in their sales or marketing efforts. Companies in food-related industries must analyze their clients base to understand how they buy studying their preferred touchpoints in each purchase stage, and why they do it, by exploring their related lifestyles and demographics in order to build strategies, platforms, and products. Each type of food category and food delivery model (BtoC and BtoB) have their particularities, but it has been proven in this thesis that food shoppers are

becoming omnichannel enthusiasts in France, in a world where 66% of consumers are already considered omnichannel shoppers (Nielsen, 2020).

### **5.5. Limits of the Study and Future Research**

Market segmentation techniques are becoming more sophisticated as new technologies emerge and data collection methods become diverse and massive. Thus, it is important to assure many respondents in latent class analysis efforts to provide more variability and volume to calculate better models. Although this research gave meaningful results based on survey data, implementing LCA analysis in R for real and transactional data could provide powerful insights for companies with large databases in terms of customers or transactions. The fact that one very small segment was found while evaluating the lowest BIC in the gaussian model, could have been caused by the sample which was in part skewed to female and young respondents. Nonetheless, this problem was solved using the second-best option and provided better interpretability and representability of the segment's size.

From a theoretical perspective, the food related-lifestyle dimensions were useful to explain some aspects of the psychographic profiles in the segments identified, especially in terms of time pressure, enjoyment, quality aspects or product information. However other dimensions were not useful enough to affirm significant differences, even if they are linked to food consumption such as eating in company or passion for cooking. This might suggest that the underlying psychographics in omnichannel food shopping behavior could be more closely related to the practical side of the purchase process rather than the post-purchase consumption itself, an approach that could be explored in future research.

The strategic potential of future studies implementing segmentation studies in the food domain could be directed to study specific food categories (fresh food, beverages, organic foods or prepared meals) and business models in the Foodtech industry (delivery apps, online groceries, etc.). These studies could be used to track the purchase behavior of customers across time, and implement solutions to develop better promotional customized strategies, based on big data analysis and complex modeling techniques; and to improve the delivery and payment options enhancing the overall purchase experience.

## VI. CONCLUSIONS

Food-related companies are facing disrupting changes in sales and distribution solutions due to the rise of digital and hybrid channels. They will need to engage in an omnichannel approach to remain competitive as customers demand lifestyle-driven and customized experiences. New challenges in the market such as the impact of the COVID-19 Pandemic in 2020 and environmental concerns are also shaping how customers buy food and interact with brands and companies both online and offline. In this context, this research started highlighting the need to segment food shoppers within the omnichannel shopping process based on the customers interaction with multiple touchpoints, aiming to identify their purchase profiles and to unveil relevant food-related lifestyle characteristics.

The omnichannel system framework proposed by (Saghiri et al., 2017) was analyzed and adapted to determine the five purchase process stages that were evaluated from the perspective of the consumer according to the touchpoint usage frequency across the food shopping process. Several multichannel segmentation studies provided the main touchpoints and the segmentation method, Latent Class Analysis, that was implemented in this research based on survey data. Previous food-shopper research unveiled the psychographic lifestyle dimensions and demographic measures that were used to characterize and to identify differences among the food shopper segments.

The segmentation results unveiled the existence of three food shopper segments: The Early Omnichannel Adopters (38.3% of customers), Curious Conservatives (51.5%) , and Uninterested Traditional shoppers (10.1%). The first segment, The Early Omnichannel Adopters, manifested using offline, online, and mobile touchpoints for purchase similar to multichannel customers found in previous research (Konus et al., 2008) (Herhausen et al., 2019) and (Lazaris et al., 2014). Despite using physical touchpoints more frequently, digital touchpoints are used as a secondary channel to search for information, to purchase, to pay or to receive their food courses, in a higher frequency compared to the other two segments. The impact of COVID-19 was moderate pushing online (+5.15%) and mobile (+2.43) purchases upward. These customers are also younger, more savvy buying food online, time-pressured, do not give too much importance to product information and quality aspects, but enjoys food shopping and cooking.

Secondly, Curious Conservatives shoppers allocated physical touchpoints to buy food at a higher average (89%) than the Early Omnichannel Adopters (60.8%) and use online touchpoints less. Some manifested using search engines rarely or buying on mobile applications, similar to store-focused customers (Konus et al., 2008) (Nakano

& Kondo, 2018). These shoppers are young as the Early Omnichannel Adopters, but are less-time pressured, not too experienced buying foods online, they enjoy food shopping less. They scored similar in shopping convenience but higher to the uninterested traditional shoppers. Similar to practical/moderately involved and convenience seekers found by (Shim et al., 2001) (Chetthamrongchai & Davies, 2000). The COVID pandemic impacted less their channels allocation than the first segment, increasing food courses mainly online (+3.63%).

In contrast, the Uninterested Traditional shoppers are the less enthusiastic segment to use digital channels to purchase food. Indeed, they scored the highest average of channel allocation on physical touchpoints even after the pandemic (98.8%). This segment visits physical stores sometimes to look for information and purchases sometimes in specialty or convenience stores apart from supermarkets. Compared to the first two segments, they give significant importance to food quality aspects, they are the least time-pressured and pay more attention to product information than early omnichannel adopters. They tend to be older than the previous segments and to live in smaller households.

It is noteworthy that the segments have a uniform interest in food and their experience since no significant differences were found in terms of enjoying eating in company, passion for cooking, pleasure, and interest in food. All showed similar and high scores in environmental concerns and quality aspects in line with current market trends and challenges. These challenges in line with all the findings exposed previously, represent new opportunities that companies in the food industry should analyze to plan, reinvent, or adapt their marketing strategies.

The integration of online, mobile touchpoints and physical stores is becoming a new trend in France and worldwide, in which marketers need to tailor digital marketing strategies to meet the customer's need for coherent product information, safe transactions, and practical purchase and delivery within the omnichannel experience. Aligning communication practices, optimal customer service, in-store solutions, and customized offers could boost profits, share-of-wallet, and market share.

Companies can implement the segmentation methodology performed in programming language software in this thesis to identify shopper segments tailored to the industry in which they operate, combining psychographic covariates and touchpoints to the products and markets they analyze. Future academic research efforts can be directed to that end, using real transactional data, monitoring customers across time or unveiling hidden relationships between inner motivations and omnichannel behavior.

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# ANNEXES

## Annex 1

### LIFESTYLE ASPECTS GROUPING POTENTIAL DIMENSIONS RELEVANT FOR THIS THESIS AND ITS SOURCES

Lifestyle Aspects Covered	Dimensions	Sources
<b>Food Quality &amp; Safety</b>	Aesthetic Orientation Brand Consumer ethnocentric orientation Freshness Health Open market advocate Organic Products Price criteria Price/ quality relation Quality Aspects Recognizes USDA label Regio centric/origin orientation Safety Taste	(Shim et al., 2001) (Nie & Zepeda, 2011)* (Shim et al., 2001) Food Related Lifestyles (1997) Food Related Lifestyles (1997) (Shim et al., 2001) Food Related Lifestyles (1997) Food Related Lifestyles (1997) Food Related Lifestyles (1997) (Gunarathne et al., 2017) (Nie & Zepeda, 2011)* (Shim et al., 2001) (Nie & Zepeda, 2011)* Food Related Lifestyles (1997)
<b>Food Shopping Enjoyment</b>	Apathy Attitudes towards advertising Enjoyment Importance to product information Participation in planning and buying / Involvement Regular Shopper Shopping as an event Shopping Locations and Frequency Specialty shops Enjoyment from shopping	(Chetthamrongchai & Davies, 2000) Food Related Lifestyles (1997) (Chetthamrongchai & Davies, 2000) Food Related Lifestyles (1997) (Björnsson , 2015) (Herrmann and Warland, 1990) (Buttle and Coates, 1984) (Björnsson , 2015) Food Related Lifestyles (1997) Food Related Lifestyles (1997)
<b>Cooking Enjoyment</b>	Attending Culinary Events Cooking Frequency Enjoyment from shopping Enjoys cooking Interest in cooking Looking for new ways Passion for Cooking Shopping List Subjective knowledge and cooking skills	(Gunarathne et al., 2017) (Nie & Zepeda, 2011)* Food Related Lifestyles (1997) (Nie & Zepeda, 2011)* Food Related Lifestyles (1997) Food Related Lifestyles (1997) (Gunarathne et al., 2017) Food Related Lifestyles (1997) (Gunarathne et al., 2017)
<b>Food as an Experience</b>	Eating in Company Pleasure and Interest Self-fulfilment in food Snack vs Meals Social event Social relationships	(Gunarathne et al., 2017) (Gunarathne et al., 2017) Food Related Lifestyles (1997) Food Related Lifestyles (1997) Food Related Lifestyles (1997) Food Related Lifestyles (1997)
<b>Novelty</b>	Food Neophobia Novelty Novelty Preferences Security	Pliner and Hobden (1992); Ritchey et al. (2003) Food Related Lifestyles (1997) (Gunarathne et al., 2017) Food Related Lifestyles (1997)
<b>Healthy Lifestyle</b>	Following a diet to keep fit Following a diet to treat illness Food Diets General health interest / Health Orientation Health Practice: Membership in a fitness club Vegetarian	(Nie & Zepeda, 2011)* (Nie & Zepeda, 2011)* (Björnsson , 2015) Roininen et al. (1999) (Nie & Zepeda, 2011)* (Nie & Zepeda, 2011)*
<b>Enviromental Awareness</b>	Community supported agriculture member Enviromental Knowledge Environmental Concerns Environmental Protection Farmer's Market Friendly Environmental Behavior	(Nie & Zepeda, 2011)* Adapted from Guagano et al. 1995 Adapted from Guagano et al. 1995 Lindeman & Väänänen (2000) (Nie & Zepeda, 2011)* Adapted from Guagano et al. 1995
<b>Food Shopping Convenience</b>	Convenience	(Chetthamrongchai & Davies, 2000) Steptoe et al. (1995) Olsen et al., (2007) and Onwezen et al. (2012)
<b>Time Concerns</b>	Time Pressure	(Chetthamrongchai & Davies, 2000)
<b>Healthy Lifestyle</b>	Health Orientation	Onwezen et al. (2012)

## Annex 2

OMNICHANNEL/MULTICHANNEL MACRO-SEGMENTS IDENTIFIED IN LITTERATURE	# RELATED SEGMENTS IDENTIFIED IN LITTERATURE
MULTI-OMNISHOPPERS	<ol style="list-style-type: none"> <li>1. Multichannel enthusiasts - <b>Konuş et al., (2008)</b></li> <li>2. Full Omnishoppers - <b>Lazaris et al. (2014)</b></li> <li>3. Partial Omnishoppers - <b>Lazaris et al. (2014)</b></li> <li>4. Non In-Store Internet Users but Potential Omnishoppers - <b>Lazaris et al. (2014)</b></li> <li>5. In-Store Internet Users and Potential Omnishoppers - <b>Lazaris et al. (2014)</b></li> <li>6. Research shoppers – After sales Internet/store - <b>Keyser et al., (2015)</b></li> <li>7. Research shoppers –aftersales: store - <b>Keyser et al., (2015)</b></li> <li>8. Call center-prone shoppers - <b>Keyser et al., (2015)</b></li> <li>9. Research online –purchase offline anti-mobile/social media - <b>Sands et al. (2016)</b></li> <li>10. Research online –purchase offline Multichannel Enthusiasts - <b>Sands et al. (2016)</b></li> <li>11. Research online –purchase offline social media enthusiasts - <b>Sands et al. (2016)</b></li> <li>12. Internet-focused, multichannel enthusiasts - <b>Sands et al. (2016)</b></li> <li>13. Versatile - convenience shopper KOREA - <b>Park &amp; Kim (2018)</b></li> <li>14. Multi-channel shopper KOREA - <b>Park &amp; Kim (2018)</b></li> <li>15. Web-roomers USA - <b>Park &amp; Kim (2018)</b></li> <li>16. Reverse-show roomers USA - <b>Park &amp; Kim (2018)</b></li> <li>17. Store-favored multichannel enthusiasts/ multimedia social customers - <b>Nakano &amp; Kondo (2018)</b></li> <li>18. Online-favored multichannel enthusiasts/PC customers - <b>Nakano &amp; Kondo (2018)</b></li> <li>19. Multiple touchpoint shoppers - <b>Herhausen et al. (2019)</b></li> <li>20. Online-to-offline shoppers - <b>Herhausen et al. (2019)</b></li> </ol>
PURE ONLINE-ORIENTED	<ol style="list-style-type: none"> <li>1. Web-focused shoppers - <b>Keyser et al., (2015)</b></li> <li>2. Web-focused shoppers , after sales: store/call Center - <b>Keyser et al., (2015)</b></li> <li>3. Internet-focused, anti-mobile - <b>Sands et al. (2016)</b></li> <li>4. Online shopper USA - <b>Park &amp; Kim (2018)</b></li> <li>5. Innovative consumers - online shopper KOREA - <b>Park &amp; Kim (2018)</b></li> <li>6. Early Adopter KOREA - <b>Park &amp; Kim (2018)</b></li> <li>7. Pragmatic online shoppers - <b>Herhausen et al. (2019)</b></li> <li>8. Extensive online shoppers - <b>Herhausen et al. (2019)</b></li> </ol>
STORE-ORIENTED CUSTOMERS	<ol style="list-style-type: none"> <li>1. Store Focused - <b>Konuş et al., (2008)</b></li> <li>2. Store-focused Shoppers - <b>Keyser et al., (2015)</b></li> <li>3. Store-focused/anti-digital customers - <b>Nakano &amp; Kondo (2018)</b></li> <li>4. Store-focused light/anti-digital customers - <b>Nakano &amp; Kondo (2018)</b></li> <li>5. Store-focused light/multimedia social customers - <b>Nakano &amp; Kondo (2018)</b></li> <li>6. Store-focused/multimedia social customers - <b>Nakano &amp; Kondo (2018)</b></li> <li>7. Traditional consumers - <b>Park &amp; Kim (2018)</b></li> <li>8. Store-focused shoppers - <b>Herhausen et al. (2019)</b></li> </ol>
UNINVOLVED CUSTOMERS	<ol style="list-style-type: none"> <li>1. Uninvolved shoppers - <b>Konuş et al., (2008)</b></li> <li>2. Omnishopping Avoiders - <b>Lazaris et al. (2014)</b></li> <li>3. In-Store Internet Users but Omnishopping Avoiders - <b>Lazaris et al. (2014)</b></li> <li>4. Indecisive shoppers - <b>Park &amp; Kim (2018)</b></li> <li>5. Uninvolved shoppers - <b>Nakano &amp; Kondo (2018)</b></li> </ol>

## Annex 3

FOOD SHOPPER MACRO-SEGMENTS IDENTIFIED IN LITTERATURE	RELATED SEGMENTS IDENTIFIED IN LITTERATURE
FOOD ENTHUSIASTS	<ol style="list-style-type: none"> <li>1. Hedonists - (<b>Chetthamrongchai &amp; Davies, 2000</b>)</li> <li>2. Creative/highly involved - (<b>Shim et al., 2001</b>)</li> <li>3. Adventurous consumers - (<b>Nie &amp; Zepeda, 2011</b>)</li> <li>4. The Health oriented believers - (<b>Björnsson , 2015</b>)</li> <li>5. Foddies - (<b>Gunarathne et al., 2017</b>)</li> <li>6. Average nutrition enthusiasts - (<b>Gunarathne et al., 2017</b>)</li> </ol>
CONSERVATIVE/RATIONAL	<ol style="list-style-type: none"> <li>1. Convenience - (<b>Chetthamrongchai &amp; Davies, 2000</b>)</li> <li>2. Practical/moderately involved - (<b>Shim et al., 2001</b>)</li> <li>3. Rational consumers - (<b>Nie &amp; Zepeda, 2011</b>)</li> <li>4. Health oriented disbelievers - (<b>Björnsson , 2015</b>)</li> <li>5. Habitual skeptics - (<b>Björnsson , 2015</b>)</li> <li>6. Average disbelievers - (<b>Björnsson , 2015</b>)</li> <li>7. LIGHT FOODIES - (<b>Gunarathne et al., 2017</b>)</li> <li>8. Traditionalists - (<b>Gunarathne et al., 2017</b>)</li> </ol>
UNINVOLVED	<ol style="list-style-type: none"> <li>1. Apathetic but regular - (<b>Chetthamrongchai &amp; Davies, 2000</b>)</li> <li>2. Time pressured convenience seekers - (<b>Chetthamrongchai &amp; Davies, 2000</b>)</li> <li>3. Aesthetic/uninvolved - (<b>Shim et al., 2001</b>)</li> <li>4. Careless customers - (<b>Nie &amp; Zepeda, 2011</b>)</li> <li>5. Conservative uninvolved - (<b>Nie &amp; Zepeda, 2011</b>)</li> <li>6. Careless - (<b>Björnsson , 2015</b>)</li> <li>7. Uninterested - (<b>Gunarathne et al., 2017</b>)</li> <li>8. Uninvolved - (<b>Gunarathne et al., 2017</b>)</li> </ol>

**Annex 4 : SURVEY (ENGLISH VERSION)**

Stages	Question	Items/Statements	Scale (EN)
Respondent Validation	Have you been a permanent resident in France for at least 6 months?	If No, Survey is closed.	Yes/No
Respondent Validation	Do you purchase groceries or prepared food regularly?	If No, Survey is closed.	Yes/No
<p><b>In this part, the following questions relate to your food purchases during the past 6 months. They concern the process and stages of food purchases. Please answer the question accordingly</b></p>			
Pre-Purchase	BEFORE buying food (groceries and / or ready meals) i.e. researching information, comparing offers, prices, etc. :  How often do you use the following points of contact and referrals?	<p>Hypermarket, supermarket or convenience store where I usually do my shopping</p> <p>References or recommendations from families and friends</p> <p>Social networks (search for information on Facebook, Instagram, YouTube, etc.)</p> <p>Search for information on Google.fr or Bing</p> <p>Search on Food, Grocery, and Meal Delivery Websites (ready meals, recipe boxes, or locally sourced groceries such as Hello Fresh, Epicery, etc.)</p> <p>Visiting a store or retailer website to search for information (such as Auchan.fr, Monoprix.fr, etc.)</p> <p>Visit the super/hyper market competitor's website to search for information.</p> <p>Email Ads (Ads received on your email from food companies or retailers)</p> <p>SMS received from a food company or a super / hypermarket.</p> <p>Finding information or comparing prices on delivery mobile Apps (UberEats, JustEat, Deliveroo, etc.)</p>	<p>(1) Never (2) Rarely (3) Sometimes (4) Most of the time (5) Always</p>
Purchase	How often do you use the following touchpoints to purchase food (groceries and/or prepared meals)	<p>Supermarkets (super / hypermarket, such as Auchan, Monoprix, LeClerc, Lidl, Carrefour, etc.)</p> <p>Specialized store (Naturalia, Biocopp, Picard Surgelés, etc.)</p> <p>Convenience Stores: Local kiosks or markets.</p> <p>Online: On the website of a super / hyper market (Auchan.fr, Monoprix.fr) or online retailer (Amazon.fr)</p> <p>Online: Locally-sourced Food Delivery Websites (La ruche que di oui, Epicery, Vité mon marché, etc.)</p> <p>Online: Subscription for the delivery of recipe boxes (Such as Hello Fresh, Quitoque, Foodette, etc.)</p> <p>Online: Subscription for the delivery of prepared meals (Season, FamileEat, etc.)</p> <p>Mobile App of a super / hypermarket or store</p> <p>Mobile App to buy locally (markets) or to reduce food waste (Such as Phenix, Too good to go, etc.)</p> <p>Mobile App for the delivery of meals / groceries (UberEats, JustEat, Epicery, Deliveroo, etc.)</p>	
Payment	How often do you use the following touchpoints for payment?	<p>Through a mobile app or the mobile version of a website.</p> <p>Online through the website on the computer or laptop.</p> <p>Face to face (credit card or cash)</p>	
Delivery	How often frequent do you consider the following delivery options?	<p>Click &amp; Collect (order online, pick up in store)</p> <p>Click &amp; Drive (order online, pick up by car)</p> <p>Home delivery by the store (supermarket, kiosk, specialty store, etc.)</p> <p>Home delivery through a third-party mobile app (UberEats, JustEat, Deliveroo, etc.)</p> <p>No delivery. Taken upon purchase in a store.</p>	
Post-Purchase	How often do you use the touchpoints and activities after food purchase?	<p>Social networks (Facebook, Instagram, Twitter, etc.) to provide feedback or to request customer service.</p> <p>Visit the supermarket's website or online store to send feedback or to request customer service.</p> <p>The mobile App to provide feedback or to requesting customer service.</p> <p>Phone Call to provide feedback or to request customer service.</p> <p>Social networks to share my experience of buying and consuming food (either while cooking or eating)</p>	
Purchase Orientation	Which channels do you use to purchase food? Please, allocate 100 points using the bar among the 3 following options:	<p><u>1. Physical Stores: (0-100)</u> Such as Supermarket . Specialty or Convenience Store.</p> <p><u>2. Web-based/Online: (0-100)</u> Such as Supermarket Website, Locally Sourced Food Delivery, Recipe Boxes, or Prepared-Meals Websites.</p> <p><u>3. Mobile: (0-100)</u> Such as Mobile App from a Retailer, for Responsible Consumption or for Food Delivery</p>	<p>0-100 (The three channel groups: 1 + 2 + 3 should sum 100)</p>
Post-COVID Change	To what extent do you consider that the arrival of COVID19 has changed your food purchasing habits, that is to say the channels used? (store, online, mobile)	If "a little, moderately, a lot or verymuch" are selected, the next question will be asked. If "never" is selected it will continue directly to online/offline experience,	<p>(1) Never (2) A little (3) Moderately (4) A lot (5) Very much</p>
Purchase Orientation post COVID	What channels do you use to buy food now? Please allocate 100 points using the bar from the following options: Click on the bar and move (or manually type the points to allocate)	<p><u>Physical stores:</u> Super / Hypermarket, Specialized store. Local kiosks or markets.</p> <p><u>Web Based / Online:</u> Supermarket website, local food delivery, recipe boxes or meals purchased online.</p> <p><u>Mobile:</u> Supermarket mobile application, for responsible / local consumption, or for food / meal delivery by a third party.</p>	<p>0-100</p>
Online Experience	How experienced are you in buying food*	... online? (Website, Mobile App, Tablet)	<p>(1) Extremely Unexperienced (2) Slightly Experienced (3) Somewhat Experienced (4) Very Experienced (5) Extremely Experienced</p>
Offline Experience		... in physical stores? (Supermarket, specialty store, etc.)	<p>(1) Extremely Unexperienced (2) Slightly Experienced (3) Somewhat Experienced (4) Very Experienced (5) Extremely Experienced</p>

In this part, you will be asked several questions regarding your food consumption and purchase lifestyle. Please kindly answer each question accordingly.

Time Pressure	Please, indicate in which degree do you agree or disagree with the following statements	<p>I am always in a rush</p> <p>There is often not enough time in the day for me to do what I want to do. I am often rushing to get everything done. Time-saving devices are a good idea</p> <p>I often feel like I am running out of time</p> <p>It is important to be able to do things quickly</p> <p>I am always looking for ways to save time</p> <p>I am constantly looking at my watch</p>
Loyalty	Please, indicate in which degree do you agree or disagree with the following statements	<p>I generally do my food* shopping in the same way.</p> <p>The brand of the product is important for me in my purchase decisions.</p> <p>I generally purchase the same brands.</p> <p>The place/platform* where I do my shopping is very important to me.</p>
Quality Aspects	Please, indicate in which degree do you agree or disagree with the following statements	<p>For me, the naturalness of the food is an important factor</p> <p>I prefer fresh products over canned products</p> <p>I would like to pay more money for animal welfare approved foods*</p> <p>I prefer to buy food from my region</p> <p>I prefer to buy foods that were traditionally made</p> <p>I prefer food with a trustworthy character (i.e. organic, Fairtrade, etc.) to foods without a label</p>
Enjoyment	Please, indicate in which degree do you agree or disagree with the following statements	<p>I like to go to several stores/websites* to get the best value for money</p> <p>I spend time carefully comparing prices before buying items</p> <p>Food shopping is a recreational activity for me</p> <p>I usually make a separate trip to another store for fresh products like vegetables and meat.</p> <p>Food shopping is part of holiday fun.</p> <p>I spend time selecting the best quality food</p>
Attitudes towards advertising	Please, indicate in which degree do you agree or disagree with the following statements	<p>I have more confidence in food products that I have seen advertised than in unadvertised products.</p> <p>I am influenced by what people say about a food product information</p> <p>Information from advertising helps me to make better buying decisions.</p>
Price Criteria	Please, indicate in which degree do you agree or disagree with the following statements	<p>I always check prices, even on small items.</p> <p>I notice when products I buy regularly change in price.</p> <p>I watch for ads on TV or the internet for shop specials and plan to take advantage of them when I go shopping.</p> <p>I always try to get the best quality for the best price.</p> <p>I compare prices between product variants in order to get the best value for money.</p> <p>It is important for me to know that I get quality for all my money.</p>
Importance to product information	Please, indicate in which degree do you agree or disagree with the following statements	<p>To me product information is of major importance. I need to know what the product contains.</p> <p>I compare labels to select the most nutritious food.</p> <p>I compare product information labels to decide which brand to try.</p>
Passion for Cooking	Please, indicate in which degree do you agree or disagree with the following statements	<p>Cooking is my hobby</p> <p>Cooking brings me joy</p> <p>Cooking is a process of self-realization</p> <p>I have a passion for cooking</p> <p>I like to try new recipes</p> <p>I invest a lot of time for cooking</p> <p>I am proud to prepare my own meals and self-invested recipes</p>
Eating in Company	Please, indicate in which degree do you agree or disagree with the following statements	<p>We often get together with friends to enjoy an easy-to-cook casual dinner</p> <p>Dinning with friends is an important part of my social life</p> <p>When I serve a dinner to friends, the most important thing is that we are together</p> <p>Going out for dinner is a regular part of our eating habits</p> <p>The food taste is much better when I eat in good company</p>
Pleasure and Interest	Please, indicate in which degree do you agree or disagree with the following statements	<p>I am very interested in food</p> <p>Before I go out eating, I am looking for information and reviews about the restaurant</p> <p>I am a real foodie at dinner</p> <p>For me, eating is a matter that incorporates all senses of feeling, smell, taste, and sight</p> <p>When I eat, I enjoy food very much</p> <p>Good drinks and food play a major role in my life</p>
Convenience Orientation	Please, indicate in which degree do you agree or disagree with the following statements	<p>I prefer food that is easy to buy</p> <p>I prefer food that is easy to prepare</p> <p>The less physical effort (work, energy) I need to buy and prepare food, the better</p> <p>I prefer meals that can be prepared and consumed quickly</p> <p>I prefer food that requires only little planning.</p>
Environmental Protection	It is important that the food that I eat on a typical day...	<p>...has been prepared in a environmental friendly way</p> <p>...has been produced in a way that has not shaken the balance of nature</p> <p>...has been packaged in a environmentally friendly way</p>
Health Orientation	Please, indicate in which degree do you agree or disagree with the following statements	<p>I am very particular about the healthiness of the food I eat</p> <p>I always follow a healthy and balanced diet</p> <p>It is important to me that my daily diet contains a lot of vitamins and minerals</p> <p>I try to eat foods that do not contain additives</p> <p>I do not eat processed foods because I do not know what they contain</p> <p>I would like to eat only organic foods*</p>

(1) Strongly disagree  
(2) Somewhat disagree  
(3) Neither agree nor disagree  
(4) Somewhat agree  
(5) Strongly agree

Revenue	Please indicate the range to which your annual household gross income belongs:	Less than 18 000 € Between 18 000 € and 24 999 € Between 25 000 € and 40 999 € Between 41 000 € and 60 000 € More than 60 000 €	Coded internally from 1 to 5
Monthly Budget	Please indicate the range to which your annual household gross income belongs:	Less than 240 € Between 240 € and 329 € Between 330 € and 529 € Between 530 € and 780 € Over 780 €	
Household Size	Please indicate your household size	1, I live alone 2 people 3 people 4 people More than 4 Personnes	
Sex	Please indicate your gender	Female Male	
Age	Please indicate your age		

Prize Draw - Participant contact form (optional)

End of Survey

## Annex 5

### DETAILED R CODE LINE BY STEP

```
# 0. Basic package load to enable code "piping" or union %>%:
library(tidyverse)
```

```
# 1. Original Dataset Import to R for analysis
DataSetFull <- read.csv("C:/Users/ChristianGJ/Google Drive
(1504527@esan.edu.pe)/IESEG/4TH TERM/THESIS/Thesis 2019-2020/Data Collection and
Analysis/ANALYSIS - Omnichannel Purchase Segmentation_CGJ Thesis/R Project/OmniFood
Segments/Inputs/DataSetFull.csv")
```

```
# 2. Creating Dataset containing only Segmentation Variables from Original Dataset
DataSet_TouchP <- read.csv("C:/Users/ChristianGJ/Google Drive
(1504527@esan.edu.pe)/IESEG/4TH TERM/THESIS/Thesis 2019-2020/Data Collection and
Analysis/ANALYSIS - Omnichannel Purchase Segmentation_CGJ Thesis/R Project/OmniFood
Segments/Inputs/DataSetFull.csv") %>% select(S1PHMassStore:S5ShareExpSM)
```

```
# 3. verifying variable Labels or headings
names(DataSet_TouchP)
```

```
# 4. Loading Careless and Psych Packages for data validation and reliability.
library(careless)
library(psych)
```

```
# Code to identify repeated answers (or strings).
mutate(string = longstring(.))
```

```
# 5. Executing code to dataset with segmentation variables. New dataset created
named "Omni_Touchpoints"
Omni_Touchpoints <- DataSet_TouchP %>% mutate(string = longstring(.))
```

```
# 6. visualize results, 1 answer with strings over 30 (repeated answers for all
questions).
View(Omni_Touchpoints)
```

```
# 7. General overview to evaluate data per Touchpoint response
summary(Omni_Touchpoints)
```

```
# 8. Removing non reliable answers that match both criteria at the same time (cuff
point). New cleaned dataset named "Omni_Touchpoints_2", removing last two columns
that synthetic variable (string).
```

```
Omni_Touchpoints_2 <- Omni_Touchpoints %>% filter(string <= 20) %>% select(-string)
```

```
# 9. Visualize new dataset "Omni_Touchpoints_2"
View(Omni_Touchpoints_2)
```

```
# 10. Loading mclust package for segmentation procedure.
library(mclust)
```

```
# 11. Segmentation: Running BIC (Bayesian Information Criterion) analysis to clean
dataset "Omni_Touchpoints_2"
BIC <- mclustBIC(Omni_Touchpoints_2)
```

```
# 12. Segmentation: To Visualize Gaussian mixture models ranking and evaluation.
BIC
```

```
# 13. Plotting BIC for Analysis
plot(BIC)
```

```
# 14. Analyzing BIC and Verifying segments identified
summary(BIC)
```

```
# 15. Selecting Gaussian model and classifying, indicating the form and number of
segments chosen -> Named as "class1", 3 segments, VEI form.
class1 <- Mclust(Omni_Touchpoints_2, modelNames = "VEI", G = 4, x = BIC)
```

```
# 16. Visualize results for "class 1" classification.
summary(class1)
```

```
# 17. Selecting 2nd best Gaussian model and classifying, -> Named as "class2", 5
segments, VEI form.
class2 <- Mclust(Omni_Touchpoints_2, modelNames = "VEI", G = 3, x = BIC)
```

```
# 18. Visualize results for "class 2" classification.
summary(class2)
```

```
# 19. Evaluating number segments using and generating ICL(Integrated Completed
Likelihood) criteria.
ICL <- mclustICL(Omni_Touchpoints_2)
```

```
# 19. Plotting ICL for analysis.
plot(ICL)
```

```
# 20. Comparing ICL results
summary(ICL)
```

```
# 22. Plotting segments size and form for visual evaluation.
```

```
drmod1 <- MclustDR(class1, lambda = 1)
drmod2 <- MclustDR(class2, lambda = 1)
```

```
plot(drmod1, what = "contour")
plot(drmod2, what = "contour")
```

```
# 23. Loading packages for segments profile visualization (lineal graphic).
library(reshape2)
```

library(tibble)

```
# 24: Segments profiles Visualization, extracting means for each segment in
"class2" (Final Classification).
means <- data.frame(class2$parameters$mean, stringsAsFactors = FALSE) %>%
  rownames_to_column() %>%
  rename(Touchpoint = rowname) %>%
  melt(id.vars = "Touchpoint", variable.name = "Segment", value.name = "Mean") %>%
  mutate(Mean = round(Mean, 2))
```

```
# 25. visualize segments profile based on touchpoints usage means.
means
```

```
# 26. Transforming "means" to seen as wide table.
Omni_segments_widetable <- spread(means, Segment, Mean)
```

```
# 27. Visualizing wide table
Omni_segments_widetable
```

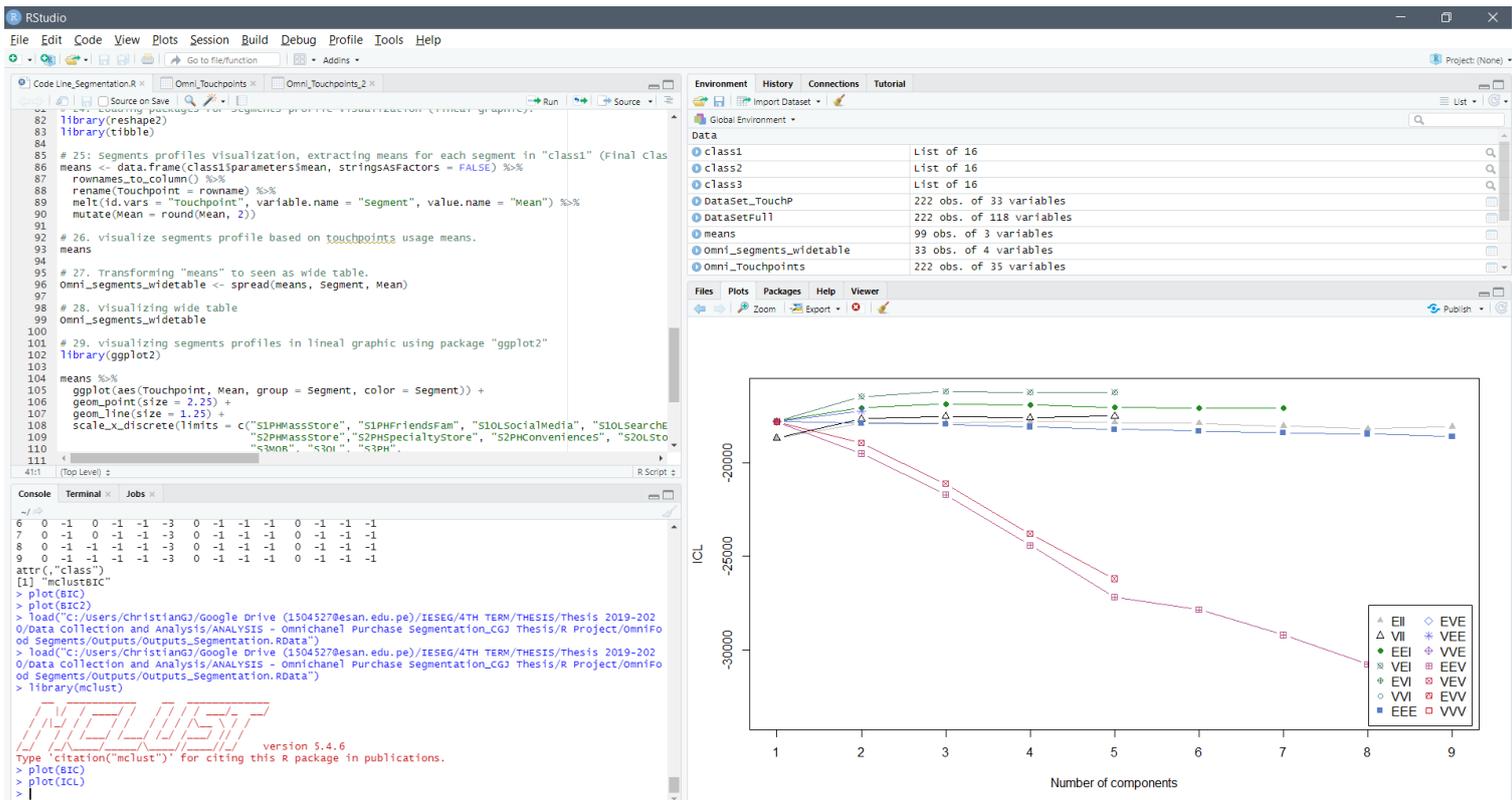
```
# 28. visualizing segments profiles in lineal graphic using package "ggplot2"
library(ggplot2)
```

```
means %>%
  ggplot(aes(Touchpoint, Mean, group = Segment, color = Segment)) +
  geom_point(size = 2.25) +
  geom_line(size = 1.25) +
  scale_x_discrete(limits = c("S1PHMassStore", "S1PHFriendsFam", "S1OLSocialMedia",
  "S1OLSearchEng", "S1OLFoodDelWeb", "S1OLStoreWeb", "S1OLMassStoreCompWeb",
  "S1OLEmailAd", "S1MOBPhoneSMS", "S1MOBApps",
  "S2PHMassStore", "S2PHSpecialtyStore",
  "S2PHConvenienceS", "S2OLStoreRetWeb", "S2OLLocalFoodDel", "S2OLRecipeBox",
  "S2OLPreparedMeal", "S2MOBStoreApp", "S2MOBAppResponC", "S2MOBAppDelivery",
  "S3MOB", "S3OL", "S3PH",
  "S4ClickCollect", "S4ClickDrive", "S4HomeDelivst",
  "S4HomeDelivApp", "S4TkonPurchase",
  "S5FeedbackSM", "S5FeedbackWebS", "S5FeedbackMobApp",
  "S5FeedbackPhone", "S5ShareExpSM")) +
  labs(x = NULL, y = "Standardized mean: Touchpoint Usage Frequency") +
  theme_bw(base_size = 14) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1), legend.position = "top")
```

```
#29. Assigning classification (class number) to data set (for each observation)
Omni_Touchpoints_2$CLUST <- class1$classification
```

```
#30. exporting classified observations as csv, file named as "classified_dataset"
write.csv(Omni_Touchpoints_2, file = "classifiedDataset", row.names = TRUE, quote =
FALSE)
```

### Annex 6 : R STUDIO USER INTERFACE



### Annex 7 : MULTINOMIAL LOGIT MODEL

#### Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	431.278	438.128	427.278			
Final	346.201	544.848	230.201	197.077	56	.000

#### Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	269.003	396	1.000
Deviance	230.201	396	1.000

#### Pseudo R-Square

Cox and Snell	.580
Nagelkerke	.684
McFadden	.461

**Annex 8**

**ANOVA ANALYSIS FOR SIGNIFICANCE DIFFERENCE EVALUATION - TOUCHPOINT USAGE FREQUENCY BY SEGMENT**

		ANOVA				
		Sum of Squares	df	Mean Square	F	Sig.
<b>S1PHMassStore</b>	Between Groups	13.945	2	6.973	5.418	<b>0.005</b>
	Within Groups	288.293	224	1.287		
	Total	302.238	226			
<b>S1PHFriendsFam</b>	Between Groups	23.343	2	11.671	13.148	<b>0.000</b>
	Within Groups	198.842	224	0.888		
	Total	222.185	226			
<b>S1OLSocialMedia</b>	Between Groups	30.907	2	15.453	19.651	<b>0.000</b>
	Within Groups	176.150	224	0.786		
	Total	207.057	226			
<b>S1OLSearchEng</b>	Between Groups	41.513	2	20.757	20.186	<b>0.000</b>
	Within Groups	230.337	224	1.028		
	Total	271.850	226			
<b>S1OLFoodDelWeb</b>	Between Groups	37.917	2	18.958	24.352	<b>0.000</b>
	Within Groups	174.383	224	0.778		
	Total	212.300	226			
<b>S1OLStoreWeb</b>	Between Groups	68.540	2	34.270	39.099	<b>0.000</b>
	Within Groups	196.332	224	0.876		
	Total	264.872	226			
<b>S1OLMassStoreCompWeb</b>	Between Groups	29.087	2	14.543	17.857	<b>0.000</b>
	Within Groups	182.429	224	0.814		
	Total	211.515	226			
<b>S1OLEmailAd</b>	Between Groups	26.673	2	13.337	18.538	<b>0.000</b>
	Within Groups	161.151	224	0.719		
	Total	187.824	226			
<b>S1MOBPhoneSMS</b>	Between Groups	17.561	2	8.780	19.696	<b>0.000</b>
	Within Groups	99.858	224	0.446		
	Total	117.419	226			
<b>S1MOBApps</b>	Between Groups	44.799	2	22.400	20.043	<b>0.000</b>
	Within Groups	250.338	224	1.118		
	Total	295.137	226			

		ANOVA				
		Sum of Squares	df	Mean Square	F	Sig.
<b>S2PHMassStore</b>	Between Groups	7.832	2	3.916	5.402	<b>0.005</b>
	Within Groups	162.371	224	0.725		
	Total	170.203	226			
<b>S2PHSpecialtyStore</b>	Between Groups	1.695	2	0.847	0.730	<b>0.483</b>
	Within Groups	259.909	224	1.160		
	Total	261.604	226			
<b>S2PHConvenienceS</b>	Between Groups	0.043	2	0.021	0.016	<b>0.984</b>
	Within Groups	294.838	224	1.316		
	Total	294.881	226			
<b>S2OLStoreRetWeb</b>	Between Groups	114.572	2	57.286	68.370	<b>0.000</b>
	Within Groups	187.684	224	0.838		
	Total	302.256	226			
<b>S2OLLocalFoodDel</b>	Between Groups	8.795	2	4.397	11.784	<b>0.000</b>
	Within Groups	83.593	224	0.373		
	Total	92.388	226			
<b>S2OLRecipeBox</b>	Between Groups	7.985	2	3.992	12.256	<b>0.000</b>
	Within Groups	72.967	224	0.326		
	Total	80.952	226			
<b>S2OLPreparedMeal</b>	Between Groups	1.494	2	0.747	4.188	<b>0.016</b>
	Within Groups	39.968	224	0.178		
	Total	41.463	226			
<b>S2MOBStoreApp</b>	Between Groups	36.875	2	18.437	26.563	<b>0.000</b>
	Within Groups	155.478	224	0.694		
	Total	192.352	226			
<b>S2MOBAppResponsC</b>	Between Groups	31.170	2	15.585	21.499	<b>0.000</b>
	Within Groups	162.381	224	0.725		
	Total	193.551	226			
<b>S2MOBAppDelivery</b>	Between Groups	66.135	2	33.068	28.417	<b>0.000</b>
	Within Groups	260.658	224	1.164		
	Total	326.793	226			

		ANOVA				
		Sum of Squares	df	Mean Square	F	Sig.
<b>S3MOB</b>	Between Groups	92.818	2	46.409	61.204	<b>0.000</b>
	Within Groups	169.851	224	0.758		
	Total	262.670	226			
<b>S3OL</b>	Between Groups	105.403	2	52.702	61.616	<b>0.000</b>
	Within Groups	191.593	224	0.855		
	Total	296.996	226			
<b>S3PH</b>	Between Groups	23.752	2	11.876	32.855	<b>0.000</b>
	Within Groups	80.970	224	0.361		
	Total	104.722	226			
<b>S4ClickCollect</b>	Between Groups	31.671	2	15.836	20.534	<b>0.000</b>
	Within Groups	172.743	224	0.771		
	Total	204.414	226			
<b>S4ClickDrive</b>	Between Groups	31.321	2	15.660	17.120	<b>0.000</b>
	Within Groups	204.899	224	0.915		
	Total	236.220	226			
<b>S4HomeDelivSt</b>	Between Groups	55.399	2	27.699	30.399	<b>0.000</b>
	Within Groups	204.108	224	0.911		
	Total	259.507	226			
<b>S4HomeDelivApp</b>	Between Groups	59.528	2	29.764	24.632	<b>0.000</b>
	Within Groups	270.675	224	1.208		
	Total	330.203	226			
<b>S4TkonPurchase</b>	Between Groups	33.289	2	16.645	15.943	<b>0.000</b>
	Within Groups	233.865	224	1.044		
	Total	267.154	226			

		ANOVA				
		Sum of Squares	df	Mean Square	F	Sig.
<b>S5FeedbackSM</b>	Between Groups	32.941	2	16.470	37.970	<b>0.000</b>
	Within Groups	97.165	224	0.434		
	Total	130.106	226			
<b>S5FeedbackWebS</b>	Between Groups	23.850	2	11.925	34.397	<b>0.000</b>
	Within Groups	77.657	224	0.347		
	Total	101.507	226			
<b>S5FeedbackMobApp</b>	Between Groups	22.866	2	11.433	32.138	<b>0.000</b>
	Within Groups	79.689	224	0.356		
	Total	102.555	226			
<b>S5FeedbackPhone</b>	Between Groups	14.713	2	7.356	14.474	<b>0.000</b>
	Within Groups	113.842	224	0.508		
	Total	128.555	226			
<b>S5ShareExpSM</b>	Between Groups	18.306	2	9.153	19.232	<b>0.000</b>
	Within Groups	106.610	224	0.476		
	Total	124.916	226			

**Annex 9**  
**TEST OF HOMOGENEITY OF VARIANCES**  
ANOVA ANALYSIS FOR SIGNIFICANCE DIFFERENCE EVALUATION - TOUCHPOINT USAGE FREQUENCY BY SEGMENT

		Levene Statistic	df1	df2	Sig.	PostHocTest
<b>S1PHMassStore</b>	Based on Mean	8.597	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	7.132	2	224	0.001	
	Based on Median and with adjusted df	7.132	2	205.889	0.001	
	Based on trimmed mean	8.265	2	224	0.000	
<b>S1PHFriendsFam</b>	Based on Mean	1.659	2	224	<b>0.193</b>	Tukey HSD
	Based on Median	1.083	2	224	0.340	
	Based on Median and with adjusted df	1.083	2	216.106	0.340	
	Based on trimmed mean	1.605	2	224	0.203	
<b>S10LSocialMedia</b>	Based on Mean	30.968	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	19.990	2	224	0.000	
	Based on Median and with adjusted df	19.990	2	196.716	0.000	
	Based on trimmed mean	30.811	2	224	0.000	
<b>S10LSearchEng</b>	Based on Mean	26.918	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	16.781	2	224	0.000	
	Based on Median and with adjusted df	16.781	2	202.252	0.000	
	Based on trimmed mean	28.144	2	224	0.000	
<b>S10LFoodDelWeb</b>	Based on Mean	36.903	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	13.628	2	224	0.000	
	Based on Median and with adjusted df	13.628	2	197.040	0.000	
	Based on trimmed mean	38.030	2	224	0.000	
<b>S10LStoreWeb</b>	Based on Mean	9.549	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	4.764	2	224	0.009	
	Based on Median and with adjusted df	4.764	2	213.381	0.009	
	Based on trimmed mean	10.157	2	224	0.000	
<b>S10LMassStoreCompWeb</b>	Based on Mean	15.929	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	12.002	2	224	0.000	
	Based on Median and with adjusted df	12.002	2	222.949	0.000	
	Based on trimmed mean	14.191	2	224	0.000	
<b>S10LEmailAd</b>	Based on Mean	32.669	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	26.061	2	224	0.000	
	Based on Median and with adjusted df	26.061	2	197.532	0.000	
	Based on trimmed mean	31.651	2	224	0.000	
<b>S1MOBPhoneSMS</b>	Based on Mean	46.455	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	19.696	2	224	0.000	
	Based on Median and with adjusted df	19.696	2	145.243	0.000	
	Based on trimmed mean	43.870	2	224	0.000	
<b>S1MOBApps</b>	Based on Mean	28.271	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	13.265	2	224	0.000	
	Based on Median and with adjusted df	13.265	2	202.483	0.000	
	Based on trimmed mean	30.042	2	224	0.000	

		Levene Statistic	df1	df2	Sig.	PostHocTest
<b>S2PHMassStore</b>	Based on Mean	0.351	2	224	<b>0.704</b>	Tukey HSD
	Based on Median	0.409	2	224	0.665	
	Based on Median and with adjusted df	0.409	2	219.190	0.665	
	Based on trimmed mean	0.838	2	224	0.434	
<b>S2PHSpecialtyStore</b>	Based on Mean	0.773	2	224	<b>0.463</b>	Tukey HSD
	Based on Median	0.675	2	224	0.510	
	Based on Median and with adjusted df	0.675	2	221.489	0.510	
	Based on trimmed mean	0.840	2	224	0.433	
<b>S2PHConvenienceS</b>	Based on Mean	0.342	2	224	<b>0.711</b>	Tukey HSD
	Based on Median	0.430	2	224	0.651	
	Based on Median and with adjusted df	0.430	2	223.337	0.651	
	Based on trimmed mean	0.326	2	224	0.722	
<b>S2OLStoreRetWeb</b>	Based on Mean	36.446	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	24.688	2	224	0.000	
	Based on Median and with adjusted df	24.688	2	212.598	0.000	
	Based on trimmed mean	37.424	2	224	0.000	
<b>S2OLLocalFoodDel</b>	Based on Mean	40.090	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	11.784	2	224	0.000	
	Based on Median and with adjusted df	11.784	2	144.450	0.000	
	Based on trimmed mean	32.731	2	224	0.000	
<b>S2OLRecipeBox</b>	Based on Mean	58.531	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	12.256	2	224	0.000	
	Based on Median and with adjusted df	12.256	2	101.113	0.000	
	Based on trimmed mean	39.178	2	224	0.000	
<b>S2OLPreparedMeal</b>	Based on Mean	18.690	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	4.188	2	224	0.016	
	Based on Median and with adjusted df	4.188	2	114.593	0.018	
	Based on trimmed mean	9.829	2	224	0.000	
<b>S2MOBStoreApp</b>	Based on Mean	61.132	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	26.563	2	224	0.000	
	Based on Median and with adjusted df	26.563	2	127.599	0.000	
	Based on trimmed mean	61.474	2	224	0.000	
<b>S2MOBAppResponsC</b>	Based on Mean	35.942	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	33.683	2	224	0.000	
	Based on Median and with adjusted df	33.683	2	216.733	0.000	
	Based on trimmed mean	36.850	2	224	0.000	
<b>S2MOBAppDelivery</b>	Based on Mean	9.684	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	12.166	2	224	0.000	
	Based on Median and with adjusted df	12.166	2	198.199	0.000	
	Based on trimmed mean	10.994	2	224	0.000	

		Levene Statistic	df1	df2	Sig.	PostHocTest
<b>S3MOB</b>	Based on Mean	36.340	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	13.953	2	224	0.000	
	Based on Median and with adjusted df	13.953	2	201.772	0.000	
	Based on trimmed mean	34.431	2	224	0.000	
<b>S3OL</b>	Based on Mean	44.793	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	22.105	2	224	0.000	
	Based on Median and with adjusted df	22.105	2	204.984	0.000	
	Based on trimmed mean	47.874	2	224	0.000	
<b>S3PH</b>	Based on Mean	16.179	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	8.532	2	224	0.000	
	Based on Median and with adjusted df	8.532	2	199.541	0.000	
	Based on trimmed mean	17.153	2	224	0.000	
<b>S4ClickCollect</b>	Based on Mean	29.274	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	18.992	2	224	0.000	
	Based on Median and with adjusted df	18.992	2	206.493	0.000	
	Based on trimmed mean	27.149	2	224	0.000	
<b>S4ClickDrive</b>	Based on Mean	22.988	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	20.844	2	224	0.000	
	Based on Median and with adjusted df	20.844	2	212.068	0.000	
	Based on trimmed mean	22.103	2	224	0.000	
<b>S4HomeDelivSt</b>	Based on Mean	47.435	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	37.177	2	224	0.000	
	Based on Median and with adjusted df	37.177	2	215.124	0.000	
	Based on trimmed mean	45.939	2	224	0.000	
<b>S4HomeDelivApp</b>	Based on Mean	13.857	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	6.903	2	224	0.001	
	Based on Median and with adjusted df	6.903	2	198.946	0.001	
	Based on trimmed mean	16.100	2	224	0.000	
<b>S4TkonPurchase</b>	Based on Mean	9.574	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	4.020	2	224	0.019	
	Based on Median and with adjusted df	4.020	2	197.979	0.019	
	Based on trimmed mean	7.978	2	224	0.000	

		Levene Statistic	df1	df2	Sig.	PostHocTest
<b>S5FeedbackSM</b>	Based on Mean	92.789	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	90.422	2	224	0.000	
	Based on Median and with adjusted df	90.422	2	157.063	0.000	
	Based on trimmed mean	94.932	2	224	0.000	
<b>S5FeedbackWebS</b>	Based on Mean	62.618	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	55.841	2	224	0.000	
	Based on Median and with adjusted df	55.841	2	168.985	0.000	
	Based on trimmed mean	68.696	2	224	0.000	
<b>S5FeedbackMobApp</b>	Based on Mean	78.411	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	32.138	2	224	0.000	
	Based on Median and with adjusted df	32.138	2	124.793	0.000	
	Based on trimmed mean	79.969	2	224	0.000	
<b>S5FeedbackPhone</b>	Based on Mean	43.010	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	14.474	2	224	0.000	
	Based on Median and with adjusted df	14.474	2	145.977	0.000	
	Based on trimmed mean	40.131	2	224	0.000	
<b>S5ShareExpSM</b>	Based on Mean	70.326	2	224	<b>0.000</b>	Dunnett's C
	Based on Median	19.232	2	224	0.000	
	Based on Median and with adjusted df	19.232	2	137.775	0.000	
	Based on trimmed mean	61.841	2	224	0.000	

**Annex 10**  
**POSTHOC TESTS – MULTIPLE COMPARISONS**  
ANOVA ANALYSIS FOR SIGNIFICANCE DIFFERENCE EVALUATION - TOUCHPOINT USAGE FREQUENCY BY SEGMENT

Dependent Variable				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
S1PHMassStore	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	-0.011	0.149		-0.37	0.34
			Uninterested Traditional	.815*	0.321		0.01	1.62
		Curious Conservatives	Early Omnichannel Adopters	0.011	0.149		-0.34	0.37
			Uninterested Traditional	.826*	0.325		0.01	1.64
		Uninterested Traditional	Early Omnichannel Adopters	-.815*	0.321		-1.62	-0.01
			Curious Conservatives	-.826*	0.325		-1.64	-0.01
S1PHFriendsFam	Tukey HSD	Early Omnichannel Adopters	Curious Conservatives	.325*	0.133	0.041	0.01	0.64
			Uninterested Traditional	1.121*	0.221	0.000	0.60	1.64
		Curious Conservatives	Early Omnichannel Adopters	-.325*	0.133	0.041	-0.64	-0.01
			Uninterested Traditional	.796*	0.215	0.001	0.29	1.30
		Uninterested Traditional	Early Omnichannel Adopters	-1.121*	0.221	0.000	-1.64	-0.60
			Curious Conservatives	-.796*	0.215	0.001	-1.30	-0.29
S1OLSocialMedia	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.444*	0.135		0.12	0.77
			Uninterested Traditional	1.264*	0.108		1.01	1.52
		Curious Conservatives	Early Omnichannel Adopters	-.444*	0.135		-0.77	-0.12
			Uninterested Traditional	.821*	0.081		0.63	1.01
		Uninterested Traditional	Early Omnichannel Adopters	-1.264*	0.108		-1.52	-1.01
			Curious Conservatives	-.821*	0.081		-1.01	-0.63
S1OLSearchEng	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.364*	0.152		0.00	0.73
			Uninterested Traditional	1.508*	0.126		1.20	1.81
		Curious Conservatives	Early Omnichannel Adopters	-.364*	0.152		-0.73	0.00
			Uninterested Traditional	1.145*	0.105		0.89	1.40
		Uninterested Traditional	Early Omnichannel Adopters	-1.508*	0.126		-1.81	-1.20
			Curious Conservatives	-1.145*	0.105		-1.40	-0.89
S1OLFoodDelWeb	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.666*	0.137		0.34	0.99
			Uninterested Traditional	1.255*	0.123		0.96	1.55
		Curious Conservatives	Early Omnichannel Adopters	-.666*	0.137		-0.99	-0.34
			Uninterested Traditional	.589*	0.086		0.38	0.80
		Uninterested Traditional	Early Omnichannel Adopters	-1.255*	0.123		-1.55	-0.96
			Curious Conservatives	-.589*	0.086		-0.80	-0.38
S1OLStoreWeb	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	1.066*	0.143		0.73	1.41
			Uninterested Traditional	1.367*	0.171		0.95	1.79
		Curious Conservatives	Early Omnichannel Adopters	-1.066*	0.143		-1.41	-0.73
			Uninterested Traditional	0.301	0.144		-0.06	0.66
		Uninterested Traditional	Early Omnichannel Adopters	-1.367*	0.171		-1.79	-0.95
			Curious Conservatives	-0.301	0.144		-0.66	0.06
S1OLMassStoreCompWeb	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.702*	0.140		0.37	1.04
			Uninterested Traditional	.868*	0.181		0.42	1.31
		Curious Conservatives	Early Omnichannel Adopters	-.702*	0.140		-1.04	-0.37
			Uninterested Traditional	0.166	0.148		-0.20	0.53
		Uninterested Traditional	Early Omnichannel Adopters	-.868*	0.181		-1.31	-0.42
			Curious Conservatives	-0.166	0.148		-0.53	0.20
S1OLEmailAd	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.609*	0.134		0.29	0.93
			Uninterested Traditional	.977*	0.117		0.70	1.26
		Curious Conservatives	Early Omnichannel Adopters	-.609*	0.134		-0.93	-0.29
			Uninterested Traditional	.368*	0.066		0.21	0.52
		Uninterested Traditional	Early Omnichannel Adopters	-.977*	0.117		-1.26	-0.70
			Curious Conservatives	-.368*	0.066		-0.52	-0.21
S1MOBPhoneSMS	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.528*	0.108		0.27	0.79
			Uninterested Traditional	.724*	0.099		0.49	0.96
		Curious Conservatives	Early Omnichannel Adopters	-.528*	0.108		-0.79	-0.27
			Uninterested Traditional	.197*	0.044		0.09	0.30
		Uninterested Traditional	Early Omnichannel Adopters	-.724*	0.099		-0.96	-0.49
			Curious Conservatives	-.197*	0.044		-0.30	-0.09
S1MOBApps	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.750*	0.162		0.36	1.14
			Uninterested Traditional	1.329*	0.166		0.93	1.73
		Curious Conservatives	Early Omnichannel Adopters	-.750*	0.162		-1.14	-0.36
			Uninterested Traditional	.579*	0.131		0.26	0.90
		Uninterested Traditional	Early Omnichannel Adopters	-1.329*	0.166		-1.73	-0.93
			Curious Conservatives	-.579*	0.131		-0.90	-0.26

Dependent Variable				Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
S2PHMassStore	Tukey HSD	Early Omnichannel Adopters	Curious Conservatives	-.382 <sup>*</sup>	0.121	<b>0.005</b>	-0.67	-0.10
			Uninterested Traditional	-0.057	0.200	0.955	-0.53	0.41
		Curious Conservatives	Early Omnichannel Adopters	.382 <sup>*</sup>	0.121	0.005	0.10	0.67
			Uninterested Traditional	0.325	0.194	0.218	-0.13	0.78
		Uninterested Traditional	Early Omnichannel Adopters	0.057	0.200	0.955	-0.41	0.53
			Curious Conservatives	-0.325	0.194	0.218	-0.78	0.13
S2PHSpecialtyStore	Tukey HSD	Early Omnichannel Adopters	Curious Conservatives	0.168	0.152	0.515	-0.19	0.53
			Uninterested Traditional	0.215	0.253	0.672	-0.38	0.81
		Curious Conservatives	Early Omnichannel Adopters	-0.168	0.152	0.515	-0.53	0.19
			Uninterested Traditional	0.047	0.246	0.980	-0.53	0.63
		Uninterested Traditional	Early Omnichannel Adopters	-0.215	0.253	0.672	-0.81	0.38
			Curious Conservatives	-0.047	0.246	0.980	-0.63	0.53
S2PHConvenienceS	Tukey HSD	Early Omnichannel Adopters	Curious Conservatives	0.029	0.162	0.983	-0.35	0.41
			Uninterested Traditional	0.026	0.269	0.995	-0.61	0.66
		Curious Conservatives	Early Omnichannel Adopters	-0.029	0.162	0.983	-0.41	0.35
			Uninterested Traditional	-0.003	0.262	1.000	-0.62	0.61
		Uninterested Traditional	Early Omnichannel Adopters	-0.026	0.269	0.995	-0.66	0.61
			Curious Conservatives	0.003	0.262	1.000	-0.61	0.62
S2OLStoreRetWeb	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	1.412 <sup>*</sup>	0.147		1.06	1.76
			Uninterested Traditional	1.665 <sup>*</sup>	0.155		1.29	2.04
		Curious Conservatives	Early Omnichannel Adopters	-1.412 <sup>*</sup>	0.147		-1.76	-1.06
			Uninterested Traditional	.253 <sup>*</sup>	0.102		0.00	0.50
		Uninterested Traditional	Early Omnichannel Adopters	-1.665 <sup>*</sup>	0.155		-2.04	-1.29
			Curious Conservatives	-.253 <sup>*</sup>	0.102		-0.50	0.00
S2OLLocalFoodDel	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.366 <sup>*</sup>	0.099		0.13	0.60
			Uninterested Traditional	.529 <sup>*</sup>	0.091		0.31	0.75
		Curious Conservatives	Early Omnichannel Adopters	-.366 <sup>*</sup>	0.099		-0.60	-0.13
			Uninterested Traditional	.162 <sup>*</sup>	0.040		0.07	0.26
		Uninterested Traditional	Early Omnichannel Adopters	-.529 <sup>*</sup>	0.091		-0.75	-0.31
			Curious Conservatives	-.162 <sup>*</sup>	0.040		-0.26	-0.07
S2OLRecipeBox	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.380 <sup>*</sup>	0.097		0.15	0.61
			Uninterested Traditional	.414 <sup>*</sup>	0.095		0.19	0.64
		Curious Conservatives	Early Omnichannel Adopters	-.380 <sup>*</sup>	0.097		-0.61	-0.15
			Uninterested Traditional	0.034	0.021		-0.02	0.08
		Uninterested Traditional	Early Omnichannel Adopters	-.414 <sup>*</sup>	0.095		-0.64	-0.19
			Curious Conservatives	-0.034	0.021		-0.08	0.02
S2OLPreparedMeal	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	0.156	0.071		-0.01	0.32
			Uninterested Traditional	.207 <sup>*</sup>	0.068		0.05	0.37
		Curious Conservatives	Early Omnichannel Adopters	-0.156	0.071		-0.32	0.01
			Uninterested Traditional	.051 <sup>*</sup>	0.020		0.00	0.10
		Uninterested Traditional	Early Omnichannel Adopters	-.207 <sup>*</sup>	0.068		-0.37	-0.05
			Curious Conservatives	-.051 <sup>*</sup>	0.020		-0.10	0.00
S2MOBStoreApp	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.795 <sup>*</sup>	0.138		0.47	1.12
			Uninterested Traditional	.966 <sup>*</sup>	0.129		0.66	1.27
		Curious Conservatives	Early Omnichannel Adopters	-.795 <sup>*</sup>	0.138		-1.12	-0.47
			Uninterested Traditional	.171 <sup>*</sup>	0.047		0.06	0.28
		Uninterested Traditional	Early Omnichannel Adopters	-.966 <sup>*</sup>	0.129		-1.27	-0.66
			Curious Conservatives	-.171 <sup>*</sup>	0.047		-0.28	-0.06
S2MOBAppResponsC	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.710 <sup>*</sup>	0.135		0.39	1.03
			Uninterested Traditional	.948 <sup>*</sup>	0.150		0.58	1.31
		Curious Conservatives	Early Omnichannel Adopters	-.710 <sup>*</sup>	0.135		-1.03	-0.39
			Uninterested Traditional	0.238	0.105		-0.02	0.50
		Uninterested Traditional	Early Omnichannel Adopters	-.948 <sup>*</sup>	0.150		-1.31	-0.58
			Curious Conservatives	-0.238	0.105		-0.50	0.02
S2MOBAppDelivery	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.843 <sup>*</sup>	0.162		0.46	1.23
			Uninterested Traditional	1.702 <sup>*</sup>	0.169		1.29	2.11
		Curious Conservatives	Early Omnichannel Adopters	-.843 <sup>*</sup>	0.162		-1.23	-0.46
			Uninterested Traditional	.860 <sup>*</sup>	0.145		0.50	1.22
		Uninterested Traditional	Early Omnichannel Adopters	-1.702 <sup>*</sup>	0.169		-2.11	-1.29
			Curious Conservatives	-.860 <sup>*</sup>	0.145		-1.22	-0.50
S3MOB	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	1.202 <sup>*</sup>	0.137		0.88	1.53
			Uninterested Traditional	1.690 <sup>*</sup>	0.118		1.41	1.97
		Curious Conservatives	Early Omnichannel Adopters	-1.202 <sup>*</sup>	0.137		-1.53	-0.88
			Uninterested Traditional	.487 <sup>*</sup>	0.069		0.32	0.65
		Uninterested Traditional	Early Omnichannel Adopters	-1.690 <sup>*</sup>	0.118		-1.97	-1.41
			Curious Conservatives	-.487 <sup>*</sup>	0.069		-0.65	-0.32
S3OL	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	1.284 <sup>*</sup>	0.149		0.93	1.64
			Uninterested Traditional	1.796 <sup>*</sup>	0.141		1.46	2.13
		Curious Conservatives	Early Omnichannel Adopters	-1.284 <sup>*</sup>	0.149		-1.64	-0.93
			Uninterested Traditional	.512 <sup>*</sup>	0.078		0.32	0.70
		Uninterested Traditional	Early Omnichannel Adopters	-1.796 <sup>*</sup>	0.141		-2.13	-1.46
			Curious Conservatives	-.512 <sup>*</sup>	0.078		-0.70	-0.32
S3PH	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	-.594 <sup>*</sup>	0.094		-0.82	-0.37
			Uninterested Traditional	-.885 <sup>*</sup>	0.081		-1.08	-0.69
		Curious Conservatives	Early Omnichannel Adopters	.594 <sup>*</sup>	0.094		0.37	0.82
			Uninterested Traditional	-.291 <sup>*</sup>	0.049		-0.41	-0.18
		Uninterested Traditional	Early Omnichannel Adopters	.885 <sup>*</sup>	0.081		0.69	1.08
			Curious Conservatives	.291 <sup>*</sup>	0.049		0.18	0.41

S4ClickCollect	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.688*	0.138		0.36	1.02
			Uninterested Traditional	1.019*	0.140		0.68	1.36
		Curious Conservatives	Early Omnichannel Adopters	-688*	0.138		-1.02	-0.36
			Uninterested Traditional	.331*	0.099		0.09	0.57
S4ClickDrive	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.736*	0.149		0.38	1.09
			Uninterested Traditional	.877*	0.171		0.46	1.29
		Curious Conservatives	Early Omnichannel Adopters	-.736*	0.149		-1.09	-0.38
			Uninterested Traditional	0.141	0.135		-0.19	0.47
S4HomeDelivSt	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.985*	0.153		0.62	1.35
			Uninterested Traditional	1.145*	0.168		0.74	1.55
		Curious Conservatives	Early Omnichannel Adopters	-.985*	0.153		-1.35	-0.62
			Uninterested Traditional	0.160	0.115		-0.12	0.44
S4HomeDelivApp	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.867*	0.166		0.47	1.26
			Uninterested Traditional	1.530*	0.173		1.11	1.95
		Curious Conservatives	Early Omnichannel Adopters	-.867*	0.166		-1.26	-0.47
			Uninterested Traditional	.663*	0.145		0.31	1.02
S4TkonPurchase	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	-.634*	0.153		-1.00	-0.27
			Uninterested Traditional	-1.163*	0.125		-1.46	-0.86
		Curious Conservatives	Early Omnichannel Adopters	.634*	0.153		0.27	1.00
			Uninterested Traditional	-.529*	0.107		-0.79	-0.27
S5FeedbackSM	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.762*	0.111		0.50	1.03
			Uninterested Traditional	.874*	0.107		0.62	1.13
		Curious Conservatives	Early Omnichannel Adopters	-.762*	0.111		-1.03	-0.50
			Uninterested Traditional	.111*	0.029		0.04	0.18
S5FeedbackWebS	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.656*	0.097		0.42	0.89
			Uninterested Traditional	.715*	0.102		0.47	0.96
		Curious Conservatives	Early Omnichannel Adopters	-.656*	0.097		-0.89	-0.42
			Uninterested Traditional	0.059	0.053		-0.07	0.19
S5FeedbackMobApp	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.633*	0.099		0.40	0.87
			Uninterested Traditional	.736*	0.093		0.51	0.96
		Curious Conservatives	Early Omnichannel Adopters	-.633*	0.099		-0.87	-0.40
			Uninterested Traditional	.103*	0.033		0.02	0.18
S5FeedbackPhone	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.501*	0.115		0.23	0.78
			Uninterested Traditional	.612*	0.114		0.34	0.89
		Curious Conservatives	Early Omnichannel Adopters	-.501*	0.115		-0.78	-0.23
			Uninterested Traditional	0.110	0.064		-0.04	0.27
S5ShareExpSM	Dunnett C	Early Omnichannel Adopters	Curious Conservatives	.545*	0.113		0.28	0.81
			Uninterested Traditional	.724*	0.104		0.48	0.97
		Curious Conservatives	Early Omnichannel Adopters	-.545*	0.113		-0.81	-0.28
			Uninterested Traditional	.179*	0.043		0.08	0.28
		Uninterested Traditional	Early Omnichannel Adopters	-.724*	0.104		-0.97	-0.48
			Curious Conservatives	-.179*	0.043		-0.28	-0.08

\*. The mean difference is significant at the 0.05 level.

**Annex 11**  
**ANOVA AND POSTHOC TESTS – COVID IMPACT ON CHANNEL CHANGE**  
ANOVA ANALYSIS FOR SIGNIFICANCE DIFFERENCE EVALUATION BETWEEN SEGMENTS

**Descriptives**

CovidCH	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Early Omnichannel Adopters	87	2.63	1.163	.125	2.38	2.88	1	5
Curious Conservatives	117	1.76	.868	.080	1.60	1.92	1	5
Uninterested Traditional	23	1.65	.775	.162	1.32	1.99	1	3
Total	227	2.08	1.071	.071	1.94	2.22	1	5

**Test of Homogeneity of Variances**

CovidCH	Levene Statistic	df1	df2	Sig.
Based on Mean	6.409	2	224	.002
Based on Median	3.283	2	224	.039
Based on Median and with adjusted df	3.283	2	205.322	.040
Based on trimmed mean	6.511	2	224	.002

**ANOVA**

CovidCH	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	42.663	2	21.332	22.046	.000
Within Groups	216.746	224	.968		
Total	259.410	226			

**Multiple Comparisons**

Dependent Variable:

(I) CLUST	Dunnnett C	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Early Omnichannel Adopters	Curious Conservatives	.872 <sup>*</sup>	0.148		0.52	1.22
	Uninterested Traditional	.980 <sup>*</sup>	0.204		0.48	1.48
	Curious Conservatives	-0.872 <sup>*</sup>	0.148		-1.22	-0.52
	Uninterested Traditional	0.109	0.180		-0.34	0.56
	Uninterested Traditional	-0.980 <sup>*</sup>	0.204		-1.48	-0.48
	Curious Conservatives	-0.109	0.180		-0.56	0.34

\*. The mean difference is significant at the 0.05 level.

**Annex 12**  
**ANOVA AND POSTHOC TESTS**  
**ON EXPERIENCE PURCHASING FOOD ONLINE AND OFFLINE**  
ANOVA ANALYSIS FOR SIGNIFICANCE DIFFERENCE EVALUATION BETWEEN SEGMENTS

**Descriptives**

OnlineX	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Early Omnichannel Adopters	87	3.08	1.014	.109	2.86	3.30	1	5
Curious Conservatives	117	1.86	.860	.080	1.71	2.02	1	4
Uninterested Traditional	23	1.61	.941	.196	1.20	2.02	1	4
Total	227	2.30	1.113	.074	2.16	2.45	1	5
OfflineX	87	4.28	.788	.084	4.11	4.44	2	5
Curious Conservatives	117	4.35	.864	.080	4.19	4.51	1	5
Uninterested Traditional	23	4.61	.583	.122	4.36	4.86	3	5
Total	227	4.35	.813	.054	4.24	4.45	1	5

**Test of Homogeneity of Variances**

OnlineX	Levene Statistic	df1	df2	Sig.
Based on Mean	.180	2	224	.836
Based on Median	.291	2	224	.748
Based on Median and with adjusted df	.291	2	184.922	.748
Based on trimmed mean	.068	2	224	.934
OfflineX	1.687	2	224	.187
Based on Mean	1.284	2	224	.279
Based on Median and with adjusted df	1.284	2	188.588	.279
Based on trimmed mean	1.804	2	224	.167

**ANOVA**

OnlineX	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	86.299	2	43.150	49.893	.000
Within Groups	193.727	224	.865		
Total	280.026	226			
OfflineX	2.017	2	1.008	1.531	.219
Between Groups	147.490	224	.658		
Within Groups	149.507	226			

**Annex 13**  
**EXPLORATORY FACTOR AND RELIABILITY ANALYSIS RESULTS**  
**FOR FOOD RELATED LIFESTYLES DIMENSIONS**

	Time Pressure	Loyalty	Quality Aspects	Enjoyment	Price Criteria	Mean	(SD)	Cronbachs Alpha	Pearson
I am always in a rush	.64					3.24	1.06	.78	
There is often not enough time in the day for me to do what I want to do. I am often rushing to get everything done. Time-saving devices are a good idea	.83					3.63	.97		
I often feel like I am running out of time	.83					3.67	1.05		
The brand of the product is important for me in my purchase decisions.		.70				3.57	1.03		.56
I generally purchase the same brands.		.70				3.95	.85		
For me, the naturalness of the food is an important factor			.62			4.26	.90	.84	
I would like to pay more money for animal welfare approved foods*			.65			3.95	1.04		
I prefer to buy food from my region			.82			3.94	.98		
I prefer to buy foods that were traditionally made			.76			3.82	1.03		
I like to go to several stores/websites* to get the best value for money				.85		2.60	1.20		.66
I spend time carefully comparing prices before buying items				.80		2.63	1.34		
I always check prices, even on small items.					.61	3.39	1.11	.79	
I always try to get the best quality for the best price.					.71	3.63	1.13		
I compare prices between product variants in order to get the best value for money.					.74	3.37	1.25		
It is important for me to know that I get quality for all my money.					.63	3.87	.91		

n=227

	Importance to Product Information	Passion for Cooking	Eating in Company	Pleasure and Interest	Convenience Orientation	Mean	(SD)	Cronbachs Alpha	Pearson
To me product information is of major importance. I need to know what the product contains.	.73					4.02	.96	.83	
I compare labels to select the most nutritious food.	.80					3.41	1.12		
I compare product information labels to decide which brand to try.	.81					3.47	1.12		
Cooking is my hobby		.84				3.32	1.23	.93	
Cooking brings me joy		.81				3.59	1.15		
Cooking is a process of self-realization		.66				3.43	1.10		
I have a passion for cooking		.82				3.03	1.32		
I like to try new recipes		.67				3.78	1.10		
I invest a lot of time for cooking		.77				2.98	1.25		
I am proud to prepare my own meals and self-invested recipes		.65				3.85	1.14		
We often get together with friends to enjoy an easy-to-cook casual dinner			.83			3.37	1.10		.60
Dinning with friends is an important part of my social life			.82			3.92	1.08		
I am very interested in food				.67		4.14	.78	.77	
When I eat, I enjoy food very much				.75		4.17	.78		
Good drinks and food play a major role in my life				.78		4.03	.97		
I prefer food that is easy to prepare					.75	3.15	1.06	.89	
The less physical effort (work, energy) I need to buy and prepare food, the better					.76	2.94	1.15		
I prefer meals that can be prepared and consumed quickly					.81	2.89	1.12		
I prefer food that requires only little planning.					.80	3.00	1.14		

n=227

	Environmental Protection	Health Orientation	Attitudes to Advertising	Mean	(SD)	Cronbachs Alpha	Pearson
It is important that the food that I eat on a typical day has been prepared in a environmental friendly way	.83			3.82	.94	.92	
It is important that the food that I eat on a typical day has been produced in a way that has not shaken the balance of nature	.88			3.89	.89		
It is important that the food that I eat on a typical day has been packaged in a environmentally friendly way	.81			3.97	.93		
I always follow a healthy and balanced diet		.75		3.67	.95	.81	
It is important to me that my daily diet contains a lot of vitamins and minerals		.71		3.73	.95		
I try to eat foods that do not contain additives		.77		3.66	1.02		
I do not eat processed foods because I do not know what they contain		.68		3.39	1.17		
I have more confidence in food products that I have seen advertised than in unadvertised products.			.84	2.21	1.05		.71
Information from advertising helps me to make better buying decisions.			.82	2.18	1.14		

n=227