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PSYCHOGRAPHIC AND BEHAVIORAL SEGMENTATION OF FOOD DELIVERY APPLICATION CUSTOMERS TO INCREASE INTENTION TO USE

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Dissertation presented as partial requirement for obtaining the Master's degree in Information Management

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ABSTRACT

This study presents a framework for segmenting Food Delivery Application (FDA) customers based on psychographic and behavioral variables as an alternative to existing segmentation. Customer segments are proposed by applying clustering methods to primary data from an electronic survey. Psychographic and behavioral constructs are formulated as hypotheses based on existing literature, and then evaluated as segmentation variables regarding their discriminatory power for customer segmentation. Detected relevant variables are used in the application of clustering techniques to find adequate boundaries within customer groupings for segmentation purposes. Characterization of customer segments is performed and enriched with implications of findings in FDA marketing strategies. This paper contributes to theory by providing new findings on segmentation that are relevant for an online context. In addition, it contributes to practice by detailing implications of customer segments in an online sales strategy, allowing marketing managers and FDA businesses to capitalize knowledge in their conversion funnel designs.

KEYWORDS

Food Delivery Applications; Psychographic segmentation; Behavioral segmentation; Clustering; Customer Segmentation

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LIST OF ABBREVIATIONS AND ACRONYMS

DM	Data Mining
FDA	Food Delivery Applications
ML	Machine Learning
MSA	Market Segmentation Analysis
O2O	Online to Offline
PCA	Principal Component Analysis

1. INTRODUCTION

1.1. BACKGROUND AND PROBLEM IDENTIFICATION

The recent digital boom has led to the development of new business models that use technology as a key resource for supplying goods and services. Among these are the O2O business models, where operations occur in both online and offline channels in a complementary way. One of the most notorious examples in the O2O industry are Food Delivery services, which use mobile applications to connect restaurants and consumers in a single platform, connecting supply and demand in a seamless way. These businesses, also known as Food Delivery Applications (FDA), have become an important sector in the worldwide economy, generating substantial revenues with positive forecasts for the years to come (Dospinescu, Dospinescu & Tatarusanu, 2020).

Considering the pandemic events of 2020, Food Delivery Applications acquired a greater importance by providing users with the means to obtaining food goods in the midst of mobility restrictions and quarantine measures, while also allowing restaurants to alleviate their economic stress through the usage of a new sales channel (Horta, Souza & Mendes, 2020). Moreover, this type of business model became an alternative for existing restaurants to provide their own mobile applications, increasing the availability of Food Delivery Applications in both platform-to-consumer and restaurant-to-consumer modalities (Statista, 2020). These events increased competition in the industry, making it important for FDA companies to focus on targeting a user's intention to use as a means of increasing frequency of usage, loyalty and revenue. However, the mixed shopping environments of O2O business models make customer perception different from traditional businesses; making it important to identify and focus on key elements that drive consumers to use the provided delivery services (Moon & Armstrong, 2019). Better yet, using these elements to understand the different typologies of FDA users allows designing marketing strategies that target specific consumers, slicing the market into specific buyer personas by applying proper customer segmentation.

Customer segmentation is one of the most common tasks of a Marketing Department. The concept of customer segmentation was developed in the 1950s by Wendell R. Smith (Smith, 1956) and has ever since been used to classify customers by using different factors and traits that allow grouping individuals with similar characteristics into actionable segments (Wu & Lin, 2005). Traditionally, customer segmentation has used demographic and geographic variables to create the different customer groupings. However, the use of these variables may be inadequate to portray and characterize customer segments with individual views and behaviors (Taylor-West, Saker & Champion, 2020). Gratefully, Marketing has undergone a major transformation in the recent years driven by the use of Digital, Social Media and Mobile Marketing (Müller, Pommeranz, Weisser & Voigt, 2018). In this digital era, businesses have attempted to gain advantage over competitors by applying Internet-oriented updated versions of traditional marketing strategies that fit new consumer behaviors (Ballestar, Grau-Carles, & Sainz, 2018). O2O companies can benefit from this by targeting specific consumer groups with the content and products that are relevant to that specific segment, gaining deeper understanding of the segment's preferences, needs and wants (An, Kwak, Jung, Salminen & Jansen, 2018); and therefore, designing marketing strategies that allow products to be marketed to the maximum possible (Rosa & Yunita, 2020). Additionally, O2O companies can explore new approaches to customer segmentation by using a mixture of variables that properly characterize customers according to their views and behavior, with the use of psychographic and behavioral constructs.

Specific to the FDA industry, understanding the users' psychological attributions becomes a competitive advantage useful for securing and retaining app users (Choi, 2020). As such, multiple studies have attempted to explain the drivers behind desired user outcomes like loyalty, satisfaction, and reuse intention; finding multiple psychographic factors that target desired behaviors among FDA consumers (Zhao and Bacao, 2020; Roh and Park, 2019; Yeo, Goh & Rezaei, 2017; Cho, Bonn & Li, 2019; Ray et. al., 2019; Jeon, Kim & Jeong, 2016; Kim & Hwang, 2020; Gunden, Morosan & DeFranco, 2020; Choi, 2020; Lee, Sung & Jeon, 2019; Verma, 2020; Koiri, Mukherjee & Dutta, 2019; Belanche, Flavián & Perez-Rueda, 2020; Nanaiah, 2020). However, few relevant studies have been produced where such factors are applied to segmentation. Moreover, a gap exists between the proven psychological drivers of desired behaviors and their applicability in marketing strategies, specifically when it comes to differentiating users into relevant groupings by dividing them through psychographic and behavioral constructs. Consequently, this study aims at performing Market Segmentation Analysis to Food Delivery Application users by using psychographic and behavioral criteria to find relevant customer segments that are suitable for marketing strategies, specifically for achieving an increase in usage intention.

In order to achieve this, a critical Literature Review is performed to deepen the understanding on the business problem at hand; to explore the existing methods of performing Market Segmentation Analysis in digital contexts with psychographic and behavioral constructs; and to map the data mining techniques applied to Market Segmentation Analysis. Additionally, existing models from previous literature are revised to identify significant relationships between psychographic constructs anteceding desired behaviors in FDA. From this, a set of candidate variables for clustering is presented and discussed. This is followed by the formulation of multiple hypotheses regarding the significance of the different constructs for differentiating FDA users.

Afterwards, a descriptive research is performed to collect information from FDA users in relation to their personal views on statements evaluating the constructs, as well as information for their recent behavior on FDA usage. This information is then prepared to undergo a complete process of Data Mining, namely the Cross Industry Standard Process for Data Mining, with the purpose of applying clustering techniques for the identification of pertinent customer groupings. Different algorithms are evaluated in regard to their outcome by using reliability measures for cluster analysis, examining for a solution that suits best the problem at hand. To close this stage, profiling is performed to the selected clustering solution, looking to characterize customer groupings with variables that allow designing marketing strategies.

Finally, cluster groupings are analyzed and compared with existing models, detailing the most notorious opportunities for FDA businesses to tackle. The results are discussed and detailed to showcase the different user typologies and their implications. Lastly, conclusions are produced and explained with a specific emphasis on narrating the contributions of this study to both theory and practice. This is complemented with the limitations of this research and the opportunities for future investigation.

1.2. STUDY OBJECTIVES

The present study will establish consumer profiles suitable for designing strategies targeting an increase in usage intention for Food Delivery Application users; using literature-based psychographic and behavioral constructs to apply clustering techniques that allow defining proper market segments.

The specific objectives include:

- To determine the set of psychographic and behavioral variables that differentiate customers based on their online behavior and views while using Food Delivery Applications, specifically regarding the continuous intention to use the delivery services.
- To propose a framework for customer segmentation based on the identified psychographic and behavioral variables that adequately characterize Food Delivery Application consumers with the purpose of increasing application usage.
- To identify the insights and opportunities that Food Delivery Application companies can capitalize in order to improve their online sales strategies.

2. LITERATURE REVIEW

This section provides a contextualization of the different themes involved in this dissertation. First, a general view of the digital landscape is provided with a drill-down on Food Delivery Applications and its current market state. Then, an overview on the Market Segmentation Analysis is performed, followed by an understanding of psychographic and behavioral segmentation variables used in previous research in specific digital contexts. A background on Data Mining follows this section, where the most relevant clustering techniques available for Market Segmentation Analysis are outlined and an overview of different algorithms used in literature is discussed. Lastly, the different themes involving this research are analyzed in conjunction to map the opportunities for researching the relevant psychographic and behavioral constructs that appropriately create groupings among Food Delivery Application users, including analysis of previous psychographic work in the FDA industry, and the relevant variables that may outline relevant segmentation criteria. Figure 2.1 showcases the conceptual model followed during the literature review.

Figure 2.1 – Conceptual Model for Literature Review[1]

2.1. FOOD DELIVERY INDUSTRY

2.1.1. Digital Landscape

The Internet has experienced a significant growth in use and potentiality, becoming a part of daily life and bringing changes to society and lifestyle (Ray et. al., 2019). Among the most notorious changes is the creation of new marketplaces, where electronic transactions allow buyers and sellers to negotiate products and services in online environments. The development of electronic commerce has been driven by multiple factors, including technological progress, improvement in education, increase in disposable income, changes in lifestyle, and increase in financial development worldwide (Koiri, Mukherjee & Dutta, 2019). Furthermore, it has extended to different channels and formats, including mobile devices and applications.

Mobile apps are software applications designed for smart phones and tablets, easily accessible and downloaded through application stores (Cho, Bonn & Li, 2019). By 2019, it was estimated that more than five billion people used mobile phones worldwide, generating a wide market of apps that provide information and services in a more efficient manner - changing consumer lifestyles and behaviors (Choi, 2020). On top of that, mobile devices have become an essential part of daily life due to the ideal

[1] Figure 2.1 shows the process used to study thoroughly the existing literature and define the constructs with highest relevancy for the problem at hand.

environment for mobile app adoption; fueled by a provided high speed internet access, the fast rhythm of modern life, the advances in interactive apps, and the proliferation of smart devices (Belanche, Flavián & Perez-Rueda, 2020). Hence, there has been a rapid growth of mobile commerce between businesses and consumers through these smart phone apps, driven by the accessibility and opportunity to exchange information in a timely manner (Lee, Sung & Jeon, 2019).

As mentioned by Yeo, Goh and Rezaei (2017), the Internet boom has propelled the success of online retailers and electronic commerce, becoming a preferred shopping medium for many consumers due to the comfort it provides, the variety of available products, real-time interactivity with sellers, and the product customization. Additionally, it has allowed new business models to emerge. The Sharing Economy is the name given to a new type of unconventional business model focused on providing target users with access to a set of resources, in contrast to selling those resources for ownership. The type of operations enabled for consumers in this business model are selling, renting, swapping, lending and borrowing goods and services; creating an on-demand, sustainable and convenient alternative for resource consumption (Williams et. al., 2020). Table 2.1 depicts 5 perspectives to Sharing Economy, namely economic, social, environmental, legal, and computing; with identified benefits and disadvantages for each one.

Perspective	Advantages	Disadvantages
Economic	Economic growth in big and intermediate cities, that can additionally aid countering excessive resource consumption while generating new sources of revenue.	Destabilize traditional, long-established markets by affecting their revenue, business practices and relevancy.
Social	Vehicle for building social capital and establishing relationships within communities.	New social challenges like digital discrimination.
Environmental	Promotion of environmental awareness with more sustainable consumption practices.	Increase in environmental pressure due to more affordable alternatives.
Legal	Evolution of regulatory frameworks based on new business models.	New ways of regulation are needed to protect the service providers, the app owners and the service receivers - based on terms of service.
Computing	Evolution of P2P algorithms for user experience, pricing, matching and safety.	New challenges for data privacy.

Table 2.1 – Sharing Economy perspectives[2].

[2] Adapted from Williams, G., Tushev, M., Ebrahimi, F., & Mahmoud, A. (2020). Modeling user concerns in Sharing Economy: the case of food delivery apps. Automated Software Engineering, 1-35. Table showcases sharing economy perspectives that influence food delivery application industry as well as disadvantages present in the evolution of these novel industries.

Similarly, Collaborative Consumption is a new type of consumer behavior where users coordinate the acquisition and distribution of goods and services through peer-to-peer dynamics using community-based online services (Correa et. al., 2019). These specific peer-to-peer business exchanges have generated substantial economic development, increasing competitiveness in multiple industries while also generating new job opportunities for people in societies with scarce resources (Williams et. al., 2020). On the same topic, Online-to-Offline (O2O) is the name used to describe industries and businesses operating on business models where transactions are initiated online and finished or consumed offline (Chen et. al, 2015). Significant advances and developments in Information Technologies have allowed information exchange and resource optimization between businesses and users. In addition, rising urbanization, changes in household composition and increasing time restrictions have driven users to outsource certain tasks, like meal preparation. The convenience this provides to consumers at saving time and effort accounts greatly on the usage increase of O2O services (Roh & Park, 2019). For business owners, using the Internet as a sales channel represents a cost-effective solution for finding new opportunities, new consumers and new marketplaces (Cho, Bonn & Li, 2019). In addition to this, exploiting the benefits provided by mobile technologies means taking advantage of the ideal environment created by a global network of interconnected people, willing to access new marketplaces at the reach of their hand (Williams et. al., 2020).

As noted by Correa et. al. (2019), the creation of new business models driven by the trends and possibilities of ‘Online-to-Offline’, ‘Collaborative Consumption’ and ‘Sharing Economy’ bring new challenges to existing industries. These challenges include diversifying out of the industry, resorting to legal confrontations with new players, innovating on the previous business models, finding other sources of income, and acquiring new companies that excel at offering new services. Consequently, the rise in competition and the confrontation with incumbent competitors means that O2O players need to be in a continuous state of innovation, guided by a deep understanding of their users and their constantly evolving expectations (Williams et.al, 2020).

Table 2.2 illustrates the most representative firms in the O2O industry. Multiple categories of O2O companies were identified by Roh and Park (2019) in their research, including transportation, space, food, and lending – among others. As shown in the mentioned table, dietary life has seen an interesting increase in usage due to the expansion of O2O businesses, with multiple companies starting to offer delivery services for food. The next section examines the causes for expansion of Food Delivery Applications, as well as the business implications for firms operating in this industry.

Category	Type	Representative firms
Transportation	Taxicab (Vehicle for hire)	Uber, Lyft (US); Didi, Chuxing (China); Ola (India); KakakoTaxi (South Korea)
	Carsharing and rental	Zipcar (US)
	Car-pooling	UberPool (US)
Space	Accommodation	Airbnb, Homeaway (US); Yanolza (South Korea)
	Workspace (SOHO: Small office/home office)	WeWork (US)
	Housing & rental apartments	Welive, Common (US)
	Parking lot	KakaoParking (South Korea)
Food	Grocery delivery	Instacart, Amazonfresh, Dreamdinners (US)
	Meal delivery	GrubHub, DoorDash, Postmates, Tapingo, DiningIn.com, Snapfinger/Kudzu, Campus Food.com, Delivery.com, UberEats, Seamless, Caviar (US); Just Eat, Deliveroo (UK); Foodora, Delivery Hero (Germany); Ele.me, Meituan waimai, Baidu Waimai (China); Yoggio, Baemin (South Korea); Wolt (Finland), FoodPanda, Delivery Chef, Yummybay (India)
	Meal kit delivery	Blueapron, HelloFresh, Plated (US), SimplyCook, Eats On, beChef, theBanchan, HelloNature (South Korea)
	Ghost restaurant	Green Summit, Munchery, Kettlebell Kitchen (US)
	Homemade food delivery	Huijiachifan (China)
Lending and crowdfunding		LendingClub (US)
Pawnshop service		Lendingbox (South Korea)
Online staffing		Amazon's Mechanical Turk, Freelancer (US)
Real estate brokerage		Zillow (US); Zigbang, Dabang (South Korea)
House cleaning		Amazon Home Services (US); HomestorySaengHwal (South Korea)
Laundry service		Washio (US); reWhite (South Korea)
Hair shop		KakaoHairshop (South Korea)
Chauffeur service		KakaoDriver (South Korea)
Flower delivery		Bloomthat (US)
Music & video streaming		Spotify (Sweden)

Table 2.2 – Representative firms in the Online-to-Offline Commerce[3].

2.1.2. Food Delivery Applications

Food Delivery Applications (FDA) comprise all mobile applications that provide the service of delivering food ordered via a mobile or web app (Thamaraiselvan, Jayadevan & Chandrasekar, 2019). This service can either be performed by the restaurant supplier or by third-party intermediaries using an aggregator business model (Yeo, Goh & Rezaei, 2017). The concept of this business model is to allow customers to place food orders through an online single window system[4], where numerous food providers have registered previously to offer their menus. Using mobile app and web technology, Online-to-Offline services are provided by FDA companies via connecting the online ordering experience with the offline process of delivering the food. The FDA provider charges the restaurant a margin for acquiring the consumer and handling the logistics of delivery, while also applying surge pricing to users, and hence, FDAs are required to maintain a cross-side network effect[5] (Ray et. al., 2019; Jain, Verma & Jaggi, 2020). In addition, FDAs may offer consumers a membership fee with special

[3] Adapted from Roh, M., & Park, K. (2019). Adoption of O2O food delivery services in South Korea: The moderating role of moral obligation in meal preparation. International Journal of Information Management, 47, 262-273. Table shows how food is one of the most competed verticals within O2O firms, with wide representation and opportunities.

[4] Single window system refers to type of system where all facilities are available in one unique place.

[5] Cross-side network effect is when the strength of one side of the market has an impact on the growth of the other. In this case, the growth of FDAs is dependent on both the increase in users and the increase in supplier restaurants.

services, as well as advertising packages for restaurants, generating multiple income streams (Choi, 2020). Therefore, FDAs work as a medium that integrates restaurants, customers and logistics partners to provide food availability, compelling offers and instant home delivery that encourages many customers to prefer online food shopping over the offline experience (Jain, Verma & Jaggi, 2020). This preference is due to the fact that consumers can browse, choose, request and fulfill orders of food in a single platform that aggregates supply from multiple restaurants, types of cuisine, prices and offers (Gunden, Morosan, & DeFranco, 2020). Figure 2.2 from Li, Mirosa and Bremer (2020) illustrates the operational model of FDAs, along with its main actors, their functions and communication streams.

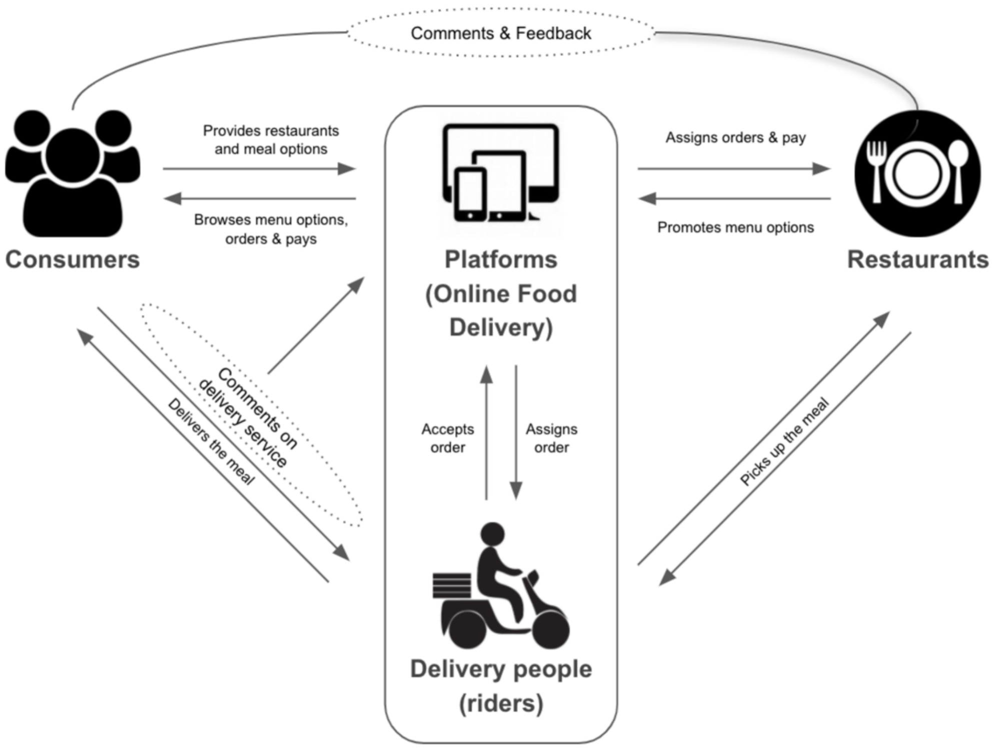

Figure 2.2 – Functions associated with Food Delivery Applications[6].

Food Delivery services can be categorized into three types of services, based on the degree of cooking as it reaches the consumer – understanding that more ready-to-eat meals will be available for the consumer at a higher cost but with less invested effort (Roh & Park, 2019). These categories correspond to grocery, meal-kit and full meal types, with some of the most recognized players in each category depicted in Table 2.2. Additionally, they can be classified between Restaurant-to-Consumer delivery, where the restaurant is in charge of all logistics, and Platform-to-Consumer delivery, where the application provider is in charge of connecting users (Statista, 2020).

There is still no consensus regarding the specific name for this industry. Given names include Digital Food Delivery (Thamaraiselvan, Jayadevan & Chandrasekar, 2019), Food Ordering and Delivery

[6] Figure 2.2 shows the business model of Food Delivery Applications and market participants. Adapted from Li, C., Mirosa, M., & Bremer, P. (2020). Review of Online Food Delivery Platforms and their Impacts on Sustainability. Sustainability, 12(14), 5528.

Applications (Reddy & Aradhya, 2020), Third-party Food Delivery Systems (Stephens, Miller & Militello, 2020), Online Food Delivery Services (Yeo, Goh & Rezaei, 2017), Online Food Delivery Systems (Gunden, Morosan, & DeFranco, 2020), Food Delivery Mobile Apps (Choi, 2020), and Online Food Delivery Aggregators (Kapoor & Vij, 2018). However, certain distinctions have been discussed between Online Food Delivery Services and Food Delivery Applications, the former being accessible through both websites and applications, while the latter can only be accessed through mobile devices (Ray et. al., 2019).

In 2019, the food delivery market accounted for 4 percent of food goods sold in chain and fast-food restaurants, with a forecasted growth rate of 3.5 percent during a five-year period (Thamaraiselvan, Jayadevan & Chandrasekar, 2019). For this same year, the estimated number of customers reached 971.6 million with average revenue per user of approximately 100 dollars (Jain, Verma & Jaggi, 2020). Only in the United States, this market represents a 26.8 billion industry, growing 23% in the past 4 years (Stephens, Miller & Militello, 2020). Figure 2.3 illustrates the annual growth rate for this industry between 2011 and early 2020.

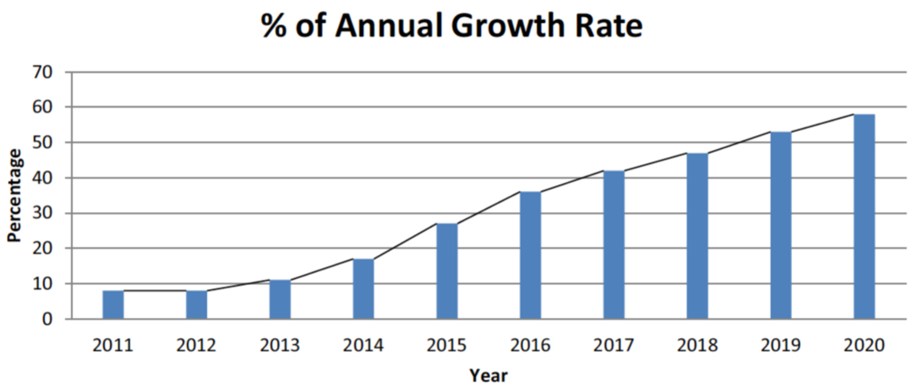

Figure 2.3 – Percentage of Annual Growth Rate between 2011 and 2020[7].

However, COVID-19[8] spiked the usage of Food Delivery Applications during 2020 due to the obligation of maintaining social distance and complying with local quarantine measures. FDAs provided consumers with a way to access food products during a period of time when restaurants had rules on capacity reduction and civilians had limitations on mobility; at the same time that it pushed businesses to migrate to delivery services as an alternative sales channel during face-to-face restrictions (Horta, Souza & Mendes, 2020). FDAs made the purchase of food safer in COVID times, in addition to the convenience, flexibility and time saving benefits that the Food Delivery industry already provided for its market (Reddy & Aradhya, 2020). Moreover, the adoption rate of FDAs was propelled in 2020 with the use of financial benefits like discounts, free delivery promotions and combos, which had an effect on consumer needs due to the greater socio-economic vulnerability being lived during the pandemic

[7] Figure 2.3 depicts the substantial growth of FDAs in the last decade, shown in CAGR. Taken from Jain, R., Verma, M., & Jaggi, C. K. (2020). Impact on bullwhip effect in food industry due to food delivery apps. OPSEARCH, 1-12.

[8] COVID-19 is global pandemic caused by a coronavirus. Control measures include quarantine, circulation restrictions and social distancing practices aimed at reducing the risk of contagion and death.

(Horta, Souza & Mendes, 2020). As described by Zhao and Bacao (2020), studies in China showed that 71.7% of 15.263 surveyed citizens were using FDAs by March 2020, with 41.6% using these applications as the preferred method for daily purchases in the times of COVID-19. Williams et. al. (2020) also identified that even though several Sharing Economy applications had a decrease in usage during 2020, like transportation applications, Food Delivery demand had a significant increase. This explains the year-on-year revenue growth of 11.1% in spite of 2020 being a year of economic complications for many industries. Furthermore, this industry is expected to behave with a Compound Annual Growth Rate[9] of 6.4% per year during the 2021-2024 period, reaching a projected worldwide revenue of US $182.3 billion (Statista, 2021).

Regardless of the pandemic, many factors have contributed to the growth of FDAs worldwide. An important factor that has contributed to the FDA expansion is the continuous growth in Internet use, technology literacy, and smart phone possession on the buyers' end (Thamaraiselvan, Jayadevan & Chandrasekar, 2019). The development of the Information Technology and Communication sector has changed the way consumers interact with these businesses, offering interactive menus, GPS tracking of the delivery, transparent delivery times, location-based services, and a variety of payment options (Reddy & Aradhya, 2020). Next to that, the use of technology has generated useful data for restaurant owners to optimize both the supply chain process and the customer relationship management (Jain, Verma & Jaggi, 2020).

New factors in the social and cultural customer dimensions have also contributed to the FDA expansion. Reddy and Aradhya (2020) noted how social and cultural changes have produced a growth in demand for quick access to cooked products, caused by changes of lifestyle, increase of double-income households, lack of time, and changing eating habits due to exposure to global cuisine. In addition, the increase in single-person households from younger generations has boosted the demand for instant and effortless meals accessed through well-designed apps, as these consumers have proven to perform less grocery shopping than other generations, as well as being more tech-savvy consumers (Cho, Bonn & Li, 2019). In general, the millennial generation has proven to be key in FDA expansion due to this understanding of technology, living the trend of experimenting with new cuisine, perceived lack of time, and less tracking of expenses (Nanaiah, 2020). Thamaraiselvan, Jayadevan & Chandrasekar (2019) also identified in their study on Indian FDAs that the increase of urban areas with shopping malls, business centers and residential apartments have also helped in the growth of this market. Similarly, Horta et. al. (2020) identified a similar behavior in Brazilian users, where the spike of FDA demand is linked to work lunch hours, to users lacking cooking abilities, or to specific locations experiencing bad weather.

The growth of delivery-focused businesses, known as ghost restaurants, has also contributed to boom in FDAs (Roh & Park, 2019). This is mainly because these businesses require less investment in store location, furniture, rent and supplies in comparison to restaurants open to public (Thamaraiselvan, Jayadevan & Chandrasekar, 2019). On the other hand, restaurants open to public drive growth of FDAs as they expand their business portfolios to delivery services, mainly as an alternative to rationalize fixed costs, gain customer visibility, maximize business output, grow in consumer base, and strengthen customer loyalty (Thamaraiselvan, Jayadevan & Chandrasekar, 2019;

[9] Compound Annual Growth Rate refers to a representational rate of yearly growth assuming constant growth during a period of time.

Jain, Verma & Jaggi, 2020). In addition, the COVID-19 pandemic has risen the existing registered food suppliers as restaurants turn to delivery channels to alleviate the pressure of imposed government restrictions; while other type of businesses like catering enterprises have also found FDAs to be an alternative during this situation (Horta, Souza & Mendes, 2020; Zhao & Bacao, 2020). Furthermore, the impact of the pandemic points towards an increase of FDA usage, as studies in China show that 70% of surveyed restaurants plan to increase investment and continue operation on FDA platforms once the health crisis has surpassed (Zhao & Bacao, 2020).

It is, however, important to mention how restaurants have made an attempt at boosting their own delivery services as a countermeasure of the FDA boom. The increase in competition is a factor that needs to be monitored and tackled by existing players in order to keep their competitive positions. Only in China, 2020 represented a year-on-year increase of 766% regarding food delivery business registrations (Zhao & Bacao, 2020). As competition rises among FDAs with these new competitors, existing players need to attract and retain users by understanding their needs and intentions to improve and accelerate the adoption process (Ray et. al, 2019). Furthermore, the usage of FDAs has started to transcend the O2O model to influence existing consumer perceptions regarding restaurants - even when the intention is to visit the restaurant - given the easy access to the displayed menus, reviews, and the photographs of the food and restaurant (Sharma & Waheed, 2018). As such, challenges among FDA companies include confronting with fierce competition, tackling a decentralized operation system, and handling multi-lateral communication with users, restaurants, and drivers (Williams et. al., 2020). Indeed, FDA competition includes continuous improvement of their high-quality retail interfaces that must be designed and enhanced to guide and persuade customers towards an effective purchase and a higher probability of reuse (Gunden, Morosan, & DeFranco, 2020).

It has been mentioned that success factors for FDAs include quality of service (food, delivery time, handling of complaints, information transparency), quality of the mobile application (trust, ease of use, security, variety of payments, live tracking) (Reddy & Aradhya, 2020); marketing strategies directed by FDAs using combos, free shipping, and price discounts (Horta et. al., 2020); convenience, mode of payment, cuisine variety, food quality, discounts, and cash backs (Koiri, Mukherjee & Dutta, 2019); and ease of use, flexible payments, real-time tracking, loyalty points, and effective customer support (Gupta, 2019). However, as noted by Cho, Bonn and Li (2019), FDA consumers do not share the same food preferences, quality expectations and opinions of perceived value while using these applications. Moreover, these consumers' perceptions affect their behavioral intention to trial the FDA services, reuse them, and ultimately, recommend it to other potential users. Finally, tackling the challenges in food delivery services means understanding the user's needs and expectations, aiming to use this knowledge into enhancing features, refining customer experience, and improving the complex and dynamic software ecosystem (Williams et. al., 2020). This becoming even more relevant as new methods become available for food delivery and customer interaction, such as robots, drones, augmented reality, and artificial intelligence (Reddy & Aradhya, 2020).

Therefore, it can be stated that the survival of an FDA company in this competitive environment depends on securing and retaining their app users, with a special focus on understanding their users' psychological attributions (Choi, 2020). As such, understanding the typology of users to target based on their particular perceptions and expectations is a relevant marketing function in FDA businesses, especially when aiming at customer acquisition, user retention and building loyalty. The next section explores Market Segmentation Analysis and its different applications in research, specifically in digital contexts that rely on psychological and behavioral attributes to segment a target population.

2.2. MARKET SEGMENTATION ANALYSIS

2.2.1. Market Segmentation Analysis

Marketing is the business role responsible for understanding the customer's needs and wants, and determining how to trade value between the company and its customers. Defining the group of customers to serve is an important decision in the process, where the company must decide, at a strategic level, which set of potential buyers will be targeted (Kotler & Armstrong, 2010). In this sense, Market Segmentation can be defined as the process of separating the market into segments, followed by the selection of a target market that allows planning a specific marketing mix for a particular product or service (Tynan & Drayton, 1987). The importance of Market Segmentation Analysis (MSA) lies on the ability of identifying relevant customer groupings that share similar characteristics. This is achieved by applying a general framework that extracts segments from previously collected and explored data, describes and profiles the identified customer groupings, and then designs a marketing mix for the most relevant customer segments (Dolnicar, Grün & Leisch, 2018).

One approach to MSA is to explore market segments based on a particular set of segmentation variables, where a data-driven methodology is applied to customer data in order to identify the relevant clusters (Dolnicar, 2004). The resulting clusters within this approach may be natural, reproducible, or constructive – varying in whether the boundaries of consumer groups are natural or answer to the specific choice of variables (Dolnicar & Leisch, 2010). The quality of the resulting clusters will depend on the selected segmentation variables used to split the data, as well as the descriptor variables used to profile the groupings. Based on the nature of the information used, four distinct segmentation criteria have been identified: geographic, socio-demographic, psychographic and behavioral variables.

Market segmentation has traditionally been performed based on socio-demographic and geographic information. Variables like gender, age, income, and nationality have typically been a part of the criteria used for customer profiling. However, research has found limitations in the use of these traditional segmentation procedures. Hultén (2007) identified that using socio-demographic criteria for categorizing customers had grown in difficulty due to the complexity of customer behavior; Johns and Gyímothy (2002) and Hung et. al. (2019) discussed the weaknesses of demographic variables as purchase behavior predictors since they are indirectly related to buying intentions; while even some time back Haley (1985) stated that consumer behavior was explained in a very low proportion by demographic variables. Particularly for digital environments, Wu and Chou (2011) concluded from their online segmentation experiment that even though demographic information is useful, it does not provide a good diagnosis on customers. The reason behind it is that the perception of web performance is key in value exchange with potential buyers, especially in implementing retention strategies for financial attainment.

As an alternative, multiple sources have proposed the use of psychographic constructs as segmentation criteria. Boston Consulting Group suggested using category-specific attitudinal constructs for segmentation algorithms instead of socio-demographic variables (Egan & Izaret, 2008);

Pandey et. al. (2015) discussed the inefficiency of socio-demographic variables on loyalty strategies in comparison to psychographic criteria; and Evans et. al. (2012) argued that while demographics describe who is interacting with online advertising, psychographics allow understanding the reasons behind specific behaviors. Furthermore, Oklander and Oklander (2017) discussed how the development of the digital environment has raised the importance of cultural and philosophical factors in comparison to socio-demographic norms, given the ease with which communities of like-minded people are created. The next section explores the psychographic and behavioral segmentation studies performed in digital contexts, and analyzes their methodology and results.

2.2.2. Psychographic and Behavioral Segmentation in Digital Contexts

Multiple studies have been performed where psychographic constructs are used as segmentation criteria. Specific to the digital context, behavioral and psychographic experiments have shown interesting results that reinforce the need to create relevant market segments that allow businesses to find insights for business growth. Nakano & Kondo (2018) used a mixture of behavioral data with psychographic variables to segment Japanese customers by their purchase channel preference and the psychological aspects that drive their purchase behavior. Their results not only allowed having an applicable segmentation scheme for online marketing, but also offered a stepping-stone for companies evaluating marketing automation strategies. Evans et. al. (2012) identified clusters of Facebook users by separating them according to perception around technological hooks used by the platform, as well as patterns of social media usage, consumer activity and self-identity constructs. As a result, 8 different Facebook user typologies were identified, allowing businesses to prompt specific advertising hooks to attract the right consumers in the Facebook network. De Corte and Van Kenhove (2017) managed to successfully explain the existing segments in digital media piracy by using pirates' differences regarding the ethical evaluation of piracy, experienced guilt, and attitude toward piracy. The resulting clusters were used to test different anti-piracy strategies based on the pirates' psychographic profile. Pandey et. al. (2015) managed to explore the existence of customer segments for an Indian internet vendor by using online lifestyle constructs to differentiate consumers. Their findings provide useful insights for boosting sales by taking notice of website design and online purchasing process. Similarly, Rohm and Swaminathan (2004) used shopping motivations to explain the differences among consumers for the online grocery shopping market. They provided companies within this industry with a general understanding of customer behavior, opportunities for strategic alliances, and requirements for delivery processes.

It is interesting to understand the existing methodological procedures used in psychographic segmentation for data gathering and evaluation. Taylor-West, Saker and Champion (2020) aimed at presenting an alternate approach to segmenting the automotive industry by using product familiarity, product involvement and product expertise as clustering criteria. In order to achieve this, an online survey was distributed through email to Ford's customers where a Likert scale was used to measure the constructs, and Cronbach's alpha coefficients were used to guarantee the reliability of the scales. Nakano & Kondo (2018) used purchase scan panel data and media log data to map consumer behavior traits in a set of product categories, accompanied by a survey that linked psychographic constructs with these behavioral traits. The survey used a 5-point Likert scale and a threshold of 0.7 for Cronbach's alpha coefficients to measure innovativeness, motivation to conform, enjoyment in shopping, brand loyalty, price consciousness and time pressure. Additionally, Hultén (2007) also used 5-point Likert scales to evaluate the constructs of satisfaction, trust, commitment, future intentions, brand satisfaction, brand familiarity, and brand attitudes. An online survey was used, along with factor loadings from a Principal Component Analysis (PCA) and a correlation matrix, to guarantee the validity of the different constructs. Similarly, De Corte and Van Kenhove (2017) measured psychographic constructs using a 7-point and 9-point Likert scale with Cronbach's alpha for digital pirate segmentation, in a similar way to how Pandey et. al. (2015) used a 7-point scale in an online survey to measure e-shopper's lifestyles. Wu and Chou (2011) used an online questionnaire that collected information in ordinal scales regarding shopping behavior, satisfaction with service and Internet usage to map customers' psychographic and behavioral characteristics for clustering; while Evans et. al. (2012) applied an online survey based on an Psychster Inc. survey using 5 point unipolar semantic-differential scales, where 90 value proposition questions were then reduced via factor analysis to identify the 8 final clustering set.

Once a general understanding of the data collection procedures has been done, it is important to understand the data mining methodologies used in segmentation exercises to understand best practices from previous research. The next section explores this, as well as some of the evaluation criteria used after performing clustering on data.

2.3. DATA MINING

2.3.1. Applied Data Mining to Market Segmentation Analysis

Data Mining (DM) is defined as the discovery of relevant patterns and structures in large data sets (Hand & Adams, 2014). Among the existing algorithms that perform pattern recognition for data mining purposes, the Machine Learning (ML) algorithms have proven to be outstanding due to their reduced number of restrictions for modeling and their ease for interpretability in comparison to other techniques (Bose & Mahapatra, 2001). The Machine Learning algorithms can be classified according to their technique into supervised learning, reinforcement learning, and unsupervised learning – where the latter is named unsupervised given that no guidance regarding cluster membership is fed into the algorithm beforehand (Kassambara, 2017). Clustering is one of the most popular unsupervised methods and it is frequently used for market segmentation tasks (Wu & Lin, 2005). This method aims at grouping observations that are similar to each other into a single class, while placing observations that are dissimilar into another class, using a specific set of measures to evaluate the class membership for each observation (Hastie, Tibshirani & Friedman, 2009).

Different clustering techniques have been used in Market Segmentation Analysis. As an example, Lefait and Kechadi (2010) applied K-Means[10] to a reduced set of data containing Recency, Frequency and Monetary Spent (RFM) from purchase logs, where dimensionality was reduced using Symbolic Aggregate Approximation[11], and 5 resulting clusters were detected. Likewise, Hung et. al. (2019) used Hierarchical Agglomerative Clustering[12] on a bank's credit card data to understand customer behavior

[10] K-Means is a partitioning algorithm that splits the data into k parts, attempting to minimize the within clusters sum of squares.

[11] Symbolic Aggregate Approximation, known as SAX, is a symbolic representation for time series data with the purpose of dimensionality reduction.

[12] Hierarchical Agglomerative Clustering is a clustering technique that builds a hierarchy of clusters based on a measure of similarity with a bottom-up approach.

for marketing purposes, settling on 3 clusters based on 3 behavioral variables. It can be affirmed that segmentation possibilities using Data Mining cover multiple techniques and strategies. However, it is important to dig into segmentation strategies in digital contexts to identify the industry's best practices.

Considering segmentation in digital contexts with psychographic and behavioral variables, Ballestar, Grau-Carles and Sainz (2018) used a two-step cluster analysis on customers from a cash back website to group visitors based on a combination of their role in a social network and their transactional behavior, resulting in eight separate clusters from 6 segmentation variables. Nakano and Kondo (2018) applied Latent Class cluster Analysis[13] that used a multinomial logit model to estimate the probability of a class membership for Japanese consumers regarding purchase channels and media touch points, with 7 relevant segments found. Similarly, Wu and Chou (2011) also applied Latent Class Analysis to apply multiple category segmentation to online shoppers as an attempt to show the benefits of soft clustering over hard clustering techniques. An et. al. (2018) managed to separate customers using Non-negative Matrix Factorization[14] on the behavioral traits present in the aggregated customer statistics from YouTube, that were later profiled using the available demographic data and automatized for six personas[15] generation. It is, therefore, important to notice the wide variety of clustering strategies that can be applied to digital contexts.

Determining the number of clusters is one of the most important steps in clustering exercises. Different methodologies have been applied in order approximate the number of clusters to a viable solution. Hung et. al. (2019) used a combination of the classic elbow method[16], the average silhouette method[17] and the gap statistic method[18], to define the optimal number for k. Amine et. al. (2015) applied Self Organizing Maps[19] to understand data structure, define the number of clusters, and determine the centroid locations, and then applied K-means using this information to optimize algorithm performance. Similarly, Lopez et. al. (2011) used the Hopfield Autonomous Recurrent Neural Network (H-ANN)[20] to detect the number of clusters and initial centroids, to later proceed with the final clustering via the K-Means algorithm. Evans et. al. (2012) on the other hand, used ANOVA[21] procedures to compare the results of different numbers of clusters and deciding on the optimal number by identifying the scenario with the highest F-value[22]. As an alternative, De Corte and Van

[13] Latent Class Analysis, also known as LCA, is a statistical technique that identifies classes in the data and uses probabilities to define class membership for observations. It is also referred to as finite mixture models.

[14] Non Negative Matrix Factorization, also known as NMF, is an unsupervised technique for dimensionality reduction.

[15] A persona refers to fictional profiles used in marketing to represent different customer types.

[16] The elbow method is a technique used to determine the optimal number of clusters, based on plotting the explained variation in the data in function of the number of k.

[17] The Average Silhouette method is a technique used for determining the optimal number of clusters, based on the variation of the silhouette score in function of the number of k. The silhouette score measures cluster quality by taking into account their cohesion and separation.

[18] The Gap Statistic method is used for determining the optimal number of k by comparing the within-cluster dispersion of the observed data with the expected null distribution.

[19] Self Organizing Maps are a type of Artificial Neural Network used as an unsupervised learning technique to represent the input data as a low dimensional map.

[20] A Hopfield Network is a type of recurrent artificial neural network typically used in optimization tasks.

[21] Analysis of Variance testing (ANOVA) is a method for analyzing the differences between group means.

[22] F Value is the ratio between the variability of between-subjects over within-subjects. In clustering, lower numbers of F Value indicate greater overlap of clusters.

Kenhove (2017) relied on the BIC and AIC measures[23] for different numbers of clusters to decide on the optimal number of segments, contrasted to a two-step evaluation based on both Ward's Method and K-Means. This is similar to the method used by Pandey et. al. (2015), where Hierarchical Clustering was first implemented to determine the optimal number for K, followed by K–means using this information as a hyper parameter.

Regarding the technological tools, the most predominant tool used in the revised clustering exercises is IBM SPSS (Ballestar, Grau-Carles and Sainz, 2018; Müller et. al., 2018; Wu & Lin, 2005; Amine et. al., 2015; De Corte & Van Kenhove, 2017). However, other tools have been used to perform the same tasks, such as Latent GOLD (Nakano & Kondo, 2018; De Corte & Van Kenhove, 2017), Anaconda (An et. al, 2018), and R Studio (Hung et. al, 2019).

With respect to cluster evaluation, different measures are applicable when performing market segmentation on research data. Lefait and Kechadi (2010) opted for using a combination of r-squared[24] and F-measure[25] as indicators of clustering performance, obtaining a relatively low performing model with few variance explained and with impure clusters. However, important conclusions were extracted from the exercise regarding customer behavior and the existence of customer groupings in artificial segments. Hung et. al. (2019) applied the Virtual Assessment of Cluster Tendency (VAT) technique[26] to evaluate the existence of clusters before applying Hierarchical Agglomerative clustering, using visualization techniques such as a Lattice Scatterplot[27] to evaluate cluster quality. Lopez et. al. (2011) used the Calinski[28] and Davies-Bouldin[29] indexes to evaluate clustering results on electricity customers from Spain, comparing results from each index to assess the overall result of 13 customer groupings. De Corte and Van Kenhove (2017) used the previously mentioned BIC and AIC scores as a first evaluation, followed by the use of ANOVA and chi-squared tests to evaluate the statistical significance between mean differences among the four identified digital pirate clusters. Pandey et. al. (2015) used Wilk's lambda to validate the existence of the proposed three clusters in the data. Similar to the clustering methodologies, the evaluation criterion depends on the researchers and the problem at hand, with a variety of alternatives to choose from.

The following section explores the existence of segmentation studies performed specifically in Food Delivery Application contexts, with an exploration of possible psychographic and behavioral segmentation variables based on proven relevant relationships from previous literature.

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[23] Bayesian and Akaike Information Criterions are measures for model selection.

[24] R-squared, also known as the coefficient of determination, is the proportion of variance explained by a set of independent variables.

[25] The F measure, also known as the F1 score, is a measure of the accuracy achieved by a model.

[26] Visual Assessment of Cluster Tendency is a tool for evaluating the existence of clusters by using grey scale visualization tools, where clusters are represented as darker blocks in a matrix's diagonal.

[27] The Lattice Scatterplot is a visualization tool that showcases the relationship among several variables at the same time.

[28] The Calinski-Harabasz Index is a metric used for cluster evaluation based on the ratio between within cluster and between cluster dispersion.

[29] Davies-Bouldin Index is a metric used for cluster evaluation based on the average similarity of clusters.

2.4. PSYCHOGRAPHIC AND BEHAVIORAL CONSTRUCTS IN FDA

2.4.1. Customer Segmentation in FDAs

Even though FDAs have been growing in recent years, there is still a big opportunity for research to apply market segmentation techniques and strategies to customers of these apps. Recently, Gunawan, Muchardie and Agustina (2021) performed a research aimed at increasing customer retention through proper segmentation of Indonesian consumers using online grocery apps. The study was focused only on millennial users, and some segmentation variables were psychographic constructs that included perceived security, perceived privacy, convenience, perceived ease of use, perceived usefulness, and social influence. However, other complementary variables were used like site design, merchandising, and information quality. As a result, 4 clusters were found, namely the Youngster Millennial, the Trust-Oriented Mid-Millennial, the Productive Millennial, and the Tech Savvy Millennial. Techniques included in this study were performed through SPSS software, obtaining reliable results.

In addition, the food industry has had segmentation studies that do not focus on the market, but on the product itself. This is the case of the Freitas, Cordeiro and Macario (2020), who performed a segmentation study looking to differentiate food elements within pictures in order to apply classification algorithms to individual elements and provide the user with a total sum of calories per meal. It is interesting to see the extent to which segmentation is applied within mobile apps and the digital industry, not only as a vehicle for food acquisition via sharing economy models, but also as an information provider of nutrition and calories when interactions are taking place through screens. With this, image recognition proves to be a useful tool for FDA companies in the near future.

However, one of the most notable segmentation studies performed in recent years within FDAs was done in China by Li, Bonn, Wang and Cho (2021). On their study, application characteristics and quality attributes were used to segment FDA users into actionable market segments, using as variables the price, perception of various food choices, perceived usefulness, convenience, design, and trustworthiness. Using the latent class model, they managed to identify four segments that were called the bargain hunters, the time conscious users, the uniqueness seekers, and the true friends. Interestingly, the authors complemented their results with business insight, not only showing the statistical relevance of their findings, but also providing specific actions for each of the segments. Despite this, and as mentioned in the introduction, the target of the present study is to complement existing research based on quality attributes with a contribution of new segments created upon psychographic and behavioral constructs.

2.4.2. Psychographic and Behavioral Segmentation in FDAs

In their study on FDAs, Yeo, Goh and Rezaei (2017) acknowledged that little research had been performed on the online food delivery market. They were able to provide useful conclusions regarding the factors that determine usage of Food Delivery Applications, but did not manage to describe their market among typologies or proportions. In addition, Ray et. al. (2019) further concluded in their study that despite the industry’s potential and the existing mobile adoption studies, very few studies have been done in the topic. Table 2.3 illustrates twelve empirical relevant studies identified by these authors in the 2017 to 2019 period, comprising both qualitative and quantitative research, and with diverse methodological approaches and objectives – with none of them being clustering tasks.

Author (Year)	Sample	Study Measures	Study Focus
Elvandari et al. (2017)	213 consumers (89% female) aged 12 to 45 years	Interviews	Influence of satisfaction, quality of service, technical requirements, and service delivery on OFD usage intentions
Pigatto et al. (2017)	Qualitative study: 30 OFD companies in Brazil	Content analysis	Analysing feasibility of websites based on its content, functionality and usability.
See-Kwong et al. (2017)	12 Qualitative interviews	Interview	Influence of revenue increase, broader customer reach, and better customer base on outsources intention.
Yeo et al. (2017)	224 university students (female 47.8%) aged 17 to 30 years	Structural Equation Modelling	Association between hedonic motivation, convenience motivation, prior-online purchase, time-saving orientation, price-saving orientation, post-usage usefulness, attitude and behavioural intention.
He et al. (2018)	An experiment based on 13 scenarios), 700 sample	Experiment	Examining the Agent-based O2O Food Ordering Model based model.
Maimaiti et al. (2018)	Review of articles on O2O market	Content analysis	Exploring the impact of OFDs on food shopping habits, increasing prevalence of overweight and obesity as well as diet-related
Sjahroeddin (2018)	405 customers (71.4% female) aged 17 to 40 years	Structural Equation Modelling	Impact of efficiency, fulfilment, system availability, privacy, perceived value, food quality and user satisfaction on OFD usage.
Suhartanto et al. (2019)	405 samples (71.4% female), aged 17 to 40 years	Structural Equation Modelling	Relationship between quality of food and service, satisfaction, perceived value and consumer loyalty towards OFDs.
Roh and Park (2018)	500 respondents (51.8% female) aged 18 to 50 years	Structural Equation Modelling	Influence of people's value systems, and moral obligations on adoption decision.
Yusra and Agus (2018)	Sample Size: 158	Regression analysis	Relationships between Mobile Service Quality and demographic information.
Correa et al. (2018)	4296 consumers in Bogotá city.	Web mining	Influence of traffic conditions on factors influencing adoption of OFDs.

Table 2.3 – Ray, Dhir, Bala and Kaur's identified relevant literature on FDAs[30]

Despite this existing research, no relevant work was found for user segmentation of Food Delivery Applications with the aforementioned variable types. Hence, it represents an opportunity for contribution in both theory and practice, by fulfilling the purpose of this research and applying an effective segmentation exercise to FDA users. Furthermore, providing insights on users' psychographic and behavioral traits enriches this study by evaluating these characteristics in the FDA context. The next section explores the psychographic and behavioral constructs that have been studied in the FDA industry, and explores relationships among these constructs that might be useful for a segmentation task.

[30] Adapted from Ray, A., Dhir, A., Bala, P. K., & Kaur, P. (2019). Why do people use food delivery apps (FDA)? A uses and gratification theory perspective. Journal of Retailing and Consumer Services, 51, 221-230. Table shows existing studies on FDAs used mainly on structural equation modelling for detecting antecedents of behaviors, without any market segmentation studies. SEM will be used as the main source for construct evaluation in further sections.

2.4.3. Psychographic and Behavioral Constructs in FDAs

The dynamics of the food ordering process make it a very interesting industry to understand through psychographic and behavioral constructs. As described by Gunden, Morosan and DeFranco (2020), FDAs reflect a specific set of circumstances that affect a buyer's motivation. This situation occurs because commoditization of meals in FDAs can be high, the service provided by FDA addresses a basic human need, the products acquired are highly perishable, and the brand landscape is fragmented among multiple companies present in a same marketplace. In that sense, Reddy & Aradhya (2020) pointed out that among the benefits that motivate consumers are comfort, time saving, variety, avoiding displacements, and assured quality. Likewise, they also concluded that among the factors influencing the buying decision are ease of payment, availability and variety of restaurant providers, convenience, better customer service, effective payment system, security, rewards system, previous experience, and word of mouth. However, it is important to acknowledge how customers have certain concerns while using FDAs, like loss of financial and personal information (Reddy & Aradhya, 2020), as well as high delivery charges (Karthika & Manojanaranjani, 2018). By understanding the factors influencing consumer behavior, businesses can design customer experiences to increase users, thrust usage and drive sales. Reddy and Aradhya (2020) noticed that website and app design is a key element in achieving trust from a customer, while Horta, Souza and Mendes (2020) discussed how FDA websites must achieve both user friendly navigation and timely response to a user's request in order to boost usage.

Reddy and Aradhya (2020) also discussed how customer satisfaction in FDAs is influenced significantly by customer experience, which itself is influenced by many factors that include performance and effort expectancy, hedonic motivation and habits, facilitating conditions, social influence, price value, online tracking, and online reviews and ratings. This is also backed by Horta, Souza and Mendes (2020) in their statement regarding convenience, hedonic motivations and usefulness being potential drivers of FDAs; and complemented by Jain, Verma and Jaggi (2020) by stating that not only hedonic motivations drive FDA usage, but also utilitarian motivations such as convenience, delivery services and availability at specific pre-fixed times. Zhao and Bacao (2020) also managed to identify the importance that relevant literature has given to the concept of trust as a factor determining a user's continuous usage of information technology, like mobile applications. Next to that, they also integrated multiple studies on a user's continuance intention of using information technology, showcasing all relevant variables identified among these studies, along with the theoretical frameworks used for this purpose. Table 2.4 showcases the results of their investigation.

From the mentioned table, it can be seen that multiple studies have been performed attempting to explain usage of Information Technologies. Different theoretical frameworks allow creating diverse sets of antecedent factors that need to be tested in order to confirm significant relations between psychographic variables and a target behavior. Thus, it is relevant to investigate the different models that have been performed in the FDA field in order to map a target behavior, along with appropriate proven psychographic factors anteceding that behavior.

The complete analysis performed in this study in regard to psychographic constructs related to FDA and its intention to use can be found in Appendix 1. The overview of these multiple FDA models and their outcomes, along with the relevant findings of possible constructs to use, can be found in table 2.5.

Relevant Studies	Theoretical Frameworks	Variables
Hung et al., 2012	ECM	Perceived usefulness Confirmation Satisfaction
Yuan et al., 2016	ECM Task-Technology Fit model TAM	Perceived technology task fit Perceived ease of use Perceived usefulness Confirmation Perceived risk Satisfaction
Alghamdi et al., 2018	UTT ECM	Performance expectancy Effort expectancy Social influence Facilitating conditions Satisfaction Confirmation Technology readiness Uncertainty Avoidance
Liébana-Cabanillas et al., 2018	UTAUT DOI	Satisfaction Service quality Effort expectancy Perceived risk Convenience Social value
Alshurideh et al., 2020	ECM TAM	Perceived ease of use Perceived usefulness Social influence Confirmation Satisfaction Continuance intention
Marinković et al., 2020	UTAUT	Performance expectancy Effort expectancy Social influence Satisfaction Perceived trust Perceived compatibility Customer involvement Epistemic value Comparative value
Tam et al., 2020	ECM UTAUT2	Confirmation Satisfaction Performance expectancy Effort expectancy Social influence Facilitating conditions Hedonic motivation Price value Habit
Wang et al., 2020	UTAUT2 TAM	Performance expectancy Effort expectancy Hedonic motivation Social influence Attitude

Table 2.4 – Summary of Studies involving continuance intention of using information technology[31]

[31] Taken from Zhao, Y., & Bacao, F. (2020). What factors determining customer continuingly using food delivery apps during 2019 novel coronavirus pandemic period?. International journal of hospitality management, 91, 102683. Table shows how intention to use is of importance for FDA studies, becoming the central desired behavior in this research. Additionally, the theoretical frameworks described in this table are used for construct analysis. See Appendix 1 and 2 for further information.

Author(s)	Target Variables	Identified Relevant Relations in the Models	
Zhao and Bacao (2020)	Continuance Intention Satisfaction Performance Expectancy	Confirmation - Satisfaction Confirmation - Performance Expectancy Perceived Task Technology Fit - Performance Expectancy Perceived Task Technology Fit - Continuance Intention Social Influence - Satisfaction Social Influence - Continuance Intention	Trust - Satisfaction Trust - Continuance Intention Performance Expectancy - Satisfaction Performance Expectancy - Continuance Intention Satisfaction - Continuance Intention
Roh and Park (2019)	Intention to use FDAs Usefulness Ease of Use Compatibility	Ease of use - Usefulness Ease of use - Intention Usefulness - Intention Compatibility - Ease of use Compatibility - Usefulness Compatibility - Intention	Convenience orientation - Ease of Use Convenience orientation - Compatibility (single) Subjective norm - Compatibility Subjective norm - Usefulness Subjective norm - Intention
Yeo, Goh and Rezaei (2017)	Behavioral intention Attitude towards OFD Convenience Motivation Post-usage Usefulness	Hedonic Motivations - Convenience Motivation Hedonic Motivations - Post-usage Usefulness Prior Online Purchase Experience - Convenience Motivation Time Saving Orientation - Convenience Motivation Time Saving Orientation - Post-usage Usefulness Price Saving Orientation - Convenience Motivation Price Saving Orientation - Post-usage Usefulness	Convenience Motivation - Post-usage Usefulness Convenience Motivation - Attitude towards OFD Convenience Motivation - Behavioral intention Post-usage Usefulness - Attitude towards OFD Post-usage Usefulness - Behavioral intention Attitude towards OFD services - Behavioral intention
Cho, Bonn and Li (2019)	Intention to continue using Perceived Value Attitude towards FDAs	Convenience - Perceived Value Design - Perceived Value Trustworthiness - Perceived Value Various food choices - Perceived Value	Perceived Value - Attitude Perceived Value - Intention Attitude towards FDAs - Intention
Ray et. al. (2019)	Intention to use	Customer experience - Intention Search of restaurants - Intention	Listing - Intention Ease of use - Intention
Jeon, Kim and Jeong (2016)	Reuse intention Arousal Pleasure	Design - Arousal Sympathy - Arousal Design - Pleasure Reliability - Pleasure	Informativity - Use intention Mobility - Use intention Pleasure - Use intention
Kim and Hwang (2020)	Eco-behavioral intention Attitude Personal Norm Ascribed Personality	Problem awareness - Ascribed responsibility Ascribed responsibility - Personal norm Personal norm - Behavioral intentions Attitudes - Behavioral intentions	Subjective norm - Behavioral intentions Perceived behavioral control - Behavioral intentions Problem awareness - Attitude Subjective norm - Personal norm
Gunden, Morosan and DeFranco (2020)	Persuasion Utilitarian web browsing Hedonic web browsing	Price saving orientaton - Utilitarian web browsing Price saving orientaton - Hedonic web browsing Hedonic web browsing - Persuasion Social Influence - Persuasion	
Choi (2020)	Reuse Intention Perceived Usefulness Perceived ease of use Satisfaction	Familiarity - Reuse Intention Familiarity - Perceived ease of use Familiarity - Perceived Usefulness Familiarity - Satisfaction	Perceived ease of use - Perceived Usefulness Perceived Usefulness - Reuse Intention Perceived Usefulness - Satisfaction Satisfaction - Reuse Intention
Lee, Sung and Jeon (2019)	Continuous intention Performance expectancy Effort Expectancy	Information quality - Performance expectancy Information quality - Effort Expectancy Performance expectancy - Continuous intention	Social influence - Continuous intention Habit - Continuous intention
Verma (2020)	Purchase Intention Transaction Reliability	Presentation - Product Availability Product Availability - Ease of use Presentation - Transaction Reliability	Ease of Use - Transaction Reliability Transaction Reliability - Purchase Intention
Koiri, Mukherjee and Dutta (2019)	Perception	Convenience - Perception Mode of Payment - Perception	Time saving - Perception Offers - Perception
Belanche, Flavián and Perez-Rueda (2020)	Intention to use WOM Intention	Attitude - Intention to use Subjective norm - Intention to use App Lifestyle compatibility - Intention to use Occupation - Intention to use Attitude - WOM Intention	Subjective norm - WOM Intention Security - WOM Intention Age - WOM Intention Intention to use - WOM Intention
Nanaiah, 2020	Ordering Frequency	Offers & discounts - Ordering Frequency	Delivery time - Ordering Frequency

Table 2.5 – Summary of Studies involving psychographic factors[32].

[32] The full table is available in Appendix 2. These studies are the entire basis for the constructs selected for clustering, for further understanding of the relevance of constructs explaining intention to use, please read Appendix 1.

Curiously, plentiful research has been done in Asian countries. Table 2.4 and Table 2.5 showcase studies from Indonesia, India, China, Malaysia, Turkey and South Korea; with three studies being from the American continent – specifically Colombia, Brazil and the United States. As suggested by Ray et. al. (2019), future research should include users from multiple nationalities and attempt at generalizing insights for a wider region. In addition, most of this work has been done in recent years, with most studies being published between 2017 and 2020.

Additionally, it can be concluded from Table 2.5 that multiple studies attempt at describing the factors anteceding a customer's intention to use an FDA, with 10 models using this behavior as a target variable (Zhao & Bacao, 2020; Roh & Park, 2019; Yeo, Goh & Rezaei, 2017; Cho, Bonn & Li, 2019; Ray et. al., 2019; Jeon, Kim & Jeong, 2016; Choi, 2020; Lee, Sung & Jeon, 2019; Verma, 2020; Belanche, Flavián & Perez-Rueda, 2020). As such, intention to use can be identified as a relevant target behavior for Food Delivery Application Companies, as it allows contributing to profits by targeting the willingness to use the App. By increasing the usage, the customer's lifetime value[33] is increased – making customers more profitable by increasing their purchase frequency. Thus, understanding the different antecedents of intention to use is also relevant for marketers designing different strategies. From Table 2.5 it can also be identified that there are 30 proven relationships between different constructs and intention to use, representing 17 different variables in total. From these 17 antecedents influencing intention to use, 9 constructs appear more than once in the reviewed models. These 9 constructs can be seen in Figure 2.5, and they will become the base for the psychographic elements explored in this research. The next section delves into them by exploring their background and precise definition.

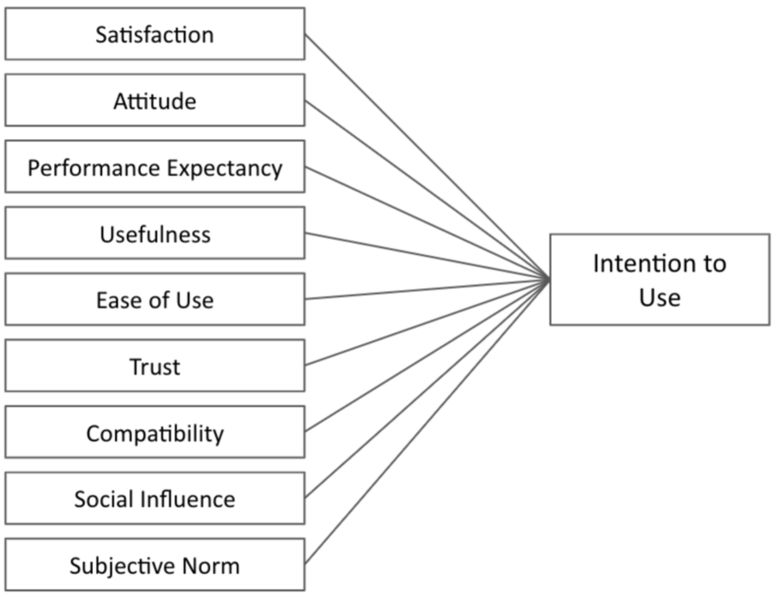

Figure 2.4 – Conceptual Model of Most Relevant Constructs related to Intention[34].

[33] Customer Lifetime Value is the prognostication of a customer's net profit contribution to a company during the entire period of the projected relationship.

[34] Figure 2.5 illustrates the relation of identified relevant antecedents with intention to use, as the central model of this study.

2.5. DEFINITION OF CONSTRUCTS

2.5.1. Satisfaction

Satisfaction proved to be a meaningful antecedent of intention to use FDAs in the studies performed by Choi (2020) and Zhao and Bacao (2020). The first of these studies defines satisfaction as the level of content a user has with respect to a previous experience with Food Delivery Applications. It is considered a crucial factor in intention to use based on the premise that satisfaction is an important variable for information technology reuse. Additionally, the hypothesis stated by Choi (2020) is based on proven previous relationships between satisfaction and intention to use in the FDA context. On the other hand, Zhao and Bacao (2020) based the definition of satisfaction on the Expectancy Confirmation Model and described it as the overall emotion-based evaluation of information technology. In this sense, a user is satisfied with a Food Delivery Application if their perceived functioning exceeds the expected functioning, leading to continuous usage. Therefore, this study proposes that:

H1: Satisfaction is a variable that allows segmenting FDA users into clusters.

2.5.2. Attitude

Attitude had a positive influence over FDA usage intention on the studies performed by Belanche, Flavián and Perez-Rueda (2020), Yeo, Goh and Rezaei (2017), and Cho, Bonn and Li (2019). The first of these studies defines attitude based on the Theory of Planned Behavior as a degree in which an individual has a favorable or unfavorable evaluation of a behavior, and as the evaluative response to the development of a possible action. Since attitudes are formed over time in a learning process, it is highly influential on behavioral intentions given that previously formed attitudes hypothetically guide behavior in the decision process. Yeo, Goh and Rezaei (2017) take the concept of attitude from the model of IT Continuance, where direct linkage is presented between attitude and behavioral intention. However, the authors base their definition of attitude from an additional study that claims that attitude is the set of user preferences when using certain technologies and devices. It is therefore expected that users having a favorable attitude towards FDAs will be more inclined to use them. Lastly, Cho, Bonn and Li (2019) present and additional complementary view stating that positive attitudes towards FDAs are created when expectations are either met or exceeded, as a function of their perceived value. Thus, the following hypothesis is proposed:

H2: Attitude is a variable that allows segmenting FDA users into clusters.

2.5.3. Performance Expectancy

Performance Expectancy was used successfully as an antecedent of FDA use intention in the studies from Lee, Sung and Jeon (2019), and Zhao and Bacao (2020). In the first case, the authors based their construct on the UTAUT model and defined it as the extent in which an individual believes that the use of a system will be helpful in improving a job’s performance. It was also stated how it is a direct determinant of behavioral intention to use, especially in cases of information technology adoption, as it has been tested in multiple studies with positive conclusions about its predictive factor. On the second case, Zhao and Bacao (2020) based the construct on the ECM model and expected users with higher performance expectancy to have a greater intention in usage. It was also noted how performance expectancy is probably the most important determinant for FDA adoption. Consequently, this study proposes that:

H3: Performance Expectancy is a variable that allows segmenting FDA users into clusters.

2.5.4. Usefulness

The studies by Roh and Park (2019), Choi (2020), and Yeo, Goh and Rezaei (2017) showed that usefulness has a significant influence on behavioral intention of FDAs. In their studies, Roh and Park (2019) and Choi (2020) base their construct on the element perceived usefulness from the Technology Acceptance Model. It is defined as the degree in which a user believes that using a specific technology improves the performance of a task, and therefore, values the benefits it provides. It is mentioned that this construct in itself relies on a user's outcome judgement, where users with more positive judgements are also expected to have a stronger intention to use towards the technological tool. It is noticeable how perceived usefulness is similar to performance expectancy, as also noted by previous research (Hamzat & Mabawonku, 2018; Alwahaishi & Snásel, 2013; Vermaut, 2016). However, Yeo, Goh and Rezaei (2017) use the concept of perceived usefulness to introduce an alternate version referred to as post-usage usefulness. The main difference with the construct used by these authors is that post-usage usefulness refers to the long-term belief of usefulness in contrast to perception. It is therefore important for FDA companies to provide useful solutions to customer needs in a long-term perspective, allowing to formulate the following hypothesis:

H4: Usefulness is a variable that allows segmenting FDA users into clusters.

2.5.5. Ease of Use

Roh and Park (2019) and Ray et. al. (2019) proved in their studies the relationship between ease of use and intention to use in the FDA setting. First, Roh and Park (2019) use the Technology Acceptance Model to present the construct ease of use, defining it as the degree to which a user expects a technological tool to be effortless. The concept of ease of use can also be known as complexity in the Innovation Diffusion Theory, and as effort expectancy in the UTAUT model. It is hypothesized that ease of use depends on a user's self-efficacy, where users with higher self-efficacy underestimate the effort required by a technological tool. Likewise, Ray et. al (2019) extend the definition of this construct by applying it directly to FDA context. It is defined as the ease and comfort for placing an order, filtering food choices and tracking an order, making the technological solution easy to understand and use. Hence, users with higher ease of use will have higher adoption rates of FDAs, increasing the usage intention. With this, the following hypothesis is formulated:

H5: Ease of Use is a variable that allows segmenting FDA users into clusters.

2.5.6. Trust

Trust was mainly used in the research from Zhao and Bacao (2020) to prove the relationship between trust and intention to use for FDAs. In their research, trust is defined as the state of individual faith in regard to intentions, with prospective actions following the proper behavior of integrity and ability. Specifically to the FDA context, they identify its importance given that trustworthiness can dictate a user's expectation towards an FDA's provided service. In other words, if a service is found to be reliable, there is higher trustworthiness from FDAs and, therefore, a higher intention to use. Additionally, trust is represented as an extension of the UTAUT model, where it is defined in terms of being a mental perception reflecting the perceived security against risk and uncertainty. Furthermore, the authors discuss trust being recognized as an important antecedent of satisfaction and adoption of information technologies, and a predictor of continuance usage.

In addition, a second research involves trust in a secondary manner through the usage of transaction reliability in FDAs as a proven antecedent of intention. In his study, Verma (2020) builds the concept of transaction reliability by discussing how it plays a critical role in building trust for the buying process, and its relation to the Consumer Value Theory as a functional element that users search for before any purchase. Based on these elements, the following hypothesis is proposed:

H6: Trust is a variable that allows segmenting FDA users into clusters.

2.5.7. Compatibility

Compatibility, also known as lifestyle compatibility, had a direct effect on intention to use FDAs on the studies performed by Roh and Park (2019), and Belanche, Flavián and Perez-Rueda (2020). Roh and Park (2019) defined it as the perceived fit of a technological solution with a user's lifestyle and values. This is due in part to the fact that technological solutions that do not fit a person's lifestyle seem to represent higher effort to use, have no advantages in its use, and hence result in a lower intention to use. Likewise, Belanche, Flavián and Perez-Rueda (2020) discussed how a person's behaviors and purchase decisions are influenced greatly by the lifestyle compatibility. As a complementary view, they argued how a consumer's lifestyle reflects the need to determine a social identity, which itself drives the adoption of a new product or service. Thus, the next hypothesis is stated:

H7: Compatibility is a variable that allows segmenting FDA users into clusters.

2.5.8. Social Influence

The studies performed by Lee, Sung and Jeon (2019), and Zhao and Bacao (2020) were successful in proving the anteceding relationship between social influence and intention to use in the FDA setting. This variable definition is based, on both studies, on the UTAUT model – defining it as an important antecedent of behavioral intentions. According to the latter, social influence reflects the degree to which a user gains willingness to use a certain technology from other individuals' encouragement. The surrounding individuals may either be family, friends, or colleagues that pressure or incite technology adoption in accordance with their own perceptions. This is complemented by Lee, Sung and Jeon (2019) by explicitly stating that stronger perceptions from peers regarding the use of a certain technology will lead to higher likelihood for the individual to adopt the same technology. Hence, the following hypothesis is stated:

H8: Social Influence is a variable that allows segmenting FDA users into clusters.

2.5.9. Subjective Norm

Roh and Park (2019), and Belanche, Flavián and Perez-Rueda (2020) used subjective norm in their models explaining the antecedents of intention to use. Roh and Park (2019) describe it as the extent in which a user receives pressure to use a specific technology from people within his circle. It is based on the fact that people may incorporate beliefs from peers into their own value systems as a way of achieving social acceptance or in the way compatibility is perceived after being influenced by others. In addition, Belanche, Flavián and Perez-Rueda (2020) argue that the exponential growth of FDAs cannot be analyzed without taking into account the important effect of subjective norms in the spread of word of mouth and influence among user groups. Hence, it becomes a relevant factor for driving intention. However, Lee, Sung and Jeon (2019) discussed in their study how social influence is analogous to subjective norm – one belonging to the UTAUT model while the other belongs to the Theory of Reasoned Action. On top of that, construct measurement revolves around the same issues in the statements used for these two variables. Therefore, subjective norm is to be excluded from being used directly, as the use of social influence is enough to measure peer pressure in FDA intention to use. With this in mind, the final conceptual model of this research is updated to the version displayed in Figure 2.5. The next section will explore the methodology to be used in the data recollection and analysis of information around this model.

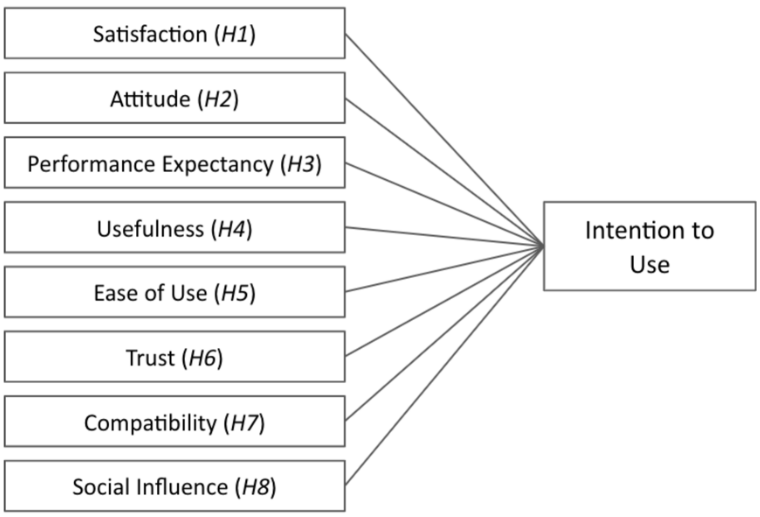

Figure 2.5 – Final Conceptual Model[35].

[35] Figure 2.5 shows the final model of this study, after removing constructs aiming at the same psychographic explanation.

3. METHODOLOGY

3.1. METHODOLOGY OVERVIEW

The present study is categorized under the conclusive descriptive research type[36], following a single cross-sectional design[37]. Tasks are grouped into different stages that are executed sequentially, having a specific objective in each task.

3.2. THEORETICAL FRAMEWORK AND FORMULATION OF HYPOTHESES

The Theoretical Framework stage consisted of performing all tasks related to literature review with the objective of defining a set of candidate variables based on relevant findings, scheming the research's design, and taking into account methodologies and best practices from previous research.

As mentioned in section 2, literature reviewing followed a specific process. First, an extensive literature review was performed to identify relevant articles and complementary work for this research from different fields like Food Delivery Applications, Market Segmentation Analysis and Data Mining. Figure 3.1 showcases an overview of the different literature resources used with their publication year. Objectives and scope were revised in accordance with findings and fine-tuned to guarantee relevance of this research for decision-making in business scenarios and contribution to theory.

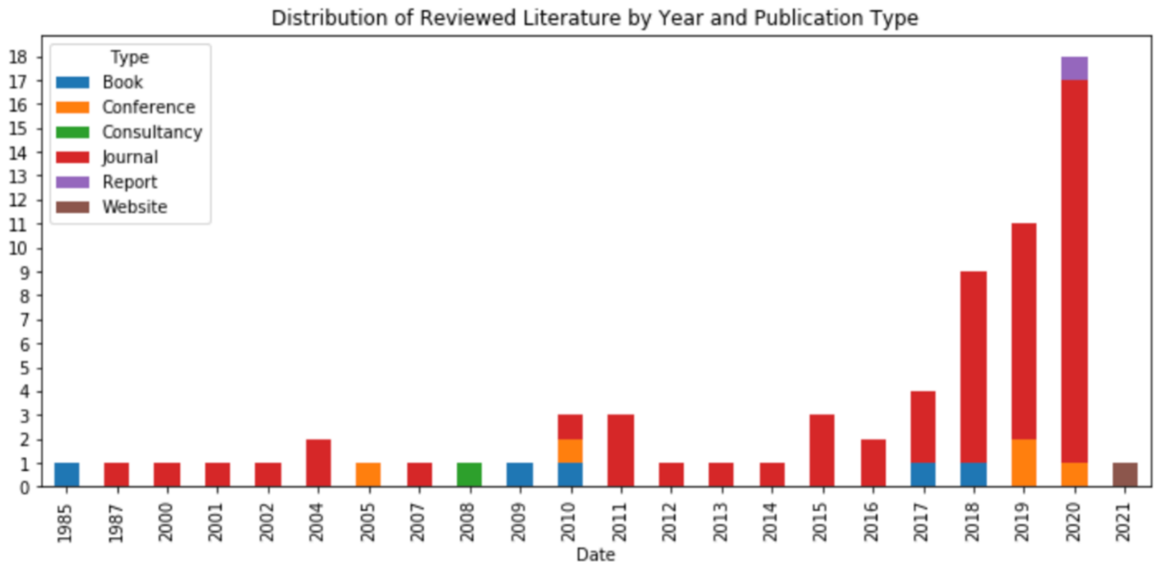

Figure 3.1 – Overview of Reviewed Literature[38].

[36] The descriptive research type is used to describe characteristics of a market or population, making use of hypotheses prior to the research and using a structured design.
[37] Single cross-sectional design means collecting a single sample from a specific target segment.
[38] Figure 3.1 shows how FDAs have been a growing topic in the research field, and the way this research used mainly recent articles to detect antecedents of intention to use.

Guidelines and premises for the research design were extracted from reviewed literature:

- Food Delivery Applications are an important industry with growth potential due to the digital boom, the changes in consumer behavior, and the context of the 2020 pandemic –as mentioned in section 2.1. It represents a relevant business problem that can be tackled through research.

- Studying the psychographic and behavioral aspect of FDA users is a relevant task that aids in the design of marketing strategies looking to drive user retention and frequency increase by targeting intention to use, as discussed in sections 2.1.2 and section 2.2. Increasing intention to use is an important task in the current competitive environment of FDAs worldwide.

- As discussed in section 2.2, Likert scales are a common and valid method of collecting data for psychographic constructs, maintaining a reliability measure like the Cronbach's alpha over a threshold of 0.6 and a scale ranging between 5 and 9. Likewise, collecting this data through online surveys is a popular method used in previous research, allowing researchers to gather information at a lower cost and a faster pace.

- Section 2.3 displays multiple data mining techniques that have been applied in Market Segmentation Analysis, showcasing a good practice of applying a two-step procedure to define an optimal number of clusters before executing the clustering algorithms. Moreover, a wide range of technological tools and evaluation techniques are available for implementing Market Segmentation, allowing researchers to define freely the tools and metrics to use.

- From section 2.5, it can be seen that limiting geographically this study is optional. However, previous research has recommended including a broad perspective as an attempt to extract insights that might be more generalizable. Hence, this study will open geographical boundaries and include a question about respondents' nationalities.

Second, the reviewed literature was used to identify relevant psychographic components that could become segmentation variables, as discussed in section 2.4. Hypotheses regarding the incidence of these variables in FDA segmentation are formulated in section 2.5 and exhibited in Table 3.1. This set of hypotheses will be tested in subsequent stages.

Construct	Hypothesis
Satisfaction	H1: Satisfaction is a variable that differentiates FDA users into clusters.
Attitude	H2: Attitude is a variable that differentiates FDA users into clusters.
Performance Expectancy	H3: Performance Expectancy is a variable that differentiates FDA users into clusters.
Usefulness	H4: Usefulness is a variable that differentiates FDA users into clusters.
Ease of Use	H5: Ease of Use is a variable that differentiates FDA users into clusters.
Trust	H6: Trust is a variable that differentiates FDA users into clusters.
Compatibility	H7: Compatibility is a variable that differentiates FDA users into clusters.
Social Influence	H8: Social Influence is a variable that differentiates FDA users into clusters.

Table 3.1 – Hypotheses Overview.

3.3. DESCRIPTIVE RESEARCH

The Descriptive Research stage aims at collecting all necessary data for hypothesis testing and customer clustering. The data required for this research corresponds to quantitative primary data gathered in a way that allows evaluation of the hypotheses showcased in Table 3.1. The medium for data collection is set to be a survey that measures the different selected constructs.

Regarding the survey structure, and based on the relevant findings of the literature review stage, the questionnaire is built to have 13 blocks of questions that use a mixture of ordinal and nominal scales in a total of 37 questions. The survey starts with a consent that discusses voluntary participation, data collection policies, ethical requirements, and general purpose of the study. It is then followed by a screening question that allows filtering out users that have not had any contact with Food Delivery Applications in the period between January 2020 and the present. The third block consists of all behavioral variables, detecting frequency of usage, tenure, and preferences on existing Food Delivery Applications. Then, blocks 5 through 12 use a 7-point Likert scale to evaluate all the psychographic variables, namely satisfaction, attitude, usefulness, performance expectancy, ease of use, social influence, trust and compatibility. The scale ranges from strongly disagree (1) to strongly agree (7), and both blocks and questions within blocks are to be shown in a randomized order. Finally, a demographic block collects information that allows characterizing the sample of respondents. Table 3.2 illustrates the structure of the questionnaire with each block's objective and number of questions. The survey was piloted beforehand using qualitative responses from 6 users, applying corrections on items manifesting interpretation or ambiguity issues. The final survey can be consulted in Appendix 3.

Block Name	Block Objective	Number of questions
Consent Form	Present the relevant information about the study, the data collection policy and conditions of participation.	0
Screening Question	Define if respondents are suitable for the survey by filtering out users with no FDA usage in the previous year.	1
Behavior Questions	Collect information about user behavior when using FDAs.	3
Likert Scale Introduction	Introduce the respondent to the scale used in construct measurement	0
Construct 1 - Satisfaction	Measure the Satisfaction construct.	4
Construct 2 - Attitude	Measure the Attitude construct.	3
Construct 3 - Usefulness	Measure the Usefulness construct.	4
Construct 4 - Performance Expectancy	Measure the Performance Expectancy construct.	4
Construct 5 - Ease of Use	Measure the Ease of Use construct.	3
Construct 6 - Social Influence	Measure the Social Influence construct.	3
Construct 7 - Trust	Measure the Trust construct.	4
Construct 8 - Compatibility	Measure the Compatibility construct.	4
Demographics	Collect information that allows characterizing the sample.	4

Table 3.2 – Survey Structure[39].

Existing questionnaires were used to formulate the psychographic evaluation of the different variables. It is important to note that current measurement items were selected in function of their

[39] Table 3.2 shows the survey structure used for obtaining data.

conciseness and clarity, looking to build a survey that is both precise and concrete. Additionally, and given the similarity between the constructs perceived usefulness and performance expectancy, the measurement statements for usefulness were built based on Yeo, Goh and Rezaei (2017)'s post-usage usefulness - in order to guarantee differentiation among these constructs. Table 3.3 displays the different reference questionnaires used from previous literature.

Construct	Source
Satisfaction	Choi, J. C. (2020). User Familiarity and Satisfaction With Food Delivery Mobile Apps. SAGE Open, 10(4), 2158244020970563.
Attitude	Cho, M., Bonn, M. A., & Li, J. J. (2019). Differences in perceptions about food delivery apps between single-person and multi-person households. International Journal of Hospitality Management, 77, 108-116.
Performance Expectancy	Lee, S. W., Sung, H. J., & Jeon, H. M. (2019). Determinants of continuous intention on food delivery apps: extending UTAUT2 with information quality. Sustainability, 11(11), 3141.
Usefulness	Yeo, V. C. S., Goh, S. K., & Rezaei, S. (2017). Consumer experiences, attitude and behavioral intention toward online food delivery (OFD) services. Journal of Retailing and Consumer Services, 35, 150-162.
Ease of Use	Roh, M., & Park, K. (2019). Adoption of O2O food delivery services in South Korea: The moderating role of moral obligation in meal preparation. International Journal of Information Management, 47, 262-273.
Trust	Zhao, Y., & Bacao, F. (2020). What factors determining customer continuingly using food delivery apps during 2019 novel coronavirus pandemic period?. International journal of hospitality management, 91, 102683.
Compatibility	Roh, M., & Park, K. (2019). Adoption of O2O food delivery services in South Korea: The moderating role of moral obligation in meal preparation. International Journal of Information Management, 47, 262-273.
Social Influence	Lee, S. W., Sung, H. J., & Jeon, H. M. (2019). Determinants of continuous intention on food delivery apps: extending UTAUT2 with information quality. Sustainability, 11(11), 3141.

Table 3.3 – Sources of previous questionnaires used in this research[40].

Design and distribution of the questionnaire is executed online, using the platform Qualtrics to create the electronic survey. This platform allows managing customer experience through the use of multiple tools, including surveys. As mentioned by De Corte and Van Kenhove (2017), and discussed in section 3.2, distributing and conducing an online survey is consistent when the medium of investigation is Internet related. Additionally, a non-probabilistic method sampling is used, as the population is not fully known given the geographic openness of this study. In accordance with the analysis of Yeo, Goh and Rezaei (2017), this sampling method is viable when the sampling frame is unavailable, data needs to be collected quickly, and low costs are desired. Particularly for this research, convenience, voluntary response, and snowball sampling were used. Table 3.4 illustrates the different distribution methods used.

Channel	Count	Percentage
Whatsapp and Email	243	67.12%
Social Media	119	32.87%

Table 3.4 – Distribution methods used for the online questionnaire[41].

[40] For further understanding on how construct questions were defined, please consult the original studies using each construct used in this study.

[41] Results of the snowball method used in this study, representing mostly Whatsapp references.

Finally, the descriptive research stage is finalized with a proper assessment of results and collected data. In total, 568 respondents accessed the electronic survey that, after submitting it to scrutiny and quality check, accounted for a total of 416 complete questionnaires – 73.24% from the total answered. Out of these, 54 responses were screened out, leaving 362 valid records for undergoing clustering.

3.4. SEGMENT EXTRACTION

The Segment Extraction stage comprises all tasks for the application of data mining models for clustering. It will follow the Cross-Standard Industry Process for Data Mining (CRISP-DM), where a standard framework for performing Data Mining projects is provided (Wirth & Hipp, 2000) – able to be used with languages like R or Python. Python is a programming language used widely for purposes like web scraping, data visualization and data science applications. Its popularity is due, among others, to the wide number of useful libraries available, its simple syntax and object-oriented design, and for providing high-level data structures (Nagpal & Gabrani, 2019). Therefore, both graphical and mathematical techniques will be used to show the results of this stage, using the programming language Python – version 3.6.12 - in the Anaconda computer program.

First, data understanding will be applied to identify the relationships among variables - as well as each variable's general statistics. It will be followed by a data preparation task, where quality issues, cleaning and transformations will be applied to the data. In Model creation, different unsupervised learning techniques will be used to detect patterns in data, evaluate hypotheses and find relevant groupings. Additionally, feature importance will be assessed in order to evaluate each variable's discriminatory power for customer segmentation.

3.4.1. Data Understanding

3.4.1.1. Data Setup and Quality Assessment

Respondents' data is extracted from Qualtrics by exporting 2 csv files: one with all answers represented in text format and another with all answers in value format. In order to work with the data, an initial set of transformations was applied to unify categorical and numerical columns into a single file – creating a single data frame with all relevant information. Applied transformations included dropping unnecessary columns, eliminating descriptive rows, setting a unique index made up of the response ID, and renaming relevant columns. In addition, a final data frame was created where incomplete surveys and screened answers were removed, leaving only complete answers from respondents who claimed having used FDAs in the period between January 2020 and January 2021.

The forementioned dataset's quality was revised by evaluating the existence of duplicate records, incomplete answers, and repeated IDs – concluding that no quality issues were present in the final data. This final dataset, used hereafter as the starting point for analysis and conclusions, includes 362 records and 38 columns. The Python libraries and functions used for data manipulation, evaluation, analysis, and visualization are described in Table 3.5.

Library	Functions and Classes
kneed	KneeLocator
matplotlib	Multiple classes and functions
numpy	Multiple classes and functions
pandas	Multiple classes and functions
pingouin	cronbach_alpha
plotly.express	box, line_polar
plotly.graph_objs	Heatmap, Layout, Figure
plotly.offline	iplot
pyclustertend	hopkins, vat, ivat
re	search
seaborn	Multiple classes and functions
scipy.cluster.hierarchy	dendrogram, linkage, fcluster
sklearn.preprocessing	MinMaxScaler, StandardScaler
sklearn.cluster	Detailed in table 3.6
sklearn.metrics	Detailed in table 3.7
sklearn.neighbors	NearestNeighbors
yellowbrick.cluster	KElbowVisualizer, InterclusterDistance

Table 3.5 – Imported Libraries[42]

3.4.1.2. Variable Behavior

The different variables are explored and analyzed, as to understand their behavior and characteristics in the sample. An Exploratory Data Analysis[43] is performed to identify data patterns and perform a thorough understanding of the data. Firstly, sociodemographic variables were explored and analyzed, finding the following insights. These results are shown in Table 3.6.

Characteristic		Frequency	Percentage
Gender	Female	212	56.60%
	Male	150	41.40%
Education	High School	8	2.20%
	Bachelor's Degree	157	43.37%
	Post Graduate	5	1.38%
	Master's Degree	183	50.55%
	PhD / Doctorate	5	1.38%
	Unspecified	4	1.10%
Frequency	Every day	11	3.03%
	A few times a week	113	31.21%
	Once a week	65	17.95%
	Once or twice a month	97	26.79%
	Less than once a month	59	16.29%
	Less than once a semester	17	4.69%
Tenure	More than 36 months	107	29.55%
	24 to 36 months	92	25.41%
	12 to 24 months	106	29.28%
	6 to 12 months	42	11.60%
	1 to 6 months	15	4.14%

Table 3.6 – Sample Characteristics

[42] For future studies, take as reference the libraries used for data analysis and modelling.

[43] Exploratory Data Analysis refers to the analysis of data to detect anomalies, find patterns and test hypotheses with the use of statistics and visualization methods.

- Regarding gender, the sample has a slightly higher representation of women, with 56,6% of respondents identifying as female (212 users), 41.4% of respondents identifying as male (150 users), and no respondents identifying with other gender representations.

- Respondents are highly educated, with at least 96% having higher education (350 users), and 53% having post-graduate education (193 users). In general, master’s degree is the most representative education level with 50.5% of share (183 users), followed by bachelor’s degree with 43.4% of share (157 users).

- Respondents’ age is between 19 and 73 years old, with a mean of 33, and approximately 75% of users being under 36. This means that, in terms of generation, most respondents belong to the millennial generation – in accordance with what was mentioned in section 2.1.2. on the importance of millennials in the expansion and adoption of FDAs.

- The sample had a total participation of 31 different nationalities. Almost 75% of all respondents are nationals from the Americas; with 233 users being from Colombia, 17 users from the United States of America, 12 from Brazil, and 9 belonging to 7 other American countries. They are followed by European respondents, who represent around a 22% of share; with 56 users being from Portugal and 22 belonging to 13 other European countries. Lastly, 3% of share are Asians with 11 users, while 1 user is African, and 1 user is from Oceania – representing 0.27% each.

- Regarding residence, 66% of users live in the Americas, 29% of users live in Europe, 2% of users live in Asia and 2% of users live in Oceania. The most significant residence countries are Colombia with 180 users, Portugal with 82 users, and United States of America with 38 users. Sample wise, this characteristic has an important incidence in results – as the screening question filtered out users with no FDA contact in the last year. This means that responses are based on experiences within residence countries from the last year. Residence distribution is shown in Figure 3.2.

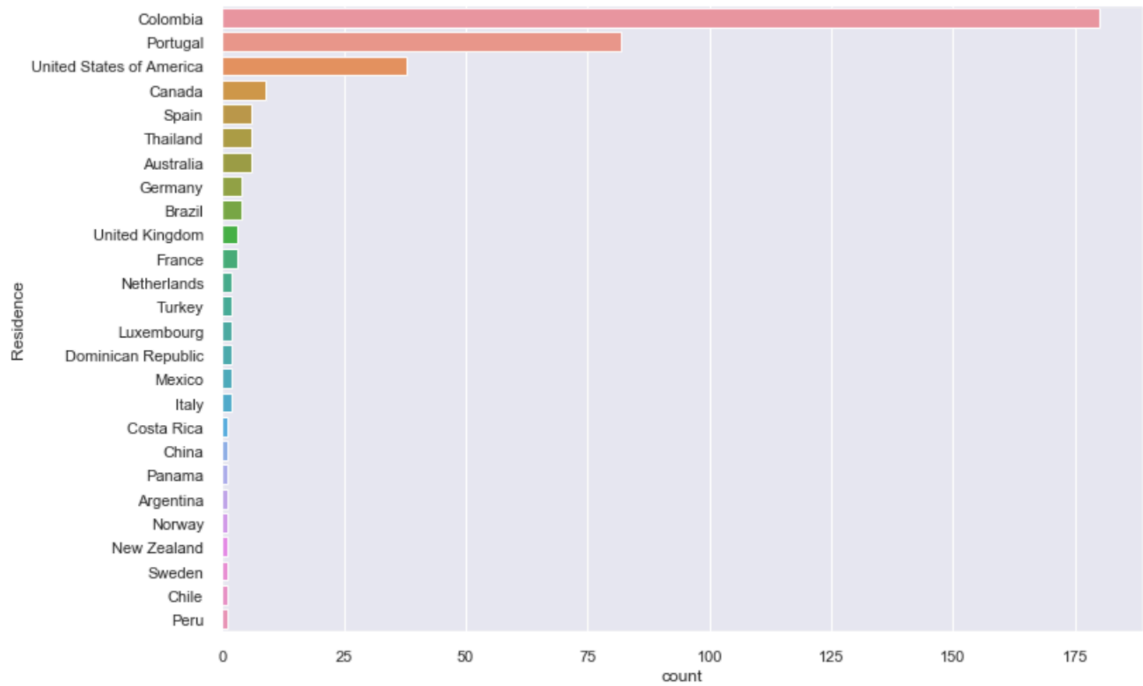

Figure 3.2 – Distribution of Country of Residence[44].

Likewise, behavioral variables were analyzed - namely frequency, tenure, and preference. Additional insights from the sample were found:

- Almost 80% of respondents use an FDA at least once a month (286 users), with around 34% using them on a weekly basis (124 users). The highest representation in frequency is found in respondents who use FDAs a few times a week, with 31.2% of share (113 users), followed by a ‘once or twice a month’ usage with 26.8% of share (97 users), and by a ‘once a week’ usage with 17.9% of share (65 users). Less frequent users have a lower representation, with 16.3% of respondents using FDAs less than once a month, and only 4.7% of respondents using FDAs less than once a semester (17 users).

- Around 84% of respondents have experience with FDAs for more than a year (305 respondents), and almost 30% have been using them for more than 3 years (107 respondents). In terms of share, 29.5% of the sample has used FDAs for over 36 months (107 users); 25.4% has experience with FDAs between 24 to 36 months (92 users); and 29.3% has used these apps between 12 to 24 months (106 users). 11.6% of the sample has only 6 to 12 months of experience with FDAs (42 users), while only 4.1% has less than 6 months of tenure (15 users).

- Preference is mainly driven by the local FDAs available in respondents' residence country – as can be seen in Figure 3.3. Only 6 users declared preferring using direct delivery from the restaurant over an FDA; and 3 users manifested having no preference between apps.

[44] Figure 3.2 illustrates country distribution for this study. See the limitations for further understanding on suggestions for future studies.

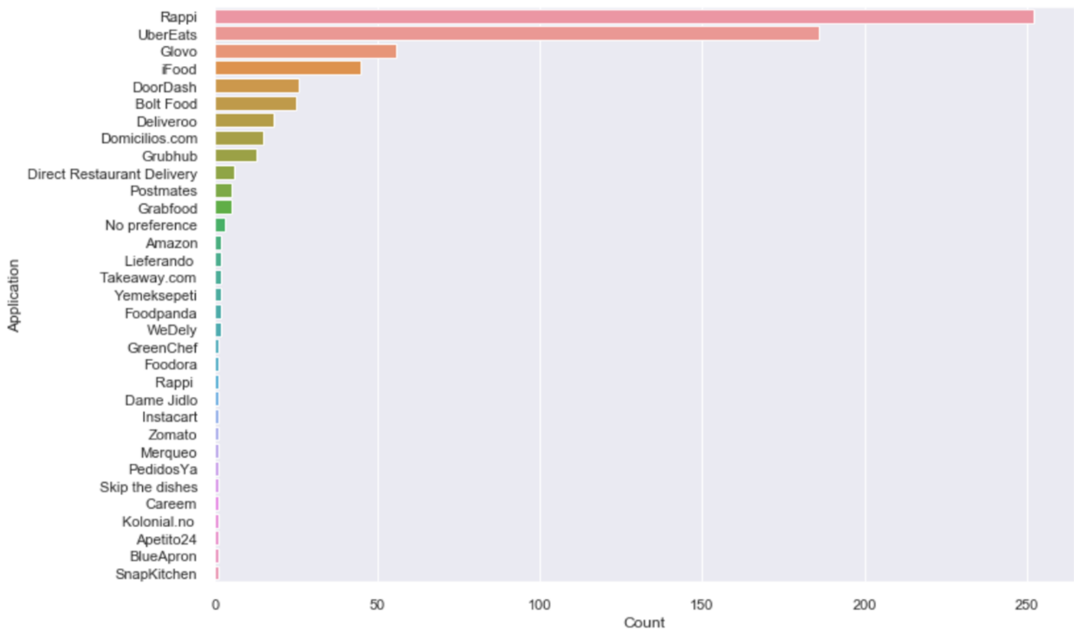

Figure 3.3 – Distribution of Application Preference[45].

3.4.1.3. Construct Validity

After having collected all the data, constructs were evaluated regarding their validity by measuring the Cronbach's alpha[46] for the used scale. This is done to ensure that constructs are reliable and consistent; guaranteeing the respondent's interpretation of the statements is the same as the intended meaning (Yeo, Goh & Rezaei, 2017). In order to assess this, a threshold of 0.6 is defined as the minimum tolerable value for Cronbach's alpha, and the factor loadings are evaluated using the Pingouin library. Table 3.7 reveals how all measured items are in the range of 0.6463 and 0.9019, exceeding the forementioned threshold. With this, it can be concluded that all constructs are viable for undergoing segment extraction.

Construct	**Cronbach's Alpha**
Satisfaction	0.8378045475692325
Attitude	0.7779390909795225
Usefulness	0.6463353513085262
Performance Expectancy	0.7698004195942156
Ease of Use	0.7897126404322795
Social Influence	0.892679344953341
Trust	0.8134914028209042
Compatibility	0.9019327477803805

Table 3.7 – Construct reliability assessment[47].

[45] Figure 3.3 shows application preference and its bias in relation to the country of residence, as well as the sample's relevance for FDA study, with few users having no preference of FDAs over other solutions.

[46] Cronbach's alpha is an indicator of scale reliability, measuring internal consistency.

[47] Table 3.7 allows concluding that all constructs are candidates for clustering, above 0.6 threshold.

3.4.2. Data Preprocessing

3.4.2.1. Data Transformation

Once construct validity is assessed and confirmed, data transformations are needed in order to create the final variables for clustering. To do this, the individual elements for each construct are merged into a single component – creating the overall measurement for each psychographic feature. Figure 3.4 shows the summary statistics for the resulting psychographic elements.

	count	mean	std	min	25%	50%	75%	max
Satisfaction	362.0	5.572514	0.957054	1.000000	5.000000	5.750000	6.000000	7.0
Attitude	362.0	5.494475	1.123410	1.666667	5.000000	5.666667	6.333333	7.0
Usefulness	362.0	5.421961	0.912719	1.750000	5.000000	5.500000	6.000000	7.0
Performance_Exp	362.0	5.409530	1.017812	2.000000	5.000000	5.500000	6.000000	7.0
Ease_Use	362.0	5.875691	0.858871	1.000000	5.666667	6.000000	6.333333	7.0
Social_Influence	362.0	4.036832	1.430398	1.000000	3.000000	4.000000	5.000000	7.0
Trust	362.0	5.433011	0.942146	1.000000	5.000000	5.750000	6.000000	7.0
Compatibility	362.0	5.026243	1.344941	1.000000	4.312500	5.375000	6.000000	7.0

Figure 3.4 – Summary statistics for Psychographic Features[48].

Likewise, the behavioral variables are transformed to create new features that are useful for undergoing clustering. A new integer feature called *YearsPurchases* represents the amount of purchases a user performs during a year, and it is created based on the frequency variable. Table 3.8 shows the applied transformations to each level in frequency. In addition, another integer feature called *MonthsOfUse* is added to the dataset, representing the number of months that a respondent has been using an FDA – based on the tenure variable. The applied transformations are shown in Table 3.9.

Level	New Value	Logic and Assumptions
Every Day	360	Purchase every day within a year
Few Times a Week	154	Assumed as purchasing 3 times a week
Once a Week	51	Taken as purchasing 1 time per week
Once or Twice a Month	24	Taken as purchasing twice a month
Less than Once a Month	4	Taken as purchasing once a trimester
Less than Once a Semester	1	Taken as purchasing once a year

Table 3.8 – Creation of the yearly purchases feature[49].

[48] Figure 3.4 shows the behavior of final psychographic constructs, showing that in general constructs have similar behavior, with Ease of Use being in average the highest scored with the lowest standard deviation, while Social Influence has the lowest average score and the highest standard deviation. Behavior is further analyzed in Results and Discussion.

[49] Table 3.8 shows the logic used to create the Yearly Purchases variable.

Level	New Value	Logic and Assumptions
More than 36 months	45	Taken as 45 months of tenure
24 to 36 months	30	Taken as 30 months of tenure
12 to 24 months	18	Taken as 18 months of tenure
6 to 12 months	9	Taken as 9 months of tenure
1 to 6 months	3	Taken as 3 months of tenure

Table 3.9 – Creation of tenure in months feature[50].

3.4.2.2. Data Preparation

Having defined that all variables are applicable to clustering algorithms, outlier detection is performed to each feature in order to clip values that may affect performance of clustering methods. This is done specifically to work with a single dataset that allows visualizing the best results for all evaluated models in the Scikit Learn library, including those who detect noise or are sensitive to outlier data (Pedregosa et. al., 2011)[51]. Table 3.10 shows the number of outliers detected for each feature through 3 different methods, namely percentiles method[52], Tukey's fences method[53], and Standard deviation method[54]. The percentiles method proves to be the least strict method in terms of the feasible range of values for each variable, detecting the least number of outliers overall. On the other hand, Tukey's fences method detects a narrower range of allowed values for each feature, proving to be a sharper method with the largest number of detected outliers. Hence, these two methods will be used in Cluster Tendency Assessment to evaluate which clipping method performs better, and there on, will be applied to the final dataset.

Variable	Percentile Method	Tukey's Fences Method	Standard Deviation Method
Satisfaction	3	13	5
Attitude	4	18	4
Usefulness	4	11	4
Performance Expectancy	4	21	4
Ease of Use	4	33	4
Social Influence	3	0	0
Trust	4	13	6
Compatibility	3	9	0
YearsPurchase	0	11	11
MonthsOfUse	0	0	0
Total Outliers	**29**	**129**	**38**

Table 3.10 – Outlier detection[55].

[50] Table 3.9 shows the logic used to create the tenure in months variable.

[51] For details on used models, please see section 3.4.3. Modeling.

[52] Percentile's method clips or removes the 1st and 99th percentile of the sample to reduce effects of outliers

[53] Tukey's fences method uses an interquartile range to determine the range of accepted values.

[54] Standard deviation method considers data points above or below 3 standard deviations to be outliers.

[55] Table 3.10 shows the results of the outlier detection analysis. Given that a single dataset was used for all modelling techniques, outlier treatment was required for techniques sensitive to outlier data.

Likewise, scaling methods are evaluated with the objective of diminishing the effect of scale and distances among all variables, including YearsPurchase and MonthsOfUse. A previous assessment on data distribution for each construct helped detecting skews, in general towards the upper answers (4 to 7). Scaling methods allow accentuating distances among data points to easily identify patterns in data for detecting non-natural clusters. Two scaling methods were applied, namely normalization[56] and standardization[57], as results may be significantly different depending on the scaling method used. The objective is to perform an evaluation of outputs from the different scaling method in order to keep the one with the best expected performance. Table 3.11 shows the final datasets that are candidates for the modeling stage.

DataSet Reference	Outlier Clipping Method	Scaling Method
Dataset 1	Percentiles	Normalization (MinMax)
Dataset 2	Tukey's Fences	Normalization (MinMax)
Dataset 3	Percentiles	Standardization (StandardScaler)
Dataset 4	Tukey's Fences	Standardization (StandardScaler)

Table 3.11 – Resulting datasets for Cluster Tendency Assessment[58].

3.4.3. Modeling

The Scikit Learn library is a Python module that offers multiple ML algorithms for academic and commercial problems at a medium scale (Pedregosa et. al., 2011). It includes different classes for clustering implementation that can be explored and used for different scenarios in this study. It is recognized as being very efficient and easy to use, and therefore, is the main library used in this research's modeling. The different available classes provided in this module for clustering are shown in Table 3.12.

Technique	Class
Affinity Propagation	AffinityPropagation()
Hierarchical Agglomerative Clustering	AgglomerativeClustering()
Balanced Iterative Reducing and Clustering using Hierarchies	Birch()
Density-based Spatial Clustering of Applications with Noise	DBSCAN()
K-Means	Kmeans()
Mini Batch K-Means	MiniBatchKMeans()
Mean Shift	MeanShift()
Ordering Points to Identify Clustering Structure	OPTICS()
Spectral Clustering	SpectralClustering()

Table 3.12 – Available clustering techniques in Scikit Learn[59].

[56] Normalization, also known as Min Max Scaling, is a scaling technique that rescales values into a range between 0 and 1.

[57] Standardization is a scaling technique that rescales values by centering the data's mean in zero with a unit standard deviation.

[58] Table 3.11 shows the dataset combinations that was tested with multiple techniques to decide on an optimal combination of outlier clipping method and scaling method that maximizes clustering result.

[59] Adapted from https://scikit-learn.org/stable/modules/clustering.html. These clustering techniques were used in model analysis.

These techniques involve different sets of assumptions and parameters that are unbeknown beforehand, and therefore, require testing to identify best performing algorithms in terms of clusters' cohesion, separation, and shape. Due to this, a two-step clustering approach is applied. First, Cluster Tendency Assessment is used to explore the existence of groups in the data, to identify the best performing dataset in terms of outlier removal and scaling method, and to extract an estimation on the number of clusters for algorithms requiring this parameter an input – also referred to as k. Secondly, modeling techniques are applied to the data to determine optimal algorithms for the problem at hand, as well as an initial set of hyperparameters for each model that allows optimizing results. With these two steps, modeling is then fine-tuned with business needs to determine the optimal solution.

Decision-making in model evaluation needs to be data-driven, and as so, different indicators need to be used for assessment. Scikit Learn is a module also known for providing methods for easy comparison of algorithms for a given application (Pedregosa et. al., 2011). Hence, this module will also be used for evaluating the results from the clustering algorithms. Table 3.13 shows the available evaluation methods in the Scikit module.

Evaluation Technique	Available Functions
Adjusted RAND Index	rand_score() adjusted_rand_score()
Mutual Information based scores	mutual_info_score() adjusted_mutual_info_score() normalized_mutual_info_score()
Homogeneity, Completeness and V-measure	homogeneity_score() completeness_score() v_measure_score()
Fowlkes-Mallows Index	fowlkes_mallows_score()
Silhouette Coefficient	silhouette_score()
Calinski-Harabasz Index	calinski_harabasz_score()
Davies-Bouldin Index	davies_bouldin_score()
Contingency Matrix	contingency_matrix()

Table 3.13 – Available evaluation methods for clustering techniques in Scikit Learn[60].

From Table 3.13, the techniques involving RAND index, Mutual Information, V-measure, Fowlkes-Mallows and Contingency Matrix require the true labels of clustered data to perform an evaluation. Hence, these techniques will not be considered - as true labels are not known in this research. Alternatively, the Silhouette, Calinski-Harabasz and Davies-Bouldin scores will be used as the definite evaluation methods for cluster quality.

3.4.3.1. Cluster Tendency Assessment

Cluster Tendency Assessment is performed to evaluate the existence of clusters in the data and define the best dataset to use for modeling purposes. A total of fifteen techniques are used to achieve

[60] Adapted from https://scikit-learn.org/stable/modules/clustering.html. These evaluation techniques give the framework of evaluation methods used in this study.

this assessment, in addition to projecting the expected number of clusters that maximizes the evaluation metrics. Methods used include:

- Dendrograms[61] and projected Silhouette scores from Hierarchical Clustering, using single, complete, average and ward linkage methods[62].
- Projected silhouette scores using K-means, Mini-batch K-means and Spectral Clustering[63].
- Distortion score elbow using K-means.
- Gap statistics using K-means.
- Calinski-Harabasz Score using K-means and Spectral clustering.
- Davies-Bouldin score using K-means
- Visual Assessment Tendency (VAT) and Hopkins's statistic[64]

Table 3.14 showcases the results from the evaluation methods used, as well as the identification of which dataset performs the best and second best for each technique. The dataset preprocessed with clipped outliers using percentiles method and standardized with StandardScaler[65] had the best overall results in 6 simulations, and second best in 3 of them. Namely, this dataset showed the best silhouette scores when simulated through agglomerative clustering with single and complete linkage, k means, spectral clustering, and Hopkins's statistic. In addition, it showed second best results for simulations for silhouette scores with agglomerative average linkage, Calinski-Harabasz score with K means, and Davies-Bouldin score with K-Means. Therefore, Dataset 3 is chosen for the modeling stage. In addition, K-Means is used multiple times to evaluate projected results. Since this model is simple, and projected results are available, it is chosen as a base model for comparison purposes when analyzing results from other algorithms.

In line with this, Visual Assessment Tendency is used to graphically evaluate the results of the Hopkins Statistic – which can be seen in Figure 3.5. It can be concluded that the data can be clustered, although the resulting clusters will be more reproducible[66] or constructive[67] instead of being natural[68]. However, reproducible and constructive clusters still manage to provide useful business insights from complementary perspectives, and as so, the results from this study can still be applied to FDA business contexts. Furthermore, projections with Dataset 3 suggest the cluster number to be 2, 4, 10 or 13; with

[61] Dendrogram is a tree-like diagram used for representing hierarchical relations between data points, as well as agglomerative clustering behavior.

[62] Linkage methods specify the way that the distance between clusters is calculated.

[63] Spectral clustering uses a similarity matrix to reduce dimensionality on a dataset, in order to perform clustering on a low dimensional space.

[64] Hopkins's statistic is a measurement of cluster tendency.

[65] StandardScaler is a class in Python that allows standardizing data.

[66] Reproducible segmentation refers to separating data when no natural boundaries exist, but still based on an underlying structure in the data. Segmentation is considered reproducible when, despite not having natural separations, different studies reveal similar results – making those results less random.

[67] Constructive segmentation refers to separating data conveniently when no natural boundaries exist, and data has no underlying structure.

[68] Natural segmentation refers to the traditional view of segmentation, where segments are naturally separated one from another.

a mode of 2, median of 2, and mean of 4. This will be a starting point for hyperparameter fine-tuning in models that require as input the number of k. The complete evaluation and comparison between datasets is available in Appendix 4.

Evaluation Method	Dataset 1	Dataset 2	Dataset 3	Dataset 4
Agglomerative dendrogram with single linkage	Second best		Best	
Agglomerative dendrogram with complete linkage		Second best	Best	
Agglomerative dendrogram with average linkage	Best		Second best	
Agglomerative dendrogram with ward linkage	Second best			Best
Silhouette score with K-means			Best	Second best
Silhouette score with Mini Batch K-means			Best	Second best
Silhouette score with Spectral Clustering	Second best	Second best	Best	
Distortion score - Elbow method with K-means	Best	Second best		
Calinski Harabasz score with K-means			Second best	Best
Calinski Harabasz score with Spectral Clustering	Second best	Best		
Davies-Bouldin score with K-means			Second best	Best
Hopkins statistic	Second best		Best	
Total Methods with Best Result	**2**	**1**	**6**	**3**
Total Methods with Second Best Result	**5**	**3**	**3**	**2**

Table 3.14 – Cluster Tendency Assessment results for different datasets[69].

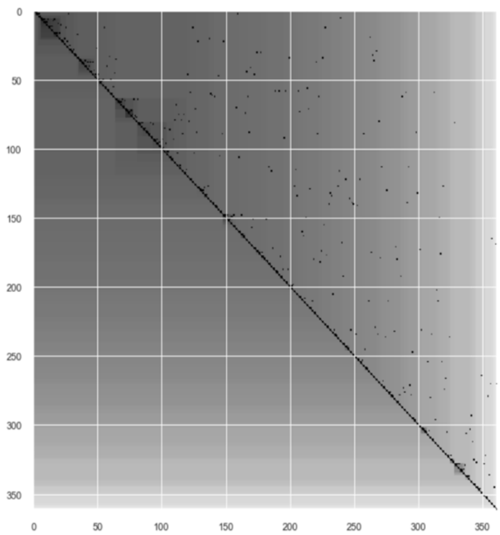

Figure 3.5 – Visual Assessment Tendency for Dataset 3[70].

Once all variables are created, a correlation analysis is performed on the final dataset in order to identify highly correlated pairs of variables, as highly correlated features create distortion in clustering outputs. Highest correlations are found in the pair or variables: performance expectancy and attitude (0.64), attitude and satisfaction (0.63), usefulness and attitude (0.62), trust and satisfaction (0.62). However, results of this analysis show that no correlation exceeds a threshold of absolute 0.7.

[69] Table 3.14 shows the logic behind decision making on optimal dataset to use for modelling stage.

[70] Figure 3.5 shows the improved visual method for clustering assessment for dataset3, where clustering may be done at the expense of having reproducible or constructive segments. iVAT performed in Python.

Therefore, all constructs and new features are viable for clustering. Figure 3.6 shows the results of this analysis.

	Satisfaction	Attitude	Usefulness	Performance_Exp	Ease_Use	Social_Influence	Trust	Compatibility	YearPurchases	MonthsOfUse
Satisfaction	1.00	0.63	0.54	0.52	0.41	0.23	0.62	0.36	0.10	-0.02
Attitude	0.63	1.00	0.62	0.64	0.36	0.40	0.48	0.57	0.31	0.13
Usefulness	0.54	0.62	1.00	0.60	0.34	0.31	0.47	0.45	0.25	0.03
Performance_Exp	0.52	0.64	0.60	1.00	0.30	0.42	0.40	0.56	0.33	0.12
Ease_Use	0.41	0.36	0.34	0.30	1.00	0.18	0.32	0.20	0.05	0.07
Social_Influence	0.23	0.40	0.31	0.42	0.18	1.00	0.29	0.42	0.17	0.01
Trust	0.62	0.48	0.47	0.40	0.32	0.29	1.00	0.31	0.02	0.01
Compatibility	0.36	0.57	0.45	0.56	0.20	0.42	0.31	1.00	0.38	0.12
YearPurchases	0.10	0.31	0.25	0.33	0.05	0.17	0.02	0.38	1.00	0.12
MonthsOfUse	-0.02	0.13	0.03	0.12	0.07	0.01	0.01	0.12	0.12	1.00

Figure 3.6 – Correlation Analysis[71].

3.4.3.2. Evaluation of Modeling Techniques

Once the final dataset is defined, the evaluation of modeling techniques provides an understanding of which algorithms could deliver better outcomes for the problem at hand, as well as the range of possible values for an evaluation metric, such as the Silhouette score. For the algorithms in Table 3.15, different parameter fine-tuning methods were applied to determine an optimal combination of inputs that allowed maximizing the Silhouette metric. This table showcases the best results achieved for each algorithm, and Appendix 5 details all specifications used for algorithm optimization.

Algorithm	Clusters	Silhouette Score	Cluster Distribution
Mean Shift	2	0.38829	[0, 352], [1, 10]
DBSCAN	2	0.351709	[-1, 26], [0, 336]
Mini Batch K-Means	2	0.272611	[0, 256], [1, 106]
K-Means	2	0.257064	[0, 234], [1, 128]
Affinity Propagation	2	0.249558	[0, 235], [1, 127]]
Birch	2	0.241101	[0, 107], [1, 255]
Agglomerative Clustering	2	0.220944	[0, 137], [1, 225]
Spectral	2	0.198844	[0, 184], [1, 178]
Optics	3	0.11255	[-1, 77], [0, 182], [1, 103]

Table 3.15 – Results from initial model evaluation[72].

This evaluation allows discarding algorithms that do not perform optimally for non-naturally clustered data, or algorithms that classify a significant amount of data points as noise. In this sense, Mean Shift[73] is discarded as a possible solution given that 97.4% of data is grouped into a single cluster;

[71] Figure 3.6 evidences how no correlations among variables create an impediment for their use in this exercise.

[72] Table 3.15 shows how the best baseline model is Mini-Batch K-Means with a silhouette score of 0.27261.

[73] Mean Shift is an algorithm that detects local maxima of density to find clusters.

DBSCAN[74] is discarded for detecting a single useful cluster; and OPTICS[75] is discarded for classifying 21.3% of data as noise. Furthermore, it can be seen that optimal clustering for the remaining solutions in terms of Silhouette score ranges from 0.272611 to 0.198844, all of them for k = 2. The best performing model is Mini-batch K-Means with a silhouette score of 0.272611 – which will be the new baseline model for analysis. However, clustering data in 2 groups does not necessarily provide the best business answers – and as so, a trade-off between the optimal Silhouette score and alternative solutions must be done in order to obtain best business results. As suggested by Dolnicar, Grün & Leisch (2018), one approach for determining the optimal number of clusters is to repeat procedures for a set of clustering quantities and evaluate all results. Based on this, the evaluation of modeling techniques is extended for cluster quantities above 2 – as can be seen in Tables 3.16, 3.17, and 3.18.

Algorithm	Silhouette Score	Cluster Distribution
Birch	0.186177	[0, 255], [1, 74], [2, 33]
Agglomerative Clustering	0.158837	[0, 225], [1, 43], [2, 94]
Mini-batch K-means	0.156329	[0, 201], [1, 37], [2, 124]
K-means	0.156329	[0, 171], [1, 56], [2, 135]
Affinity Propagation	0.144655	[0, 36], [1, 163], [2, 163]
Spectral	0.123532	[0, 140], [1, 97], [2, 125]

Table 3.16 – Results for model evaluation with k=3[76]

Algorithm	Silhouette Score	Cluster Distribution
Spectral	0.189875	[0, 325], [1, 9], [2, 17], [3, 11]
Birch	0.176225	[0, 243], [1, 48], [2, 60], [3, 11]
Agglomerative Clustering	0.136545	[0, 170], [1, 21], [2, 139], [3, 32]
Birch	0.135681	[0, 162], [1, 50], [2, 137], [3, 13]
Mini-batch K-means	0.123881	[0, 116], [1, 68], [2, 117], [3, 61]
K-means	0.123686	[0, 86], [1, 56], [2, 109], [3, 111]

Table 3.17 – Results for model evaluation with k=4[77]

Algorithm	Silhouette Score	Cluster Distribution
Birch	0.169280	[0, 217], [1, 34], [2, 11], [3, 12], [4, 88]
Agglomerative Clustering	0.139236	[0, 139], [1, 21], [2, 31], [3, 32], [4, 139]
Birch	0.134052	[0, 137], [1, 50], [2, 150], [3, 13], [4, 12]
Spectral	0.131743	[0, 308], [1, 17], [2, 9], [3, 11], [4, 17]
Mini-batch K-means	0.126119	[0, 48], [1, 140], [2, 75], [3, 32], [4, 67]
K-means	0.122822	[0, 86], [1, 28], [2, 97], [3, 81], [4, 70]

Table 3.18 – Results for model evaluation with k=5[78]

[74] DBSCAN stands for density based spatial clustering of applications with noise, and it is an algorithm with the ability to detect data groups with arbitrary shape.

[75] OPTICS stands for ordering points to identify clustering structure, and it is an extension of DBSCAN.

[76] Table 3.16 shows best performing model with 3 clusters (Agglomerative) among evaluated techniques.

[77] Table 3.17 shows best performing model with 4 clusters (BIRCH) among evaluated techniques.

[78] Table 3.18 shows best performing model with 5 clusters (BIRCH) among evaluated techniques.

Evaluating model performance for cluster quantity above 2 allows finding alternate solutions that may maximize the trade-off between cluster quality and business purpose. Possible Silhouette scores in these alternatives range from 0.186177 to 0.122822 – with some alternatives being rejected due to unbalanced cluster distribution. Overall, the best performing algorithm for each number of k will be examined to determine if richer insights are extracted in comparison to k = 2. This means taking each result and contrasting outcomes with the baseline model to find the best fit between cluster quality and business insights. The next section will cover:

- Analysis of the baseline model's result, which is a Mini-Batch K-Means model achieving a silhouette score of 0.272611 with 2 clusters.
- Analysis of the best performing model with 3 resulting clusters, which is an Agglomerative clustering model with a Silhouette score of 0.158837.
- Analysis of the best performing model with 4 resulting clusters, which is a BIRCH[79] model with a Silhouette score of 0.176225.
- Analysis of the best performing model with 5 resulting clusters, which is a BIRCH model with Silhouette score of 0.169280.
- Comparison between perspectives and conclusion on which model fits best the research problem.

3.4.4. Evaluation

3.4.4.1. Best performing model for k=2 (baseline model)

Evaluation is first done by understanding the characteristics of the base model, which had the best results in regard to the Silhouette score – equal to 0.272611. This Mini-Batch K-Means model outputs data in 2 clusters, with 70.7% of data in a cluster (256 users) and 29.3% of data in another cluster (106 users). The parameters used for this result are stated in Appendix 5. Figure 3.7 shows the behavior of each cluster in a polar graph, allowing to easily detect how one cluster collects users with higher values in all features, while the other cluster holds users with lower values.

Complementing this view on data with individual boxplots for each feature allows detecting variables with higher importance. Higher discriminatory power between clusters can be observed in attitude, performance expectancy, compatibility, and year purchases. Likewise, variables like satisfaction, usefulness, social influence, and trust also showed relevance at the moment of differentiating user groups. However, ease of use and months of use showed less importance – with differences between groups being less obvious. Figure 3.8 shows the results from the individual boxplots.

[79] BIRCH stands for balanced iterative reducing and clustering using hierarchies. It is based on a clustering feature tree that is used to perform multilevel clustering.

Figure 3.7 – Polar graph for best performing model (Mini-Batch K-Means) at k = 2[80].

Furthermore, control variables can be examined for additional pattern detection. However, no significant differences or traits in age, education, gender, nationality, residence, or channel within resulting clusters were found in comparison to the sample. Table 3.19 shows the contrast of control variables between these 2 clusters.

	Cluster 0 Results		Cluster 1 Results	
Variable	**Level**	**Percentage**	**Level**	**Percentage**
Frequency	A few times a week	37.89%	Once or twice a month	34.91%
Tenure	12 to 24 months	29.69%	More than 36 months	30.19%
Gender	Female	59.38%	Female	56.60%
Nationality	Colombia	68.75%	Colombia	53.77%
Residence	Colombia	51.95%	Colombia	44.34%
Education	Master's degree	51.95%	Master's degree	47.17%
Channel	Anonymous	66.80%	Anonymous	67.92%
Continent	Americas	66.41%	Americas	66.04%

Table 3.19 – Comparison of control variables of Mini-Batch K-Means for k=2[81]

Finally, in depth cluster evaluation can be performed by analyzing each construct, along with its elements, using the scores' Likert equivalencies. This allows characterizing the resulting clusters with the information provided in the survey and the measurement tool. Likert equivalencies for this modeling solution can be found in Table 3.20.

[80] Axis represented in the form of polar coordinates. Plotted using Line_Polar from Plotly, in order to show segment differences on used variables.

[81] Table 3.19 compares categorical variables in clusters. No significant differences were found.

Figure 3.8 – Boxplots for best performing model (Mini-Batch K-Means) at k = 2[82].

[82] Y axis for all boxplots corresponds to the standardized results of the 7-point Likert scale for evaluated constructs. For mean comparison between clusters, please see Table 3.20.

Construct	Element	Cluster 0 Results		Cluster 1 Results	
		Mean Score	Likert Equivalent	Mean Score	Likert Equivalent
Satisfaction	Overall	5.898438	Agree	4.785377	Somewhat agree
	SA1	5.84375	Agree	4.839623	Somewhat agree
	SA2	5.71875	Agree	4.698113	Somewhat agree
	SA3	5.835938	Agree	4.320755	Neither agree nor disagree
	S4	6.195312	Agree	5.283019	Somewhat agree
Attitude	Overall	6.002604	Agree	4.267296	Neither agree nor disagree
	AT1	6.417969	Agree	5.5	Agree
	AT2	5.953125	Agree	3.849057	Neither agree nor disagree
	AT3	5.636719	Agree	3.45283	Somewhat Disagree
Usefulness	Overall	5.787109	Agree	4.540094	Somewhat agree
	US1	5.761719	Agree	4.150943	Neither agree nor disagree
	US2	5.621094	Agree	4.075472	Neither agree nor disagree
	US3	6.273438	Agree	5.339623	Somewhat agree
	US4	5.492188	Somewhat agree	4.59434	Somewhat agree
Performance Expectancy	Overall	5.839844	Agree	4.370283	Neither agree nor disagree
	PE1	5.863281	Agree	4.04717	Neither agree nor disagree
	PE2	5.332031	Somewhat agree	3.650943	Neither agree nor disagree
	PE3	5.976562	Agree	4.754717	Somewhat agree
	PE4	6.1875	Agree	5.028302	Somewhat agree
Ease of Use	Overall	6.045573	Agree	5.465409	Somewhat agree
	EU1	6.179688	Agree	5.584906	Agree
	EU2	6.082031	Agree	5.518868	Agree
	EU3	5.875	Agree	5.292453	Somewhat agree
Social Influence	Overall	4.476562	Neither agree nor disagree	2.974843	Somewhat Disagree
	SI1	4.496094	Neither agree nor disagree	3	Somewhat Disagree
	SI2	4.375	Neither agree nor disagree	2.90566	Somewhat Disagree
	SI3	4.558594	Somewhat agree	3.018868	Somewhat Disagree
Trust	Overall	5.740234	Agree	4.691038	Somewhat agree
	TR1	5.777344	Agree	4.481132	Neither agree nor disagree
	TR2	5.523438	Agree	4.556604	Somewhat agree
	TR3	5.960938	Agree	4.933962	Somewhat agree
	TR4	5.699219	Agree	4.792453	Somewhat agree
Compatibility	Overall	5.543945	Agree	3.775943	Neither agree nor disagree
	CO1	5.589844	Agree	3.745283	Neither agree nor disagree
	CO2	5.777344	Agree	4.367925	Neither agree nor disagree
	CO3	5.28125	Somewhat agree	3.367925	Somewhat Disagree
	CO4	5.527344	Agree	3.622642	Neither agree nor disagree

Table 3.20 – Likert scale results for Mini-Batch K-Means model at k=2[83]

The previous information allows characterizing the resulting clusters in 2, as follows:

- *Cluster 0 - The Brand Ambassadors:* Around 71% of users are characterized as being more satisfied customers, with positive attitude towards FDA usage and finding a positive compatibility of FDAs with their lifestyle. They are open to recommending an app to others, perceiving FDAs to be useful and having a positive expected outcome from their use, trusting the app. They find FDAs easy to use and have a rather neutral perception of social influence in FDA usage, with a slight susceptibility to being influenced by others' opinions. They also use FDAs more frequently.

- *Cluster 1 - The Unconvinced:* Approximately 29% of users are less satisfied customers, inclining more towards being neutral in satisfaction and with neutral attitude towards FDA usage - especially in desirability to use. In addition, they do not find FDAs to be compatible with their lifestyle and have neutral outcome expectations from their usage. These customers

[83] Likert scale equivalencies are used as the base for cluster characterization in k=2

are more neutral in their usefulness perception, as well as in their trust for FDAs. They find FDAs slightly less easy to use than cluster 0 and are not influenced by society into using them. Hence, their FDA usage is significantly lower in comparison to the other cluster.

3.4.4.2. Best performing model for k=3

The best performing model for k=3 is a Hierarchical Agglomerative Model, with a Silhouette score of 0.158837. The model outputs data in 3 clusters, distributed in a way that 62.1% of data is in cluster 0 (225 users), 25.6% of data is in cluster 2 (94 users), and 11.9% of data is in cluster 1 (43 users). These results are obtained by passing as arguments the number of desired clusters, the Ward[84] linkage method, and the Euclidean distance metric[85]. Figure 3.9 shows the model's polar graph, allowing to evaluate cluster behavior overall. In general, cluster 0 groups users with the highest values in all features, while cluster 1 has the lowest values in almost all features. Cluster 2 is an intermediate level between the other segments, with a slight change in ranking in the yearly purchases and months of use features.

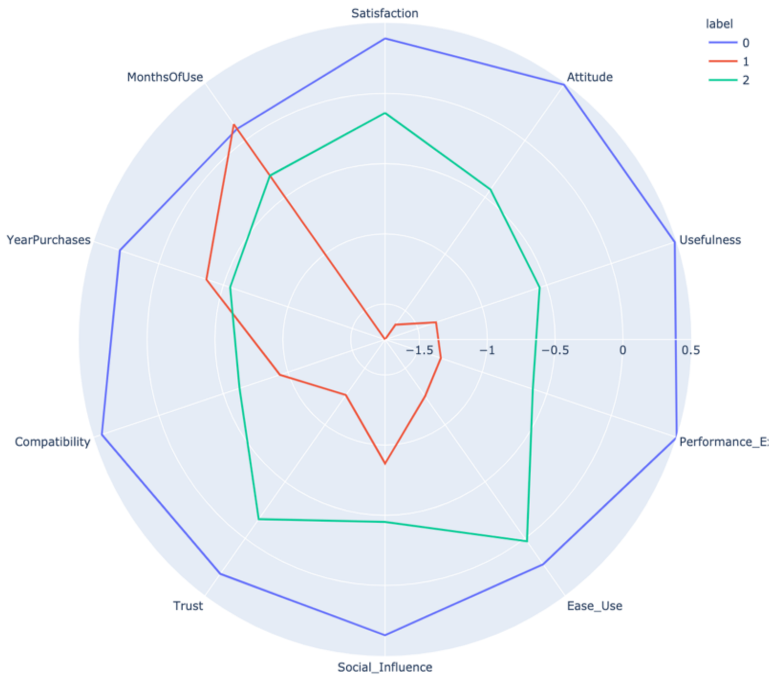

Figure 3.9 – Polar graph for best performing model (Agglomerative clustering) at k = 3[86].

The individual boxplots show how higher discriminatory power between clusters can be observed in satisfaction, attitude, usefulness, performance expectancy, and trust. They are followed by variables

[84] Ward linkage method seeks to merge clusters in Hierarchical Agglomerative clustering aiming at minimizing the error sum of squares in each merge.

[85] A distance metric is a function that outputs a distance between two points. The Euclidean distance is the length of a straight line between points, calculated with their Cartesian coordinates by applying the theorem of Pythagoras.

[86] Axis represented in the form of polar coordinates. Plotted using Line_Polar from Plotly , in order to present segment differences on used variables.

like social influence, yearly purchases, and compatibility - who also showed importance in differentiating segments. Ease of use and months of use showed less importance, similar to the results from k=2 modeling. Figure 3.10 displays the feature boxplots for the model.

Figure 3.10 – Boxplots for best performing model (Agglomerative clustering) at k = 3[87].

Moreover, control variables are also examined, finding that cluster 2 has a significant share of Portuguese residents in comparison to other clusters. In addition, cluster 2 also has different behavior in education, where the most significant level is bachelor's degree – while other clusters are dominated by master's degree. Users from this cluster also accessed the survey through Mail and WhatsApp, more than through social media. These concentrations in cluster 2 are also evidenced in cluster 1, which has

[87] Y axis for all boxplots corresponds to the standardized results of the 7-point Likert scale for evaluated constructs. For mean comparison between clusters, please see Table 3.22.

a higher representation of people from the Americas and with master's degree - in comparison to the sample. Table 3.21 shows the contrast of control variables between clusters for this model.

	Cluster 0 Results		Cluster 1 Results		Cluster 2 Results	
Variable	Level	Percentage	Level	Percentage	Level	Percentage
Frequency	A few times a week	43.11%	Once or twice a month	27.91%	Once or twice a month	40.43%
Tenure	More than 36 months	32.44%	More than 36 months	34.88%	12 to 24 months	30.85%
Gender	Female	59.56%	Female	55.81%	Female	57.45%
Nationality	Colombia	72.89%	Colombia	62.79%	Colombia	44.68%
Residence	Colombia	55.11%	Colombia	55.81%	Portugal	35.11%
Education	Master's degree	53.78%	Master's degree	65.12%	Bachelor's degree	54.26%
Channel	Anonymous	64.00%	Anonymous	69.77%	Anonymous	73.40%
Continent	Americas	69.78%	Americas	76.74%	Americas	53.19%

Table 3.21 – Comparison of control variables for Agglomerative clustering k=3[88]

As mentioned previously, using the scores' Likert equivalencies allows characterizing the resulting clusters with the information provided in the survey and the measurement tool. The model's results are shown in Table 3.22.

Analyzing all the previous information allows characterizing the 3 clusters, as follows:

- *Cluster 0 - The Brand Ambassadors:* 62% of users have high levels of satisfaction with FDAs, with a great attitude towards them, and a positive impression of their usefulness and performance. They find FDAs easy to use and can be influenced by their social circle into using them or not. They have high trust in FDAs and find them compatible with their lifestyle, resulting in a high frequency of purchases.
- *Cluster 1 - The Skeptics:* 12% of users are slightly unsatisfied with FDAs, with a slight negative attitude towards them, and no expectations regarding usefulness or performance. They manage to use FDAs relatively easy and cannot be influenced by their social circle in regard to usage. They need to be convinced about the app's trustworthiness, and do not find FDAs neither compatible nor incompatible with their lifestyle. All of this results in a low frequency of purchases.
- *Cluster 2 - The High Potentials:* made up of 26% of users that are in general satisfied with FDAs, with a good attitude towards them and a relatively good impression of their usefulness and performance. They find FDAs easy to use and cannot be influenced by their social circle in regard to usage. They have a relatively good level of trust towards the app, but do not find FDAs neither compatible nor incompatible with their lifestyle. All of this results in the lowest frequency of purchases in comparison to the other clusters, representing a great opportunity to build loyalty and increase RFM, by increasing purchase frequency from monthly to weekly. Sample wise, these users are slightly younger and mostly have a bachelor education, with a good representation from Portugal.

[88] Table 3.21 compares categorical variables in clusters. Significant differences were found (detailed in text)

Construct	Element	Cluster 0 Results		Cluster 1 Results		Cluster 2 Results	
		Mean Score	Likert Equivalent	Mean Score	Likert Equivalent	Mean Score	Likert Equivalent
Satisfaction	Overall	5.943333	Agree	3.895349	Neutral	5.452128	Somewhat agree
	SA1	5.884444	Agree	3.860465	Neutral	5.521277	Agree
	SA2	5.773333	Agree	3.674419	Neutral	5.37234	Somewhat agree
	SA3	5.88	Agree	3.348837	Somewhat Disagree	5.159574	Somewhat agree
	S4	6.235556	Agree	4.697674	Somewhat agree	5.755319	Agree
Attitude	Overall	6.042963	Agree	3.666667	Neutral	5.01773	Somewhat agree
	AT1	6.448889	Agree	4.860465	Somewhat agree	6.021277	Agree
	AT2	5.977778	Agree	3.348837	Somewhat Disagree	4.712766	Somewhat agree
	AT3	5.702222	Agree	2.790698	Somewhat Disagree	4.319149	Neutral
Usefulness	Overall	5.865556	Agree	4.168605	Neutral	4.933511	Somewhat agree
	US1	5.92	Agree	3.697674	Neutral	4.510638	Somewhat agree
	US2	5.711111	Agree	3.837209	Neutral	4.478723	Neutral
	US3	6.306667	Agree	4.883721	Somewhat agree	5.776596	Agree
	US4	5.524444	Agree	4.255814	Neutral	4.968085	Somewhat agree
Performance	Overall	5.922222	Agree	4.063953	Neutral	4.797872	Somewhat agree
Expectancy	PE1	5.951111	Agree	3.790698	Neutral	4.553191	Somewhat agree
	PE2	5.435556	Somewhat agree	3.55814	Neutral	4	Neutral
	PE3	6.04	Agree	4.534884	Somewhat agree	5.106383	Somewhat agree
	PE4	6.262222	Agree	4.372093	Neutral	5.531915	Agree
Ease of Use	Overall	6.072593	Agree	4.775194	Somewhat agree	5.907801	Agree
	EU1	6.208889	Agree	4.837209	Somewhat agree	6.053191	Agree
	EU2	6.124444	Agree	4.767442	Somewhat agree	5.946809	Agree
	EU3	5.884444	Agree	4.72093	Somewhat agree	5.723404	Agree
Social	Overall	4.542222	Somewhat agree	2.79845	Somewhat Disagree	3.393617	Somewhat Disagree
Influence	SI1	4.551111	Somewhat agree	2.883721	Somewhat Disagree	3.414894	Somewhat Disagree
	SI2	4.457778	Neutral	2.790698	Somewhat Disagree	3.244681	Somewhat Disagree
	SI3	4.617778	Somewhat agree	2.72093	Somewhat Disagree	3.521277	Neutral
Trust	Overall	5.725556	Agree	4.232558	Neutral	5.281915	Somewhat agree
	TR1	5.742222	Agree	3.906977	Neutral	5.255319	Somewhat agree
	TR2	5.506667	Agree	4.255814	Neutral	5.053191	Somewhat agree
	TR3	5.946667	Agree	4.465116	Neutral	5.521277	Agree
	TR4	5.706667	Agree	4.302326	Neutral	5.297872	Somewhat agree
Compatibility	Overall	5.615556	Agree	3.767442	Neutral	4.191489	Neutral
	CO1	5.648889	Agree	3.627907	Neutral	4.265957	Neutral
	CO2	5.857778	Agree	4.44186	Neutral	4.606383	Somewhat agree
	CO3	5.373333	Somewhat agree	3.44186	Somewhat Disagree	3.744681	Neutral
	CO4	5.582222	Agree	3.55814	Neutral	4.148936	Neutral

Table 3.22 – Likert scale results for Agglomerative clustering model at k=3[89]

3.4.4.3. Best performing model for k=4

The best Silhouette score for the k=4 models is 0.176225, and it is achieved with a BIRCH model parametrized with the number of clusters equal to 4, a threshold[90] of 1.5, and a branching factor[91] of 30. It outputs 67.1% of data in cluster 0 (243 users), 16.6% of users in cluster 2 (60 users), 13.2% of users in cluster 1 (48 users), and 3% of users in cluster 3 (11 users). The polar graph for this result is shown in Figure 3.11. Similar to previous results, cluster 0 holds users who have the highest values for all features, while cluster 3 holds users with smaller values. Cluster 1 and cluster 2 have intermediate values, exchanging for specific variables. Cluster 1 scores higher than cluster 2 in yearly purchases,

[89] Likert scale equivalencies are used as the base for cluster characterization in k=3

[90] The threshold parameter in BIRCH is used to determine the maximum radius allowed for merging a new sample with the closest subcluster. If the radius exceeds the threshold, a new subcluster group is created.

[91] The branching factor in BIRCH is used to determine the maximum number of subclusters per node, also known as the maximum number of children per node.

months of use, compatibility, social influence, and performance expectancy; while cluster 2 has higher results in satisfaction, attitude, usefulness, ease of use and trust.

Figure 3.11 – Polar graph for best performing model (BIRCH) at k = 4[92].

The boxplots evidence a higher discriminatory power in variables like compatibility, satisfaction, attitude, and yearly purchases. Likewise, other variables have relevant discriminatory power like performance expectancy and usefulness. However, ease of use and months of use once more showed less importance – along with social influence and trust. Figure 3.12 shows the results from this analysis.

Furthermore, control variables are also examined for pattern detection in the resulting clusters. Similar to the results from the previous model, cluster 2 also shows a higher representation of Portugal residents holding in its majority a bachelor's degree, with half of users in this cluster living in Europe. Table 3.23 shows the comparison of control variables between these 2 clusters.

	Cluster 0 Results		Cluster 1 Results		Cluster 2 Results		Cluster 3 Results	
Variable	**Level**	**Percentage**	**Level**	**Percentage**	**Level**	**Percentage**	**Level**	**Percentage**
Frequency	A few times a week	36.63%	A few times a week	43.75%	Less than once a month	45.00%	Less that once a semester	45.45%
Tenure	More than 36 months	34.57%	12 to 24 months	31.25%	12 to 24 months	30.00%	12 to 24 months	36.36%
Gender	Female	57.61%	Female	58.33%	Female	63.33%	Female	54.55%
Nationality	Colombia	69.55%	Colombia	68.75%	Colombia	41.67%	Colombia	54.55%
Residence	Colombia	52.67%	Colombia	60.42%	Portugal	38.33%	Colombia	45.45%
Education	Master's degree	51.03%	Master's degree	58.33%	Bachelor's degree	51.67%	Master's degree	63.64%
Channel	Anonymous	64.61%	Anonymous	66.67%	Anonymous	80.00%	Anonymous	54.55%
Continent	Americas	69.14%	Americas	81.25%	Europe	51.67%	Americas	63.64%

Table 3.23 – Comparison of control variables of BIRCH model for k=4[93]

[92] Axis represented in the form of polar coordinates. Plotted using Line_Polar from Plotly, in order to present segment differences on used variables.

[93] Table 3.23 compares categorical variables in clusters. Significant differences were found (detailed in text)

Figure 3.12 – Boxplots for best performing model (BIRCH) at k = 4[94].

Finally, in depth cluster evaluation can be performed by analyzing each construct, along with its elements, using the scores' Likert equivalencies. This characterizes clusters with the measurement tool used to collect data. These equivalencies can be found in Table 3.24.

[94] Y axis for all boxplots corresponds to the standardized results of the 7-point Likert scale for evaluated constructs. For mean comparison between clusters, please see Table 3.24.

		Cluster 0 Results		Cluster 1 Results		Cluster 2 Results		Cluster 3 Results	
Construct	Element	Mean Score	Likert Equivalent	Mean Score	Likert Equivalent	Mean Score	Likert Equivalent	Mean Score	Likert Equivalent
Satisfaction	Overall	5.907407	Agree	4.348958	Neutral	5.662500	Agree	3.022727	Somewhat Disagree
	SA1	5.888889	Agree	4.270833	Neutral	5.683333	Agree	2.909091	Somewhat Disagree
	SA2	5.72428	Agree	4.166667	Neutral	5.633333	Agree	3.000000	Somewhat Disagree
	SA3	5.823045	Agree	3.916667	Neutral	5.383333	Somewhat agree	2.363636	Disagree
	S4	6.193416	Agree	5.041667	Somewhat agree	5.950000	Agree	3.818182	Neutral
Attitude	Overall	5.965706	Agree	4.340278	Neutral	5.050000	Somewhat agree	2.545455	Somewhat Disagree
	AT1	6.395062	Agree	5.479167	Somewhat agree	6.100000	Agree	3.909091	Neutral
	AT2	5.917695	Agree	3.854167	Neutral	4.733333	Somewhat agree	2.272727	Disagree
	AT3	5.584362	Agree	3.687500	Neutral	4.316667	Neutral	1.454545	Strongly disagree
Usefulness	Overall	5.711934	Agree	4.609375	Somewhat agree	5.279167	Somewhat agree	3.340909	Somewhat Disagree
	US1	5.674897	Agree	4.416667	Neutral	4.900000	Somewhat agree	2.727273	Somewhat Disagree
	US2	5.539095	Agree	4.375000	Neutral	4.700000	Somewhat agree	3.000000	Somewhat Disagree
	US3	6.246914	Agree	5.187500	Somewhat agree	5.966667	Agree	4.272727	Neutral
	US4	5.386831	Somewhat agree	4.458333	Neutral	5.550000	Agree	3.363636	Somewhat Disagree
Performance	Overall	5.858025	Agree	4.708333	Somewhat agree	4.608333	Somewhat agree	2.931818	Somewhat Disagree
Expectancy	PE1	5.925926	Agree	4.437500	Neutral	4.200000	Neutral	2.272727	Disagree
	PE2	5.320988	Somewhat agree	4.270833	Neutral	3.750000	Neutral	2.636364	Somewhat Disagree
	PE3	5.934156	Agree	4.979167	Somewhat agree	5.183333	Somewhat agree	3.818182	Neutral
	PE4	6.251029	Agree	5.145833	Somewhat agree	5.300000	Somewhat agree	3.000000	Somewhat Disagree
Ease of Use	Overall	6.043896	Agree	5.173611	Somewhat agree	6.011111	Agree	4.484848	Neutral
	EU1	6.185185	Agree	5.250000	Somewhat agree	6.133333	Agree	4.636364	Somewhat agree
	EU2	6.082305	Agree	5.250000	Somewhat agree	6.100000	Agree	4.181818	Neutral
	EU3	5.864198	Agree	5.020833	Somewhat agree	5.800000	Agree	4.636364	Somewhat agree
Social	Overall	4.445816	Neutral	3.500000	Neutral	3.255556	Somewhat Disagree	1.606061	Disagree
Influence	SI1	4.440329	Neutral	3.604167	Neutral	3.350000	Somewhat Disagree	1.454545	Strongly disagree
	SI2	4.378601	Neutral	3.395833	Somewhat Disagree	3.050000	Somewhat Disagree	1.636364	Disagree
	SI3	4.518519	Somewhat agree	3.500000	Neutral	3.366667	Somewhat Disagree	1.727273	Disagree
Trust	Overall	5.729424	Agree	4.348958	Neutral	5.375000	Somewhat agree	3.931818	Neutral
	TR1	5.744856	Agree	4.145833	Neutral	5.300000	Somewhat agree	3.727273	Neutral
	TR2	5.506173	Agree	4.354167	Neutral	5.150000	Somewhat agree	3.727273	Neutral
	TR3	5.950617	Agree	4.562500	Somewhat agree	5.616667	Agree	4.272727	Neutral
	TR4	5.716049	Agree	4.333333	Neutral	5.433333	Somewhat agree	4.000000	Neutral
Compatibility	Overall	5.636831	Agree	4.473958	Neutral	3.520833	Neutral	2.159091	Disagree
	CO1	5.654321	Agree	4.291667	Neutral	3.750000	Neutral	2.090909	Disagree
	CO2	5.876543	Agree	5.104167	Somewhat agree	4.000000	Neutral	2.636364	Somewhat Disagree
	CO3	5.378601	Somewhat agree	4.104167	Neutral	3.050000	Somewhat Disagree	2.000000	Disagree
	CO4	5.63786	Agree	4.395833	Neutral	3.283333	Somewhat Disagree	1.909091	Disagree

Table 3.24 – Likert scale results for BIRCH model at k=4[95]

The analyzed data allows giving characterization to clusters, as is detailed next:

- *Cluster 0 - The Brand Ambassadors:* composed of 67% of users that feel satisfied with FDAs, using them with the most positive attitude and finding them to be highly compatible with their lifestyle. They feel that FDAs are very useful, have great expectations regarding their performance, and find them very easy to use. In general, most of these users have no pressure on using apps based on social influence. They trust the apps and have the highest frequency of purchase.

- *Cluster 1 - The Heartless Shoppers:* made up of 13% of users that are neither satisfied nor dissatisfied with FDAs, with a neutral attitude towards them, a neutral position regarding trust, and finding them neither compatible nor incompatible with their lifestyle. However, they find good use in FDAs, have good expectations regarding their performance, and find them relatively easy to use. This results in a good frequency of purchase. In addition, most of these users have no pressure on using apps based on social influence.

- *Cluster 2 - The High Potentials:* these 16% of users feel satisfied with FDAs, with a good attitude towards them, but finding to be neither compatible nor incompatible with their

[95] Likert scale equivalencies are used as the base for cluster characterization in k=4.

lifestyle. They do find a good use for FDAs, have good expectations regarding performance, and find them relatively easy to use. They tend to be unlikely to use apps based on social influence and have a slight positive perception regarding FDA trustworthiness. They are also relatively new users in comparison to other clusters, with a low frequency of purchase.

- *Cluster 3 - The Nonconformists:* a 3% of users that are dissatisfied and unwilling to recommend FDAs to others, with a bad attitude towards them - especially in regard to desirability to use. They do not find them useful and have negative expectations regarding their performance, with no defined position on whether they are easy to use or not. They do not allow their actions to be driven by social pressure and have a neutral position regarding trust. They believe FDAs to be incompatible with their lifestyle, resulting in the lowest frequency of purchase among all users.

3.4.4.4. Best performing model for k=5

The best Silhouette score for a number of clusters equal to 5 is 0.168290, which is achieved with a BIRCH model. The result is accomplished by passing as parameters the desired number of clusters, the threshold set to 1.5, and the branching factor set to 70. It produces 5 clusters distributed with 59.9% of data in cluster 0 (217 users), 24.3% of data in cluster 4 (88 users), 9.4% of data in cluster 1 (34 users), 3.3% of data in cluster 3, and 3% of data in cluster 2 (11 users). Figure 3.13 shows the polar graph for all features, allowing to identify how cluster characteristics are less evident when the sample is segmented into 5 groups. Still, it is clear that cluster 2 holds all users with the lowest values for all features, while cluster 3 is dominated by users with a high number of purchases.

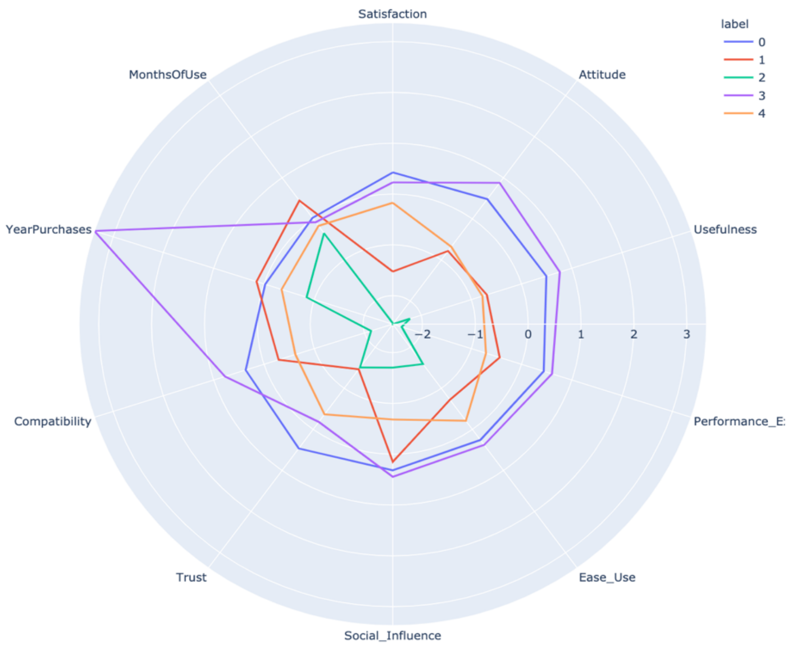

Figure 3.13 – Polar graph for best performing model (BIRCH) at k = 5[96].

[96] Axis represented in the form of polar coordinates. Plotted using Line_Polar from Plotly, in order to present segment differences on used variables.

The complementary view of individual boxplots shows how compatibility, satisfaction and yearly purchases are the most important features in this solution. They are followed by performance expectancy, social influence, and attitude – who also hold discriminatory power relevant enough for clustering. Among the weaker variables are again present ease of use and months of use – accompanied by usefulness and trust. Figure 3.14 shows the results from these individual boxplots.

Figure 3.14 – Boxplots for best performing model (BIRCH) at k = 5[97].

[97] Y axis for all boxplots corresponds to the standardized results of the 7-point Likert scale for evaluated constructs. For mean comparison between clusters, please see Table 3.26.

From examining the control variables, it can be detected how cluster 1 and cluster 3 have a higher representation of people from the Americas in comparison to other clusters. In addition, cluster 0 has a higher share of people with bachelor's degree, but the trend of having a cluster with Portuguese residents with bachelor's degree does no longer hold. Table 3.25 shows the comparison of control variables between these 5 clusters.

	Cluster 0 Results		Cluster 1 Results		Cluster 2 Results		Cluster 3 Results		Cluster 4 Results	
Variable	**Level**	**Percentage**	**Level**	**Percentage**	**Level**	**Percentage**	**Level**	**Percentage**	**Level**	**Percentage**
Frequency	A few times a week	35.94%	A few times a week	50.00%	Less that once a ser	45.45%	Every day	91.67%	Once or twice a moı	32.95%
Tenure	12 to 24 months	29.49%	More than 36 mont	47.06%	12 to 24 months	36.36%	24 to 36 months	50.00%	12 to 24 months	29.55%
Gender	Female	58.06%	Female	52.94%	Female	54.55%	Female	75.00%	Female	60.23%
Nationality	Colombia	67.28%	Colombia	82.35%	Colombia	54.55%	Colombia	83.33%	Colombia	48.86%
Residence	Colombia	48.39%	Colombia	79.41%	Colombia	45.45%	Colombia	75.00%	Colombia	38.64%
Education	Bachelor's degree	47.93%	Master's degree	64.71%	Master's degree	63.64%	Master's degree	75.00%	Master's degree	52.27%
Channel	Anonymous	67.28%	Anonymous	67.65%	Anonymous	54.55%	Anonymous	66.67%	Anonymous	68.18%
Continent	Americas	64.06%	Americas	88.24%	Americas	63.64%	Americas	91.67%	Americas	60.23%

Table 3.25 – Comparison of control variables of BIRCH model for k=5[98]

Lastly, using Likert equivalencies for deeper cluster understanding in this solution proves to be more challenging than the previous models. Characterizing the resulting clusters with the information from the measurement tool is not a clear task, as differences between groupings are less obvious. However, characterization can be performed with the provided information. The details for the Likert equivalencies are shown in Table 3.26.

[98] Table 3.25 compares categorical variables in clusters. Significant differences were found (detailed in text)

Construct	Element	Cluster 0 Results		Cluster 1 Results		Cluster 2 Results		Cluster 3 Results		Cluster 4 Results	
		Mean Score	Likert Equivalent	Mean Score	Likert Equivalent	Mean Score	Likert Equivalent	Mean Score	Likert Equivalent	Mean Score	Likert Equivalent
Satisfaction	Overall	5.973502	Agree	4.154412	Neutral	3.022727	Somewhat Disagr	5.791667	Agree	5.420455	Somewhat agree
	SA1	5.944700	Agree	4.147059	Neutral	2.909091	Somewhat Disagr	5.583333	Agree	5.443182	Somewhat agree
	SA2	5.815668	Agree	3.852941	Neutral	3.000000	Somewhat Disagr	5.333333	Somewhat agree	5.363636	Somewhat agree
	SA3	5.866359	Agree	3.676471	Neutral	2.363636	Disagree	6.000000	Agree	5.181818	Somewhat agree
	S4	6.267281	Agree	4.941176	Somewhat agree	3.818182	Neutral	6.250000	Agree	5.693182	Agree
Attitude	Overall	6.030722	Agree	4.627451	Somewhat agree	2.545455	Somewhat Disagr	6.472222	Agree	4.742424	Somewhat agree
	AT1	6.437788	Agree	5.588235	Agree	3.909091	Neutral	6.833333	Strongly agree	5.840909	Agree
	AT2	5.990783	Agree	4.205882	Neutral	2.272727	Disagree	6.500000	Strongly agree	4.386364	Neutral
	AT3	5.663594	Agree	4.088235	Neutral	1.454545	Strongly disagree	6.083333	Agree	4.000000	Neutral
Usefulness	Overall	5.867512	Agree	4.786765	Somewhat agree	3.340909	Somewhat Disagr	6.104167	Agree	4.735795	Somewhat agree
	US1	5.912442	Agree	4.676471	Somewhat agree	2.727273	Somewhat Disagr	6.333333	Agree	4.170455	Neutral
	US2	5.603687	Agree	4.735294	Somewhat agree	3.000000	Somewhat Disagr	6.166667	Agree	4.397727	Neutral
	US3	6.341014	Agree	5.176471	Somewhat agree	4.272727	Neutral	6.333333	Agree	5.647727	Agree
	US4	5.612903	Agree	4.558824	Somewhat agree	3.363636	Somewhat Disagr	5.583333	Agree	4.727273	Somewhat agree
Performance Expectancy	Overall	5.857143	Agree	4.977941	Somewhat agree	2.931818	Somewhat Disagr	6.020833	Agree	4.698864	Somewhat agree
	PE1	5.843318	Agree	4.676471	Somewhat agree	2.272727	Disagree	6.166667	Agree	4.590909	Somewhat agree
	PE2	5.336406	Somewhat agree	4.647059	Somewhat agree	2.636364	Somewhat Disagr	5.333333	Somewhat agree	3.897727	Neutral
	PE3	6.023041	Agree	5.117647	Somewhat agree	3.818182	Neutral	6.166667	Agree	4.965909	Somewhat agree
	PE4	6.225806	Agree	5.470588	Somewhat agree	3.000000	Somewhat Disagr	6.416667	Agree	5.340909	Somewhat agree
Ease of Use	Overall	6.096774	Agree	5.215686	Somewhat agree	4.484848	Neutral	6.194444	Agree	5.715909	Agree
	EU1	6.244240	Agree	5.323529	Somewhat agree	4.636364	Somewhat agree	6.166667	Agree	5.829545	Agree
	EU2	6.138249	Agree	5.205882	Somewhat agree	4.181818	Neutral	6.083333	Agree	5.840909	Agree
	EU3	5.907834	Agree	5.117647	Somewhat agree	4.636364	Somewhat agree	6.333333	Agree	5.477273	Somewhat agree
Social Influence	Overall	4.486943	Neutral	4.245098	Neutral	1.606061	Disagree	4.666667	Somewhat agree	3.064394	Somewhat Disagree
	SI1	4.502304	Somewhat agree	4.323529	Neutral	1.454545	Strongly disagree	4.666667	Somewhat agree	3.102273	Somewhat Disagree
	SI2	4.373272	Neutral	4.088235	Neutral	1.636364	Disagree	4.666667	Somewhat agree	3.022727	Somewhat Disagree
	SI3	4.585253	Somewhat agree	4.323529	Neutral	1.727273	Disagree	4.666667	Somewhat agree	3.068182	Somewhat Disagree
Trust	Overall	5.865207	Agree	4.080882	Neutral	3.931818	Neutral	5.270833	Somewhat agree	5.099432	Somewhat agree
	TR1	5.889401	Agree	3.823529	Neutral	3.727273	Neutral	5.000000	Somewhat agree	5.056818	Somewhat agree
	TR2	5.645161	Agree	3.970588	Neutral	3.727273	Neutral	5.083333	Somewhat agree	4.943182	Somewhat agree
	TR3	6.092166	Agree	4.470588	Neutral	4.272727	Neutral	5.666667	Agree	5.227273	Somewhat agree
	TR4	5.834101	Agree	4.058824	Neutral	4.000000	Neutral	5.333333	Somewhat agree	5.170455	Somewhat agree
Compatibility	Overall	5.513825	Agree	4.639706	Somewhat agree	2.159091	Disagree	6.062500	Agree	4.190341	Neutral
	CO1	5.562212	Agree	4.352941	Neutral	2.090909	Disagree	6.083333	Agree	4.284091	Neutral
	CO2	5.760369	Agree	5.323529	Somewhat agree	2.636364	Somewhat Disagr	6.083333	Agree	4.647727	Somewhat agree
	CO3	5.271889	Somewhat agree	4.323529	Neutral	2.000000	Disagree	5.750000	Agree	3.715909	Neutral
	CO4	5.460829	Somewhat agree	4.558824	Somewhat agree	1.909091	Disagree	6.333333	Agree	4.113636	Neutral

Table 3.26 – Likert scale results for BIRCH model at k=5[99]

Once conclusions from characterizing profiles are performed, the following descriptions are made to fit the mentioned results:

- *Cluster 0 - The App Ambassadors:* this group is made up of 60% of users that are highly satisfied with FDAS and find them greatly compatible with their lifestyles. They have a high purchase frequency and a positive attitude towards them. These users find them useful, have great performance expectations for them, trust them and find them easy to use. In addition, they manifest no reaction to social influence in regard to using apps for delivery services.

- *Cluster 1 - The Heartless Shoppers:* these 9% of users are neutral on satisfaction; but have a slight positive attitude towards FDAS - finding some compatibility between the apps and their lifestyle. Regardless of this, they have a slightly higher tenure than other clusters and show a great purchase frequency. They find some use in FDAs, have relatively good performance expectations for them, and find them moderately easy to use. They have no reaction to social influence and no position on trust.

- *Cluster 2 - The Nonconformists:* are a 3% of users that are dissatisfied and are incompatible with FDAs in their lifestyle. They have a negative attitude towards them, do not find them useful and have bad performance expectations. In addition, they have no position on how

[99] Likert scale equivalencies are used as the base for cluster characterization in k=5

easy they are to use or if they are trustworthy, with negative reactions to social pressure on using these apps. All these perceptions result in the lowest purchase frequency overall.

- *Cluster 3 - The All Stars:* a 3% of users that are highly satisfied, highly compatible with FDAs and have the highest purchase frequency - almost daily. They have a positive attitude towards them, trust them, find them useful and easy to use. They also have great performance expectations for FDAs and are slightly prone to being socially influenced into using them.
- *Cluster 4 - The Intermittent Misfits:* they are 24% of users that are satisfied, have a slightly positive attitude towards FDAs and trust them; but are neutral on compatibility with lifestyle, resulting on a relatively low purchase frequency. They find some use for them and manifest no difficulty in their interactions with the apps. Also, they have relatively good performance expectations, and a slight negative reaction to social influence.

3.4.4.5. Model Comparison and Decision

After thoroughly analyzing the results from the best performing solutions, it is necessary to decide upon a single model that outperforms the rest in terms of cluster quality and business fit. This final set of solutions, composed of 4 models providing between 2 and 5 clusters, have Silhouette scores ranging from 0.158837 to 0.272611. Comparatively, the business characterizations performed in sections 3.4.4.1 to 3.4.4.4 allow concluding that having cluster quantities above 2 provide richer insights and more actionable segments than the baseline model, which delivers a relatively simple segmentation of users. In addition, these comparisons also allow concluding that clusters tend to be more reproducible than constructive, as certain segments tend to reappear throughout different algorithms, parameters, and approaches. For example, the segment defined as Brand Ambassadors is present in all solutions, while the segments High Potentials, Heartless Shoppers and Non-conformists are present in at least 2 solutions.

Figure 3.15 allows comparing all 4 solutions in a simple way, by showcasing cluster characteristics in all variables along with a measurement of cluster quality. From this, it can be concluded that the best solution for performing market segmentation of FDA users with psychographic and behavioral variables is the BIRCH model with 4 resulting clusters. This is stated given that it has better defined segments than the BIRCH model with 5 clusters and the Agglomerative model with 3 clusters; while also delivering a better business solution than the Mini-batch K-means baseline model with 2 clusters. That is, Birch with 4 clusters not only detects the same cluster with most variables at their lower levels detected in MiniBatch Kmeans with 2 clusters, but also manages to separate the bigger cluster into 3 segments, without renouncing to an acceptable silhouette score. Hence, this model will be used in the next section to completely profile the 4 resulting segments with the available information from psychographic, behavioral, socio-demographic and geographic data.

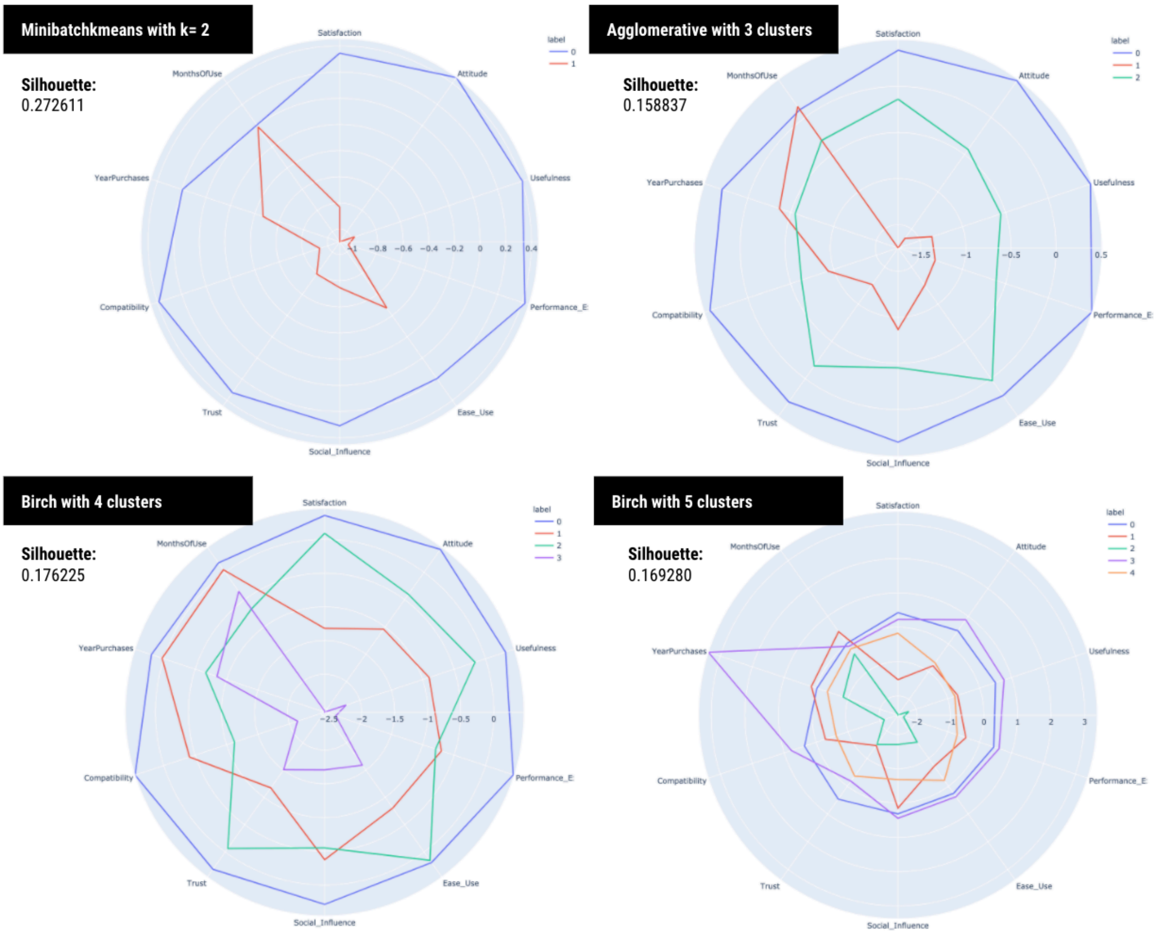

Figure 3.15 – Polar graph and Silhouette score comparison for best solutions[100].

3.5. SEGMENT PROFILING

The Segment Profiling stage concludes the research by further analyzing the results for the BIRCH model with 4 clusters and enhancing the previously discussed customer profiles with more detailed data.

In particular for this model, some variables played more important roles than others when achieving separation of data into groups. The attitude feature managed to separate users into 4 different levels, becoming the best segregator among psychographic constructs (positive, neutral, partially positive, and partially negative attitudes towards FDAs). Similarly, the variable compatibility managed the biggest gap amid results, exposing very distant perspectives among cluster results (compatible, neutral, and incompatible). Other variables achieved interesting separation of data, allowing to clearly identify differences between clusters - like satisfaction (satisfied, partially satisfied, neutral), usefulness (useful, partially useful, partially unuseful), and performance expectancy (very good expectations, good expectations, bad expectations). Finally, the remaining features exposed less discriminatory power while still managing to separate users into three different levels, as seen in ease

[100] Axis represented in the form of polar coordinates. Plotted using Line_Polar from Plotly. From overall view of all graphs it can be stated that Birch of 4 clusters is the best solution.

of use (easy, somewhat ease, neutral), social influence (neutral, partially uninfluenceable, uninfluenceable), and trust (high, partially high, neutral). This final characterization of the 4 clusters is depicted in Table 3.27.

Variable	Cluster 0 Brand Ambassadors	Cluster 1 Heartless Shoppers	Cluster 2 High Potentials	Cluster 3 Non Conformists	Sample Results
Satisfaction	Satisfied (6)	Neutral (4)	Satisfied (6)	Partially Dissatisfied (3)	Satisfied (6)
Attitude	Positive (6)	Neutral (4)	Partially Positive (5)	Partially Negative (3)	Partially Positive (5)
Usefulness	Useful (6)	Partially Useful (5)	Partially Useful (5)	Partially Unuseful (3)	Partially Useful (5)
Performance Expectancy	Very good expectations (6)	Good expectations (5)	Good expectations (5)	Bad expectations (3)	Good expectations (5)
Ease of Use	Easy to use (6)	Somewhat easy (5)	Easy to use (6)	Neutral (4)	Easy to use (6)
Social Influence	Neutral (4)	Neutral (4)	Partially uninfluenceable (3)	Uninfluenceable (2)	Neutral (4)
Trust	High (6)	Neutral (4)	Partially high (5)	Neutral (4)	Partially high (5)
Compatibility	Compatible (6)	Neutral (4)	Neutral (4)	Incompatible (2)	Somewhat Compatible (5)

* numbers in parenthesis indicate the likert equivalent

Table 3.27 – Final Characterization with Psychographic variables[101]

This is further analyzed with summary statistics for each segments' psychographic variables. The three variables with least discriminatory power also show standard deviations higher than 1, meaning that clusters contain users from multiple levels and are not as pure as other labels from other variables. This can be seen in ease of use (Heartless shoppers – 1.06; Non-conformists – 1.24), social influence (Brand ambassadors – 1.24; Heartless shoppers – 1.27; High potentials – 1.47), and trust (Heartless shoppers – 1.06; Non-conformists – 1.41). Likewise, other variables with better performance also presented similar behavior, like satisfaction (Non-conformists – 1.24), attitude (High potentials – 1.10) and compatibility (High potentials – 1.27; Non-conformists – 1.01). Nevertheless, a closer look at these deviations allows concluding that it does not affect the overall classification of users as the High potentials and Non-conformists contain multiple actionable elements that allow creating segment strategies unaffected by this overlap. The summary statistics are presented in Table 3.28.

However, it is also important to state that no single variable presents a pure representation of the segments' labels, as from the analysis of the summary statistics and the boxplots presented before, it can be seen how overlapping among clusters is unavoidable. Nevertheless, the stronger features manage to have a great proportion of data holding the pure label assigned through the cluster's mean. Hence, the segment characterization in this study still depicts a trustworthy method of applying marketing strategies for FDA users.

Regarding behavioral variables, characterization is slightly more challenging given that these two variables are synthetic and were created from categorical variables. In the case of yearly purchases, differentiation among clusters is easy to detect as the majority of users in each cluster is clearly inclined towards a specific frequency period. Still, it is noticeable how no clear differentiation is achieved among groups. Contrarily, months of use does not allow a trustworthy characterization of cluster users based on their tenure. However, it does provide a way to tackle users within clusters to drive less loyal users to desired behaviors. Customers within each cluster were further grouped into 3 categories that will be discussed in the results: short-tenure (users that became FDA customers during the COVID-19 pandemic period, approximately between January 2020 and March 2021), middle-tenure (users that

[101] Table 3.27 shows an overview of each cluster in the final solution with its Likert equivalente for each psychographic construct.

became FDA customers before the COVID-19 pandemic period, approximately between January 2019 and January 2020), and long-tenure (users having a relationship with FDAs for longer than 3 years). Table 3.29 shows the final characterization with behavioral variables.

Variable	Metric	Cluster 0 Brand Ambassadors	Cluster 1 Heartless Shoppers	Cluster 2 High Potentials	Cluster 3 Non Conformists	Sample Results
Satisfaction	Mean	5.90	4.34	5.66	3.02	5.57
	Std. Dev.	0.60	0.85	0.59	1.24	0.95
	Min	3.75	1.75	3.75	1.00	1.00
	25	5.50	3.75	5.25	2.25	5.00
	50	6.00	4.50	6.00	3.00	5.75
	75	6.25	5.00	6.00	4.12	6.00
	Max	7.00	6.00	6.75	4.50	7.00
Attitude	Mean	5.96	4.34	5.05	2.54	5.49
	Std. Dev.	0.67	0.96	1.10	0.65	1.12
	Min	4.00	2.66	2.66	1.66	1.66
	25	5.66	3.66	4.33	2.00	5.00
	50	6.00	4.33	5.16	2.66	5.66
	75	6.33	4.75	6.00	2.83	6.33
	Max	7.00	7.00	7.00	4.00	7.00
Usefulness	Mean	5.71	4.60	5.27	3.34	5.42
	Std. Dev.	0.68	0.93	0.79	0.88	0.91
	Min	3.50	1.75	3.25	1.75	1.75
	25	5.25	4.00	4.75	2.62	5.00
	50	5.75	4.75	5.50	3.50	5.50
	75	6.25	5.25	5.81	4.12	6.00
	Max	7.00	6.25	7.00	4.50	7.00
Performance Expectancy	Mean	5.85	4.70	4.60	2.93	5.40
	Std. Dev.	0.64	0.85	0.96	0.75	1.01
	Min	3.75	3.00	2.00	2.00	2.00
	25	5.50	4.25	4.18	2.37	5.00
	50	6.00	4.75	4.75	2.75	5.50
	75	6.25	5.25	5.25	3.50	6.00
	Max	7.00	6.50	6.25	4.25	7.00
Ease of Use	Mean	6.04	5.17	6.01	4.48	5.87
	Std. Dev.	0.69	1.06	0.67	1.24	0.85
	Min	4.00	1.00	4.00	2.66	1.00
	25	5.66	5.00	5.66	3.66	5.66
	50	6.00	5.33	6.00	4.33	6.00
	75	6.66	6.00	6.33	5.50	6.33
	Max	7.00	6.33	7.00	6.00	7.00
Social Influence	Mean	4.44	3.50	3.25	1.60	4.03
	Std. Dev.	1.24	1.27	1.47	0.49	1.43
	Min	1.00	1.00	1.00	1.00	1.00
	25	4.00	2.58	2.00	1.00	3.00
	50	4.33	3.66	3.00	2.00	4.00
	75	5.50	4.41	4.33	2.00	5.00
	Max	7.00	6.00	7.00	2.00	7.00
Trust	Mean	5.72	4.34	5.37	3.93	5.43
	Std. Dev.	0.66	1.06	0.79	1.41	0.94
	Min	3.25	1.75	2.00	1.00	1.00
	25	5.50	3.50	4.93	3.37	5.00
	50	5.75	4.50	5.62	4.50	5.75
	75	6.00	5.25	6.00	4.87	6.00
	Max	7.00	6.00	6.50	5.50	7.00
Compatibility	Mean	5.63	4.47	3.52	2.15	5.02
	Std. Dev.	0.84	0.95	1.27	1.01	1.34
	Min	1.00	1.00	1.50	1.00	1.00
	25	5.25	4.00	2.50	1.50	4.31
	50	5.75	4.50	3.50	2.00	5.37
	75	6.00	5.00	4.31	2.62	6.00
	Max	7.00	6.00	7.00	4.50	7.00

Table 3.28 – Summary statistics for Psychographic variables

Variable	Cluster 0 Brand Ambassadors	Cluster 1 Heartless Shoppers	Cluster 2 High Potentials	Cluster 3 Non Conformists	Sample Results
Months of Use	Mostly experienced - long-tenure (63%) - middle-tenure (28%) - short-tenure (9%)	Mostly Experienced - long-tenure (56%) - middle-tenure (31%) - short-tenure (13%)	Mostly Recent - long-tenure (27%) - middle-tenure (30%) - short-tenure (43%)	Unable to determine - long-tenure (36%) - middle-tenure (37%) - short-tenure (27%)	Mostly Experienced - long-tenure (55%) - middle-tenure (29%) - short-tenure (16%)
Purchases	Very frequent - Weekly (64%) - Monthly (34%) - Semiannually (2%)	Frequent - Weekly (50%) - Monthly (44%) - Semiannually (6%)	Somewhat frequent - Weekly (15%) - Monthly (77%) - Semiannually (8%)	Ocassional - Weekly (0%) - Monthly (55%) - Semiannually (45%)	Frequent - Weekly (52%) - Monthly (43%) - Semiannually (5%)

Table 3.29 – Final Characterization with Behavioral variables[102]

As for sociodemographic and control variables, a drilldown on differences between clusters allows finding interesting perspectives to complement the segment profiles. Regarding gender, there is a slight change in proportions in 2 clusters in comparison to the population. The High potentials have a higher representation of individuals identifying as female, while the Non-conformists have a higher representation of individuals identifying as male, both in comparison to the sample's proportions. Regarding education, it is interesting to notice how the Non-conformists have a higher proportion of well-educated users, also having the highest fraction of masters and PhD graduates from all segments. Similarly, the High potentials have the highest representation of high school and bachelor graduates, and the Heartless shoppers have higher representations of masters and high school graduates in comparison to the population. If these findings are contrasted with their age, no real trend is found between education and age as cluster means are very similar, except for the High potentials, where most of its users are 30 years old or less. These users also show a higher representation of residents from Europe over all other segments, while the Heartless shoppers have a higher concentration of people from the Americas. Finally, High potentials also exhibit a higher proportion of answers from Email and WhatsApp in comparison to the sample, while Non-conformists have a higher participation from Social Media. These results are shown in Table 3.30.

[102] Table 3.29 shows an overview of each cluster in the final solution with its Likert equivalents for each behavioral construct.

	Characteristic	Cluster 0 Brand Ambassadors	Cluster 1 Heartless Shoppers	Cluster 2 High Potentials	Cluster 3 Non Conformists	Sample Results
Gender	Female	57.61%	58.33%	63.33%	54.54%	58.56%
	Male	42.38%	41.66%	36.66%	45.45%	41.43%
Education	High School	0.82%	4.16%	6.66%	0.00%	2.20%
	Bachelor's Degree	43.62%	35.41%	51.66%	27.27%	43.37%
	Master's Degree	51.02%	58.33%	40.00%	63.63%	50.55%
	PhD / Doctorate	1.64%	0.00%	0.00%	9.09%	1.38%
	Other	2.88%	2.08%	1.66%	0.00%	2.48%
Frequency	Every day	4.52%	0.00%	0.00%	0.00%	3.03%
	A few times a week	36.62%	43.75%	5.00%	0.00%	31.21%
	Once a week	23.04%	6.25%	10.00%	0.00%	17.95%
	Once or twice a month	25.92%	25.00%	31.66%	27.27%	26.79%
	Less than once a month	8.23%	18.75%	45.00%	27.27%	16.29%
	Less than once a semester	1.64%	6.25%	8.33%	45.45%	4.69%
Tenure	More than 36 months	34.56%	29.16%	11.66%	18.18%	29.55%
	24 to 36 months	27.98%	27.08%	15.00%	18.18%	25.41%
	12 to 24 months	28.39%	31.25%	30.00%	36.36%	29.28%
	6 to 12 months	6.17%	12.50%	30.00%	27.27%	11.60%
	1 to 6 months	2.88%	0.00%	13.33%	0.00%	4.14%
Continent	Americas	69.13%	81.25%	43.33%	63.63%	66.29%
	Europe	26.33%	16.66%	51.66%	27.27%	29.28%
	Oceania	2.46%	0.00%	1.66%	0.00%	1.93%
	Asia	2.05%	2.08%	3.33%	9.09%	2.48%
Channel	Whatsapp and Email	64.60%	66.67%	80.00%	54.54%	67.12%
	Social Media	35.39%	33.33%	20.00%	45.45%	32.87%
Age	Mean	33.27	35.58	29.56	34.09	32.98
	Min	19	21	21	24	19
	25	29	32	24	32	28
	50	33	34	27	34	33
	75	36	38	34	36	36
	Max	73	64	66	46	73

Table 3.30 – Final Characterization with Sociodemographic and Control variables[103]

In closing, segment profiles can be fully completed with descriptions covering all available information, as follows:

- *Cluster 0 - The Brand Ambassadors:* this segment makes up for 67% of users and are, in general terms, the ideal set of customers for an FDA. They have the highest purchase frequency from all segments, being very frequent shoppers. 64% of users in this segment make weekly purchases, while 34% purchases on a monthly basis and only 2% buys through FDAs semiannually. They feel satisfied with their experiences in FDA usage (μ: 5.90; σ: 0.60), finding them useful (μ: 5.71; σ: 0.68) and with very good expectations on their performance (μ: 5.85; σ: 0.64). Their attitudes towards FDAs are positive (μ: 5.96; σ: 0.67) as they find them to be compatible with their lifestyles (μ: 5.63; σ: 0.84). They feel FDAs are easy to use (μ: 6.04; σ: 0.69), have high trust on their usage (μ: 5.72; σ: 0.66), and have a neutral perception regarding social influence on utilization (μ: 4.44; σ: 1.24). Most of these consumers are experienced users, with 63% of them being long-tenured. However, a significant proportion is still middle-tenured (28%) and short-tenured (9%). Sample wise, these users have no significant differences in socio-demographic variables.

[103] Table 3.30 shows an overview of each cluster in the final solution with its distributions for sociodemographic variables.

- *Cluster 1 - The Heartless Shoppers:* 13% of respondents are in this segment, made up of consumers mainly characterized for being good shoppers but dominated on neutral or partially positive perceptions. They are neither satisfied nor unsatisfied with FDAs (μ: 4.34; σ: 0.85), declaring a neutral perception in their attitudes towards them (μ: 4.34; σ: 0.96) and are indecisive on whether these apps are compatible or not with their lifestyles (μ: 4.47; σ: 0.95). They also show no defined position on whether they find FDAs to be trustworthy (μ: 4.34; σ: 1.06) or if they are socially influenceable into using them (μ: 3.50; σ: 1.27). However, they do feel FDAs are partially useful (μ: 4.60; σ: 0.93), find them easy to use (μ: 5.17; σ: 1.06), and have relatively good expectations on their performance (μ: 4.70; σ: 0.85). This leads to a good purchase frequency, where most users in this segment can be classified as recurrent shoppers. 50% of Heartless shoppers purchase on a weekly basis, 44% buy on a monthly basis, and only 6% does it semiannually. They are mostly experienced with FDAs, with 56% being long-tenured, 31% being middle tenured and 13% being short-tenured. Sample wise, they have a higher representation of masters and high school graduates in comparison to the population (58.33% and 4.66%, respectively) and have the highest concentration of people residing in the Americas over all segments (81.25%).

- *Cluster 2 - The High Potentials:* 16% of users are part of this segment, dominated by a younger population with a somewhat frequent purchase habit that, even with positive perceptions on most psychographic elements, has still to define whether FDAs are compatible or not with their lifestyle (μ: 3.52; σ: 1.27). They feel satisfied with these apps (μ: 5.66; σ: 0.59), have a partially positive perception on their trustworthiness (μ: 5.37; σ: 0.79), and have partially positive attitudes towards them (μ: 5.05; σ: 1.10). Even though they are young, this segment is characterized as being unlikely to use FDAs based on social influence exerted from peers (μ: 3.25; σ: 1.47). They find FDAs partially useful (μ: 5.27; σ: 0.79), with somewhat good expectations on their performance (μ: 4.60; σ: 0.96) and finding them easy to use (μ: 6.01; σ: 0.67). This is manifested in their purchase frequency, where most of them have monthly purchases (77%), followed by weekly consumers (15%) and only a small proportion being semi-annual users (8%). They are mostly recent users, with 43% being short-tenured, 30% being middle tenured and 37% being long-tenured. Sample wise, they have the highest representation of high school and bachelor graduates (6.66% and 51.66%, respectively); consequent with their age, as 58.33% of its population is 30 years old or younger. They have a slightly higher representation of individuals identifying as female in comparison to the sample (63.33%) and show the highest share of European residents over all other segments. (51.66%)

- *Cluster 3 - The Nonconformists: the* last 3% of users make up this segment, portrayed as having unfavorable perceptions regarding FDAs and their use, reflected in their very low purchase frequency. These users feel partially dissatisfied (μ: 3.02; σ: 1.24) and declare FDAs to be incompatible with their lifestyles (μ: 2.15; σ: 1.01). In congruence with this, they assume negative attitudes towards these apps (μ: 2.54; σ: 0.65), finding them partially unuseful (μ: 3.34; σ: 0.88), and with bad expectations on their performance (μ: 2.93; σ: 0.75). Hence, they are not influenceable by society into using FDAs (μ: 1.60; σ: 0.49). However, they do not find the apps difficult to use nor do they distrust them, revealing to be neutral both on ease of use (μ: 4.48; σ: 1.24) and trust (μ: 3.93; σ: 1.41). As expected, their shopping habits are undesirable – with most of the segment characterized as being occasional shoppers. Their frequency is either monthly (55%) or semiannually (45%), with no one in this segment having weekly purchases. Their tenure is mixed, with 36% being long-tenured, 37% being middle-tenured, and 27% being short-tenured. Sample wise, they distinguish themselves apart for having the highest representation of post-graduates – with no high school graduate users, 27.27% share of bachelors and 63.63% of master graduates. Additionally, they hold the highest share of PhD graduates in comparison to other segments (9%). Lastly, they have a slightly higher representation of individuals identifying as male in comparison to the sample (45.45%).

4. RESULTS AND DISCUSSION

As stated in Table 3.1, one of the purposes in this study is to determine if the discriminatory power of the psychographic variables selected for clustering is enough to be considered good variables for segmentation exercises. Furthermore, the behavioral variables used in this research are also prone to be evaluated in FDA context. Table 4.1 shows a qualitative analysis based on the behavior of the forementioned variables on all four evaluated models, segregating their performance on most relevant, relevant, and weak clustering variables.

Variable	Most Relevant	Relevant	Weak / Irrelevant
Satisfaction	Agglomerative (k=3) Birch (k=4) Birch (k=5)	Minibatch Kmeans (k=2) Kmeans (k=2)	
Attitude	Minibatch Kmeans (k=2) Kmeans (k=2) Agglomerative (k=3) Birch (k=4)	Birch (k=5)	
Usefulness	Agglomerative (k=3)	Minibatch Kmeans (k=2) Kmeans (k=2) Birch (k=4)	Birch (k=5)
Performance Expectancy	Minibatch Kmeans (k=2) Agglomerative (k=3)	Kmeans (k=2) Birch (k=4) Birch (k=5)	
Ease of Use			Minibatch Kmeans (k=2) Kmeans (k=2) Agglomerative (k=3) Birch (k=4) Birch (k=5)
Social Influence	Kmeans (k=2)	Minibatch Kmeans (k=2) Agglomerative (k=3) Birch (k=5)	Birch (k=4)
Trust	Agglomerative (k=3)	Minibatch Kmeans (k=2) Kmeans (k=2)	Birch (k=4) Birch (k=5)
Compatibility	Minibatch Kmeans (k=2) Kmeans (k=2) Birch (k=4) Birch (k=5)	Agglomerative (k=3)	
YearsPurchases	Minibatch Kmeans (k=2) Kmeans (k=2) Agglomerative (k=3) Birch (k=4) Birch (k=5)		
MonthsOfUse			Minibatch Kmeans (k=2) Kmeans (k=2) Agglomerative (k=3) Birch (k=4) Birch (k=5)

Table 4.1 – Feature importance assessment[104]

It is noticeable how some variables occupy different positions on different models, while others retain their positions on multiple runs. The yearly purchases feature played an important role in all scenarios, while the variables compatibility, attitude, satisfaction, and performance expectancy proved to be between very relevant and relevant in all models. Other features interchange roles in different simulations, being very relevant in some clustering solutions, while being weak variables in others. These variables are usefulness, social influence, and trust. Finally, ease of use and months of use were found to be weak in all models – even though some discrimination was achieved with their use. Therefore, hypotheses involving the use of these variables for clustering is accepted for all psychographic constructs, as all of them provided useful information in the final solution.

Moreover, analyzing the overall results allows gaining further insights for the FDA industry. On one hand, it is very positive to see how usability and user experience practices applied to mobile app design

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have been successful at implementing easy to use interfaces. This given that 3 out of 4 segments described FDAs to be easy to use, and the non-conformists segment had a neutral position even when most other variables have negative associations for this group. This means that, in general, almost no one finds FDAs difficult to use. Another insight worth mentioning is how FDAs have managed to build trust in their users. No segment manifested having trust issues while using these apps, although there is still an opportunity to guide unconvinced segments, like the Heartless shoppers and Non-conformists, into having a positive perception on trust. Sample wise, 92% of respondents had either neutral or positive perceptions on trust; and 97% of respondents had either neutral or positive perceptions on ease of use. Additionally, it is important to mention how social influence is not an aspect that FDAs need to take into account when designing marketing strategies with this segmentation model. This because even though no segment is particularly described as being influenceable, 44% of the sample claimed to have some sort of influence from society into using FDAs. This means that the clustering solution was not able to group these influenceable users into a single category, or that social influence is not as important in generating distance between users as other variables used for modeling. As such, it can be concluded that even though ease of use, social influence and trust are important psychological aspects that need to be tackled by FDAs, they are not key elements for marketing strategies at the moment of this study.

In addition, and having segment profiles created based on research findings, it is necessary to enrich results by determining the general implications for Food Delivery Application companies targeting customers in their online sales strategy design. By using psychographic and behavioral segmentation, FDAs can increase loyalty in their customer base, decide on product enhancements, and aim marketing efforts at increasing app usage and purchase frequency.

As a starting point, it is important to highlight how the largest customer segment is composed of ideal consumers who purchase frequently and have very positive perceptions about these apps. This segment, the Brand Ambassadors, is a segment that needs to be delighted and protected. The main objective that FDAs must pursue for this group is to continue building their loyalty towards FDAs, and achieving a higher usage based on new, innovative features that thrill and hook these users. Even though they purchase frequently, there is still a big opportunity to push purchase frequency within the segment, as 37% of these users do not have weekly purchases. Also, even if this is the most valuable customer segment, some further research must be done on customer needs and wants, as there are opportunities to increase satisfaction, compatibility, and attitude. By further developing initiatives that rise perceptions on these constructs, FDAs will have better retention strategies and be better prepared for the increasing base of competitors entering the FDA industry.

A deeper look into the Brand Ambassadors delimits business actions that need to be pursued. It is of great importance to protect this great mass of consumers that are satisfied with FDAs and find them of use in their lifestyles and routines. FDAs should increase protection measures for this segment aiming for loyalty and retention, especially in the period following COVID-19 vaccination and deconfinement measures, which reduces significantly the dependence of users on FDAs as a way for supplying food. A way to do this is to delight these users by understanding what surprises them and what makes them desire to use FDAs; providing new features, new restaurant offerings and better services that match expectations and lifestyles. Furthermore, and given that they represent the segment with the highest share, the needs and wants of these users should drive product increments and product roadmaps by using their characteristics as the main buyer persona for app innovation and new releases. This is especially important in the design of service differentiators that allow standing out from the competition, where using the Brand Ambassadors as the main user of customer journey mapping becomes of great use. This will allow FDA designers to detect improvement opportunities for providing faster delivery services, easier access to information, and more time-saving features. These users should also be the base for all massive communications, like ATL and branding strategies, given that it allows targeting nonregistered users with characteristics that are ideal for new customers. In line with this, these users should also be targeted with referral campaigns, given that the Brand Ambassadors are willing to recommend an app to others and exert social influence into using them. Notwithstanding that these users are satisfied; FDAs need to nurture customer relationships and push business development with partnerships that match both the user's compatibility with lifestyle and with the way the desire to feed themselves. All of these elements need to be intertwined into a full loyalty and rewards program, leading to higher satisfaction, a more positive attitude, and a better fit into lifestyle - increasing intention to use and hence the frequency of purchases[105].

The next segment to tackle is that one composed of the Heartless shoppers, where FDAs should aim at convincing and conquering them, inducing involvement in a way that allows pushing users from this segment into the Brand Ambassadors. The best way to do this is by offering a stellar experience, increasing satisfaction, compatibility, and attitude – especially in short-term initiatives following the COVID-19 pandemic period. This is important because, even though most of them became users before the pandemic period, they have a high perception that FDAs match the current situation that they are living. Increasing these psychographic elements may induce higher involvement, and therefore, an increase in usage.

Achieving psychological and emotional involvement in this segment is a critical step that FDAs need to impulse. It means building loyalty in this segment and creating links that reinforce retention and use. To start, it is important to perform market research in order to understand the specific elements that generate dissatisfaction or fall short to meet expectations in the Heartless Shoppers, as well as understanding desire to use, app advocacy, fit in lifestyle and preferences. The results of market research will allow activating marketing campaigns and product improvements that increase perceptions and judgements on FDAs, rising usage intention and engagement. Furthermore, involving these users in business decisions – like validating features and epics in the product roadmap – allows having a critical review with a straightforward evaluation. Lastly, and as these consumers need to be conquered, operational KPIs need to be monitored carefully since any failure to provide the expected service (delivery time, food quality, food tracking, easy process of food ordering) can result in customer churn or a reduction in intention to use. FDAs need to aim at providing these users with charming experiences that build loyalty, especially built on trust, usefulness, and expected performance, in order to increase satisfaction and compatibility[106].

The third segment to focus on are the High Potentials, where FDAs need to boost and engage these consumers. Given their potential, a strategy involving offers, promotions and discounts is adequate for

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[105] Business objectives and suggested actions for the Brand Ambassadors are based on findings presented in section 3.5, with a special focus on construct elements SA2, SA3, AT2, AT3, CO1, CO2, CO3, CO4, PE1, PE2, PE3, PE4, SI3, US1, US2 – available in Table 3.24.

[106] Business objectives and suggested actions for the Heartless Shoppers are based on findings presented in section 3.5, with a special focus on construct elements SA1, SA2, SA3, SA4, SA4, AT2, AT3, CO1, CO2, CO4, PE1, PE2, PE3, PE5, US1, US2, US4, TR1, TR2, TR3 – available in Table 3.24.

increasing intention to use and purchase frequency. It is important for FDAs to seize the opportunity of having customers who already feel satisfied with FDAs and are only needing to find a fit with lifestyle or a motivation to increase purchases and use. By doing this, the High Potentials segment may become a steppingstone in the customer lifetime value for user evolution, leading to becoming Brand Ambassadors eventually.

Firstly, FDAs need to address the understanding of these user's lifestyles and find potential spots of where delivery services may match. It is important to include an understanding of work environments and living conditions – as these factors are crucial in the rise of FDA usage in certain communities. A special focus should be given to understanding wage and expenses, as low purchase frequency may be related to the fact that this segment is younger and has less academic background than other groups. Once a match has been found, marketing strategies should aim at communicating value propositions that fit these user's lifestyles, current situation in life, and daily routines. If this is accompanied by interesting offers, promotions, and discounts – especially in the areas of interest of this segment and in accordance with wage insights – it is very likely that engagement will be achieved. Additionally, comprehension of the High Potentials' lifestyles may incur in interesting product developments that drive desirability, increase the app's importance in daily life, and potentialize the willingness to recommend. In addition, exposure to the partnerships developed for the Brand Ambassadors may also increase the way High Potentials perceive compatibility between food options offered in FDAs and their desired nutrition. This may also help retain these users, as over 40% of them started using FDAs during the pandemic period[107].

Finally, the last segment to face is the Non-conformists, who should work as a segment with a strategy of "listen and learn" - especially through Customer Service. Understanding their pain points and non-conformities will allow FDAs to detect pitfalls in service or value proposition. If required, proactive research may be performed using low-cost methods to understand these users' personalities, lifestyles, experiences, and expectations.

Having in mind that the main objective is to learn from this segment's nonconformities, FDAs should first listen to their complaints and service gaps, evaluating with qualitative studies the reasons behind these users' lack of motivations, unwillingness to recommend, low expectations, and minimum-service requirements, as findings in these fields may help determining a minimum viable product when designing new releases. In this same line, Non-conformists make an ideal extreme user when evaluating new features, bug resolution, and product enhancement - given their critical reception to FDAs in general. However, and given that these users represent a small proportion of consumers, no hard actions should be implemented. Resources should not be allocated exclusively to this segment, but rather included in tactics directed to other segments, as possibly neighboring tactics might have an effect on attitude, perception or compatibility – converting some Non-conformist users into one of the other desirable segments[108].

[107] Business objectives and suggested actions for the High Potentials are based on findings presented in section 3.5, with a special focus on construct elements SA2, SA3, AT3, PE1, CO1, CO2, CO3, CO4 – available in Table 3.24.

[108] Business objectives and suggested actions for the Non-conformists are based on findings presented in section 3.5, with a special focus on construct elements SA1, SA2, AT2, AT3, CO1, CO3, CO4, SI1, SI2, SI3, PE1, PE4 – available in Table 3.24.

5. CONCLUSIONS

The Food Delivery Industry is a market that has been increasing in importance in the past decade, not only because of its relevance in the digital age, but also because of the worldwide events occurring in recent years. Among factors catalyzing its growth are millennial adoption, societal changes in household composition, concentration of office spaces in urban areas, and internalization of food choices. The rising interest in these services has increased competition and, therefore, forced Food Delivery Applications to become fast-paced businesses focused on growth and differentiation.

An important lever for growth in Food Delivery Applications is managing to retain users, guaranteeing better income flows from recurrent consumers who purchase periodically. As such, visualizing customers' intention to use is a key element in the design of marketing strategies that aim at increasing purchase frequency in their customer base. Understanding predecessors of intention to use, from a Consumer Behavior perspective, discloses elements with a strong incidence on FDA adoption that must be tackled as a means for increasing transactions.

By understanding technology adoption models and their applications to the Food Delivery industry, significant antecedents of intention to use were identified and analyzed – namely satisfaction, attitude, usefulness, performance expectancy, ease of use, social influence, trust, and compatibility. These psychological factors with incidence on usage intention become key drivers for accomplishing business objectives. However, consumer typology varies in regard to psychographic factors, and as such, FDA businesses must first understand market composition in terms of these variables.

Using a variety of data mining techniques, and based on psychographic and behavioral features, market segments for the FDA industry were identified and analyzed. Using the forementioned features in conjunction with purchase frequency and tenure, allowed identifying four segments: The Brand Ambassadors, a group of ideal consumers with frequent purchases; the Heartless Shoppers, users with great purchase behavior but low involvement; the High Potentials, a group with high involvement but relatively low number of purchases; and the Non-conformists, a small group of users with no involvement and very low purchase frequency.

To conclude, a complete scenario of market composition was achieved with the use of alternate segmentation methods. Not only was it achievable, but also viable and valuable for companies competing in the Food Delivery industry. It provided a different method for market segmentation that shines light on psychological aspects that affect intention to use - a central element in user's willingness to purchase. By targeting the antecedents of intention to use in their marketing efforts, FDA companies drive buying frequency, customer lifetime value and profits. Furthermore, by deploying these marketing tactics based on the identified segments, Food Delivery companies boost revenue by focalizing on specific consumer profiles that are undetectable in traditional market segmentation methods.

6. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORKS

The execution of this study encountered several limitations that may be addressed in future works to enhance results and complement findings from this research. Machine learning projects, and in particular unsupervised learning techniques like clustering, require making decisions based on assumptions and interpretations from data, like the ideal number of clusters, the quantity of features to use, or the understanding of results for profiling purposes. Hence, future works may tackle certain aspects that may improve findings based on more accurate information that ease decision-making.

First, sampling and distribution have an opportunity for improvement. Given the budget and scope of this research, the sampling methods described in section 3.3 resulted in a high participation from Colombian users. Even if geographic features were not part of the clustering set, cultural aspects involving consumer behavior have incidence on psychographic constructs, and therefore, may have an effect on results. In addition, a higher participation of educated users may also alter depiction of reality in comparison to standard FDA users. Future researchers are encouraged to distribute questionnaires evenly among geographies and populations as a way to avoid bias resulting from cultural beliefs and social norms.

Secondly, this research did not have access to real behavioral data from specific customers, resulting in a low number of behavior variables being used. As a consequence, these variables were collected mainly in survey questions as categorical data, sacrificing the impact of real, continuous behavioral data. It is highly recommended for future researchers to obtain sponsorship from an FDA company, as to nurture psychographic constructs with real RFM data that will most likely lead to richer business insights.

Next, there is an opportunity for researchers and businesses aiming at having more defined clusters to apply this same methodology but reducing the number of variables. As discussed in the results, certain variables like ease of use, social influence and trust had low discriminatory power or implied less urgent business decisions. Removing them from the clustering set may shine light on segments with more concise and separated clusters – or even in new ways to visualize FDA customers.

Lastly, soft clustering approaches were not used in this research, and hence, observations have a sole classification. As the data showed, the cluster overlap is high, meaning customers are more likely to belong to multiple classes instead of only one. Researchers are encouraged on using soft clustering approaches, like Gaussian models, to evaluate multi-class membership that may lead to more structured business suggestions for real world market segmentation situations.

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8. APPENDIX 1 – STRUCTURAL EQUATION MODELING IN FDAS

In their study aimed at understanding what factors drive FDA usage after the COVID-19 pandemic in China, Zhao and Bacao (2020) found that user satisfaction is the main variable influencing reuse. They based their study on three existing technology adoption frameworks, namely Expectancy Confirmation Model (ECM)[109], Unified Theory of Use and Acceptance of Technology Model (UTAUT)[110] and Task-Technology Fit Model[111]. They concluded that perceived task-technology fit, trust, performance expectancy and social influence are all significant factors determining continuous usage. They were also able to show how effort expectancy and confirmation did not prove to be significant in having a direct relationship with usage, but rather affect one of the previously mentioned significant factors. On one hand, effort expectancy was found to be insignificant towards satisfaction and performance expectancy, while confirmation has an incidence in both of them. Figure 8.1 depicts the model of this study, with all hypotheses and results.

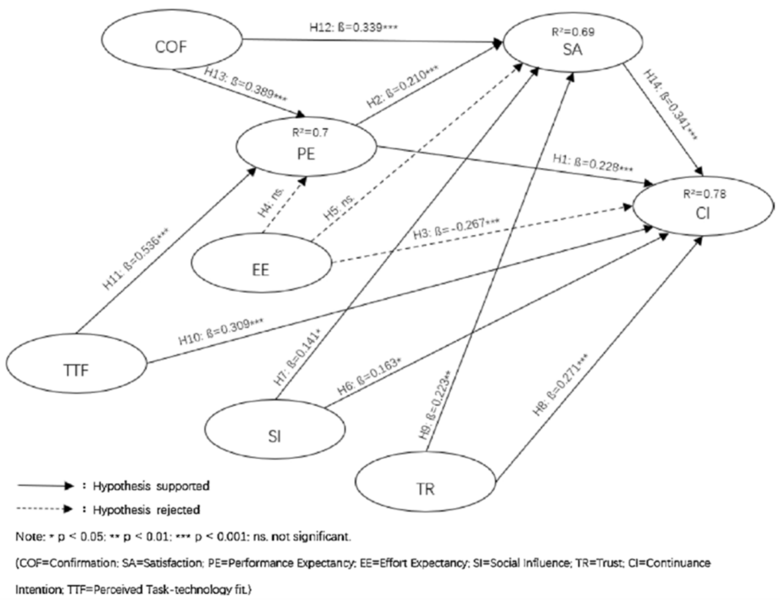


Figure 8.1 – Zhao and Bacao's Model and Hypothesis Results[112].

On another perspective, Roh and Park (2019) attempted to identify the impact of value systems and moral obligations on FDA adoption in South Korea. This was based largely on the belief that moral obligation restricts individuals from acting on convenience and that it has a symbolic sense to share a

[109] Expectancy Confirmation Model, known as ECM, is a model that uses three dimensions to evaluate the usage intention of technology. It is based on performance expectancy, confirmation and satisfaction.

[110] Unified Theory of Acceptance and Use of Technology model, known as UTAUT, is a model for explaining technology acceptance. It is based on performance expectancy, effort expectancy, facilitating conditions and social influence.

[111] Task-Technology Fit Model, known as TTF, is a model that evaluates technology adoption based on the fit between the information technology's capabilities and the task that the user must perform.

[112] Taken from Zhao, Y., & Bacao, F. (2020). What factors determining customer continuingly using food delivery apps during 2019 novel coronavirus pandemic period?. International journal of hospitality management, 91, 102683.

meal at home. Such restrictions may come from guilt of ordering food in comparison to preparing it at home, inclination towards meal cooking for family members, and existing negative perceptions of convenience food. Their study was based on existing models for technology adoption, such as the Technology Acceptance Model (TAM)[113] and Innovation Diffusion Theory[114], finding that people with high moral obligation are more resistant to their convenience-seeking impulses than people with low moral obligation, therefore, having less adoption intention of FDAs. In this study, high moral obligation was evaluated as being married, while low moral obligation was evaluated as being single. In addition, they managed to prove that intention is positively influenced by ease of use and usefulness, with an emphasis on the influence that compatibility and subjective norm apply on it. Likewise, ease of use is influenced by compatibility and convenience orientation, while usefulness is influenced by compatibility and subjective norm. Figure 8.2 shows the evaluated constructs and the results from the hypotheses testing. Significant differences were found between these married and single groups, with a higher effect of convenience orientation on compatibility, and compatibility on intention, in the singles group. Likewise, ease of use and usefulness were found to be highly significant in the married group in comparison to the singles sample.

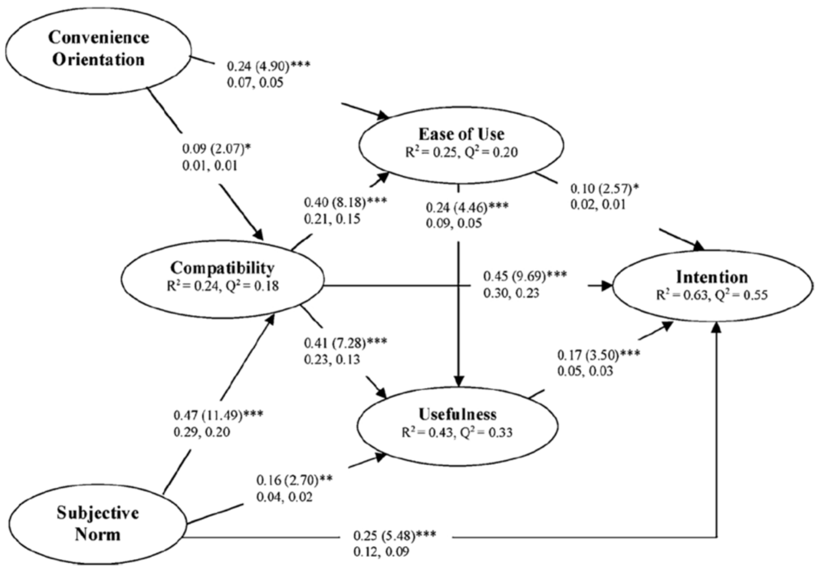


Figure 8.2 – Roh and Park's Model and Path Analysis Results[115].

Yeo, Goh and Rezaei (2017) provided a complementary viewpoint in their Malaysian study about the structural relationships among previous consumer experiences, attitudes, and behavioral intention towards FDA. Constructs used in this research were based on the Technology Acceptance Model

[113] Technology Acceptance Model (TAM) describes a user's attitudes and intentions to accept and use new technology. It is based in perceived usefulness and perceived ease of use.

[114] Innovation Diffusion Theory suggests that the innovation characteristics of technology drive its adoption, based on relative advantage, complexity, compatibility, trial ability, and observability.

[115] Taken from Roh, M., & Park, K. (2019). Adoption of O2O food delivery services in South Korea: The moderating role of moral obligation in meal preparation. International Journal of Information Management, 47, 262-273.

(TAM), the Contingency Framework[116] and the Extended Model of IT Continuance[117]. They managed to illustrate how the behavioral intention towards FDAs is influenced by the attitude of the person towards FDAs, with both of them having positive influence from convenience motivation and post usage usefulness. The two latter ones are themselves influenced by hedonic motivations, time saving orientation and price saving orientation. In addition, convenience motivation was also found to be influenced by prior online purchase experience, while post usage usefulness is not affected by this variable. Figure 8.3 displays the model of attitude and behavior tackled in the mentioned research, with all tested relationships.

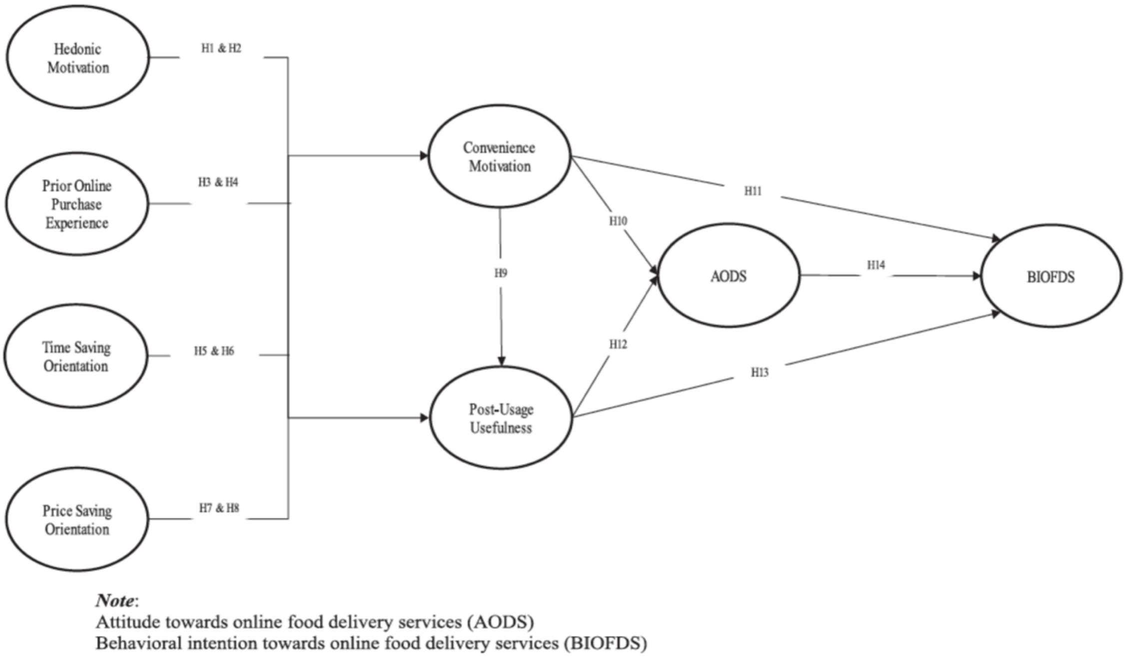


Figure 8.3 – Yeo, Goh and Rezaei's Model Schema for Behavioral Intention [118].

Moreover, Cho, Bonn and Li (2019) conducted an additional relevant study in China, where several quality attributes were tested with respect to their impact towards user perceived value, attitude and intention to use. It was concluded that there is a positive influence of convenience, design, trustworthiness and variety of food choices on perceived value, which itself influences both the attitude towards FDAs and the intention of further use. It was also detected that price did not have a relevant influence on this model, while trustworthiness was found to be the most significant attribute. Their analysis was extended to identify relevant changes in the model's structure between single-

[116] The Contingency Framework by Anderson and Srinivasan is a model showing support between satisfaction and loyalty in e-commerce environments, moderated by inertia, perceived value, trust, purchase size and convenience motivation.

[117] Extended Model of IT Continuance is an extended version of the Continuance Model proposed by Oliver in 1980, explaining the continuance behavior of technology by using the variables disconfirmation, post usage usefulness, satisfaction, IT self-efficacy and facilitating conditions.

[118] Taken from Yeo, V. C. S., Goh, S. K., & Rezaei, S. (2017). Consumer experiences, attitude and behavioral intention toward online food delivery (OFD) services. Journal of Retailing and Consumer Services, 35, 150-162

person and multi-person households. Findings point to a higher relevance of convenience and design in multi-person households, while price and variety are valued in greater proportion by single-person household users. Trustworthiness once more was identified as being very significant regardless of household composition. Figure 8.4 depicts the resulting model, with all tested relationships between constructs.

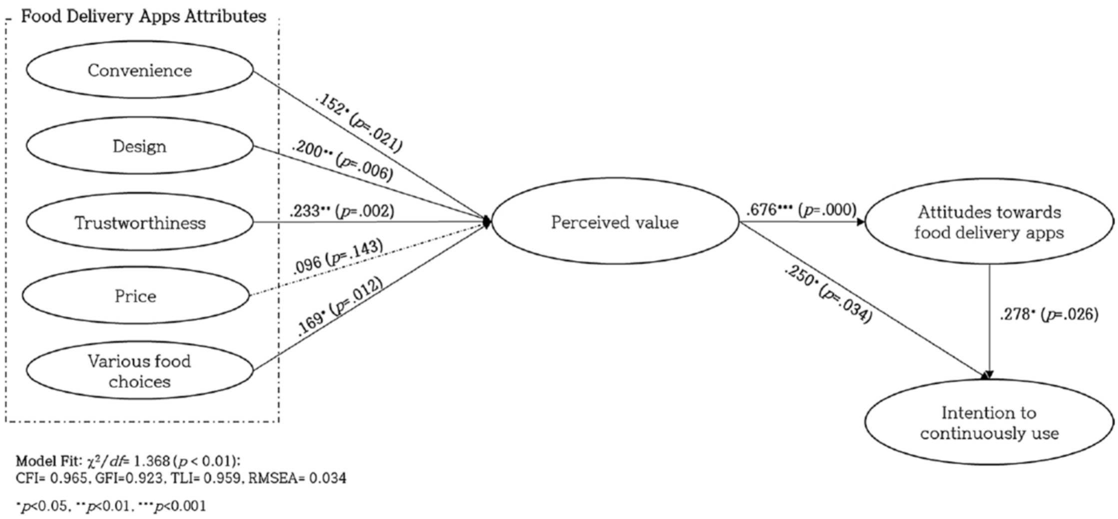


Figure 8.4 – Cho, Bonn and Li's Model and Hypothesis Results[119].

Furthermore, Ray et. al. (2019) endeavored to understand the motives that explain FDA adoption in India by evaluating the association between uses and gratification with intention to use. They based the evaluated constructs on the Uses and Gratification Theory[120], measuring the influence on intention of convenience, customer experience, societal pressure, search of restaurants, delivery experience, listings, ease-of-use and quality control – as shown in Figure 8.5. They were able to prove the high importance of customer experience and ease of use, with search of restaurants falling closely behind. Likewise, they proved that listings had a negative but significant impact on intention.

[119] Taken from Cho, M., Bonn, M. A., & Li, J. J. (2019). Differences in perceptions about food delivery apps between single-person and multi-person households. International Journal of Hospitality Management, 77, 108-116.

[120] Uses and Gratification Theory refers to a model explaining the uses and gratification behind a consumer's choice of medium to satisfy needs.

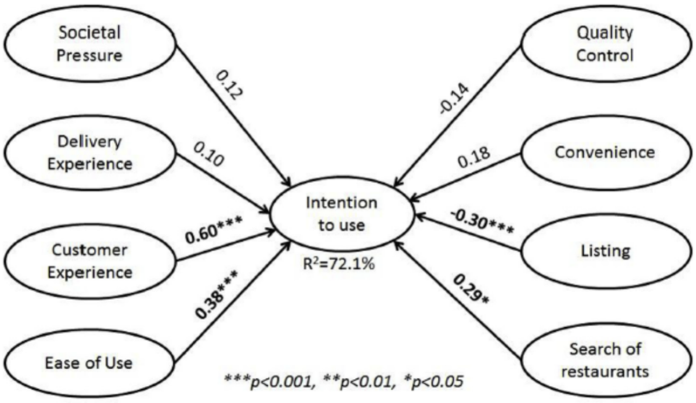


Figure 8.5 – Ray, Dhir, Bala and Kaur's Model and Hypothesis Results[121].

Additional relevant studies include Koiri, Mukherjee and Dutta's (2019) model explaining the factors impacting FDA perception on consumers from the Indian city of Guwahati, where Time savings, Offers, Convenience and Payment Mode were found to be relevant. Variety seeking, which was also tested in this study, was found to be irrelevant for perception. Figure 8.6 shows the conceptual model from this study. Similarly, Nanaiah (2020) also designed and tested a model that intended to explain several factors influencing the ordering frequency in college students from the Indian city of Bangalore. This study found that there was a positive relationship between offers, discounts and delivery time with the frequency of FDA usage, while no relationship was found for the variables user design, number of registered restaurants and charged penalties. Figure 8.7 illustrates the research's conceptual model. Also, Kim and Hwang (2020) contributed to this topic by providing insights from the formation of eco-friendly behavioral intention towards using drone delivery services in FDAS from South Korea. This research was based on the Norm Activation Model[122] and Theory of Planned Behavior[123], integrating multiple constructs into a single model oriented at understanding drivers of the eco-friendly usage of drones. The research concluded stating that moral obligation and subjective norm are critical aspects that need to be triggered by companies pushing drone delivery services. Figure 8.8 shows the model of this research.

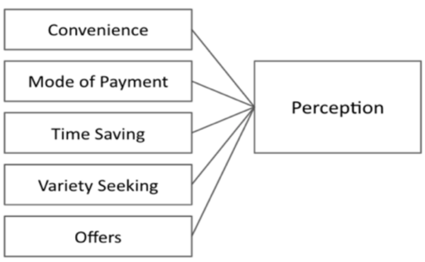


Figure 8.6 – Koiri, Mukherjee and Dutta's Conceptual Model for Perception[124].

[121] Taken from Ray, A., Dhir, A., Bala, P. K., & Kaur, P. (2019). Why do people use food delivery apps (FDA)? A uses and gratification theory perspective. Journal of Retailing and Consumer Services, 51, 221-230.

[122] The Norm Activation Model, known as NAM, is a model that examines altruistic and eco-friendly behavioral intentions

[123] The Theory of Planned Behavior, known as TPB, is a theory relating behavior to beliefs through constructs such as attitude, subjective norms and perceived behavioral control.

[124] Adapted from Koiri, S. K., Mukherjee, S., & Dutta, S. (2019). A Study on Determining the Factors Impacting Consumer Perception Regarding the Online Food Delivery Apps in Guwahati. GIS Business, 14.

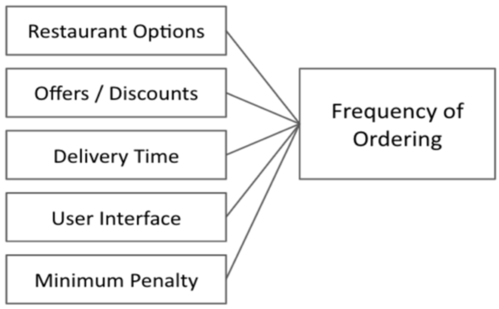


Figure 8.7 – Nanaiah's Conceptual Model for Frequency of Ordering[125].

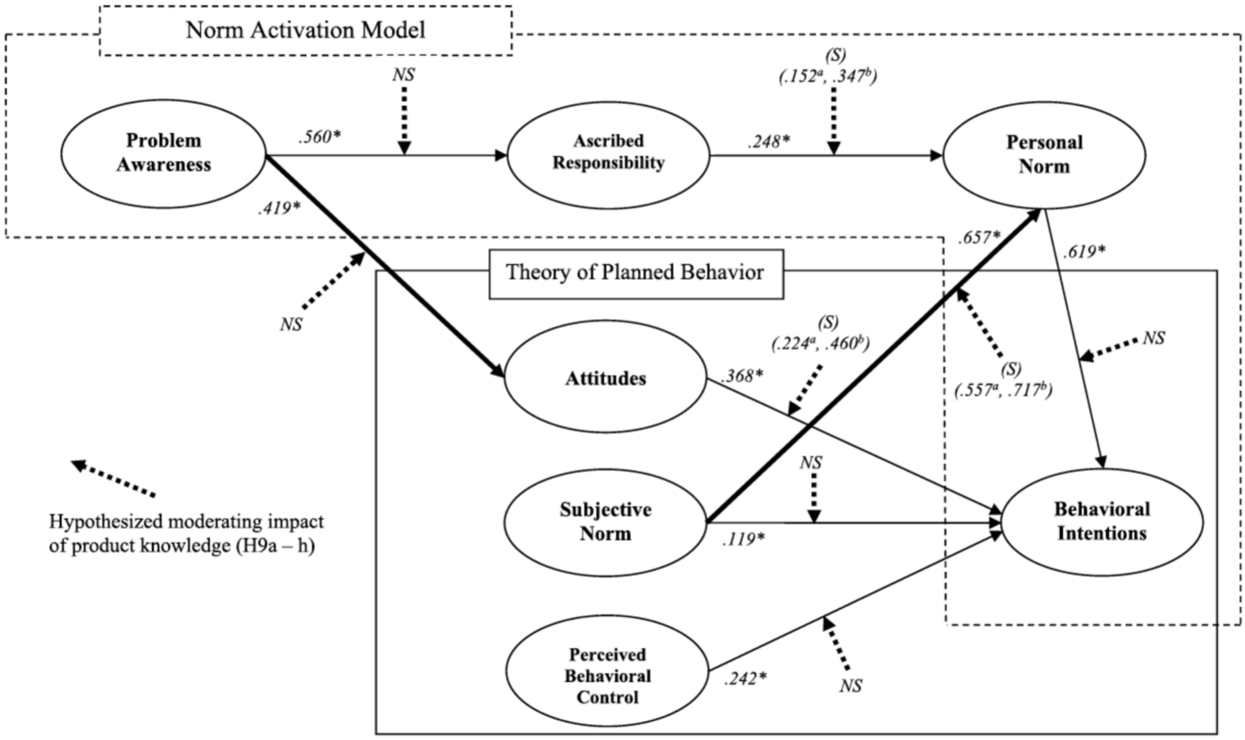


Figure 8.8 – Kim and Hwang's Model Results for Eco-Friendly Behavioral Intention[126].

Jeon, Kim and Jeong (2016) performed a complementary study where they intended to discover the relationship between service quality attributes of FDAS with the emotional response and willingness to use in South Korean residents. In order to understand this relationship, the research

[125] Adapted from Nanaiah, P. N. (2020). A Study on Consumer Behaviour and the Impact of Food Delivery Apps on the College Students in Bangalore. International Journal of Research in Engineering, Science and Management, 3(3), 462-466.

[126] Taken from Kim, J. J., & Hwang, J. (2020). Merging the norm activation model and the theory of planned behavior in the context of drone food delivery services: Does the level of product knowledge really matter?. Journal of Hospitality and Tourism Management, 42, 1-11.

team based their constructs on the PAD theory[127], specifically pleasure and arousal. It was concluded that the design and sympathy attributes in FDA service quality influences positively arousal, even though arousal was found to have no effect on willingness to use. The reliability and design attributes were concluded to have an influence over pleasure, with pleasure – along with informativity and mobility – having a positive influence on willingness to use. The conceptual model of this research is shown in Figure 8.9.

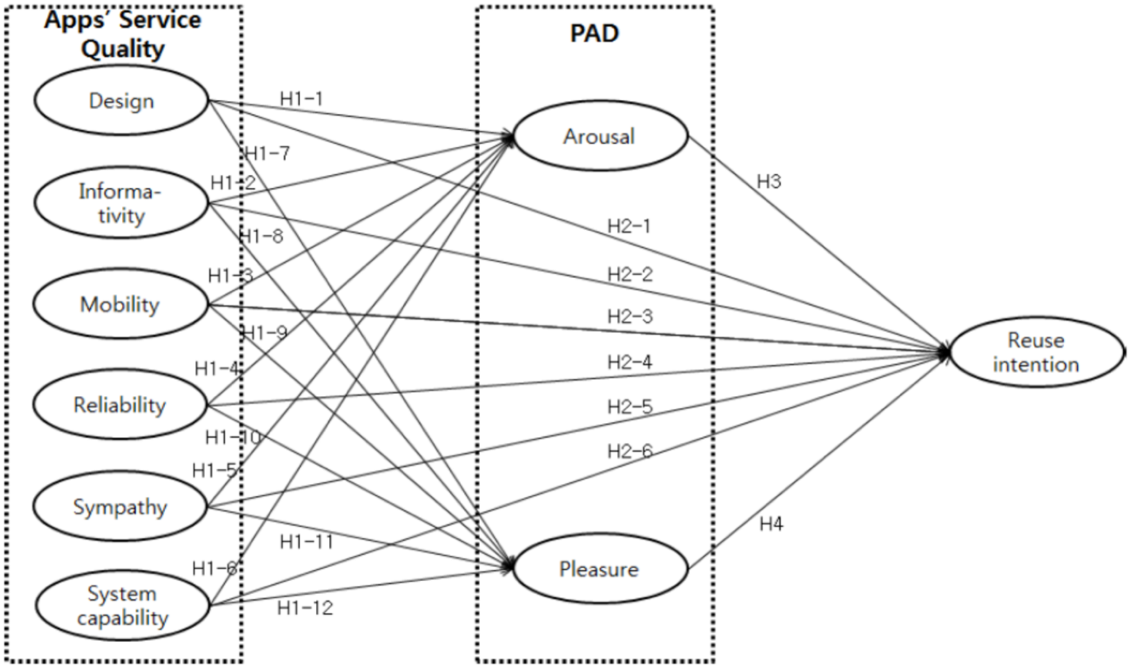


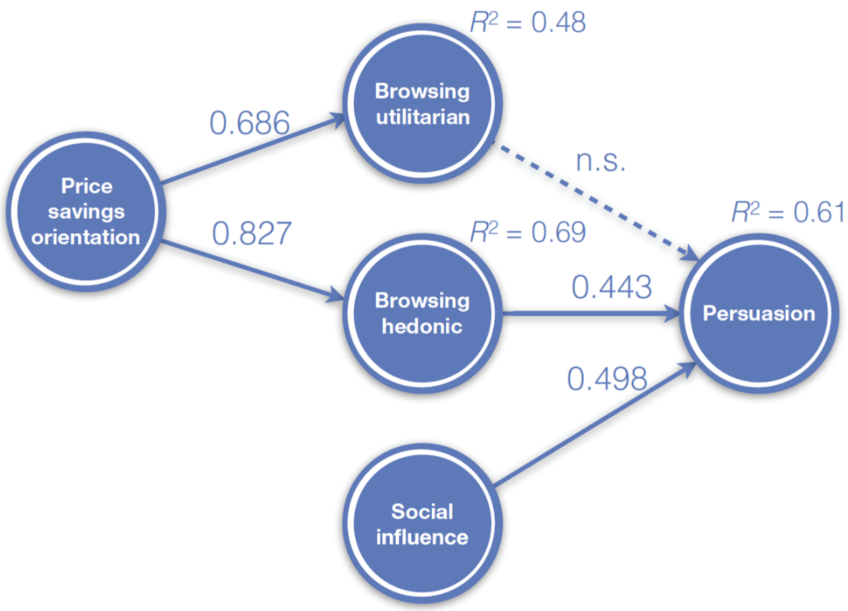
Figure 8.9 – Jeon, Kim and Jeong's Conceptual Model for Willingness to Use[128].

Gunden, Morosan and DeFranco (2020) presented another interesting model, which consisted on explaining what persuades an American customer to use FDAs. Based on the Theory of Persuasive Information on Information Systems[129], the researchers hypothesized on the influence of utilitarian and hedonic web browsing on persuasion, as well as the effects of price orientation and social influences on this same variable. It was found that all relationships in this model were highly significant, in exception of the link between utilitarian web browsing with persuasion. As a result, this research concluded that price saving orientation, hedonic web browsing, and social influence are all strong predictors for persuasion in the FDA context. Figure 8.10 shows the results of this model.

[127] PAD stands for Pleasure, Arousal and Dominance, and it consists of an emotional state model.

[128] Taken from Jeon, H. M., Kim, M. J., & Jeong, H. C. (2016). Influence of smart phone food delivery apps' service quality on emotional response and app reuse intention-Focused on PAD theory. Culinary science and hospitality research, 22(2), 206-221.

[129] The theory of persuasive information on Information Systems states that consumers can be influenced by Information Systems into changing initial behaviors in a non-coercive manner. This is achieved through the interactions between the user and the Information System, which are easy to achieve and are designed with endogenous intent.

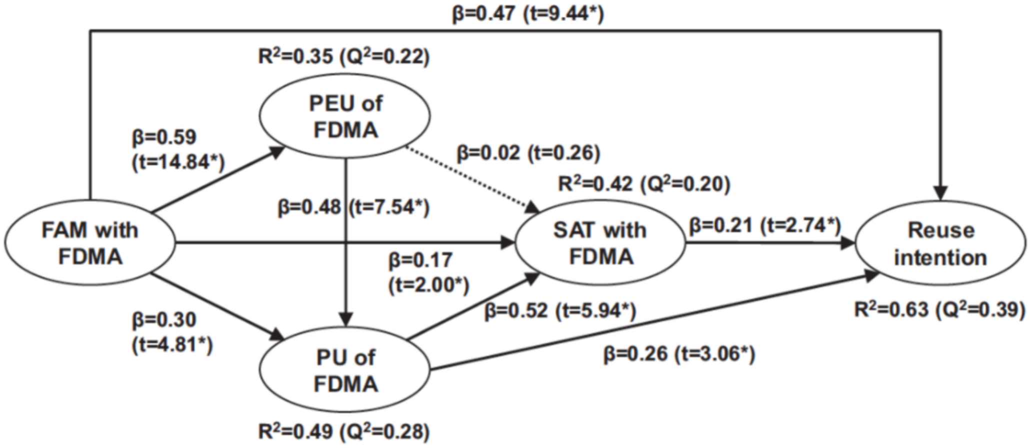


Notes: $\chi^2 = 368.261$; $df = 182$; Normed; $\chi^2 = 2.02$; CFI = 0.941; TLI = 0.932; RMSEA = 0.057

Figure 8.10 – Gunden, Morosan and DeFranco's Model and Results for Persuasion[130].

Choi (2020) sought to understand the drivers behind the reuse intention of FDAs in consumers from South Korea. Based on the Technology Acceptance Model, the constructs perceived ease of use and perceived usefulness were modeled against intention to reuse, along with the added constructs of familiarity and satisfaction. It was found that familiarity leads to positively increasing both the perceived ease of use and perceived usefulness, with perceived ease of use itself having a positive influence over perceived usefulness. However, perceived ease of use did not have a significant influence over satisfaction, while perceived usefulness and familiarity both did. Regarding reuse intention, it was found that familiarity, satisfaction, and perceived usefulness all have a positive influence on this behavior, with satisfaction being the strongest predictor. Overall, the results from this research point out that users that feel more familiar with an application are less likely to switch to a competitor app, having a higher feeling of satisfaction, and therefore, are more likely to continue using it. Figure 8.11 shows the model's schema and results.

[130] Taken from Jeon, H. M., Kim, M. J., & Jeong, H. C. (2016). Influence of smart phone food delivery apps' service quality on emotional response and app reuse intention-Focused on PAD theory. Culinary science and hospitality research, 22(2), 206-221.



Note. A solid arrow stands for a significant path, and a broken arrow represents an insignificant path. SRMR = 0.04; NFI = 0.89. PLS-SEM = partial least squares structural equation modeling; FDMA = food delivery mobile app; FAM = familiarity; PEU = perceived ease of use; PU = perceived usefulness; SAT = satisfaction; SRMR = standardized root mean residual; NFI = normed fix index. *p = .05.

Figure 8.11 – Choi's Model and Results for Reuse Intention[131].

Lee, Sung and Jeon (2019) also contributed to the understanding of continuous FDA usage in South Korea by attempting to explain continuous use intention with constructs derived from the Unified Theory of Acceptance and Use of Technology 2[132] (UTAUT2) model. Even more, they decided to expand the model's constructs with the factor information quality anteceding continuous intention, performance expectancy and effort expectancy. This construct was included because it is recognized as being a fundamental factor for building trust. They concluded that continuous intention was driven by performance expectancy, habit and social influence, with information quality having an indirect incidence through performance expectancy. As such, it was affirmed that the perceived usefulness a user has based on app design and reliable information leads to higher usage as the real benefits, like time saving or cuisine variety, become tangible. Figure 8.12 shows the conceptual model and results from this research.

[131] Taken from Choi, J. C. (2020). User Familiarity and Satisfaction With Food Delivery Mobile Apps. SAGE Open, 10(4), 2158244020970563.

[132] The Unified Theory of Acceptance and Use of Technology 2 is an augmented version of the UTAUT model that includes psychological and cognitive factors, like value, price habit and hedonic motivation.

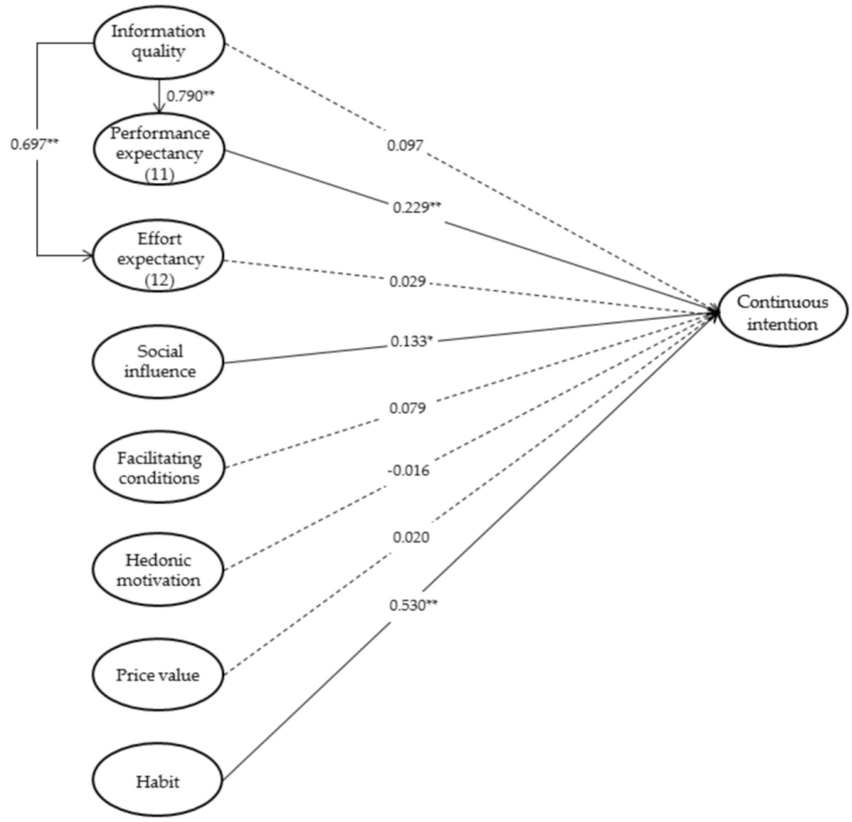


Figure 8.12 – Lee, Sung and Jeon's Model and Results for Reuse Intention[133].

In addition, Verma (2020) used the Stimulus-Organism-Response Theory[134] and the Consumer Value Theory[135] to design a model that explains purchase intention on Indian FDAs using transaction reliability as an antecedent. Likewise, transaction reliability is mapped to having product presentation, product availability and ease of use as stimuli anteceding it. On top of that, the research aimed at understanding differences in these relations between the male and female gender. The entire model was tested and supported, in exception of the influence of product availability over transaction reliability. It was also concluded that males have a higher perception of transaction reliability with better presentation and ease of use, while females perceive abundance in product availability with better presentation. The study suggests that food presentation on mobile devices generates a sense of product availability, which itself eases the use of the application. It also concluded that gender is a moderator for mediation effects. Figure 8.13 shows the structural model and hypotheses results of this research.

[133] Taken from Lee, S. W., Sung, H. J., & Jeon, H. M. (2019). Determinants of continuous intention on food delivery apps: extending UTAUT2 with information quality. Sustainability, 11(11), 3141.

[134] The Stimulus-Organism-Response Theory, known as SOR, is a theory stating that it is possible to stimulate user's emotions and internal state to obtain desired behavioral responses.

[135] Consumer Value Theory, known as CVT, is a theory stating that purchase intention is influenced by what consumers believe they get from using a service, namely the perceived utility and epistemic values.

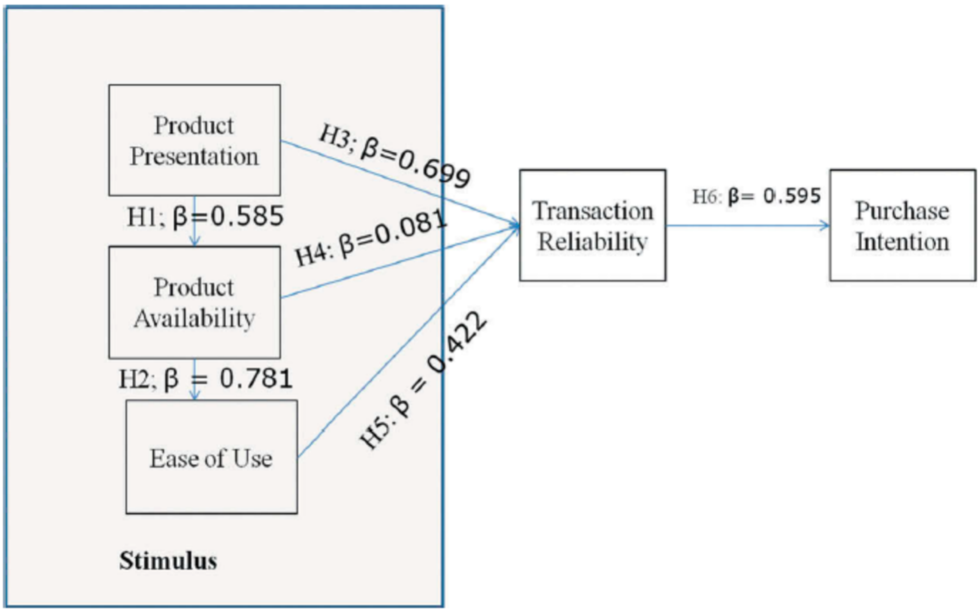


Figure 8.13 – Verma's Structural Model and Results for Purchase Intention[136].

Finally, Belanche, Flavián and Perez-Rueda (2020) created a model based in the Theory of Planned Behavior to explain both intention to use FDAs and intention to spread references about an FDA. Specifically, the constructs attitude, subjective norms, perceived control, security and app lifestyle compatibility were modeled and tested on citizens from the United States. This was performed along with the demographic variables age, gender and occupation, which fulfilled the role of control variables. Multiple relations were supported, allowing the research team to conclude that both attitude and subjective norms have a strong prediction power regarding intention to use and on word of mouth. Regarding intention to use, it is also influenced positively by the customer's lifestyle compatibility, while word of mouth intention is influenced by security. Interestingly, it was also concluded that older customers need to perceive control over the application before manifesting an interest to recommend it. The model tested by the authors is shown in Figure 8.14.

[136] Taken from Lee, S. W., Sung, H. J., & Jeon, H. M. (2019). Determinants of continuous intention on food delivery apps: extending UTAUT2 with information quality. Sustainability, 11(11), 3141.

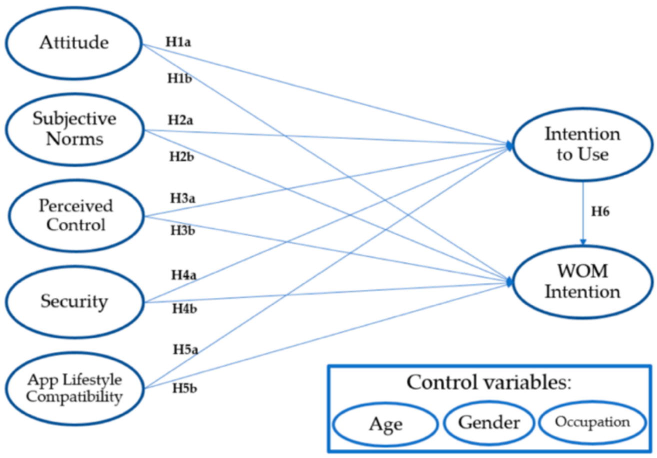


Figure 8.14 – Belanche, Flavián and Perez-Rueda's Structural Model and Results for Purchase Intention[137].

In addition, Table 8.1 summarizes the conclusions of the relevant complementary studies previously mentioned in the Literature Review. Conclusions form these models are used as clustering variables in section 3 and detailed in Appendix 2.

Author (Year)	**Research Objective**	**Relevant Conclusions**
Elvandari et al. (2017)	Influence of satisfaction, quality of service, technical requirements, and service delivery on OFD usage intentions	Order conformity, politeness / friendliness of delivery staff, cleanliness of food box, condition received ordered food, and affordable delivery costs influence customer behavior.
Pigatto et al. (2017)	Analysing feasibility of websites based on its content, functionality and usability.	Social platforms are publicizing and effectively increasing business visibility; requiring to focus on the content, functionality, and usability of a site.
See-Kwong et al. (2017)	Influence of revenue increase, broader customer reach, and better customer base on outsources intention.	The increase of revenue, broader customer reach, and willingness to create a better customer base influences business owners to outsource food delivery services.
He et al. (2018)	Examining the Agent-based O2O Food Ordering Model based model.	Food quality, preparation time, the takeaway time, and duration of online ordering are significant predictors of the agent-based food ordering mode.
Maimaiti et al. (2018)	Exploring the impact of OFDs on food shopping habits, increasing prevalence of overweight and obesity as well as diet-related Non-Communicable Diseases.	There are safety issues related to food and hygiene, as well as for the delivery staff because of increasing road accidents. Organisations should not only focus on improving success, but also looking at ways of reduce internal issues.
Suhartanto et al. (2019)	Relationship between quality of food and service, satisfaction, perceived value and consumer loyalty towards OFDs.	Importance of customers' delight in hygiene.
Yusra and Agus (2018)	Relationships between Mobile Service Quality and demographic information.	Personal innovativeness influences customer delight and faith.
Correa et al. (2018)	Influence of traffic conditions on factors influencing adoption of OFDs.	Traffic conditions had no association with transaction volume and delivery time fulfillment, except for some mild association between early deliveries and customer comments.

Table 8.1 – Conclusions of Complementary Studies on FDAs[138]

[137] Taken from Belanche, D., Flavián, M., & Pérez-Rueda, A. (2020). Mobile Apps Use and WOM in the Food Delivery Sector: The Role of Planned Behavior, Perceived Security and Customer Lifestyle Compatibility. Sustainability, 12(10), 4275.

[138] Adapted from Ray, A., Dhir, A., Bala, P. K., & Kaur, P. (2019). Why do people use food delivery apps (FDA)? A uses and gratification theory perspective. Journal of Retailing and Consumer Services, 51, 221-230

9. APPENDIX 2 – RELEVANT MODELS INVOLVING FOOD DELIVERY APPLICATIONS

Research Objective	Author(s)	Country	Explained Variables	Identified Relevant Relations	Discarded Relations
Understanding factors that influence continuous usage of FDAs after COVID 19 pandemic.	Zhao and Bacao (2020)	China	Continuance Intention Satisfaction Performance Expectancy	Confirmation - Satisfaction Confirmation - Performance Expectancy Perceived Task Technology Fit - Performance Expectancy Perceived Task Technology Fit - Continuance Intention Social Influence - Satisfaction Social Influence - Continuance Intention Trust - Satisfaction Trust - Continuance Intention Performance Expectancy - Satisfaction Performance Expectancy - Continuance Intention Satisfaction - Continuance Intention	Effort Expectancy - Continuance Intention Effort Expectancy - Performance Expectancy Effort Expectancy - Satisfaction
Evaluating the influence of moral obligations in FDA adoption.	Roh and Park (2019)	South Korea	Intention to use FDAs Usefulness Ease of Use Compatibility	Ease of use - Usefulness Ease of use - Intention Usefulness - Intention Compatibility - Ease of use Compatibility - Usefulness Compatibility - Intention Convenience orientation - Ease of Use Convenience orientation - Compatibility (single) Subjective norm - Compatibility Subjective norm - Usefulness Subjective norm - Intention	Convenience orientation - Compatibility (married)

Explaining the structural relationships between consumer experiences, attitudes and behavioral intention towards FDAs.	Yeo, Goh and Rezaei (2017)	Malaysia	Behavioral intention Attitude towards OFD Convenience Motivation Post-usage Usefulness	Hedonic Motivations - Convenience Motivation Hedonic Motivations - Post-usage Usefulness Prior Online Purchase Experience - Convenience Motivation Time Saving Orientation - Convenience Motivation Time Saving Orientation - Post-usage Usefulness Price Saving Orientation - Convenience Motivation Price Saving Orientation - Post-usage Usefulness Convenience Motivation - Post-usage Usefulness Convenience Motivation - Attitude towards OFD Convenience Motivation - Behavioral intention Post-usage Usefulness - Attitude towards OFD Post-usage Usefulness - Behavioral intention Attitude towards OFD services - Behavioral intention	Prior Online Purchase Experience - Post-usage Usefulness
Exploring quality attributes through perceptions, and understanding the difference between single and married individuals.	Cho, Bonn and Li (2019)	China	Intention to continue using Perceived Value Attitude towards FDAs	Convenience - Perceived Value Design - Perceived Value Trustworthiness - Perceived Value Various food choices - Perceived Value Perceived Value - Attitude Perceived Value - Intention Attitude towards FDAs - Intention	Price - Perceived Value
Understanding the motives behind FDA usage by associating uses and gratification to intention.	Ray et. al. (2019)	Not specified	Intention to use	Customer experience - Intention Search of restaurants - Intention Listing - Intention Ease of use - Intention	Convenience - Intention Societal pressure - Intention Delivery experience - Intention Quality Control - Intention

Identifying factors influencing emotional response and willingness to use apps in the surge of food delivery services.	Jeon, Kim and Jeong (2016)	South Korea	Reuse intention Arousal Pleasure	Design - Arousal Sympathy - Arousal Design - Pleasure Reliability - Pleasure Informativity - Use intention Mobility - Use intention Pleasure - Use intention	Informativity - Arousal Mobility - Arousal Reliability - Arousal System Capability - Arousal Informativity - Pleasure Mobility - Pleasure Sympathy - Pleasure System Capability - Pleasure Design - Use intention Reliability - Use intention Sympathy - Use intention System Capability - Use intention Arousal - Use intention
Explaining the drivers behind ecofriendly behavior intention of drone food delivery services.	Kim and Hwang (2020)	South Korea	Eco-behavioral intention Attitude Personal Norm Ascribed Personality	Problem awareness - Ascribed responsibility Ascribed responsibility - Personal norm Personal norm - Behavioral intentions Attitudes - Behavioral intentions Subjective norm - Behavioral intentions Perceived behavioral control - Behavioral intentions Problem awareness - Attitude Subjective norm - Personal norm	
Exposing the relationship between consumer persuasion and available information in FDAs.	Gunden, Morosan and DeFranco (2020)	United States	Persuasion Utilitarian web browsing Hedonic web browsing	Price saving orientation - Utilitarian web browsing Price saving orientation - Hedonic web browsing Hedonic web browsing - Persuasion Social Influence - Persuasion	Utilitarian web browsing - Persuasion

Examining relationships between reuse intention and familiarity, satisfaction, perceived ease of use and perceived usefulness.	Choi (2020)	South Korea	Reuse Intention Perceived Usefulness Perceived ease of use Satisfaction	Familiarity - Reuse Intention Familiarity - Perceived ease of use Familiarity - Perceived Usefulness Familiarity - Satisfaction Perceived ease of use - Perceived Usefulness Perceived Usefulness - Reuse Intention Perceived Usefulness - Satisfaction Satisfaction - Reuse Intention	Perceived ease of use - Satisfaction
Identifying the key determinants that affect use intention of FDAs, using the UTAUT2 model.	Lee, Sung and Jeon (2019)	South Korea	Continuous intention Performance expectancy Effort Expectancy	Information quality - Performance expectancy Information quality - Effort Expectancy Performance expectancy - Continuous intention Social influence - Continuous intention Habit - Continuous intention	Information quality - Continuous intention Effort Expectancy - Continuous intention Facilitating Conditions - Continuous intention Hedonic motivation - Continuous intention Price value - Continuous intention
Examining how FDAs affect user's cognitive and affective states, along with subsequent behavior.	Verma (2020)	India	Purchase Intention Transaction Reliability	Presentation - Product Availability Product Availability - Ease of use Presentation - Transaction Reliability Ease of Use - Transaction Reliability Transaction Reliability - Purchase Intention	Product Availability - Transaction Reliability
Analyzing the factors impacting FDA consumer perception.	Koiri, Mukherjee and Dutta (2019)	India	Perception	Convenience - Perception Mode of Payment - Perception Time saving - Perception Offers - Perception	Variety Seeking - Perception

Understanding the main motivations leading consumers to use and recommend FDAs.	Belanche, Flavián and Perez-Rueda (2020)	United States	Intention to use WOM Intention	Attitude - Intention to use Subjective norm - Intention to use App Lifestyle compatibility - Intention to use Occupation - Intention to use Attitude - WOM Intention Subjective norm - WOM Intention Security - WOM Intention Age - WOM Intention Intention to use - WOM Intention	Perceived Control - Intention to use Security - Intention to use Age - Intention to use Gender - Intention to use Perceived Control - WOM Intention App Lifestyle compatibility - WOM Intention Gender - WOM Intention Occupation - WOM Intention
Comprehending the factors influencing FDA usage frequency.	Nanaiah, 2020	India	Ordering Frequency	Offers & discounts - Ordering Frequency Delivery time - Ordering Frequency	Restaurant options - Ordering Frequency User interface - Ordering Frequency Penalties charged - Ordering Frequency

10.APPENDIX 3 – ELECTRONIC QUESTIONNAIRE

Block	Questions and Statements	Code name
Screening Question	Between January 2020 and today, have you used a Food Delivery Application (like UberEats, iFood, Glovo, Bolt Food or Rappi) at least once?	Q1_Screening
Behavior Questions	How frequent do you use any food delivery application?	Q2_Frequency
	Do you have any preference on Food Delivery Applications? You may choose multiple answers:	Q3_Preferences
	How long have you been using food delivery applications?	Q4_Tenure
Construct Satisfaction (SA)	(SA1) Overall, I am satisfied with the Food Delivery Applications that I use.	Q5_SA1
	(SA2) The Food Delivery Applications that I use meet my expectations.	Q6_SA2
	(SA3) I recommend my Food Delivery Applications to others who intend to use these services.	Q7_SA3
	(SA4) The Food Delivery Applications that I use are beneficial tools for ordering food and having it delivered at my preferred location.	Q8_SA4
Construct Attitude (AT)	(AT1) Using a Food Delivery Application is useful	Q9_AT1
	(AT2) I am strongly in favor of ordering food through a delivery application.	Q10_AT2
	(AT3) I desire to use a delivery app when I purchase food	Q11_AT3
Construct Usefulness (US)	(US1) Using a Food Delivery Application enables me to accomplish food shopping more quickly than using traditional approaches.	Q12_US1
	(US2) Using a Food Delivery Application enhances my effectiveness in shopping or seeking for information.	Q13_US2
	(US3) I find the services provided by Food Delivery Applications to be useful.	Q14_US3
	(US4) I consider that using Food Delivery Applications and their services to be a privilege.	Q15_US4
Construct Performance Expectancy (PE)	(PE1) I find Food Delivery Applications to be useful in my daily life	Q16_PE1
	(PE2) Using Food Delivery Applications increases my chances of purchasing foods that are important to me.	Q17_PE2
	(PE3) Using a Food Delivery Application enables me to accomplish the purchasing process more quickly.	Q18_PE3
	(PE4) I can save time when I use a Food Delivery Application for purchasing foods.	Q19_PE4
Construct Ease of Use (EU)	(EU1) I find it easy to order food using a Food Delivery Application.	Q20_EU1
	(EU2) My operation of a Food Delivery Application is clear and understandable.	Q21_EU2
	(EU3) Using a Food Delivery Application does not require a lot of mental effort.	Q22_EU3
Construct Social Influence (SI)	(SI1) People who are important to me think that I should use Food Delivery Apps for purchasing foods	Q23_SI1
	(SI2) People who influence my behavior think that I should use Food Delivery Apps for purchasing food.	Q24_SI2
	(SI3) People whose opinions I value prefer that I use Food Delivery Apps for purchasing food.	Q25_SI3
Construct Trust (TR)	(TR1) I believe Food Delivery Applications are trustworthy.	Q26_TR1
	(TR2) I believe Food Delivery Applications keep customers' interests in mind.	Q27_TR2
	(TR3) I feel secure in ordering and receiving food through Food Delivery Applications.	Q28_TR3
	(TR4) The information provided by my Food Delivery Applications is reliable.	Q29_TR4
Construct Compatibility (CO)	(CO1) Using a Food Delivery Application fits well with my lifestyle	Q30_CO1
	(CO2) Using a Food Delivery Application is compatible with my current situation in life.	Q31_CO2
	(CO3) Ordering food using a Food Delivery Application is compatible with the way I feed myself.	Q32_CO3
	(CO4) Ordering food using a Food Delivery Application fits well with the way I live my daily life.	Q33_CO4
Demographics	How old are you?	Q34_Age
	Select the gender you mostly identify with	Q35_Gender
	What is your Nationality?	Q36_Nationality
	What is your highest level of education (completed):	Q37_Education

11.APPENDIX 4 – CLUSTER TENDENCY ASSESSMENT

Complete Cluster Tendency Assessment

Best option	Second best

Evaluation Method	Evaluation description for expected result	Dataset 1		Dataset 2		Dataset 3		Dataset 4	
		Best K	Projection	Best K	Projection	Best K	Projection	Best K	Projection
Agglomerative dendrogram with single linkage and silhouette	Closest to 1	2	0.243 **	2	0.196	2	0.264 *	2	0.224
Agglomerative dendrogram with	Closest to 1	2	0.155	2	0.212 **	2	0.369 *	2	0.102
Agglomerative dendrogram with average	Closest to 1	2	0.38 *	2	0.232	2	0.346 **	2	0.290
Agglomerative dendrogram with ward	Closest to 1	2	0.242 **	2	0.162	2	0.221	2	0.277 *
Silhouette score with K-means	Closest to 1	2	0.23	2	0.238	2	0.257 *	2	0.250 **
Silhouette score with Mini Batch K-means	Closest to 1	2	0.234	2	0.234	2	0.256 *	2	0.255 **
Silhouette score with Spectral Clustering	Closest to 1	2	0.275 **	2	0.275 **	2	0.378 *	2	0.194
Distortion score - Elbow method with K-means	Lower the better	9	88086 *	9	114141 **	10	1666.467	10	1675.471
Gap statistic with K-means	Higher the better	13	0.836162	13	0.583967	13	-2.113252	10	-2.146255
Gap statistic with K-means	1-standard-error method	5	0.764693	4	0.517446	4	-2.192965	4	-2.202655
Calinski Harabasz score with K-means	Higher the better	2	115,709	2	126748	2	132764 **	2	136456 *
Calinski Harabasz score with Spectral Clustering	Higher the better	2	106587 **	2	109700 *	2	31267	3	28646
Davies-Bouldin score with K-means	Lower the better	10	1.675890	2	1.620155	2	1.559055 **	2	1.55276 *
Hopkins statistic	Closer to zero	N/A	0.339658 **	N/A	0.375574	N/A	0.332344 *	N/A	0.374745
Total Methods with Best Option			**2**		**1**		**6**		**3**
Total Methods with Second Best Option			**5**		**3**		**3**		**2**
Overall Result with Best and Second Best Option			**7**		**4**		**9**		**5**
Mode for projected number of clusters			**2**		**2**		**2**		**2**
Mean for projected number of clusters			**4**		**4**		**4**		**3**
Median for projected number of clusters			**2**		**2**		**2**		**2**

* Best option for the evaluation technique ** Second Best option for evaluation technique

12.APPENDIX 5 – SPECIFICATIONS FOR EVALUATING MODELING TECHNIQUES

Algorithm	Pre-parameter Finetuning	Evaluated parameters and levels	Best and Second Best Results	Final Parameters used	Cluster Distribution	Silhouette Score
K-Means	Information from the cluster tendency assessment is used as input.	n_clusters_list = (2, 3, 4, 10, 13)	N/A	n_clusters = 2 init = 'k-means++' n_init = 10 random_state = 42	[0 - 234] [1 - 128]	0.257064
Minibatch K-means	Information from the cluster tendency assessment is used as input.	n_clusters_list = (2, 3, 4, 10, 13) batch_size_list = (10, 30, 50, 70)	1st: For n_cluster = 2, batch_size = 30, silhouette score= 0.2726117 2nd: For n_cluster = 2, batch_size = 50, silhouette score= 0.249221	n_clusters=2 init='k-means++' batch_size=30 random_state=42	[0 - 256] [1 - 106]	0.272611
Agglomerative Clustering	Distortion, Silhouette, Calinski Harabasz and Davies-Bouldin scores are plotted to find optimal number of K. Parameter is fine-tuned based on these results.	n_clusters_list = (2, 3, 4, 11) linkage_list = ("single", "complete", "average", "ward") affinity_list = ("euclidean", "manhattan", "cosine")	1st: For n_cluster = 2, linkage = average, affinity = manhattan, silhouette score is 0.355414. However, it has 91.5% of data in a single cluster. 2nd: For n_cluster = 2, linkage = ward, affinity = euclidean, silhouette score is 0.220943.	n_clusters= 2 linkage="ward" affinity="euclidean"	[0 - 137] [1 - 225]	0.220943
Mean Shift	The bandwidth is estimated with sklearn. Then it is used as a reference to see results above and below this value while parameter fine tuning.	bandwidth_list = (2.5064, 3.5064, 4.5064) cluster_all_list = (True, False)	1st: For bandwidth = 3.5064, cluster_all = True, silhouette score= 0.388289. However, this result has 97% of results in a single cluster. 2nd: For bandwidth = 3.5064, cluster_all = False, silhouette score = 0.246143. However, 89 records are classified as outliers, and 1 cluster has a single data point.	bandwidth=3.5064 cluster_all=True	[0 - 352] [1 - 10]	0.388289
Affinity Propagation	Default parameter of median for the preference is tested (33 clusters with 0.096449 score)	preference_list = (-1000,-800, -600, -200) damping_list = (0.5, 0.6, 0.7, 0.8, 0.9)	1st: For preference = -1000, damping 0.5, silhouette score = 0.249557. 2nd: For preference = -1000, damping 0.9, silhouette score = 0.162948.	random_state=42 preference=-1000 damping=0.5	[0 - 235] [1 - 127]	0.249557
DBSCAN	Epsilon is estimated using nearest neighbors to map points vs distances and identify the knee point. This is used as a reference to estimate the number of min_samples using Silhouette, Calinski-Harabasz and Davies-Bouldin scores.	min_samples_list = (10, 15, 16, 28, 29) eps_list = (1.9138, 2.9138, 3.9138) algorithm_list = ("ball_tree", "kd_tree", "brute", "auto") leaf_size_list = (15, 30, 45)	1st: For min_samples = 15, eps = 2.913822, algorithm = ball_tree, leaf_size = 30, silhouette score is 0.351709. However, it is only 1 cluster and 26 records classified as outliers. 2nd: For min_samples = 10, eps = 2.913822, algorithm = ball_tree, leaf_size = 45, silhouette score is 0.349789. However, it is only 1 cluster and 25 records classified as outliers.	N/A	N/A	N/A
OPTICS	A reachability plot is used to define initial parameter candidates for maximum epsilon. Minimum samples are defined from the pre-parameter tuning of DBSCAN.	min_samples_list = (10, 15, 16, 28, 29) eps_list = (1.9138, 2.9138, 3.9138) algorithm_list = ("ball_tree", "kd_tree", "brute", "auto") leaf_size_list = (15, 30, 45)	1st: For min_samples = 29 , cluster_method = dbscan, metric = manhattan, max_eps = 5, silhouette score is 0.199510. However, one cluster is for outliers - out of 2. 3rd: For min_samples = 28, cluster_method = dbscan, metric = cosine, max_eps = 0.35, silhouette score is 0.112550.	min_samples=28 cluster_method="dbscan" metric="cosine" max_eps=0.35	[-1 - 77] [0 - 182] [1 - 103]	0.11255
BIRCH	Information from the cluster tendency assessment is used as input.	n_clusters_list = (2, 3, 4, 10, 13) threshold_list = (0.3, 0.5, 1, 1.5) branching_factor_list = (30, 50, 70)	1st: For n_cluster = 2, threshold = 1.5, branching_factor = 50, silhouette score is 0.336903. However, out of 2 clusters, one has only 33 records. 2nd: For n_cluster = 2, threshold = 1, branching_factor = 50, silhouette score is 0.241101.	n_clusters=2 threshold=1 branching_factor=50	[0 - 107] [1 - 255]	0.241101
Spectral Clustering	Information from the cluster tendency assessment is used as input.	n_clusters_list = (2, 3, 4, 10, 13) threshold_list = (0.3, 0.5, 1, 1.5) branching_factor_list = (30, 50, 70)	1st: For n_cluster = 3, assign_labels = discretize, eigen_solver = arpack, affinity = rbf, silhouette score is 0.201528. However, clusters 1 is highly concentrated. 2nd: For n_cluster = 2, assign_labels = discretize, eigen_solver = arpack, affinity = nearest_neighbors, silhouette score is 0.198844.	n_clusters=2, assign_labels="discretize" eigen_solver = "arpack", affinity = "nearest_neighbors" random_state=42	[0 - 184] [1 - 178]	0.198844