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Next Best Action: Optimizing Communication Channels by Customer Segment in the Telecommunications Industry

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NEXT BEST ACTION: OPTIMIZING COMMUNICATION CHANNELS BY CUSTOMER SEGMENT IN THE TELECOMMUNICATIONS INDUSTRY

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Internship Report

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Abbreviations list

ATGC	Attitude toward Gamified Communication
B2C	Business-to-Consumer
C	Convenience
CE	Customer Experience
CRM	Customer Relationship Management
I	Innovation
L	Loyalty
N/A	Not Available
NBA	Next Best Action
OP	Openness to personalization
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
RA	Risk Aversion
RFM	Recency, Frequency, Monetary
TAM	Technology Acceptance Model
TP	Time Pressure
WUDT	Willingness to use digital touchpoints

Abstract

As part of the completion of the Master's degree in Economics of Business and Strategy at the Faculty of Economics of University of Porto, this report was developed, inspired by the curricular internship carried out at *NOS Comunicações S.A*, a leading telecommunications company in Portugal. The focus of the work is to explore how Next Best Action (NBA) strategies can be optimized by segmenting customers into different clusters to identify the most effective communication channels for each. The main objective is to create customer clusters based on behavioral and demographic data and determine the ideal communication channel for each segment, enhancing the efficiency of NBA strategies.

This study mainly involves collecting data through a survey to analyze customer behavior and preferences in different communication channels. In other words, it uses a combination of data analysis and cluster analysis to categorize customers based on their preferences for different communication touchpoints (such as email, telephone, physical store, etc.) and behaviors. In this way, by taking advantage of customer profiles and historical interactions data, the main objective of identifying the most effective communication channels is facilitated, guaranteeing personalized and efficient customer engagement.

The survey results will be compared with an internal analysis developed as part of the NBA project *Best Way to Reach* at *NOS Comunicações S.A*., in which I was directly involved during my curricular internship. The results will provide insights into the importance of selecting the right communication channels, ensuring alignment with customer expectations and adapting to their unique preferences. This work demonstrates that optimizing communication strategies through data-driven insights can improve customer retention, satisfaction and overall company performance.

The implications of this study are relevant for marketing and customer relationship management (CRM) professionals in the telecommunications sector, as well as for other industries looking to improve their customer engagement strategies through data-driven decision making.

Key words: Communication Channels, Customer Segmentation, NBA, Omnichannel and Multichannel Communication, Telecommunications.

Resumo

No âmbito da conclusão do Mestrado em Economia da Empresa e Estratégia da Faculdade de Economia da Universidade do Porto, foi desenvolvido este relatório, inspirado no estágio curricular realizado na NOS Comunicações S.A. O foco do trabalho é explorar a otimização dos canais de comunicação tendo em conta a segmentação dos clientes, relevante para as estratégias *Next Best Action (NBA),* no sector das telecomunicações.

Este estudo envolve, essencialmente, a recolha de dados através um inquérito para analisar o comportamento e as preferências dos clientes em diferentes canais de comunicação. Por outras palavras, utiliza uma combinação de análise de dados e análise de clusters para categorizar os clientes com base nas suas preferências por diferentes pontos de contacto de comunicação (tais como e-mail, telefone, loja física, etc.) e comportamentos. Desta forma, tirando partido dos perfis dos clientes e dos dados históricos das interações, o objetivo principal de identificar os canais de comunicação mais eficazes é facilitado, garantindo um envolvimento personalizado e eficiente do cliente.

Os resultados do inquérito serão comparados com uma análise interna desenvolvida no âmbito do projeto de NBA *Best Way to Reach*, na NOS Comunicações S.A., no qual estive diretamente envolvida durante o meu estágio curricular. Os resultados permitirão perceber a importância de selecionar os canais de comunicação certos, garantindo o alinhamento com as expectativas dos clientes e adaptando-se às suas preferências únicas. Este trabalho demonstra que a otimização das estratégias de comunicação através de insights orientados por dados pode melhorar a retenção de clientes, a satisfação e o desempenho global da empresa.

As implicações deste estudo são relevantes para os profissionais de marketing e de gestão da relação com os clientes (CRM) no sector das telecomunicações, bem como para outras indústrias que procuram melhorar as suas estratégias de envolvimento dos clientes através da tomada de decisões baseada em dados.

Palavras-chave: Canais de Comunicação, Segmentação de Clientes, NBA, Comunicação Omnicanal e Multicanal, Telecomunicações.

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1 Introduction

Optimizing customer communications has emerged as a key objective for organizations seeking to improve engagement, retention and the overall customer experience in an increasingly competitive and digitalized business environment. The rapid expansion of digital communication channels and touchpoints presents both opportunities and challenges, requiring businesses to adopt data-driven and personalized communication strategies (Hallikainen et al., 2019). The incorrect channel selection, however, might result in poor communication, which lowers engagement, increases churn, and wastes money (Bayer, 2010). According to Valentini et al. (2011), customers are 40% more likely to accept an offer when they get information via their preferred channel.

The telecommunications sector is particularly dependent on an effective communication strategy, given the high volume of interactions generated daily, including billing notifications, marketing campaigns, customer support, and personal recommendations. Nevertheless, a lot of businesses continue to use general segmentation techniques without taking into account the unique communication channel preferences of each client (Bayer, 2010). A study by Alt et al. (2021) found that 56% of customers claim they reject messages that are not given by the channel they choose, and 74% of consumers express frustration when they get irrelevant communications from their telecom provider.

The Next Best Action (NBA) strategy is determining the optimal course of action for a client based on their past interactions and digital behavior (Bhandari et al., 2017) and it is a great way to improve customer interactions. It uses predictive analytics and customer data to identify the best action or message for each customer at a specific time (Rudskaia & Eremenko, 2019). To get the most out of this strategy, businesses need to figure out which ways to communicate are best for each group of customers. This makes sure that the right message is sent through the best ways to reach customers (Kim & Sugai, 2008).

This dissertation explores how important is for companies to implement a NBA strategy to enhance customer engagement, with a particular focus on identifying the most effective communication channels for different customer segments in the telecommunications industry.

1.1 Research gap and research problems

Significant progress has been made in the literature on multichannel communication and customer segmentation (Alt et al., 2021; De Keyser et al., 2015; Konuş et al., 2008; Nakano & Kondo, 2018; Neslin et al., 2006), particularly when considering consumer behavior and digital interactions (Hallikainen et al., 2019; Lemon & Verhoef, 2016; Nakano & Kondo, 2018; Sands et al., 2016; Verhoef et al., 2015). Nonetheless, there are still significant gaps in the allocation of communication channels to each client segment, particularly when considering Next Best Action (NBA) strategy. With emphasis on the telecommunications industry, this study aims to close these gaps by investigating the best ways to communicate with each group.

Although many studies examine customer segmentation according to the channels via which they obtain information or make purchases (Alt et al., 2021; De Keyser et al., 2015; Hallikainen et al., 2019; Konuş et al., 2008; Kumar & Venkatesan, 2005; Nakano & Kondo, 2018; Sands et al., 2016; Valentini et al., 2011; Van Nguyen et al., 2024), few specifically identify the most efficient channels for communication (Nakano & Kondo, 2018; Valentini et al., 2011). De Keyser et al. (2015), for instance, examined consumer segmentation during the search, purchase, and after-sales stages, emphasizing the value of continuous contacts for customer happiness and retention. However, the study focuses more on consumer preferences for various channels along the purchasing journey than it does on which channels are most productive for each sector. The same way, Rudskaia and Eremenko (2019) looked at how digital clustering can be used to forecast customer behavior and optimize interactions, but they did not connect this segmentation to the selection of the best channel for each communication.

On the other hand, Van Nguyen et al. (2024) and Valentini et al. (2011) have already addressed the topic of channel effectiveness for various segments in a more implicit manner, implying that particular customer profiles are associated with particular communication channels, but they haven't explored how this allocation can be dynamically optimized to maximize engagement and conversions. Furthermore, the tailoring of content (such product recommendations and offers) is the main emphasis of current NBA research, but picking the best channel for each encounter is not covered.

Although Hallikainen et al. (2019) do not incorporate this study with NBA logic, they also do investigate the classification and relative significance of digital channels for various

segments. The fact that businesses using NBA frequently employ the incorrect channel to contact with a consumer who may be better reached by another means undermines the strategy's effectiveness, indicating a significant gap. Another important factor is the absence of research on the telecom industry, which faces particular difficulties because of its high customer attrition rate, ongoing engagement requirements, and incredibly varied clientele (Bayer, 2010). Many researches on customer segmentation show that multichannel communication strategies can be applied in both retail industry (Konuş et al., 2008; Nakano & Kondo, 2018; Sands et al., 2016; Valentini et al., 2011; Van Nguyen et al., 2024) and services industry (Alt et al., 2021; De Keyser et al., 2015; Hallikainen et al., 2019; Kumar & Venkatesan, 2005), but few focus on the Telecommunications industry (De Keyser et al., 2015; Hallikainen et al., 2019), which leaves a knowledge gap about how telecom operators can successfully customize their interactions. For instance, Alt et al. (2021) investigated digital touchpoints in the insurance industry, demonstrating how diverse consumer categories engage via various channels. However, they did not apply their findings specifically to the telecom industry. In the meantime, Bayer (2010) examined segmentation tactics in the telecom industry but they did not connect segmentation to selecting the most suitable communication channels to each consumer profile.

As a result, there is a serious lack of research into the telecommunications industry's optimization of communication channels for each consumer segment, especially when it comes to the NBA, which is the focus of this dissertation.

1.2 Research objectives (and expected outcomes)

The goal of this research is to explore how customers perceive and interact with the communication channels offered by telecommunications operators and how these perceptions relate to the customers' individual characteristics and usage behavior. Ultimately, the goal is to identify the most appropriate channels for each customer segment — such as mobile applications, email, telephone, or physical stores — to support more effective and personalized communication strategies.

To achieve this, the study sets out the following specific objectives:

- To explore customer perceptions and preferences regarding key communication channels in the telecommunications sector.
- To identify relevant behavioral, and demographic variables that influence how customers engage with each channel.

- To segment customers using clustering techniques based on their characteristics and channel-related perceptions and identify the optimum channels for each segment to improve efficiency and effectiveness of communication.
- Understand how customers perceive the personalization of communications in the context of the NBA.
- Evaluate the potential of gamification as a strategy to increase engagement, drive digital channel usage, and build brand loyalty.
- Compare the results obtained with internal company results to validate the conclusions.

1.3 Adopted methodology

This study uses a quantitative methodology, with a questionnaire (Appendix A) as the primary data collection instrument. The survey was designed to capture consumers' perceptions of the Next Best Action concept, the importance of personalizing business interactions, and the identification of the most appropriate communication channel for each type of customer. The gathered data will be subjected to analysis using Smart-SPSS.

The study also quantifies the relevance of each communication channel, assigning scores according to customer segments. This makes it possible to understand behavioral patterns and preferences, which will help formulate strategic recommendations. Finally, the results obtained will be compared with the data collected during the internship, allowing a critical assessment of the applicability and effectiveness of business practices in the context of Next Best Action as well as the identification of any discrepancies between consumer perception and the companies' approach to personalized communication.

1.4 Structure of the thesis

The remainder of this work is organized as follows. The next chapter presents a comprehensive literature review that addresses the research objectives. Following that, the methodology section provides an overview of the research approach, including details on data gathering, sample characteristics, variables, and analysis methods. The study's findings are then carefully addressed after they have been presented and verified. After that, a chapter is presented detailing the internship program and the key conclusions of the related research along with a section for the comparison of the results of the internship with those of the dissertation. The final chapter is the conclusion, which summarizes the main theoretical contributions, managerial implications, limitations, and suggestions for future research.

2 Literature Review

2.1 Multichannel and Omnichannel Communication

2.1.1 Evolution of Communication Channels

Communication plays an essential role in the relationship between companies and customers, serving as a fundamental mechanism for transferring information, exchanging ideas and building relationships, and in the business context this is no exception. According to Sonea and Câmpeanu-sonea (2020), communication is not only the transmission of information, but also the interaction between two parties who share a common goal, directly influencing the content, form and results of this process.

Trust within an organization, whether internally or in relationships with customers, suppliers and partners, is directly dependent on how communication is conducted and results from management's commitment to quality, innovation and effective communication, leading to positive word-of-mouth that boosts the company's reputation and growth (Sonea & Câmpeanu-sonea, 2020). Transparency, honesty and personalized service are key factors in strengthening this trust and ensuring customer loyalty. Thus, companies that prioritize customer well-being over immediate profit build stronger, longer-lasting relationships. Sonea and Câmpeanu-sonea (2020) points out that companies that offer products that meet customers' real needs and consistent and engaging communication, rather than focusing solely on profitability, generate high levels of trust and loyalty over time. Some companies manage to create emotional connections with their consumers, fostering engagement and identification with the brand, making the company-customer relationship more than just a commercial transaction (Sonea & Câmpeanu-sonea, 2020).

Over the years, communication channels have evolved significantly (Alt et al., 2021; Neslin et al., 2006), moving from traditional face-to-face and written interactions to several different digital formats, such as telephone calls, emails, text messages and video calls (Rapp et al., 2013; Sands et al., 2016; Shorey et al., 2024; Verhoef et al., 2015). This shift has positioned internet-based channels as important complements to traditional ones, fundamentally reshaping business models and consumer shopping behavior which has allowed companies to adopt more efficient communication strategies, optimizing customer relations and increasing the accessibility of information (Alt et al., 2021; Verhoef et al., 2015).

2.1.2 Customer journey and touchpoints

With the advance of digitalization, consumers have started to interact with brands in a more dynamic way, using multiple channels throughout their purchasing journey – from initial research to finalizing the transaction, which has shortened the decision cycle, with many consumers switching from offline to online research, expecting more personalized offers (Alt et al., 2021). In this context, choosing the right communication channel has become a crucial strategic factor for organizations, directly influencing customer experience, behavior and engagement (Dalla Pozza et al., 2018; Lemon & Verhoef, 2016).

Each communication channel – whether physical, digital or hybrid – acts as a touchpoint, i.e. a point of interaction between the company and the client. These touchpoints occur at different stages and contexts of the journey (Lemon & Verhoef, 2016) and can be functional (e.g., websites, search engines), social (e.g., social media), or community-based (e.g., catalogs) (Hallikainen et al., 2019). When used in combination, they enhance convenience, information availability and decision-making quality (Alt et al., 2021; Grewal et al., 2017).

In this complex environment, effective communication management requires companies to understand how customers choose the channels they interact with. Valentini et al. (2011) identify three main factors that influence this choice: individual preferences, behavioral dependence, and the impact of marketing. These factors evolve over time – consumers, as they gain experience, become less reactive to marketing actions and more loyal to channels that offer them convenience and familiarity. Therefore, understanding this consumer learning is essential for defining and effective communication strategy.

2.1.3 Multichannel Management: Challenges and Opportunities

The multichannel approach arises precisely to respond to the diversity of preferences and behaviors. It entails using two or more marketing channels to target specific client segments (Kumar & Venkatesan, 2005; Rudskaia & Eremenko, 2019), allowing consumers to choose the most convenient channel for each decision stage. Neslin et al. (2006), define multichannel management as the process of planning, aligning, and assessing the use of different channels seeking to enhance customer value through strategies of acquisition, loyalty, and development. However, although it recognizes the existence of segmentation by channel, there is no universal model to describe it (Neslin et al., 2006).

Empirical studies indicate that multichannel consumers tend to spend more than those who only use one channel (Kumar & Venkatesan, 2005; Neslin et al., 2006). This difference, according to Neslin et al. (2006), can be attributed to greater loyalty, greater exposure to promotional actions and more active selection on the part of the consumer. Kumar and Venkatesan (2005) state that multichannel shoppers are not necessarily more loyal than single-channel shoppers. In addition, multichannel customers usually initiate more contact with the company, demonstrating involvement and knowledge of the available channels (Kumar & Venkatesan, 2005). Highly interpersonal channels such as telephone or direct contact, help to reduce the perception of the risk and increase trust, especially in more complex products (Kumar & Venkatesan, 2005).

Despite the benefits, the multichannel approach also has limitations. Duplication of channels can lead to cannibalization, where increased online sales reduce physical sales without improving profits (Neslin et al., 2006). In addition, multichannel companies face significant challenges, such as data integration, channel evaluation, resource allocation and strategy coordination (Neslin et al., 2006).

2.1.4 Omnichannel Strategy and Opti-channel

In response to these limitations, the concept of omnichannel has emerged, sometimes referred as cross-channel management, considered a natural evolution of multichannel management (Verhoef et al., 2015). While multichannel focuses on presence in multiple channels, omnichannel aims to fully integrate these channels, providing the customer with a fluid, continuous and frictionless experience between digital and physical (Rudskaia & Eremenko, 2019; Verhoef et al., 2015). In an omnichannel strategy, the barriers between different channels and devices become almost invisible – consumer switch between computer, smartphone and physical store naturally, expecting consistency in all interactions (Hallikainen et al., 2019; Verhoef et al., 2015).

As well as offering convenience, omnichannel allows for more effective personalization, supported by technologies including artificial intelligence, big data and machine learning – a concept known as Opti-channel (Rudskaia & Eremenko, 2019). This model seeks not only to integrate but also to optimize communication, offering each customer the most appropriate channel according to their profile and context. In this sense, it is essential for companies to gather and analyze personalized data in order to gain deeper insights into the behavior and preferences of their consumers (Rudskaia & Eremenko, 2019).

The importance of this strategic evolution is visible in contemporary shopping behavior. Consumers often access the internet to look for information or compare prices, even if the final purchase takes place in a physical store – known as webrooming (Verhoef et al., 2015). The reverse also happens (showrooming), where customers try out the product physically before purchasing it online (Verhoef et al., 2015). This behavior requires companies to be prepared to offer integrated experience, regardless of the channel used.

2.2 Next Best Action and Personalization

2.2.1 Concept and Importance of Next Best Action (NBA)

Understanding consumer behavior and predicting their needs has become a strategic focus for companies in today's competitive marketplace. This desire has led to the emergence of the Next Best Action (NBA) strategy, a data-driven marketing and customer relationship management strategy that uses historical, behavioral and contextual data to suggest the best course of action at every stage of the journey, whether it is an offer, a piece of content or an interaction (Cao & Zhu, 2022; Hallikainen et al., 2019; Rudskaia & Eremenko, 2019). Unlike traditional marketing, which relies on predefined customer journeys, NBA dynamically adapts to consumer behavior, increasing personalization and effectiveness (Sands et al., 2016).

The "next best action" concept is a customer-centric approach based on the idea that each customer should receive a recommendation that is specific to their current situation, past contacts and potential future paths (Fraihat et al., 2022). Based on continuously updated data, this method requires a customized, dynamic, sequential and interactive decision-making process (Cao & Zhu, 2022). In fact, to be effective, it is necessary to take into account a number of factors when suggesting personalized activities, including the customer's history and current circumstances, the evolution of their preferences and the organization's strategic goals (Fraihat et al., 2022; Sands et al., 2016). As a result, each action should be designed to generate both immediate value and long-term impact (Cao & Zhu, 2022).

The implementation of multichannel and omnichannel communications strategies is essential to NBA performance. According to Nakano and Kondo (2018), omnichannel strategies integrate multiple channels to provide a consistent and customized experience across touchpoints, whereas multichannel strategies utilize a variety of separate channels to reach customers. The increasing popularity of digital touchpoints, such as chatbots, social

media, email and mobile applications, in NBA deployments can be attributed to their capacity to collect data and engage users in real time (Hallikainen et al., 2019).

2.2.2 Technology Enabling NBA: CRM and Predictive Analytics

The development of machine learning techniques, data science and artificial intelligence has made it possible to automate the suggestion and selection of customized actions, even in complex situations involving numerous interactions and large amounts of data (Cao & Zhu, 2022; Rudskaia & Eremenko, 2019). The digitalization of data and the growth of online behavior have created special opportunities for large-scale behavioral data mining (Khodabandehlou & Zivari Rahman, 2017). Learning experiences that support the customization of recommendations are built using the digital footprints left by customers, including what they watch, read and rate (Khodabandehlou & Zivari Rahman, 2017). These customized insights are made possible by machine learning methods that identify trends in huge datasets and enable systems to adjust dynamically to user preferences. The adoption of predictive analytics combined with machine learning has led to significant advancements in NBA strategy, particularly with regard to real-time segmentation and automated decision-making (Rudskaia & Eremenko, 2019). To compare different profiles and make customized decisions based on a shared representational space, predictive models enable the transformation of historical behavior, current circumstances and customer sensibilities into universal vector representations that serve as the basis for recommendations (Cao & Zhu, 2022; Surendro, 2019). Because predictive analytics techniques allow for the extraction of patterns, trends and preferences from large volumes of digital data, organizations are increasingly using them to achieve this goal (Ghorbantanhaei et al., 2024; Khodabandehlou & Zivari Rahman, 2017), thereby anticipating consumer needs and interacting with them through the most effective channels (Kim & Sugai, 2008).

This type of strategy is closely related to the idea of analytical CRM, where a key objective is to predict customer behavior, such as churn, purchase trends or campaign response (Kuang et al., 2023; Surendro, 2019; Zhang et al., 2013). By anticipating trends, optimizing resource allocation, implementing targeted marketing and personalizing the experience for the correct audience at the optimal time, this kind of technological sophistication enables companies to move from a reactive to a proactive approach (Ghorbantanhaei et al., 2024). As such, the NBA is a natural evolution of fixed systems that

have been replaced by flexible methods that are better suited to fostering satisfaction and loyalty (Ghorbantanhaei et al., 2024).

2.2.3 NBA in the Telecommunications industry

This technique is particularly important in the telecom industry as operators compete with each other and customers have the option to switch providers, demanding a value-based and personalized approach (Deval et al., 2019). According to Fraihat et al. (2022) and Zhang et al. (2013), telecom customers are becoming more selective and want real-time offers and communications tailored to their interests and needs. To retain customers and ensure sustainable long-term revenue (Fraihat et al., 2022), increase engagement, improve retention and sustain long-term growth (Cao & Zhu, 2022; Deval et al., 2019; Ghorbantanhaei et al., 2024), it is critical to identify and propose the optimal offer for each individual.

Despite the potential for personalized recommendation systems, their implementation in the telecommunications sector is especially demanding, given the industry's unique characteristics. As Zhang et al. (2013) point out, telecommunications products and services are highly complex, combining devices with detailed sub-services (such as tariffs, data packages, discounts and rewards). In addition, they are frequently updated, but customers only use one product at a time, which limits the amount of comparative feedback available. Also, many customers express preferences using subjective terms such as "good" or "interested", making it difficult to automatically analyze and generate effective recommendations. Furthermore, Fraihat et al. (2022) claims that the data characterizing the behavior of a large customer base can be described as extremely noisy. Only intelligent systems, such as recommender systems, can automatically process and suggest the best options for each customer, based on their profiles, behaviors and explicit or implicit preferences, especially with hundreds of products and frequent updates (Adomavicius & Tuzhilin, 2005; Bobadilla et al., 2010; Manouselis & Costopoulou, 2007; Zhang et al., 2013; Zhang et al., 2011).

The telecommunications industry has widely adopted these systems, which are among the most effective online personalization applications, to improve the shopping experience, increase conversion rates and reduce abandonment (Adomavicius & Tuzhilin, 2005; Bobadilla et al., 2010; Zhang et al., 2011). The NBA uses the same reasoning, but it goes beyond simply suggesting products. It combines AI, predictive analytics and personalization to make tactical and strategic decisions about the best time, channel and

content to engage with each customer to optimize the value and impact of the action (Cao & Zhu, 2022).

2.3 Client Segmentation and Effective Communication

2.3.1 Concept and relevance of customer segmentation

An essential technique for tailoring marketing tactics and increasing the effectiveness of cross-channel communications is customer segmentation. It is important to increase customer retention, loyalty and identification of the value of each customer (Koul & Philip, 2021). According to Alt et al. (2021) and Koul and Philip (2021), segmentation involves identifying and describing groups of buyers according to their different needs and desires. Koul and Philip (2021) recognizes six different segmentation types for customer segmentation: Psychographic, Geographic, Demographic, Behavioral, Propensity-Based and Value-Based. There are two main methods for this process: either segmenting using descriptive variables (such as demographics, geography or psychographics) and then profiling behavior, or segmenting behavior and using demographic variables to describe it (Alt et al., 2021).

Studies indicate that customer communication preferences vary by segment, highlighting the need to optimize NBA execution for each group (Konuş et al., 2008; Kumar & Venkatesan, 2005). For example, younger and tech-savvy consumers are more likely to prefer digital channels like social media and smartphone applications, whereas old consumers may still rely on more conventional touchpoints like phone calls and emails (Shorey et al., 2024). Grasping these differences is crucial to enhancing the effectiveness of NBA strategies (Sands et al., 2016).

2.3.2 Insights from previous segmentation research

In the context of digital channel use, Alt et al. (2021) segmented potential life insurance customers according to their personal characteristics, information-seeking behavior and preferred purchase channels. Their study revealed four segments – young fully offliners, mature fully offliners, committed online searchers and cross-channel onliners - with 55% of the sample still being classified as fully offliners. Similarly, De Keyser et al. (2015); Konuş et al. (2008); Nakano and Kondo (2018) identified clusters of customers who use digital and physical channels across the various phases of the customer journey – from

information search to purchase and after-sales – leading to segments such as multichannel enthusiasts, store-oriented customers, and highly involved shoppers.

These studies show that segmentation is critical to build successful multichannel customer management strategies (De Keyser et al., 2015; Neslin et al., 2006). Segmentation based on actual behavior data (including channel usage patterns, rather than just attitudes) provides a more accurate reflection of customer preferences and habits (Gensler et al., 2012; Konuş et al., 2008; Nakano & Kondo, 2018). For instance, De Keyser et al. (2015) extended Konuş et al. (2008) research and identified six clusters based on preferences at each stage: research shoppers (online search, in-store purchase), web-focused shoppers (online in both stages), store-focused shoppers, research shoppers (online search, internet/in-store purchase), web-focused shoppers (online search, store/call center purchase) and call center-prone shoppers.

Channel choice and use are strongly related to consumer characteristics such as age, loyalty, level of engagement, technological literacy and attitudes towards innovation (De Keyser et al., 2015; Konuş et al., 2008; Nakano & Kondo, 2018). These studies show that younger consumers tend to prefer mixed or digital and mobile channels, while older customers stick to face-to-face channels. Beyond demographics, psychographic, variables such as innovativeness, pleasure derived from shopping, customer loyalty, sensitivity to price, and perceived time pressure also influence channel choice (Konuş et al., 2008). Innovative consumers show a greater affinity for digital channels, while the most loyal show single-channel behavior (Konuş et al., 2008).

On the other hand, Hallikainen et al. (2019) highlight that differences between segments are often more related to technology readiness and internet use than to age or gender alone. They found that functional digital touchpoints such as email, websites and search engines were most frequently preferred, regardless of demographic profile.

2.3.3 Techniques used for Customer segmentation

To identify these patterns, researchers can apply simpler segmentation techniques, such as Recency, Frequency, Monetary Value (RFM) models, which are typically used to classify customers in terms of loyalty, profitability, and abandonment risk (Fraihat et al., 2022), or opt for more advanced clustering techniques such as K-Means Clustering Algorithm, Hierarchical Clustering, Density-Based Clustering, Affinity Propagation

Clustering, among others (Koul & Philip, 2021). K-means, which is particularly effective when dealing with large datasets (Tripathi et al., 2018) is very simple to use and is considered by Koul and Philip (2021) as the best clustering technique comparing to others. Clustering allows software to identify the most important aspects of customer behavior while improving the precision of individual offers helping to identify customers who are likely to churn, upgrade or respond to specific campaigns (Bayer, 2010; Fraihat et al., 2022; Rudskaia & Eremenko, 2019). These methods make it possible to create microsegments based on real data, allowing companies to tailor offers and communications with high precision (Bayer, 2010; Fraihat et al., 2022; Rudskaia & Eremenko, 2019). This type of advanced segmentation is fundamental in a highly competitive market context, where mechanical divisions by age, gender or location are no longer sufficient (Rudskaia & Eremenko, 2019). Table B.1, in Appendix B, shows some different techniques used in previous studies of clustering.

2.3.4 Strategic Advantages and Effects of Customer Segmentation

In the telecommunications industry, segmentation has moved beyond the traditional distinctions such as prepaid/postpaid or business/consumer. Companies are now using advanced customer lifecycle and value-based segmentation to improve customer retention, personalize offers and align marketing with specific growth objectives (Bayer, 2010). Micro-segments allow companies to set goals for each group while delivering timely, relevant communications (Bayer, 2010).

In addition, research by Hallikainen et al. (2019); Nakano and Kondo (2018); Sands et al. (2016) reveals that multichannel customer segmentation continues to evolve with the integration of mobile and social media, while other segments still avoid these channels. These findings reflect broader trends in channel adoption, choice and usage, driven by marketing factors, channel attributes, social influence, situational context and individual differences.

Therefore, understanding the link between customer profiles and preferred channels is essential for effective communication management. Customer who value direct contact tend to prefer channels such as physical stores or call centers, especially when the product is complex or when they need clarification (De Keyser et al., 2015). On the other hand, more autonomous and transactional customers opt for digital channels, showing less loyalty and sometimes a lower average purchase price (De Keyser et al., 2015). In this context, segmentation based on actual channel usage behavior (rather than just attitudes or intentions)

offers a more accurate representation of reality (Gensler et al., 2012; Konuş et al., 2008; Nakano & Kondo, 2018).

Finally, segmentation is useful not only for targeting, but also for cost optimization. Identifying which segments use which channels (and in what stages of the journey) can help companies reduce investment in underutilized channels and prioritize those that deliver better engagement or revenue ((De Keyser et al., 2015; Nakano & Kondo, 2018; Rudskaia & Eremenko, 2019). Research consistently shows that store-focused or call-center-oriented customers may have higher loyalty but lower revenue, while research shoppers tend to be more profitable and web-focused shoppers are less loyal (De Keyser et al., 2015; Nakano & Kondo, 2018). Companies that adopt granular segmentation and apply differentiated strategies based on customer preferences and behaviors are able to optimize resources, increase the return on marketing efforts and strengthen loyalty (Hallikainen et al., 2019; Neslin et al., 2006).

Table 1 provides an overview of past segmentation studies, and the touchpoints analyzed across diverse industries and countries.

From fully offline shoppers to highly engaged multichannel users, the results show a wide range of customer clusters, derived from demographic and psychographic analysis. Despite sectoral differences, there is a common trend towards increasing integration of online and offline touchpoints in the customer journey. Additionally, some studies have expanded segmentation to encompass stages like information search (Alt et al., 2021; Konuş et al., 2008; Sands et al., 2016; Van Nguyen et al., 2024) and after-sales interactions (De Keyser et al., 2015; Sands et al., 2016; Van Nguyen et al., 2024), whilst others have only focused on purchase behavior (Hallikainen et al., 2019; Kumar & Venkatesan, 2005; Valentini et al., 2011). Despite the variety of sectors analyzed and the diversity of segmentation approaches, there is still limited research directly connecting customer segmentation to communication channel optimization, particularly in the telecommunications sector in Portugal.

Table 1 *Overview of Previous Customer Segmentation Studies and Channel Usage*

Authors	Touchpoints	Client clusters	Field of study	Country
Alt et al. (2021)	Family, friends Professional search engine Company webpage Professional website, platform	Young fully offliners Mature fully offliners Committed online searchers Cross-channel onliners	Insurance	Romania
De Keyser et al. (2015)	Brick-and-mortar stores Internet Call center.	Research shoppers - after sales: store Web-focused shoppers Store-focused shoppers Research shoppers – after sales: Internet / store Web-focused shoppers – after sales: store/call center Call center-prone shoppers	Telecom retailer	The Netherlands
Hallikainen et al. (2019)	Websites Email Search engines Social networks Photo and video content communities Discussion forums Blogs	Anti-digital Anti-social media Majority Digital Channel Enthusiasts	Telecommunication services Information technology services Furniture solutions and workplace-related services Healthcare services Security services	ND
Konuş et al. (2008)	Store Internet Catalog	Multichannel enthusiasts Uninvolved Shoppers Store-focused consumers	Retail stores (mortgage, health insurance, holidays, books, computers, electronics and clothing)	The Netherlands
Kumar and	Direct mail Telephone sales	Shopped in a single channel Shopped in two channels	High technology hardware and	ND

Venkatesan (2005)	E-mail Sales personnel Online website Brick and mortar retail stores	Shopped in three channels Shopped in four channels	software manufacturer	
Nakano and Kondo (2018)	Brick-and-mortar stores Online stores Media touchpoints of PC Media touchpoints of mobile Social media	Store-focused/anti-digital customers Store-focused light/anti-digital customer Store-focused light/multimedia social customers Store-focused/multimedia social customers Uninvolved shoppers Online-favored multichannel enthusiasts/PC customers Store-favored multichannel enthusiasts/multimedia social customers	Supermarkets, convenience stores, drugstores, department stores, specialty stores and online stores include Internet supermarkets, e commerce sites, and direct sales sites of brands.	Japan
Sands et al. (2016)	Brick-and-mortar Online store Mobile Social media	ROPO, anti-mobile/social media ROPO, multichannel enthusiasts ROPO, social media enthusiasts Internet-focused, anti-mobile Internet-focused, multichannel enthusiasts	Clothing, holiday travel and consumer electronics categories	Australia
Valentini et al. (2011)	Physical stores Catalogs Internet website Email	Learners Stayers	Book Club retailer	ND (Europe)
Van Nguyen et al. (2024)	Search engine Social Media Retailers Website E-WOM (forums, blogs and comments) Retailers' store	Digital Switchers Showroomers Offline Channel switchers Webroomers	Electronic goods retailers	Vietnam

2.3.5 Key variables for Clustering

2.3.5.1 Demographic variables

In consumer segmentation, demographic characteristics are frequently employed as fundamental components that provide an essential understanding of the client. When paired with behavioral and psychographic characteristics, they are particularly useful in characterizing and distinguishing consumer groups, even if they are not necessarily reliable indicators of channel choice on their own (Konuş et al., 2008)

Age is among the demographic factors that are most frequently utilized. It has been demonstrated by research that various age groups typically prefer distinct communication channels (De Keyser et al., 2015; Hallikainen et al., 2019; Konuş et al., 2008; Kumar & Venkatesan, 2005; Nakano & Kondo, 2018; Sands et al., 2016). While older groups may have a higher preference for traditional channels or in-store interactions, younger customers, for instance, are often more at ease with digital channels like smartphone applications (Alt et al., 2021).

Another factor that may influence channel choice is location or proximity to a physical store, especially in industries such as telecommunications where both online and offline service alternatives are available. According to Van Nguyen et al. (2024), the place of residence/location affects the choice of preferred channel.

Also, average daily Internet usage is becoming increasingly important in today's segmentation. It acts as a proxy for digital engagement by indicating how comfortable and knowledgeable a customer is with digital environments. According to Hallikainen et al. (2019) and Van Nguyen et al. (2024), consumers with higher online activity tend to show greater engagement with companies through digital channels and respond favorably to NBA initiatives presented via web, push, or app.

Although demographic segmentation occasionally uses characteristics such as gender (De Keyser et al., 2015; Hallikainen et al., 2019; Konuş et al., 2008; Nakano & Kondo, 2018) or education (Hallikainen et al., 2019; Nakano & Kondo, 2018), NBA research does not provide convincing evidence that these variables are relevant to channel selection.

2.3.5.2 Psychographic variables

Internal consumer attributes such as attitudes, beliefs, personality traits, and lifestyle choices are captured by psychographic variables (Konuş et al., 2008; Koul & Philip, 2021). These characteristics are particularly useful in the context of next best action (NBA) and multichannel communications because they go beyond demographic or transactional parameters to show how and why customers interact with specific channels (Nakano & Kondo, 2018; Valentini et al., 2011).

Technology adoption, or an individual's willingness to adopt and use new technologies, is a key psychographic component. This idea comes from the Technology Acceptance Model (TAM) , which explains behavioral intention through perceptions of usefulness and ease of use (Alt et al., 2021). According to Alt et al. (2021), higher levels of technology acceptance among customers make them more receptive to digital channels such as push notifications, company websites, and mobile applications.

Another important factor in channel preference is innovation, or the propensity to adopt novel solutions before others. Innovative customers are more likely to experiment with new digital touchpoints and respond favorably to communications sent through unusual or gamified platforms, according to Valentini et al. (2011).

Channel selection is also significantly influenced by convenience. According to Van Nguyen et al. (2024), customers are increasingly looking for interactions that are quick, easy, and available. People are choosing methods that save time and effort, such as SMS, in-app notifications, or one-click digital journeys, as they have a greater need for convenience.

Another factor is time pressure. According to Sands et al. (2016) and Konuş et al. (2008), people who feel time-constrained are more likely to choose rapid and low-effort communication forms, selecting direct and quick communications (like push or SMS) over channels that need more sustained attention (like phone calls or emails).

Risk aversion refers to a consumer's sensitivity to perceived insecurity or uncertainty throughout the communication process. Clients who are risk-averse tend to avoid new or unofficial channels in favor of more trustworthy, safe ones, such as official emails or in-person support. This trait affects reliance on traditional vs digital media (Konuş et al., 2008).

Finally, loyalty is a stable consumer attribute that reflects an individual's commitment and predisposition to maintain a long-term relationship with a company (Konuş et al., 2008;

Nakano & Kondo, 2018). Loyal consumers tend to respond more positively to NBA strategies and may show greater openness to experimenting with new communication channels recommended by their trusted brand.

2.3.5.3 Behavioral Variables

Behavioral factors explain how customers behave depending on their prior encounters, routines, and interactions with various brands and media. When it comes to NBA and omnichannel strategies, behavioral features provide valuable insights into how people interact with various touchpoints and frequently have a higher predictive potential than demographics alone (Valentini et al., 2011). In fact, Koul and Philip (2021) view behavioral segmentation as one successful segmentation method. It is the most popular since it makes data collection simple.

Customer experience, or the overall impression consumers have of their previous encounters with a business, is a crucial behavioral component. According to Lemon and Verhoef (2016); Van Nguyen et al. (2024), customers who have had positive experiences in the past are more likely to interact with future messages using the same channels. Negative experiences, however, may lead customers to avoid channels or be reluctant to respond to NBA offers, regardless of their timeliness or relevance.

Another crucial factor is the willingness to use digital touchpoints. As digitalization spreads across businesses, this characteristic helps differentiate between cautious and proactive consumers. Alt et al. (2021) found that there are notable disparities in customer segments' propensity to use websites, social networks, and other digital platforms for information and purchases, further supporting the importance of this behavioral variable in multichannel contexts.

Noorbehbahani et al. (2019) discovered that attitude toward gamified communication (ATGC) has also gained relevance in digital contexts. Though not often included in traditional NBA frameworks, recent studies suggest that gamified elements, such as challenges, incentives, and interactive experiences, can enhance engagement, particularly among customers who appreciate competition, excitement, and entertainment (Hamari & Koivisto, 2015). This variable can be used in customer segmentation to identify customers who are more receptive to interactive or fun communication forms.

Finally, openness to personalization reflects consumers' willingness to receive tailored communications and customized recommendations. According to Koul and Philip (2021), customers with higher openness to personalization are more inclined to accept NBA strategies, especially when recommendations are AI-driven or automated, since they perceive them as relevant and value-enhancing.

2.3.5.4 Telecommunications Variables

Finally, this study also includes a small set of variables specific to the telecommunications sector. These were selected due to their relevance within the scope of the industry, since the study is carried out in partnership with a major telecommunications operator. Some of these variables were identified in previous academic research, while others were inspired by knowledge gained during the author's internship, where they emerged as particularly significant in the implementation of customer communication strategies.

The first variable is contract type, which refers to the structure of the customer's plan (e.g., prepaid versus postpaid or bundled versus individual services). According to Ribeiro et al. (2024), this variable is often used in the telecommunications industry to distinguish between different consumer profiles and is considered extremely significant for customizing communication methods and NBA suggestions.

Membership in a loyalty program is another crucial factor that demonstrates a client's long-term engagement with the company (Ribeiro et al., 2024). It is an important feature for segmenting responses to NBA techniques because customers who are part of loyalty programs may have different communication preferences and be more open to personalized offers.

Lastly, a key component of this study is the variable Preferred Communication Channel. Although it is theoretically an outcome variable, it is examined here in various interactions common in the telecom sector, such as information requests, technical assistance, and contract renewals. Understanding how preferences change depending on the situation provides a more sophisticated understanding of which channels (e.g., SMS, apps, email, and call centers) are best suited for each client group in different service scenarios.

A summary of the variables used in this study, including their type, relevance, and the authors who have previously examined them, can be found in Appendix B, table B.2.

2.4 Gamification as a strategy to attract consumers to digital channels

The intentional use of gamification to improve consumer engagement and accelerate adoption of digital channels is becoming more widely recognized. According to (Hosseini & Haddara, 2019), gamification is the process of applying features of games to non-gaming environments to increase participation and encourage specific behaviors. Although, Huotari and Hamari (2017) consider it as the act of improving services by incorporating elements of gameful experiences to help users create value, rather than simply adding superficial game features. For instance, these can appear in the form of apps, websites or even ads-on games, using game mechanics to keep consumers active, interactive navigation and ads integrated into games respectively (Huotari & Hamari, 2017; Noorbehbahani et al., 2019). Some of the most common examples are point accumulation systems, progress bars, goals and challenges, storytelling, among others (Hosseini & Haddara, 2019). This way, gamification makes digital platforms more engaging and appealing. By increasing the number of visits, interactions and time spent on the platforms it improves user engagement, improves the effectiveness of digital advertising, and strengthens brand loyalty, in addition to significantly improving the business experience (Hosseini & Haddara, 2019; Huotari & Hamari, 2017; Noorbehbahani et al., 2019).

To sum up, gamification is proving to be an effective tactic for attracting customers to digital channels by enhancing the user experience, encouraging voluntary participation, and strengthening value creation. When done right, gamification not only fosters an instant connection with consumers, but also creates ongoing bonds based on enjoyment and loyalty.

3 Methodology

3.1 Data Collection and Sample

To investigate the determinants that lead customers to prefer specific communication channels, data were collected using a non-probability convenience sampling method, which selects participants based on accessibility and availability (Malhotra et al., 2017). This sampling method was chosen as it suited the purpose of the study and the available resources. However, since participants were not randomly selected, the results cannot be generalized to the entire population, and the sample may not be fully representative (Malhotra et al., 2017). The questionnaire (Appendix A) was developed in Google Forms and distributed online via social media platforms and messaging apps. Participation was voluntary and anonymous, and all respondents were required to give their informed consent before starting the survey. The collected data served as the basis for the quantitative analysis conducted in this research, including descriptive statistics, reliability testing and segmentation via cluster analysis.

The targets population consisted of customers with an operating telecommunications system, regardless of their service provider. The questionnaire was available to complete between 09/06/2025 and 12/07/2025, and a total of 200 valid responses were obtained after cleaning the data. Responses were excluded if participants did not provide consent, leaving a significant portion (more than 30%) of the survey unanswered or provided inconsistent or duplicate entries.

The sample reflects a varied set of customer profiles regarding gender, income level, digital usage habits and experience with telecoms services. Table C.1, in Appendix C, presents the sample characteristics (N = 200), considering factors such as age, gender, monthly income, education level, telecommunications operator and most used channel to contact the operator.

The age distribution of the sample is concentrated in two main groups: 18–24-year-olds (30.5%) and 45–54-year-olds (32.5%). Participants aged 55 to 64 represent 21%, while the remaining age categories account for 4.5% (25 to 34), 4.0% (35 to 44) and 7.5% (above 65).

In terms of income, participants who reported no income (20.0%) and those with monthly salaries between €2,000 and €2,999 (23.1%) stood out. Other categories include €1,000–€1,499 (14.5%), €1,500–€1,999 (11.0%) and €3,000–€4,999 (11.0%), while only 3.0% earn over €5,000, 7.5% less than €1,000, and 10.0% did not disclose their income.

Education levels are high, with 46.5% holding a bachelor's degree and 31.0% a master's or postgraduate degree. Just 0.5% have a PhD, while 20.5% have completed secondary education and 1.5% have other levels, including basic education or technical courses.

Participants tend to be women aged 18–24 or 45–54 with a bachelor's degree who earn between €2,000 and €2,999 per month or have no disclosed income.

3.2 Measurements

The online questionnaire is composed of six sections: (1) demographic data, (2) contextual information, (3) psychographic variables, (4) customer experience dimensions, being divided into the four types of channels, (5) attitude toward gamification and (6) openness to personalization. To ensure clarity and relevance, the questionnaire was initially tested with a small number of participants.

Demographic and contextual variables, such as age, income, location, telecommunications operator, digital usage, contract type, distance to store, and loyalty program membership, were collected as categorical or ordinal variables using predefined intervals, categorical option or yes/no options.

Psychographic and behavioral dimensions were captured using multi-item Likert scales, based on a 5-point range from 1 (strongly disagree') to 5 (strongly agree'), unless noted otherwise. The constructs used in this research are explained in Table 2 above, along with the authors who have already studied them. The full list of items used for each variable is presented in Appendix C, in Table C.2. These items were based on measures previously validated in the literature, also mentioned in Table C.2, in order to minimize any potential issues that could arise from the way the questions were formulated, to allow for data comparability and to guarantee the validity of the study. To analyze all the data collected by the above-mentioned questionnaire, programs such as Microsoft Office Excel and IBM SPSS

were used. Statistical analysis of the data allowed us to gather crucial information to understand the role that information channels play in users' lives.

The Innovation construct aimed to assess respondents' openness to using new and technologically advanced solutions in the purchasing process. This was assessed through five items adapted from the scale proposed by Goldsmith and Hofacker (1991). The Time Pressure construct aimed to capture respondents' perceptions of how much time they had to interact with the company or complete the purchasing process. Three items adapted from Beatty and Ferrell (1998) addressed issues such as sense of urgency, time availability and frequency of feeling pressured by time. Consumer loyalty was assessed using six items adapted from Zeithaml et al. (1996), later reduced to four, which analyzed the probability of purchasing again, recommend the company and maintain an ongoing relationship with the brand. The constructs Perceived Usefulness and Perceived Ease of Use were adapted based on the analysis developed by Davis (1989) within the Technology Acceptance Model (TAM), one of the most prominent models for explaining users' acceptance of technology. These constructs were operationalized through a set of items that sought to assess, respectively, consumers' perceptions of the functional value of the channels (e.g., whether they help them resolve requests or increase the efficiency of interaction with the company) and the ease associated with their use (e.g., clarity, comprehensibility, and simplicity of navigation). The items were applied separately to each channel (App, Email, Phone, and Store), allowing for a comparative analysis between different points of contact. The Convenience construct was assessed using 20 items adapted from Berry et al. (2002), 5 for each of the 4 channels, with a view to understanding the extent to which consumers value quick, flexible, and convenient access to services, including aspects such as no travel or ease of use at any time. To measure Customer Experience, we sought to capture how consumers evaluate their interaction with the brand, taking into account the clarity of information, speed of response, and ease of tracking orders. The 12 items included, adapted from Klaus and Maklan (2012), were also applied individually to each channel (App, Email, Telephone, and Store), allowing us to identify any differences in the perception of quality between them. The Risk Aversion construct was designed to evaluate how uncomfortable consumers feel in situations involving uncertainty or potential loss when interacting with the company. Twelve items adapted from Featherman and Pavlou (2003) were included to address concerns relating to privacy, the use of channels and service failures. As with other constructs, the statements were evaluated separately for each channel. To assess Willingness to Use Digital Touchpoints

(WUDT), 28 items (7 per channel) were used, inspired by the internship I made at NOS, which presented different situations (such as solving technical problems or dealing with billing) and asked respondents to what extent they would be willing to use each channel. This format allowed us to map the degree of openness to channels depending on the purpose of the interaction. Attitude Toward Gamified Communication (ATGC) was measured using three items adapted from Venkatesh and Davis (2000), with the aim of understanding the extent to which consumers value the introduction of playful elements (such as rewards, challenges, or rankings) in their interactions with the brand. As in the previous constructs, the items were evaluated independently for each channel. Finally, the construct Openness to Personalization was based on three items adapted from Chellappa and Sin (2005), which measured consumers' acceptance of the personalization of content, services, or communications based on their behaviors and preferences. The items were also applied by channel, which made it possible to identify contexts in which consumers demonstrate greater openness to this type of approach.

All the variables were created with dependability and relevance to the study's goals in mind, making it possible to evaluate the causes and effects of channel choice and usage patterns in the telecom industry with clarity.

3.3 Data Analysis Procedures

3.3.1 Data preparation

Data collected through the questionnaire were transferred from Google Forms to Microsoft Excel, where they were first verified for accuracy and completeness. It was then imported into IBM SPSS Statistics software, where all statistical analyses were performed.

The first step consisted of preparing and cleaning the database. All responses with more than 30% of questions unanswered, as well as inconsistent or duplicate records, were excluded. In addition, categorical variables were numerically coded so that they could be used in subsequent analyses.

3.3.2 Data Analysis

For categorical variables, absolute and relative frequencies were calculated, while for scale variables, a more complete analysis was made, including mean, mode, maximum,

minimum, median and standard deviation. A more detailed analysis was carried out to understand, for each item and channel, the overall pattern of respondents' answers.

The following stage involved examining the reliability of the scales. This was done by calculating Cronbach's alpha coefficient for each construct. According to Ribeiro et al. (2021) Cronbach's alpha (α) is a widely used statistic for evaluating the reliability of a questionnaire, as it indicates the level of internal consistency among the items within a given scale and that aim to measure the same concept. Its values fall between 0 and 1, with higher scores indicating more consistent answers (Hair et al., 2019; Ribeiro et al., 2021). Results that are extremely near or over 0.90 may suggest excessive duplication of content, i.e., the inclusion of duplicate items that assess the exact same feature of the construct, but α values equal to or greater than 0.70 are considered acceptable (Hair et al., 2019).

Although, before performing the cluster analysis, the responses to the individual items of each construct were aggregated. Specifically, the mean score of the items belonging to each scale (e.g., the five items that measured Convenience) was calculated in order to obtain a single indicator for each construct and channel. This procedure, in line with the approach proposed by Davis (1989), allowed the reduction of the number of variables, ensured that each construct was represented in line with its theoretical definition, and produced more stable measures by minimizing random variation across items. After this step, the sample was segmented using the K-means clustering technique, as it is one of the most widely used and computationally efficient techniques for dividing data into homogeneous groups (Fraihat et al., 2022) based on previously selected demographic, psychographic and behavioral variables. This technique makes it easier to identify unique consumer profiles by maximizing similarity within clusters and minimizing the gaps between them. Given the goal of this study was to put people in groups based on comparable communication channel perceptions and behaviors, its widespread use in consumer segmentation settings (Cheng et al., 2016) supports its applicability here. Furthermore, the same methodology was used for the segmentation conducted during the internship project, making the current approach especially suitable as it allows for direct comparison of results.

Since the dataset combined variables measured on different scales (e.g., behavioral constructs in Likert scales from 1 to 5, as well as sociodemographic variables with binary or broader numerical ranges), a standardization procedure was applied prior to the clustering analysis. The variables were converted to z-scores (mean = 0; standard deviation = 1),

ensuring their direct comparability and avoiding the overrepresentation of variables with larger scales or variances in the formation of groups (Moisl, 2010). Following this step, different numbers of clusters were tested in order to identify the most appropriate solution, with the final solution being defined as 5 groups. The five-cluster solution offers a clearer segmentation, as it increases the possibility of associating each cluster with a predominant communication channel (app, email, telephone, or physical store), thus providing more useful insights for the interpretation of customer profiles.

4 Results Analysis

4.1 Descriptive Statistics Analysis

After this analysis, Table C.3 presents a new one, the descriptive statistics for the items, allowing us to observe the central tendency and dispersion of responses for each variable, which provides an initial insight into the respondents' response patterns.

The analysis of the descriptive statistics of the items provides a detailed understanding of the participants' perceptions of each channel and dimensions evaluated.

The descriptive statistics reveal that the items predominantly have mean values between 3 and 4, suggesting moderately positive evaluations across constructs, with medians and modes generally converging around 4, which reinforces the internal consistency of the responses. Standard deviations mostly fall close to 1, indicating an acceptable level of variability that avoids excessive dispersion or uniformity. The full utilization of the 1–5 scale also demonstrates that the items are sensitive enough to capture different perceptions. Once recoded, reverse-coded items display values in line with the rest of the scale, confirming the adequacy of the measurement. Looking across channels, telephone and physical stores tend to obtain the highest evaluations in terms of usefulness, ease of use and overall experience, whereas the app and especially email register comparatively lower averages, pointing to a more moderate perception of their efficiency and convenience. Also, the app can gain greater relevance if the company invests in improving their perceived usefulness and usability, associating incentives (gamification) and ensuring transparency in the processing of personal data. Overall, these results indicate that the items behave as expected, with no anomalies that could compromise the validity of the constructs. This supports their aggregation and subsequent use in reliability and clustering analyses.

4.2 Internal Consistency Analysis

Subsequently, internal consistency and reliability were examined by calculating Cronbach's alpha for each variable, as well as the alpha value that would result if individual items were excluded, within a given construct (Table C.4).

The reliability analysis indicates that all constructs have Cronbach's alpha values above 0.70, which is considered acceptable, demonstrating good internal consistency of the

scales (Hair et al., 2019). The only exceptions were the Time Pressure construct, which had a particularly low alpha value and was therefore excluded from the analysis, and item RA_8R, which negatively impacted the reliability of the Risk Aversion scale and was consequently removed. The item OP_3 has an alpha, if the item is deleted, quite high compared to the other items because, despite being included in the OP construct, it measures the share of information that leads to personalization. Overall, the results confirm that the remaining constructions are reliable and adequate for subsequent analyses.

4.3 Clustering Analysis

After computing the aggregated mean values for each construct and standardizing the variables, the k-means cluster analysis was performed. Table 2 presents the results, displaying the standardized mean scores of the variables across the six clusters, which enables the recognition of the key patterns of channel preference and consumer characteristics within each group.

Table 2 *Standardized mean values of the aggregated channel measures for each of the five clusters*

		Cluster A	Cluster B	Cluster C	Cluster D	Cluster E	F	Sig.
App	Perceived usefulness	0.68	-0.62	-0.92	-0.23	0.28	20.281	0.000
	Perceived ease of use	0.57	-0.72	-0.21	0.03	0.32	18.730	0.000
	Convenience	0.68	-0.67	-0.78	-0.26	0.34	22.759	0.000
	Risk aversion	0.31	-0.37	-0.57	-0.59	0.47	10.796	0.000
	Customer experience	0.68	-0.65	-0.91	-0.35	0.38	24.558	0.000
	Willingness to use digital touch points	0.61	-0.55	-0.49	0.09	0.05	12.480	0.000
Email	Perceived usefulness	0.62	0.19	-0.79	0.27	-0.89	25.653	0.000
	Perceived ease of use	0.69	0.08	-1.03	0.27	-0.80	24.933	0.000
	Convenience	0.55	0.09	-0.38	0.02	-0.64	11.805	0.000
	Risk aversion	0.54	-0.07	-0.77	-0.35	-0.23	6.970	0.000
	Customer experience	0.77	-0.13	-0.70	0.30	-0.67	20.904	0.000
	Willingness to use digital touch points	0.55	0.19	-0.96	0.19	-0.72	17.160	0.000
Telephone	Perceived usefulness	0.34	-0.43	0.50	-0.17	0.18	5.853	0.000
	Perceived ease of use	0.48	-0.52	0.34	-0.54	0.36	13.699	0.000
	Convenience	0.49	-0.42	0.47	-0.45	0.16	9.084	0.000
	Risk aversion	0.55	-0.22	-1.54	-0.74	0.26	16.995	0.000
	Customer experience	0.58	-0.44	0.33	-0.53	0.15	11.481	0.000
	Willingness to use digital touch points	0.59	-0.36	0.98	-0.31	-0.12	10.476	0.000
Physical store	Perceived usefulness	0.49	-0.34	-1.92	0.17	0.06	13.276	0.000
	Perceived ease of use	0.57	-0.56	-2.31	0.23	0.26	28.714	0.000
	Convenience	0.59	-0.34	-2.29	0.15	0.01	19.838	0.000
	Risk aversion	0.48	-0.36	-0.03	-0.58	0.23	9.255	0.000
	Customer experience	0.68	-0.47	-2.45	0.08	0.15	29.907	0.000

	Willingness to use digital touch points	0.50	-0.23	-1.21	0.38	-0.23	9.089	0.000
	Innovation	0.59	-0.15	-1.35	-0.55	-0.03	11.539	0.000
	Loyalty	0.71	-0.20	-0.38	-0.73	-0.06	13.477	0.000
	Attitude toward gamified communication	0.21	-0.55	-1.16	0.18	0.49	13.315	0.000
	Openness to personalization	0.41	-0.25	-1.44	-0.23	0.15	7.880	0.000
	Age	0.16	0.60	0.01	-0.76	-0.51	17.457	0.000
	Genre	-0.11	-0.20	-0.48	0.68	0.12	4.498	0.002
	Gross income	0.30	-0.22	-0.81	0.09	-0.02	3.200	0.014
	Education level	0.25	0.45	0.17	-0.71	-0.43	11.935	0.000
	Online time	-0.05	0.41	0.26	-0.55	-0.23	5.871	0.000
	Time as a client	0.34	0.18	-0.33	-1.06	-0.04	11.087	0.000
	Loyalty program	0.44	-0.10	-0.04	-0.44	-0.09	4.266	0.002
	Last contact with the company	0.20	0.05	-0.03	-0.30	-0.13	1.338	0.257
	Distance to the store	-0.04	0.13	0.10	-0.07	-0.13	0.548	0.701

The detailed interpretation of the final centers allows us to understand how each cluster differs, not only in terms of channel preferences, but also in terms of behavioral variables (innovation, loyalty, gamification, personalization) and sociodemographic variables.

The 1st Cluster (A) corresponds to the group of customers with a strong preference for all channels, being most favorable to the app. This group scores very high on almost all dimensions associated with the application (PU = +0.68; PEOU = +0.57; C = +0.68; CE = +0.68; WUDT = +0.61), demonstrating above-average perceptions of usefulness, ease, and digital experience. In addition, they also reveal very positive assessments of email, telephone, and physical stores (scores between z = +0.48 and z = +0.77), indicating a multichannel predisposition. In terms of attitudes, they stand out for their high innovation (z = +0.59), loyalty (z = +0.71), attitude towards gamification (z = +0.21), and openness to personalization (z = +0.41), constituting the most digital, innovative, and loyal profile. Customers in this group are slightly older than average (z = +0.16), mostly male (z = −0.11), with above-average income (z = +0.30) and education (z = +0.25), but they do not stand out for spending more time online, being very close to the average (z = -0.05). These customers stand out for having been with the operator longer (z = +0.34), greater adherence to the loyalty program (z = +0.44), and relatively frequent contact with the company (z = +0.20).

Cluster B shows customers' preference for email. The variables related to this channel have positive scores (PU = +0.19, PEOU = +0.08, C = 0.09, WUDT = +0.19), whereas the remaining channels have negative scores, particularly the app (PU = –0.31, CE = –0.35) and the physical store (PU = –0.15, CE = –0.32). This group values the simplicity and effectiveness of email but is negative in terms of innovation, loyalty and gamification, showing little emotional involvement with the brand. In sociodemographic terms, the group consists of older customers (z = +0.60), who are more likely to be male (z = -0.20) and have above-average education (z = +0.45), but below-average income (z = -0.22). They have been customers for some time (z = +0.18) and spend a lot of time online (z = +0.41). Also, the membership of the loyalty program and the frequency of contact with the operator are both close to average (z = −0.010 and z = +0.05, respectively).

Cluster C shows a clear preference for the telephone. This segment has high scores on the telephone channel, particularly in terms of usefulness (PU = +0.50) and willingness to use the channel (WUDT = +0.98) and scores positively in terms of ease of use (PEOU =

+0.34), convenience (C = +0.47) and customer experience (CE = 0.33). In contrast, they record very negative values for other channels (scores ranging from z = -1.03 to z = -0.21), especially for physical stores (scores ranging from z = -2.45 to z = -1.21). From a behavioral point of view, the values are also remarkably low, mainly showing a lack of innovation (z = -1.35), a negative attitude towards gamification (z = -1.16) and a lack of openness to personalization (z = -1.44). This suggests that they clearly prefer traditional telephone interaction and reject more personalized marketing approaches. This cluster includes customers in the middle age range of the sample, who are mostly male (z = -0.48) and have very low or no income (z = -0.81), but have above-average education levels (z = 0.17). They are newer customers (z = -0.33) whose loyalty program membership is close to average (z = -0.04). They spend above-average time online (z = +0.26), while their contact with the operator is close to average (z = −0.03).

Cluster D corresponds to a group with a moderate profile that values traditional, easy-to-use channels above all else. It has positive scores for email (PU = +0.27; PEOU = +0.27; CE = +0.30; WUDT = +0.19), suggesting perceptions of above-average usefulness, ease of use, and user experience. Physical stores are also viewed favorably (PU = +0.17; PEOU = +0.23; convenience = +0.15; WUDT = +0.38), confirming greater proximity and trust in this channel. In contrast, the app (PU = −0.23; CE = −0.36) and telephone (PU = −0.17; PEOU = −0.54; CE = −0.53; WUDT = −0.31) receive lower ratings, particularly regarding ease of use and user experience. In terms of attitude, this cluster shows low innovation (−0.55) and weak loyalty (−0.73), accompanied by less openness to personalization (−0.23), although a positive position is revealed in relation to gamification (+0.18). From a sociodemographic perspective, this is the youngest group (−0.76), with a female majority (+0.68), average income (+0.09) and a very low level of education (−0.71). These customers are new to the company (−1.06), spend little time online and have lower loyalty program membership (−0.44) and less contact with the operator (−0.30). Overall, this cluster shows a preference for in-person and email channels, adopting a critical stance towards other channels and demonstrating limited engagement with the brand.

The final Cluster (E) demonstrates a clear rejection of email (PU = −0.89; PEOU = −0.80; C = −0.64; CE = −0.67; WUDT = −0.72) contrasting with positive evaluations of the app (PU = +0.28; PEOU = +0.32; CE = +0.34), the telephone (PU = +0.18; PEOU = +0.36; CE = +0.15) and the physical store (PU = +0.06; PEOU = +0.26; CE = 0.15). Thus,

this group demonstrates a preference for direct contact channels and is more open to the app, while maintaining the view that email is an unattractive option. In terms of attitude, the group reveals receptivity to gamification ($z = +0.49$) and some openness to personalization ($z = +0.15$). However, they show innovation ($z = -0.03$) and loyalty ($z = -0.06$) close to the average, suggesting a more pragmatic than emotional involvement with the brand. In terms sociodemographic, this is a younger ($z = -0.51$) and slightly more female ($z = +0.12$) cluster. Income is close to the average ($z = -0.02$), but the level of education is lower ($z = -0.43$), and they spend less time online ($z = -0.23$). Customer tenure is in line with the average ($z = -0.04$), but loyalty program membership is significantly lower ($z = -0.61$), as are contacts with the company ($z = -0.13$).

In addition to the variables already discussed, it is important to highlight that the variables Last contact with the company (Sig. = 0.257) and Distance to the store (Sig. = 0.701) did not present statistically significant differences between clusters, as the significance is higher than 0.05. This indicates that neither the recency of customer interaction nor their physical proximity to a store serve as discriminating elements in segmentation. By contrast, most of the attitudinal and channel-related variables revealed highly significant differences (Sig. = 0.000), which confirms the robustness of the model. Notably, the dimensions associated with the physical store – such as perceived ease of use ($F = 28.714$), customer experience ($F = 29.097$), and convenience ($F = 19.883$) – emerged as particularly discriminating, suggesting that the store remains a central channel that polarizes customer profiles. While some groups assign it very high value, others express strong resistance, which accentuates its role in distinguishing between segments. Furthermore, psychographic constructs such as loyalty and innovation also varied significantly across clusters, indicating that the segmentation captures not only differences in channel preferences but also deeper behavioral and attitudinal traits that shape customer interaction patterns.

In summary, the analysis identified five distinct customer profiles, each associated with a preferred channel. Cluster A – Digital Multichannel corresponds to the most complete and loyal group, with an emphasis on the app, but also positive evaluations of email, telephone, and physical stores. Cluster B – Inbox Customers shows a greater connection to email, preferring this simple digital channel, albeit with low attitudinal involvement. Cluster C – Resistant Phone Users is clearly oriented towards the telephone, but very resistant to other channels, especially physical stores. Cluster D – Traditional Young People show a

greater predisposition towards email and physical stores, but maintains weak perceptions of other channels, reflecting a younger and less loyal profile. Finally, Cluster E – Physical-Digital is mainly associated with the app and the physical store, avoiding email, and represents a young group with moderate engagement but openness to new forms of interaction such as gamification.

Overall, the results show that all channels find favorable user segments, but also reveal the coexistence of resistant groups, which reinforces the importance of communication strategies differentiated by profile.

5 Internship at NOS

5.1 NOS Comunicações SA

Offering a variety of consumers voice, internet, television, and mobile data options, NOS is one of Portugal's top telecom providers (NOS, n.d.). Its aim is to utilize the most cutting-edge technology to provide a remarkable communications and entertainment experience. It is also the private firm that invests the most in research and development in this area in Portugal, with the goal of providing the best long-term solutions for sustainable societal growth (NOS, n.d.).

5.2 Internship Context

The curricular internship was carried out as part of my Master's degree in Economics of Business and Strategy and took place between February 17th and May 30th, on a hybrid basis (three days in person and two days in remote work). I worked in the CRM area, more specifically in the Next Best Action (NBA) team, which is dedicated to combining data analysis, personalized marketing, technology and business strategy.

I was mainly involved in the project to best reach the consumers, which focused on identifying the most appropriate communication channels for each customer. This project, which inspired me for the topic of this report, aims to understand the multichannel behavior of NOS customers, segment them according to their usage patterns and determine the most effective ways of personalized communication for each cluster, with the goal of increasing campaign efficiency and customer retention by using the ideal channel to each type of customer.

At the same time, I participated in other strategic CRM projects, such as initiatives that aimed at improving the personalization of interactions with customers. In these projects, I helped build the logic that allows personalized interactions to be scheduled on the company's internal platform to ensure that when a customer interacts with NOS – whether by phone, store, app or any other channels – a personalized recommendation is ready to be communicated based on their history, profile and moment of the journey.

5.3 Internship study

The primary goal of the internship project is to determine the best communication channel for each client based on their characteristics and behaviors. Rather than assuming that all clients should be engaged through the same channels (such as physical store, email, or app), this project aims to customize the approach. It strongly aligns with NOS's core principles of customer experience and data-driven marketing strategy: personalization and operational efficiency. The project was initiated in response to existing challenges in NOS's communication processes, where optimizing customer touchpoints is essential to enhance both efficiency and user experience, and this optimization will be supported by a data-driven model. To do this, a methodology was developed that creates a scoring model, segmenting customers based on their interactions and predicting which communication channels are most effective for each segment. This model is applied to the journey where consumers have technical problems, where the interaction of the different clusters with the company is analyzed, measuring the impact on open rates, clicks and inbound contacts.

The scoring model analyzes customer behavior in the different contact channels, considering both the frequency of interaction and the probability of response, over a 12-month period. The focus is on fixed customers with a membership of more than 3 months, from the B2C segment. Each customer is assigned a value from 0 to 4, a scoring model based on quartiles, which reflects the level of interaction on each channel. The channels analyzed include interactions such as the number of calls made, the probability of calls answered, the number of visits to the physical store, the number days with interactions on the mobile app and the email opening rate. The results of this study are presented below.

In the Inbound (Customer Calling the company) channel, 40% of the customer base has never made a call, while the remaining 60% show some level of interaction, ranging from sporadic contact to heavy users (see figure D.1). This shows the importance of the telephone channel for a significant proportion of customers, especially those who are looking for support or have less affinity with digital solutions.

Regarding the Outbound (company calling the customer) channel, although 34% of customers do not have a service history, 66% respond to calls with varying degrees of probability, with 16% being the percentage of people who are more likely to answer (see figure D.2). This information makes it possible to anticipate who is most willing to answer,

reducing ineffective attempts and optimizing resources to increase communication efficiency.

Physical stores remain a relevant point of contact, with 47% of customers showing some level of face-to-face interaction, which includes occasional visits and frequent customers (see figure D.3). However, 53% of the base has never visited a NOS store, which indicates an opportunity for growth or a need for digital alternatives.

Despite growing digitalization, more than half of the customer base (57%) does not use the company's apps. However, 43% have had some kind of interaction with the apps, showing the potential for increased adoption of these platforms (see figure D.4). There is a balanced split between occasional and heavy users.

In the email channel, there is a mixed distribution: 22% of customers have never opened emails, and there is insufficient data for analysis of the remaining 36%. Conversely, 20% of customers consistently open emails, suggesting that this channel effectively reaches a significant proportion of customers (see figure D.5).

To identify patterns of customer interaction with the various communication channels, a clustering model using the K-means algorithm was applied to the scoring data per channel. These patterns are shown in table 4, which indicates the average level of interaction between customers in each cluster and this channel. The higher the value, the greater the intensity of use of that channel within the cluster. The values are normalized, i.e. they have been adjusted to allow comparison between channels and clusters (normally with mean 0 and standard deviation 1). This analysis made it possible to group customers into six distinct clusters, each with their own behavioral characteristics (see table 5) and varying levels of interaction with the channels evaluated. The clusters identified are:

Cluster A - Disconnected (24%): Customers with low general interaction, avoiding contact mainly on outbound and email channels.

Cluster B - Technologically Reactive (13%): Profile with high telephone interaction (essentially inbound) and moderate low use of apps.

Cluster C - Digital Self-Service (18%): Customers who favor digital channels, with strong use of apps and moderate use of telephone interaction and email.

Cluster D - Store First (14%): Customers with a high frequency of physical visits to stores, combined with reasonable interactions on telephone.

Cluster E - Inbox Customers (15%): Profile with high interaction via email, but less activity on human and physical channels.

Cluster F - Responsive to Call (17%): Customers with a high propensity to respond to outbound calls, with very low involvement in other channels.

Table 3 *Channel contact patterns by customer segment*

Cluster	Store	Inbound	App	Outbound	Email
A	0.42	0.43	0.38	-0.53	-0.45
B	0.65	3.36	0.56	1.42	0.41
C	0.70	1.79	3.48	1.52	1.23
D	3.65	1.98	0.85	1.44	0.57
E	0.48	0.69	0.60	1.57	3.27
F	0.46	0.54	0.39	3.10	-0.20

Table 4 *Customer Segment Insights*

Cluster	Segment	Channel	Insights
A	Disconnected	None	▪ Customers with low interaction on all channels, avoiding contact mainly on outbound and email. ▪ Difficulty in contacting them effectively.
B	Technologically Reactive	Inbound	▪ They call the company, when necessary, but do not interact on digital channels.
C	Digital Self-Service	Apps	▪ Highly digital and proactive. ▪ In addition to using apps, they show reasonable engagement in inbound and outbound. They avoid physical stores.
D	Store First	Store	▪ Customers who prefer human contact. ▪ They frequently visit the store and call the company, but they don't interact via email or apps.
E	Inbox Customers	Email	▪ They call the company, when necessary, but do not interact on digital channels.
F	Responsive to Call	Outbound	▪ High engagement with outbound calls, but low interaction on all other channels.

To evaluate the predictive effectiveness of the model, it was applied to the "Technical Resolution Journey" after February 14, 2025, when customers were already classified into their respective clusters. The campaign's key performance metrics revealed an overall open rate of 33%, a click-through rate (CTR) of 1.1%, a landing page open rate of 0.8%, and an inbound rate of 0.5%. Cluster analysis revealed significant differences: "Digital Self-Service" stood out with low inbound rate and high open and click rates, which supports its autonomous nature. However, despite sending fewer mailings, the "Call Responsive" and "Phone Reactive" groups generated the most return calls, confirming the relationship between predicted response and behavioral history. As anticipated, the "Disconnected" group had extremely poor reactivity, indicating the need for alternative strategies for this profile, such as gamification or more disruptive communication methods, like SMS.

The model was also applied to a second journey, where a different distribution of profiles was observed. Here, the most common cluster was 'Reactive Telephone' (37%), followed by 'Digital Self-Service' (27%) and 'Store First' (25%). These differences between the two journeys highlight the importance of adapting communication strategies to both the customer profile and the nature of the context in which the interaction occurs — whether technical, commercial or relational. This segmentation reveals the existence of distinct profiles, from customers who avoid contact to those who use digital channels intensively or prefer human interaction. Understanding these clusters is fundamental for personalizing communication and optimizing resources on the different channels.

Following the validation of the proof of concept, the project evolved to include more in-depth analyses, particularly regarding distinguishing between servicing and sales profiles. In the case of servicing, a new K-Means segmentation was applied based exclusively on support interactions (store, inbound, outbound, app and email). This identified clusters with diverse profiles, ranging from users who were exclusively digital (strong in app, weak in other channels) to those who were strongly dependent on telephone or face-to-face service, as well as hybrid and multichannel profiles. This analysis revealed that certain segments have rigid preferences for human contact and require closer monitoring, particularly during critical processes.

At the same time, customer purchasing behavior over the last four years was analyzed based on the dominant purchasing channel rather than clustering. It was found that 75% of sales were made through assisted channels: outbound accounted for 49%, physical stores

accounted for 26%, and inbound for 19%. In turn, the digital channel represented only 3% of total purchases, revealing clear growth potential in this area and justifying investment in strategies that encourage digital conversion.

Comparing service and sales profiles revealed an important duality: segments that prefer digital channels are adept at self-resolution and non-intrusive communication yet remain underrepresented in terms of purchase volume. Conversely, customers who interact more with assisted channels generate more sales but require greater operational effort and human support. This dichotomy creates opportunities for new strategies to gradually transition more dependent profiles to more efficient channels while respecting the pace and preferences of each customer. Table 6 shows the results of the channel contact patterns by customer segment in the service analysis, while Figure D.6 shows the sales interaction analysis by channel (see Appendix D).

Table 5 *Channel contact patterns by customer segment in servicing*

Cluster	Name	Store	Inbound	Outbound	App	Email
0	Digital-First	0.47	0.85	0.12	3.11	0.47
1	Ghost Clients	0.36	0.42	0.07	0.12	0.09
2	Hybrids Store & Inbound	3.51	1.68	0.25	0.72	0.67
3	Recurring inbound	0.64	3.30	0.36	1.14	0.48
4	Email engaged	0.55	1.00	0.14	1.07	3.21
5	Proactive Multichannel	1.45	3.00	2.53	1.47	1.00

5.4 Comparative Analysis of Results

This section aims to integrate and compare the results obtained in my study with those of the segmentation analysis carried out in the NOS internship project.

The internship study and the dissertation share the same overarching goal of segmenting customers according to their multichannel behavior, yet they are based on different methodological approaches. On the one hand, the internship project used behavioral data, obtained from CRM records of NOS to group customers based on their actual interactions across channels such as inbound and outbound calls, store visits, app usage, and email open rates. On the other hand, the dissertation relied on attitudinal and perceptual data collected through a survey, which included constructs such as perceived

usefulness, perceived ease of use, convenience, risk aversion, customer experience, loyalty, innovation, and openness to gamification and personalization. While the internship analysis reflects what customers do, the dissertation analysis provides insights into how customers perceive and evaluate the channels, as well as their predisposition to adopt new practices. This complementarity reinforces the robustness of segmentation as a tool to understand heterogeneous customer behavior.

In terms of results, both studies converge on the identification of digital segments. In the internship analysis, clusters such as Digital Self-Service or Digital-First emerged, characterized by strong engagement with the app and low reliance on human-assisted channels. Similarly, in the dissertation, the Digital Multichannel group revealed high evaluations of the app and positive attitudes towards innovation and loyalty, positioning itself as the most digital and proactive profile. These findings confirm the existence of a customer base that is willing to adopt digital tools, supporting strategies of self-service and automation.

A second parallel lies in the identification of assisted or traditional segments. The internship identified groups such as Store First and Recurring Inbound, which demonstrate a preference for physical stores or telephone interaction. In the dissertation, comparable results were observed with the Resistant Phone Users, who clearly value telephone contact while resisting other channels, and the Traditional Young People, who combine preference for stores and email with low engagement in digital solutions. These segments reveal the persistence of customers who demand human support and perceive value in proximity and direct contact.

Both studies also highlight the presence of hybrid profiles, combining digital and traditional channels. In the internship, clusters such as Hybrid Store & Inbound or Proactive Multichannel were identified, while in the dissertation, the Physical-Digital cluster demonstrated openness to both app and physical store interactions, despite rejecting email. These groups underline the coexistence of multiple touchpoints in the same customer journey, reinforcing the importance of maintaining consistency and integration across channels.

Finally, both analyses identified resistant or low-engagement segments. In the internship, the Disconnected or Ghost Clients clusters showed very low levels of interaction, posing challenges for engagement. Similarly, the dissertation revealed clusters with negative

perceptions of certain channels, such as the Inbox Customers (strong email preference but low overall involvement) or the Resistant Phone Users. These segments suggest that some customers deliberately avoid certain channels, requiring innovative strategies such as gamification or disruptive communication to stimulate engagement.

Taken together, the results from both the internship and the dissertation confirm that there is no universal communication channel that can effectively reach all customers. Instead, customer heterogeneity leads to the coexistence of digital, assisted, hybrid, and resistant profiles. This emphasizes the managerial need to design differentiated channel strategies, aligning behavioral patterns with attitudinal insights, in order to maximize efficiency and personalization in multichannel communication.

A comparison of the results from the internship and dissertation reveals three clear points of convergence. Both studies identified three profiles: an email-focused profile (Inbox Customers), a digital-oriented profile (Digital Self-Service in the internship and Digital Multichannel in the dissertation) and a telephone-dependent profile (Responsive to Call and Resistant to Phone Users). These overlaps confirm the robustness of the segmentation approach, as both behavioral (internship) and attitudinal (dissertation) data converge in highlighting the same fundamental customer types.

Beyond these coincidences, however, the studies also reveal complementary differences. The internship study identified a 'Disconnected' cluster characterized by very low interaction across all channels, which was not replicated in the dissertation study. Conversely, the dissertation revealed a Physical-Digital group combining store and app preferences but rejecting email, which did not emerge in the internship analysis. These divergences emphasize the added value of combining different types of data: behavioral segmentation captures patterns of actual use, while attitudinal segmentation reveals perceptions and latent predispositions that may not yet be observable.

Together, the overlaps and differences reinforce the conclusion that multichannel customer behavior is heterogeneous and that a comprehensive understanding requires the integration of both observed interactions and attitudinal tendencies.

6 Conclusion

6.1 Theoretical Contributions

This dissertation sets out to understand customer heterogeneity in multichannel behavior within the telecommunications sector, with a particular focus on perceptions of communication channels, personalization, and engagement strategies. The analysis of customer perceptions and preferences across the main channels (app, email, telephone, and store) revealed that each channel attracts favorable segments but also faces resistance from others. This finding confirms that effectiveness is not universal, but highly dependent on the profile of each customer.

Attention was also given to the role of behavioral and demographic variables. Characteristics such as innovation, loyalty, age, gender, and tenure were shown to influence channel adoption and engagement. More innovative and loyal customers tended to be open to digital solutions, whereas resistant groups displayed stronger reliance on traditional interactions. By applying clustering techniques, the study identified five distinct customer profiles: Digital Multichannel, Inbox Customers, Resistant Phone Users, Traditional Young People, and Physical-Digital. These segments illustrate that different types of customers value different channels, thus offering guidance on the optimum way to reach each group.

Another important aspect concerns perceptions of personalization within the NBA (Next Best Action) context. While digital-oriented clusters were receptive to customized communications, more traditional segments expressed lower levels of acceptance, reinforcing the need to adapt the degree of personalization to each profile. Furthermore, the analysis emphasized the potential of gamification as a driver of engagement and digital channel adoption. Younger and more digital customers revealed greater enthusiasm for gamified strategies, whereas resistant clusters showed little interest, suggesting that gamification can be effective, but only for specific segments.

Finally, the comparison with internal company data validated several conclusions. The convergence between behavioral segments (identified in the internship) and attitudinal segments (revealed by the dissertation) underscores the robustness of the results and enriches the theoretical understanding of multichannel behavior by integrating both perspectives.

6.2 Managerial Implications

From a managerial perspective, the findings confirm that there is no single communication channel capable of engaging all customers. Instead, differentiated strategies are needed, considering the diversity of profiles identified. Companies should design communication strategies that align with the characteristics and preferences of each segment: digital adopters can be effectively engaged through apps and personalized messages, while traditional groups require human support through telephone or physical stores.

Personalization also needs to be carefully adjusted. Digital-oriented customers show openness to customized interactions, but more resistant segments may interpret them as intrusive. Similarly, gamification can be used selectively to attract younger, innovative-driven customers, while not overinvesting in clusters where this strategy would be ineffective. In practice, the results suggest that companies should pursue a balanced multichannel strategy, gradually encouraging customers to adopt more efficient digital channels without disregarding the importance of assisted contact for those who value it most.

6.3 Limitations and future research directions

Nevertheless, some limitations must be acknowledged. The number of survey responses was relatively low, which prevents the findings from being generalized to the wider population. Moreover, the reliance on self-reported perceptions may not fully capture actual behaviors, while the internship project was limited to a single company and a specific set of customer journeys, restricting the external validity of the results.

Future research should build on these limitations. Studies with larger and more diverse samples would strengthen the generalizability of results, and long-term plans could provide insights into how customer profiles evolve over time. Another promising direction is to examine how the content of communication interacts with channel effectiveness – for example, whether offers, technical information, or loyalty initiatives are more effective when delivered through specific channels. Finally, combining attitudinal data with actual behavioral evidence in a unified model could yield even richer insights into customer heterogeneity and multichannel management. channels.

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Appendix

Appendix A – Survey in Portuguese

Comportamento do Consumidor na Escolha de Canais Digitais e Tradicionais no Setor das Telecomunicações

Este questionário faz parte de um estudo desenvolvido no âmbito de uma **dissertação** de Mestrado em Economia da Empresa e da Estratégia, realizada na Faculdade de Economia da Universidade do Porto. O objetivo principal desta investigação é **compreender as preferências e perceções dos consumidores relativamente aos canais de comunicação** utilizados pelas operadoras de telecomunicações.

A participação é totalmente **voluntária, anónima e confidencial**. Não será recolhida qualquer informação que permita identificar os participantes individualmente. Os dados obtidos serão usados exclusivamente para fins académicos e tratados de forma agregada. Os resultados poderão vir a ser incluídos em trabalhos científicos, sempre **salvaguardando o anonimato dos respondentes**.

Este inquérito destina-se a indivíduos com **18 ou mais anos de idade**. O tempo estimado para o seu preenchimento é de aproximadamente **6 minutos**.

Em caso de dúvidas ou questões relacionadas com o estudo, poderá contactar a autora do projeto através do e-mail: up202004814@fep.up.pt

Muito obrigada pela sua colaboração!

Joana Calçada

Consentimento informado*

Confirmo que tenho 18 anos ou mais, que li e compreendi as informações apresentadas sobre este estudo. Reconheço que a minha participação é totalmente voluntária e que posso interrompê-la a qualquer momento, sem necessidade de justificar.

□ Concordo

□ Discordo

Caraterização da amostra

Estas questões são necessárias para a caraterização da amostra do estudo.

1. Idade

□ Menos de 18 anos

□ Entre 18 e 24 anos

□ Entre 25 e 34 anos

□ Entre 35 e 44 anos

□ Entre 45 e 54 anos

□ Entre 55 e 64 anos

□ Mais de 65 anos

2. Género

□ Feminino

□ Masculino

□ Outro

□ Prefiro não responder

3. Rendimento Bruto

□ Sem rendimento

□ Menos de 600€

□ 600€ - 999€

□ 1000€ - 1499€

□ 1500€ - 1999€

□ 2000€ - 2999€

□ 3000€ - 4999€

□ 5000€ ou mais

□ Prefiro não responder

4. Nível mais elevado de educação que completou

□ Ensino básico (até 9º ano)

□ Ensino Secundário (10º ao 12º ano)

□ Formação profissional (ex: curso técnico)

□ Licenciatura (Bacharelato)

□ Mestrado ou Pós-graduação

□ Doutoramento ou superior

□ Prefiro não responder

Informações adicionais para caraterização da amostra

5. Em média, quanto tempo passa, por dia, online?

□ Menos de 1 hora

□ 1 – 2 horas

□ 3 – 4 horas

□ 5 – 6 horas

□ 7 – 8 horas

□ 9 horas ou mais

□ Prefiro não responder

6. Qual a sua operadora de telecomunicações?

□ Vodafone

□ NOS

□ MEO

□ NOWO

□ DIGI

□ Other:_____

7. Há quanto tempo é cliente da sua operadora de telecomunicações?

□ Menos de 1 ano

□ 1 a 3 anos

□ 4 a 6 anos

□ 7 a 10 anos

□ Mais de 10 anos

□ Não sei

8. Possui um contrato de fidelização com a sua operadora de telecomunicações

□ Sim

□ Não

□ Não sei

9. Quantas vezes teve contacto com a sua operadora de telecomunicações no último ano (por telefone, presencialmente, e-mail ou outro canal)?

□ Nenhuma vez

□ 1 a 2 vezes

□ 3 a 5 vezes

□ 6 a 10 vezes

□ Mais de 10 vezes

10. Que canal habitualmente usa para comunicar com a sua operadora de telecomunicações?

□ Telefone

□ E-mail

□ App

□ Loja

11. Qual a distância da sua residência/local de trabalho à loja de telecomunicações da sua operadora mais próxima?

□ Menos de 1 km

□ 1 – 5 km

□ 6 – 10 km

□ 11 – 20 km

□ Mais de 20 km

□ Não sei

Para as seguintes afirmações, indique a resposta que melhor se aplica a si, de 1 Discordo totalmente a 5 Concordo totalmente.

	1-Discordo Totalmente	2-Discordo	3-Não concordo nem discordo	4-Concordo	5-Concordo Totalmente
Normalmente, sou uma das primeiras pessoas a experimentar novas tecnologias.	○	○	○	○	○
Se soubesse que um novo canal de comunicação digital estava disponível, teria interesse em experimentá-lo.	○	○	○	○	○
Gosto de experimentar novos serviços digitais.	○	○	○	○	○
Gosto de arriscar com novos produtos de alta tecnologia.	○	○	○	○	○
Procuro frequentemente informações sobre novas tecnologias.	○	○	○	○	○
Tenho tempo limitado para interagir com a empresa.	○	○	○	○	○
Não me sinto apressada/o quando interajo com a empresa.	○	○	○	○	○
Costumo sentir-me pressionada/o pelo tempo.	○	○	○	○	○
Recomendaria a empresa a alguém que me pedisse conselhos.	○	○	○	○	○
Incentivaria amigos e familiares a utilizarem os serviços da empresa.	○	○	○	○	○

Considero a empresa a minha primeira escolha para serviços de comunicação.	○	○	○	○	○
Planeio continuar a ter uma relação com a empresa nos próximos anos.	○	○	○	○	○
Mudaria facilmente para um concorrente se tivesse um problema.	○	○	○	○	○
Continuaria a utilizar os serviços desta empresa mesmo que os preços aumentassem face aos concorrentes.	○	○	○	○	○

Comunicação com a operadora através da aplicação móvel (APP)

Nesta parte, vamos focar-nos na **aplicação móvel (APP)** da sua operadora.

Para as seguintes afirmações, indique a resposta que melhor se aplica a si, de 1 Discordo totalmente a 5 Concordo totalmente.

	1-Discordo Totalmente	2-Discordo	3-Não concordo nem discordo	4-Concordo	5-Concordo Totalmente
Usar a APP ajuda-me a resolver pedidos de serviços de forma mais eficiente.	○	○	○	○	○
Usar a APP melhora a minha produtividade e eficiência ao interagir com a empresa.	○	○	○	○	○
A APP seria útil para gerir a minha experiência como cliente.	○	○	○	○	○
No geral, considero a APP útil para gerir as minhas interações com a empresa.	○	○	○	○	○
Considero que seria fácil conseguir fazer o que quero através APP.	○	○	○	○	○
A minha interação com a APP é clara e fácil de compreender.	○	○	○	○	○

No geral, considero a APP fácil de usar.	○	○	○	○	○
Acho fácil contactar a empresa através da APP.	○	○	○	○	○
A APP está disponível em horários convenientes para mim.	○	○	○	○	○
Normalmente, é rápido concluir o que preciso quando contacto a empresa através da APP.	○	○	○	○	○
Recebo rapidamente os benefícios/resultados do contacto através da APP.	○	○	○	○	○
Acompanhar o serviço através da APP é simples.	○	○	○	○	○
Acredito que usar a app pode levar à perda de privacidade ou dados.	○	○	○	○	○
Acredito que usar a app pode causar frustração ou stress.	○	○	○	○	○
No geral, acredito que usar a app parece arriscado.	○	○	○	○	○
A APP oferece exatamente o que eu preciso.	○	○	○	○	○
Sinto-me seguro/a e confiante ao usar a APP.	○	○	○	○	○
A APP funciona bem.	○	○	○	○	○
Quero saber o meu Pin/Puk, utilizaria a APP?	○	○	○	○	○
Quero tratar de temas de faturação, utilizaria a APP?	○	○	○	○	○
Quero adquirir novos serviços, utilizaria a APP?	○	○	○	○	○
Quero saber preços dos serviços, utilizaria a APP?	○	○	○	○	○
Quero desativar os meus serviços, utilizaria a APP?	○	○	○	○	○
Quero resolver problemas técnicos	○	○	○	○	○

em casa, utilizaria a APP?					
Quero receber uma oferta relevante, utilizaria a APP?	○	○	○	○	○

Comunicação com a Operadora por E-Mail

Aqui abordamos a comunicação por **email** com a operadora.

Para as seguintes afirmações, indique a resposta que melhor se aplica a si, de 1 Discordo totalmente a 5 Concordo totalmente.

	1-Discordo Totalmente	2-Discordo	3-Não concordo nem discordo	4-Concordo	5-Concordo Totalmente
Usar o email ajuda-me a resolver pedidos de serviço de forma mais eficiente.	○	○	○	○	○
Usar o email melhora a minha produtividade e eficiência ao interagir com a empresa.	○	○	○	○	○
O email seria útil para gerir a minha experiência como cliente.	○	○	○	○	○
No geral, considero o email útil para gerir as minhas interações com a empresa.	○	○	○	○	○
Considero que seria fácil conseguir fazer o que quero através do email.	○	○	○	○	○
A minha interação com o email é clara e fácil de compreender.	○	○	○	○	○
No geral, considero o email fácil de usar.	○	○	○	○	○
Acho fácil contactar a empresa através do email.	○	○	○	○	○
O email está disponível em horários convenientes para mim.	○	○	○	○	○
Normalmente, é rápido concluir o que preciso quando	○	○	○	○	○

contacto a empresa por email.					
Recebo rapidamente os benefícios/resultados do contacto por email.	○	○	○	○	○
Acompanhar o serviço por email é simples.	○	○	○	○	○
Acredito que usar o email pode levar à perda de privacidade ou dados.	○	○	○	○	○
Acredito que usar o email pode causar frustração ou stress.	○	○	○	○	○
No geral, acredito que usar o email parece arriscado.	○	○	○	○	○
O email oferece exatamente o que eu preciso.	○	○	○	○	○
Sinto-me seguro/a e confiante ao usar o email.	○	○	○	○	○
O email funciona bem.	○	○	○	○	○
Quero saber o meu Pin/Puk, utilizaria o email?	○	○	○	○	○
Quero tratar de temas de faturação, utilizaria o email?	○	○	○	○	○
Quero adquirir novos serviços, utilizaria o email?	○	○	○	○	○
Quero saber preços dos serviços, utilizaria o email?	○	○	○	○	○
Quero desativar os meus serviços, utilizaria o email?	○	○	○	○	○
Quero resolver problemas técnicos em casa, utilizaria o email?	○	○	○	○	○
Quero receber uma oferta relevante, utilizaria o email?	○	○	○	○	○

Comunicação com a operadora através de Telefone

Esta secção foca-se nas **chamadas telefónicas** como meio de contacto com a operadora.

Para as seguintes afirmações, indique a resposta que melhor se aplica a si, de 1 Discordo totalmente a 5 Concordo totalmente.

	1-Discordo Totalmente	2-Discordo	3-Não concordo nem discordo	4-Concordo	5-Concordo Totalmente
As chamadas telefónicas ajudam-me a resolver pedidos de serviço de forma mais eficiente.	○	○	○	○	○
As chamadas telefónicas melhoram a minha produtividade e eficiência ao interagir com a empresa.	○	○	○	○	○
As chamadas telefónicas seriam úteis para gerir a minha experiência como cliente.	○	○	○	○	○
No geral, considero as chamadas telefónicas úteis para gerir as minhas interações com a empresa.	○	○	○	○	○
Considero que seria fácil conseguir fazer o que quero através de chamadas telefónicas.	○	○	○	○	○
A minha interação por chamadas telefónicas é clara e compreensível.	○	○	○	○	○
No geral, considero as chamadas telefónicas fáceis de usar.	○	○	○	○	○
Acho fácil contactar a empresa por chamadas telefónicas.	○	○	○	○	○
As chamadas telefónicas estão disponíveis em horários convenientes para mim.	○	○	○	○	○
Normalmente, é rápido concluir o que preciso quando contacto a empresa por chamada telefónica.	○	○	○	○	○
Recebo rapidamente os benefícios/resultados do contacto por chamada telefónica.	○	○	○	○	○

Acompanhar o serviço por chamada telefónica é simples.	○	○	○	○	○
Acredito que usar chamadas telefónicas pode levar à perda de privacidade ou de dados.	○	○	○	○	○
Acredito que usar chamadas telefónicas pode causar frustração ou stress.	○	○	○	○	○
No geral, acredito que usar chamadas telefónicas parece arriscado.	○	○	○	○	○
As chamadas telefónicas oferecem exatamente o que eu preciso.	○	○	○	○	○
Sinto-me seguro/a e confiante ao usar as chamadas telefónicas.	○	○	○	○	○
As chamadas telefónicas funcionam bem.	○	○	○	○	○
Quero saber o meu Pin/Puk, utilizaria as chamadas telefónicas?	○	○	○	○	○
Quero tratar de temas de faturação, utilizaria as chamadas telefónicas?	○	○	○	○	○
Quero adquirir novos serviços, utilizaria as chamadas telefónicas?	○	○	○	○	○
Quero saber preços dos serviços, utilizaria as chamadas telefónicas?	○	○	○	○	○
Quero desativar os meus serviços, utilizaria as chamadas telefónicas?	○	○	○	○	○
Quero resolver problemas técnicos em casa, utilizaria as chamadas telefónicas?	○	○	○	○	○
Quero receber uma oferta relevante, utilizaria as chamadas telefónicas?	○	○	○	○	○

Comunicação com a operadora na Loja

Nesta parte, queremos saber a sua opinião sobre o **atendimento presencial nas lojas da operadora**.

Para as seguintes afirmações, indique a resposta que melhor se aplica a si, de 1 Discordo totalmente a 5 Concordo totalmente.

	1-Discordo Totalmente	2-Discordo	3-Não concordo nem discordo	4-Concordo	5-Concordo Totalmente
Usar lojas físicas ajuda-me a resolver pedidos de serviço de forma mais eficiente.	○	○	○	○	○
Usar lojas físicas melhora a minha produtividade e eficiência ao interagir com a empresa.	○	○	○	○	○
As lojas físicas seriam úteis para gerir a minha experiência como cliente.	○	○	○	○	○
No geral, considero as lojas físicas úteis para gerir as minhas interações com a empresa.	○	○	○	○	○
Considero que seria fácil conseguir fazer o que quero através de lojas físicas.	○	○	○	○	○
A minha interação por lojas físicas é clara e compreensível.	○	○	○	○	○
No geral, considero as lojas físicas fáceis de usar.	○	○	○	○	○
Acho fácil contactar a empresa através das lojas físicas.	○	○	○	○	○
As lojas físicas estão disponíveis em horários convenientes para mim.	○	○	○	○	○
Normalmente, é rápido concluir o que preciso quando contacto a empresa numa loja física.	○	○	○	○	○
Recebo rapidamente os benefícios/resultados do contacto através das lojas físicas.	○	○	○	○	○

Acompanhar o serviço através das lojas físicas é simples.	○	○	○	○	○
Acredito que usar as lojas físicas pode levar à perda de privacidade ou de dados.	○	○	○	○	○
Acredito que usar as lojas físicas pode causar frustração ou stress.	○	○	○	○	○
No geral, acredito que usar as lojas físicas parece arriscado.	○	○	○	○	○
As lojas físicas oferecem exatamente o que eu preciso.	○	○	○	○	○
Sinto-me seguro/a e confiante ao usar as lojas físicas.	○	○	○	○	○
As lojas físicas funcionam bem.	○	○	○	○	○
Quero saber o meu Pin/Puk, utilizaria as lojas físicas?	○	○	○	○	○
Quero tratar de temas de faturação, utilizaria as lojas físicas?	○	○	○	○	○
Quero adquirir novos serviços, utilizaria as lojas físicas?	○	○	○	○	○
Quero saber preços dos serviços, utilizaria as lojas físicas?	○	○	○	○	○
Quero desativar os meus serviços, utilizaria as lojas físicas?	○	○	○	○	○
Quero resolver problemas técnicos em casa, utilizaria as lojas físicas?	○	○	○	○	○
Quero receber uma oferta relevante, utilizaria as lojas físicas?	○	○	○	○	○

Incentivos (recompensas, pontos, desafios)

Esta secção apresenta afirmações sobre situações em que empresas oferecem recompensas, pontos ou desafios, como forma de incentivo.

Para as seguintes afirmações, indique a resposta que melhor se aplica a si, de 1 Discordo totalmente a 5 Concordo totalmente.

	1-Discordo Totalmente	2-Discordo	3-Não concordo nem discordo	4-Concordo	5-Concordo Totalmente
Tenciono usar a app se esta me oferecer recompensas como pontos ou descontos.	○	○	○	○	○
Prevejo usar a app no futuro se receber recompensas ou ofertas exclusivas.	○	○	○	○	○
Preferiria usar a app da operadora nas minhas interações com a empresa se me oferecesse benefícios ou incentivos.	○	○	○	○	○

Personalização

Por fim, queremos perceber a sua opinião sobre abordagens personalizadas — quando uma empresa ajusta comunicações, ofertas ou serviços aos interesses de cada cliente.

Para as seguintes afirmações, indique a resposta que melhor se aplica a si, de 1 Discordo totalmente a 5 Concordo totalmente.

	1-Discordo Totalmente	2-Discordo	3-Não concordo nem discordo	4-Concordo	5-Concordo Totalmente
Valorizo quando uma empresa presta um serviço personalizado.	○	○	○	○	○
Valorizo quando as recomendações da empresa são personalizadas com base nas minhas preferências de utilização.	○	○	○	○	○
Sinto-me confortável em fornecer informações sobre mim à empresa em troca de serviços e produtos personalizados.	○	○	○	○	○

Appendix B

Table B. 1 *Techniques used for segmentation in previous studies*

Authors	Techniques for customer segmentation
Alt et al. (2021); Van Nguyen et al. (2024)	TwoStep Cluster Analysis
De Keyser et al. (2015); Hallikainen et al. (2019); Konuş et al. (2008); Nakano and Kondo (2018); Sands et al. (2016)	Latent Class Cluster Analysis (LCCA)
Fraihat et al. (2022)	Enhanced K-Means Clustering
Dalla Pozza et al. (2018)	Multinomial Regression and Counting

Table B. 2 *Key variables for Clustering*

Variables	Type	Importance	Authors who have studied
Age	Demographic	Age may affect multichannel behavior and adoption of digital channels.	Alt et al. (2021); De Keyser et al. (2015); Hallikainen et al. (2019); Konuş et al. (2008); Nakano and Kondo (2018); Ribeiro et al. (2024); Sands et al. (2016)
Proximity to a physical store	Demographic	Physical distance between the customer's residence and the nearest physical store influences channel choice.	NOS
Average Daily Internet usage	Demographic	The average number of hours consumers spend on the internet per day shapes their familiarity and comfort with digital channels.	Hallikainen et al. (2019); Ribeiro et al. (2024)
Perceived usefulness (PU)	Psychographic	The extent to which using a channel improves the company's productivity or effectiveness.	Alt et al. (2021)
Perceived ease of use (PEOU)	Psychographic	The level to which customers consider a channel intuitive and easy to use.	(Alt et al., 2021; Van Nguyen et al., 2024)
Innovation	Psychographic	Propensity to adopt new solutions and experiment with new channels.	De Keyser et al. (2015); Hallikainen et al. (2019); Konuş et al. (2008); Nakano and Kondo (2018); Sands et al. (2016)
Convenience	Psychographic	Preference for channels that save time and effort and provide quick, accessible interactions.	Alt et al. (2021); Van Nguyen et al. (2024)
Time pressure	Psychographic	The extent to which consumers feel constrained by a lack of time leads them to prefer fast, low-effort channels.	Alt et al. (2021); Konuş et al. (2008); Sands et al. (2016); Valentini et al. (2011); Van Nguyen et al. (2024)
Risk aversion	Psychographic	Tendency to avoid uncertainty or insecurity, preferring traditional and trustworthy channels.	De Keyser et al. (2015); Hallikainen et al. (2019); Ribeiro et al. (2024)
Loyalty	Psychographic	The degree to which consumers remain loyal to a company and avoid switching to competitors.	Konuş et al. (2008); Nakano and Kondo (2018); Ribeiro et al. (2024); Sands et al. (2016)

Customer Experience	Behavioral	The quality of consumers' past interactions with the company influences their likelihood of reusing the same channels in the future.	Ribeiro et al. (2024)
Willingness to use digital touchpoints	Behavioral	Propensity of consumers to choose specific digital channels for specific tasks (e.g., solving requests, information seeking and purchasing).	Alt et al. (2021); NOS
Attitude toward Gamified Communication	Behavioral	Openness to interactive and gamified elements in communication (e.g., rewards, challenges).	NOS
Openness to personalization	Telco	The degree to which consumers value and accept personalized communications and tailored recommendations, without perceiving them as intrusive.	NOS
Contract Type	Telco	Nature of the consumer's contractual relationship with the company (e.g., prepaid, postpaid), affecting flexibility and channel interactions.	Ribeiro et al. (2024)
Loyalty Program Membership	Telco	Whether the consumer participates in the company's loyalty program, which can increase engagement and openness to communications.	NOS, Ribeiro et al. (2024)
Preferred communication channel	Telco	Self-reported main channel that consumers choose for receiving company communications.	NOS

Appendix C

Table C. 1 *Sample characteristics*

		Number of answers	Total % of the sample
Age	Between 18 and 24 years old	61	30.5%
	Between 25 and 34 years	9	4.5%
	Between 35 and 44 years old	8	4.0%
	Between 45 and 54 years old	65	32.5%
	Between 55 and 64 years old	42	21%
	Over 65 years old	15	7.5%
Gender	Female	116	58.0%
	Male	83	41.5%
	Prefer not to answer	1	0.5%
Monthly income	Without income	40	20.0%
	Less than 600€	7	3.5%
	600€ - 999€	8	4.0%
	1000€ - 1499€	29	14.5%
	1500€ - 1999€	22	11.0%
	2000€ - 2999€	46	23.0%
	3000€ - 4999€	22	11.0%
	5000€ or more	6	3.0%
	Prefer not to answer	20	10%
Education Level	Doctorate or higher	1	0.5%
	Basic education (up tp 9th grade)	1	0.5%
	Secondary Education (10th to 12th grade)	41	20.5%
	Basic education (up tp 9th grade)/Vocational education (e.g., technical course)	2	1.0%
	Bachelor's degree	93	46.5%

	Master's or Postgraduate degree	62	31.0%
Telecommunications Operator	Vodafone	74	37%
	NOS	31	15.5%
	MEO	94	47%
	DIGI	1	0.5%
Most used Channel to contact the operator	APP	32	16%
	Email	10	5%
	Telephone	125	62.5%
	Physical Store	33	16.5%

Table C. 2 *Items used for each construct*

Variable	Author	Items
Perceived Usefulness (PU)	F. D. Davis	**PU_1** Using the APP helps me resolve service requests more efficiently
		PU_2 Using email helps me resolve service requests more efficiently
		PU_3 Using phone calls helps me resolve service requests more efficiently
		PU_4 Using physical stores helps me resolve service requests more efficiently
		PU_5 Using the APP improves my productivity and efficiency when interacting with the company
		PU_6 Using email improves my productivity and efficiency when interacting with the company
		PU_7 Using phone calls improves my productivity and efficiency when interacting with the company
		PU_8 Using physical stores improves my productivity and efficiency when interacting with the company
		PU_9 The APP would be useful in managing my customer experience.
		PU_10 The email would be useful in managing my customer experience.
		PU_11 Phone calls would be useful in managing my customer experience.
		PU_12 Physical stores would be useful in managing my customer experience.
		PU_13 Overall, I find the APP useful for managing my interactions with the company
		PU_14 Overall, I find email useful for managing my interactions with the company
		PU_15 Overall, I find phone calls useful for managing my interactions with the company
		PU_16 Overall, I find physical stores useful for managing my interactions with the company

Perceived Ease of Use (PEOU)	F. D. Davis	**PEOU_1** I would find it easy to get the APP to do what I want it to do.
		PEOU_2 My interaction through the APP is clear and understandable
		PEOU_3 Overall, I find the APP easy to use.
		PEOU_4 I would find it easy to get the email to do what I want them to do.
		PEOU_5 My interaction through email is clear and understandable
		PEOU_6 Overall, I find email easy to use.
		PEOU_7 I would find it easy to get what I want through phone calls.
		PEOU_8 My interaction through phone calls is clear and understandable
		PEOU_9 Overall, I find phone calls easy to use.
		PEOU_10 I would find it easy to get what I want through physical stores.
		PEOU_11 My interaction through physical stores clear and understandable
		PEOU_12 Overall, I find physical stores easy to use.
Innovation	Goldsmith, R. E., & Hofacker, C. F. (1991).	**I_1** I am usually among the first to try new digital communication services.
		I_2 If I heard that a new digital communication channel was available, I would be interested in trying it.
		I_3 I like to experiment with new digital services.
		I_4 I enjoy taking chances on new high-tech products.
		I_5 I often seek out information about new technologies.
Convenience	L. L. Berry, K. Seiders and D. Grewal	**C_1** I think it is easy to contact the company through the APP.
		C_2 The APP is available at times convenient for me.
		C_3 It usually takes little time to complete what I need when I contact the company through the APP.
		C_4 I receive the benefits/results of the contact through the APP quickly.
		C_5 Following up on the service through the APP is simple.

		C_6 I think it is easy to contact the company through the email.
		C_7 The email is available at times convenient for me.
		C_8 It usually takes little time to complete what I need when I contact the company through email.
		C_9 I receive the benefits/results of the contact through the email quickly.
		C_10 Following up on the service through the email is simple.
		C_11 I think it is easy to contact the company through phone calls.
		C_12 The phone calls are available at times convenient for me.
		C_13 It usually takes little time to complete what I need when I contact the company through phone calls.
		C_14 I receive the benefits/results of the contact through the phone calls quickly.
		C_15 Following up on the service through phone calls is simple.
		C_16 I think it is easy to contact the company through physical stores.
		C_17 The physical stores are available at times convenient for me.
		C_18 It usually takes little time to complete what I need when I contact the company through physical stores.
		C_19 I receive the benefits/results of the contact through physical stores quickly.
		C_20 Following up on the service through physical stores is simple.
Time pressure	S. E. Beatty and M. E. Ferrell	**TP_1** I have limited time available for interacting with the company.
		TP_2 I do not feel rushed when interacting with the company.
		TP_3 I usually find myself pressed for time.
Risk aversion	M. S. Featherman and P. A. Pavlou	**RA_1** I believe using the app may lead to loss of privacy or data.
		RA_2 I believe using the app may cause frustration or stress.
		RA_3 Overall, I believe using the app feels risky.

		RA_4 I believe using email may lead to loss of privacy or data.
		RA_5 I believe using email may cause frustration or stress.
		RA_6 Overall, I believe using email feels risky.
		RA_7 I believe using phone calls may lead to loss of privacy or data.
		RA_8 I believe using phone calls may cause frustration or stress.
		RA_9 Overall, I believe using phone calls feels risky.
		RA_10 I believe using physical stores may lead to loss of privacy or data.
		RA_11 I believe using physical stores may cause frustration or stress.
		RA_12 Overall, I believe using physical stores feels risky.
Loyalty	V. A. Zeithaml, L. L. Berry and A. Parasuraman	**L_1** I would recommend the company to someone who seeks my advice.
		L_2 I would encourage friends and family to use the company services.
		L_3 I consider the company my first choice for communication services.
		L_4 I plan to increase my engagement with the company in the next few years.
		L_5 I would easily switch to a competitor if I experienced a problem.
		L_6 I would continue to do business with this company if its prices increased somewhat.
Customer experience	P. “Phil” Klaus and S. Maklan	**CE_1** The APP provides what I really need.
		CE_2 I feel secure and confident using the APP.
		CE_3 The APP works well.
		CE_4 The email provides what I really need.
		CE_5 I feel secure and confident using the email.
		CE_6 The email works well.

		CE_7 The phone calls provide what I really need.
		CE_8 I feel secure and confident using phone calls.
		CE_9 The phone calls work well.
		CE_10 The physical stores provide what I really need.
		CE_11 I feel secure and confident using the physical stores.
		CE_12 The physical stores work well.
Willingness to use digital touchpoints	NOS	**WUDT_1** I want to know my PIN/PUK. Would I use the app?
		WUDT_2 I want to deal with billing issues. Would I use the app?
		WUDT_3 I want to purchase new services. Would I use the app?
		WUDT_4 I want to know the prices of services. Would I use the app?
		WUDT_5 I want to deactivate my services. Would I use the app?
		WUDT_6 I want to report technical problems at home. Would I use the app?
		WUDT_7 I want to receive a relevant offer. Would I use the app?
		WUDT_8 I want to know my PIN/PUK. Would I use email?
		WUDT_9 I want to deal with billing issues. Would I use email?
		WUDT_10 I want to purchase new services. Would I use email?
		WUDT_11 I want to know the prices of services. Would I use email?
		WUDT_12 I want to deactivate my services. Would I use email?
		WUDT_13 I want technical support at home. Would I use email?
		WUDT_14 I want to receive a relevant offer. Would I use email?
		WUDT_15 I want to know my PIN/PUK. Would I use phone calls?
		WUDT_16 I want to deal with billing issues. Would I use phone calls?
		WUDT_17 I want to purchase new services. Would I use phone calls?
		WUDT_18 I want to know the prices of services. Would I use phone calls?

		WUDT_19 I want to deactivate my services. Would I use phone calls?
		WUDT_20 I want to report technical problems at home. Would I use phone calls?
		WUDT_21 I want to receive a relevant offer. Would I use phone calls?
		WUDT_22 I want to know my PIN/PUK. Would I go to a physical store?
		WUDT_23 I want to deal with billing issues. Would I go to a physical store?
		WUDT_24 I want to purchase new services. Would I go to a physical store?
		WUDT_25 I want to know the prices of services. Would I go to a physical store?
		WUDT_26 I want to deactivate my services. Would I go to a physical store?
		WUDT_27 I want to deal with technical problems at home. Would I go to a physical store?
		WUDT_28 I want to receive a relevant offer. Would I go to a physical store?
Attitude toward Gamified Communication	V. Venkatesh and F. D. Davis	**ATGC_1** I intend to use the app if it offers me rewards like points or discounts.
		ATGC_2 I predict I will use the app in the future if I receive rewards or exclusive offers.
		ATGC_3 I would prefer to use the NOS app for my interactions with the company if it offers me benefits or incentives.
Openness to personalization	R. K. Chellappa and R. G. Sin	**OP_1** I value it when a company provides personalized service.
		OP_2 I value when the company's recommendations are personalized for my usage experience preferences.
		OP_3 I am comfortable providing information about me to this firm in return for personalized services and products.

Table C. 3 *Descriptive statistics*

Construct	Items	Mean	Mode	Median	Maximum	Minimum	Standard Deviation
Innovation	I_1	3.06	2	3	5	1	1.09
	I_2	3.23	4	3	5	1	1.04
	I_3	3.37	4	4	5	1	1.09
	I_4	3.04	4	3	5	1	1.11
	I_5	3.33	4	3	5	1	1.14
Time pressure	TP_1	3.28	4	3	5	1	1.12
	TP_2R	2.90	2	3	5	1	1.05
	TP_3	2.88	3	3	5	1	1.04
Loyalty	L_1	3.98	4	4	5	1	0.76
	L_2	3.90	4	4	5	1	0.83
	L_3	3.93	4	4	5	1	0.88
	L_4	4.02	4	4	5	1	0.83
	L_5R	3.05	4	3	5	1	1.17
	L_6	2.70	2	3	5	1	1.06
Perceived Usefulness	PU_1	3.39	4	3	5	1	0.97
	PU_2	3.37	3	3	5	1	1.00
	PU_3	3.67	4	4	5	1	0.85
	PU_4	3.54	4	4	5	1	0.88
	PU_5	3.10	4	3	5	1	1.04
	PU_6	3.07	4	3	5	1	1.02
	PU_7	3.17	4	3	5	1	1.03
	PU_8	3.19	4	3	5	1	1.06
	PU_9	4.05	4	4	5	1	0.80
	PU_10	3.81	4	4	5	1	0.97
	PU_11	3.91	4	4	5	1	0.86
	PU_12	4.00	4	4	5	1	0.83

	PU_13	3.75	4	4	5	1	0.99
	PU_14	3.46	4	4	5	1	1.11
	PU_15	3.68	4	4	5	1	0.99
	PU_16	3.73	4	4	5	1	0.97
Perceived Ease of Use	PEOU_1	3.46	4	4	5	1	0.89
	PEOU_2	3.51	4	4	5	1	0.93
	PEOU_3	3.57	4	4	5	1	0.89
	PEOU_4	3.01	3	3	5	1	1.03
	PEOU_5	3.29	4	3	5	1	0.98
	PEOU_6	3.45	4	4	5	1	0.98
	PEOU_7	3.88	4	4	5	1	0.89
	PEOU_8	3.90	4	4	5	1	0.84
	PEOU_9	3.93	4	4	5	1	0.90
	PEOU_10	3.68	4	4	5	1	1.01
	PEOU_11	3.90	4	4	5	1	0.87
	PEOU_12	3.91	4	4	5	1	0.91
Convenience	C_1	3.17	3	3	5	1	0.91
	C_2	3.80	4	4	5	1	0.90
	C_3	3.33	3	3	5	1	0.88
	C_4	3.35	3	3	5	1	0.91
	C_5	3.52	4	4	5	1	0.93
	C_6	3.01	3	3	5	1	1.03
	C_7	3.48	4	4	5	1	0.98
	C_8	2.90	3	3	5	1	0.98
	C_9	2.98	3	3	5	1	0.94
	C_10	3.15	3	3	5	1	0.97
	C_11	3.41	4	4	5	1	1.07
	C_12	3.37	4	4	5	1	1.01
	C_13	3.51	4	4	5	1	1.04
	C_14	3.60	4	4	5	1	0.97

	C_15	3.49	4	4	5	1	1.08
	C_16	3.71	4	4	5	1	0.97
	C_17	3.30	4	4	5	1	1.08
	C_18	3.66	4	4	5	1	1.00
	C_19	3.74	4	4	5	1	0.94
	C_20	3.60	4	4	5	1	1.00
Risk Aversion	RA_1	2.70	2	3	5	1	0.98
	RA_2	2.65	2	2	5	1	1.02
	RA_3	2.16	2	2	5	1	0.89
	RA_4	2.42	2	2	5	1	0.93
	RA_5	2.83	3	3	5	1	0.99
	RA_6	2.32	2	2	5	1	0.89
	RA_7	2.22	2	2	5	1	0.93
	RA_8	3.20	4	3	5	1	1.12
	RA_9	2.17	2	2	5	1	0.88
	RA_10	2.10	2	2	5	1	0.92
	RA_11	2.85	3	3	5	1	1.09
	RA_12	1.99	2	2	5	1	0.87
Customer Experience	CE_1	3.11	3	3	5	1	0.80
	CE_2	3.58	4	4	5	1	0.82
	CE_3	3.53	4	4	5	1	0.87
	CE_4	2.79	3	3	5	1	0.91
	CE_5	3.53	4	4	5	1	0.87
	CE_6	3.39	3	3	5	1	0.84
	CE_7	3.53	4	4	5	1	0.88
	CE_8	3.83	4	4	5	1	0.77
	CE_9	3.57	4	4	5	1	0.96
	CE_10	3.64	4	4	5	1	0.93
	CE_11	3.98	4	4	5	1	0.81
	CE_12	3.80	4	4	5	1	0.90

Willingness to use digital touchpoints	WUDT_1	3.67	4	4	5	1	1.08
	WUDT_2	3.39	4	4	5	1	1.03
	WUDT_3	3.33	4	4	5	1	1.10
	WUDT_4	3.51	4	4	5	1	1.09
	WUDT_5	3.30	4	4	5	1	1.18
	WUDT_6	2.80	2	3	5	1	1.14
	WUDT_7	3.27	4	3	5	1	1.12
	WUDT_8	2.32	2	2	5	1	1.17
	WUDT_9	3.08	4	3	5	1	1.13
	WUDT_10	2.78	4	3	5	1	1.15
	WUDT_11	2.82	4	3	5	1	1.14
	WUDT_12	3.05	4	3	5	1	1.21
	WUDT_13	2.58	2	2	5	1	1.19
	WUDT_14	3.01	4	3	5	1	1.13
	WUDT_15	3.16	4	3	5	1	1.21
	WUDT_16	3.71	4	4	5	1	1.01
	WUDT_17	3.70	4	4	5	1	1.03
	WUDT_18	3.53	4	4	5	1	1.09
	WUDT_19	3.84	4	4	5	1	0.94
	WUDT_20	4.16	4	4	5	1	0.82
	WUDT_21	3.57	4	4	5	1	1.10
	WUDT_22	3.25	4	4	5	1	1.29
	WUDT_23	3.73	4	4	5	1	1.03
	WUDT_24	3.89	4	4	5	1	0.99
	WUDT_25	3.61	4	4	5	1	1.07
	WUDT_26	3.85	4	4	5	1	1.00
	WUDT_27	3.35	4	4	5	1	1.16
	WUDT_28	3.39	4	4	5	1	1.15
Attitude towards gamified communication	ATGC_1	3.82	4	4	5	1	1.03
	ATGC_2	3.82	4	4	5	1	0.99

	ATGC_3	3.85	4	4	5	1	0.98
Openness to personalization	OP_1	4.37	4	4	5	1	0.62
	OP_2	4.21	4	4	5	1	0.79
	OP_3	3.44	4	4	5	1	1.10

Table C. 4 *Internal Consistency Analysis*

Construct		Items	Cronbach's Alpha	Cronbach's Alpha if the item was excluded
Innovation		I_1	0.891	0.866
		I_2		0.869
		I_3		0.857
		I_4		0.855
		I_5		0.890
Loyalty		L_1	0.838	0.793
		L_2		0.789
		L_3		0.792
		L_4		0.788
		L_5R		0.860
		L_6		0.847
Perceived usefulness	APP	PU_1	0.938	0.905
		PU_2		0.910
		PU_3		0.943
		PU_4		0.912
	Email	PU_5	0.948	0.942
		PU_6		0.932
		PU_7		0.932
		PU_8		0.921
	Telephone	PU_9	0.915	0.887
		PU_10		0.906
		PU_11		0.903
		PU_12		0.865
	Physical Stores	PU_13	0.933	0.923
		PU_14		0.928
		PU_15		0.899

		PU_16		0.903
Perceived Ease of Use	APP	PEOU_1	0.905	0.929
		PEOU_2		0.804
		PEOU_3		0.848
	Email	PEOU_4	0.874	0.857
		PEOU_5		0.756
		PEOU_6		0.850
	Telephone	PEOU_7	0.877	0.866
		PEOU_8		0.762
		PEOU_9		0.850
	Physical Stores	PEOU_10	0.916	0.917
		PEOU_11		0.865
		PEOU_12		0.855
Convenience	APP	C_1	0.903	0.887
		C_2		0.904
		C_3		0.859
		C_4		0.872
		C_5		0.880
	Email	C_6	0.886	0.855
		C_7		0.897
		C_8		0.836
		C_9		0.853
		C_10		0.850
	Telephone	C_11	0.863	0.845
		C_12		0.873
		C_13		0.811
		C_14		0.813
		C_15		0.823
	Physical Stores	C_16	0.901	0.869
		C_17		0.921

		C_18		0.869
		C_19		0.865
		C_20		0.869
Risk Aversion	APP	RA_1	0.749	0.654
		RA_2		0.715
		RA_3		0.629
	Email	RA_4	0.752	0.611
		RA_5		0.860
		RA_6		0.505
	Telephone	RA_7	0.848	-
		RA_9		-
	Physical Stores	RA_10	0.754	0.570
		RA_11		0.883
		RA_12		0.553
Customer Experience	APP	CE_1	0.777	0.753
		CE_2		0.692
		CE_3		0.643
	Email	CE_4	0.790	0.750
		CE_5		0.789
		CE_6		0.593
	Telephone	CE_7	0.811	0.683
		CE_8		0.777
		CE_9		0.756
	Physical Stores	CE_10	0.898	0.845
		CE_11		0.867
		CE_12		0.849
Willingness to use digital touchpoints	APP	WUDT_1	0.855	0.861
		WUDT_2		0.839
		WUDT_3		0.827
		WUDT_4		0.833

		WUDT_5		0.814
		WUDT_6		0.842
		WUDT_7		0.826
	Email	WUDT_8	0.908	0.912
		WUDT_9		0.894
		WUDT_10		0.884
		WUDT_11		0.889
		WUDT_12		0.895
		WUDT_13		0.892
		WUDT_14		0.890
	Telephone	WUDT_15	0.854	0.864
		WUDT_16		0.830
		WUDT_17		0.816
		WUDT_18		0.821
		WUDT_19		0.831
		WUDT_20		0.840
		WUDT_21		0.828
	Physical Stores	WUDT_22	0.888	0.876
		WUDT_23		0.864
		WUDT_24		0.871
		WUDT_25		0.856
		WUDT_26		0.880
		WUDT_27		0.876
		WUDT_28		0.881
Attitude towards gamified communication		ATGC_1	0.941	0.886
		ATGC_2		0.891
		ATGC_3		0.961
Openness to personalization		OP_1	0.704	0.601
		OP_2		0.418

	OP_3	0.853

Appendix D

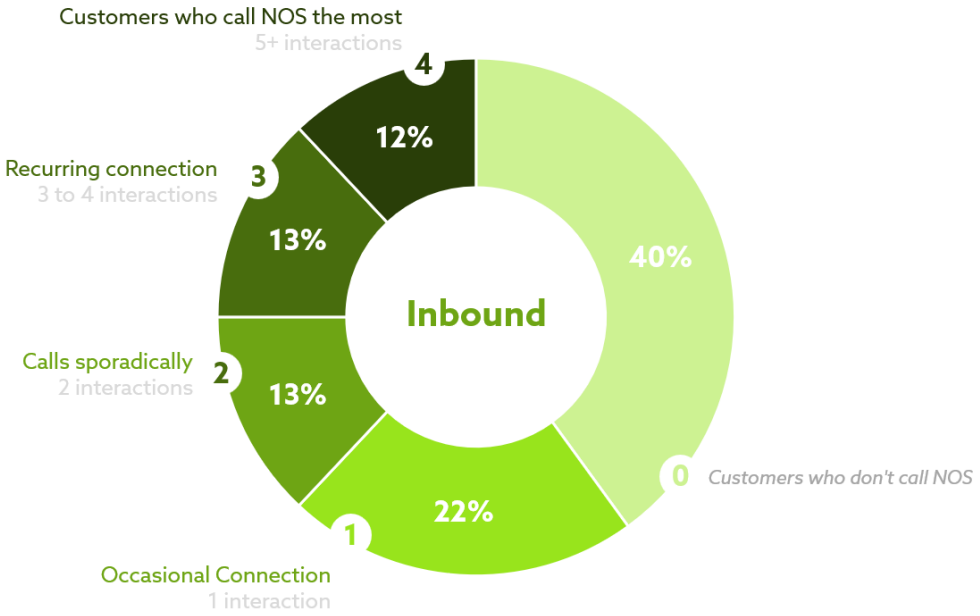


Figure D. 1 Scoring Model | Distribution of customers by channel, Inbound

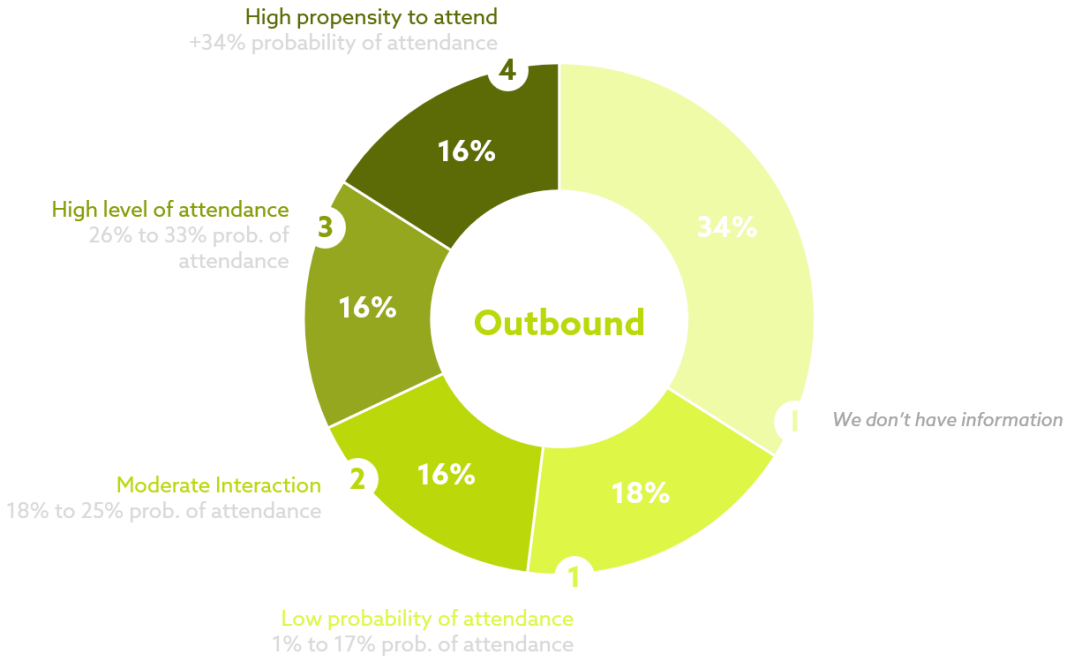


Figure D. 2 Scoring Model | Distribution of customers by channel, Outbound

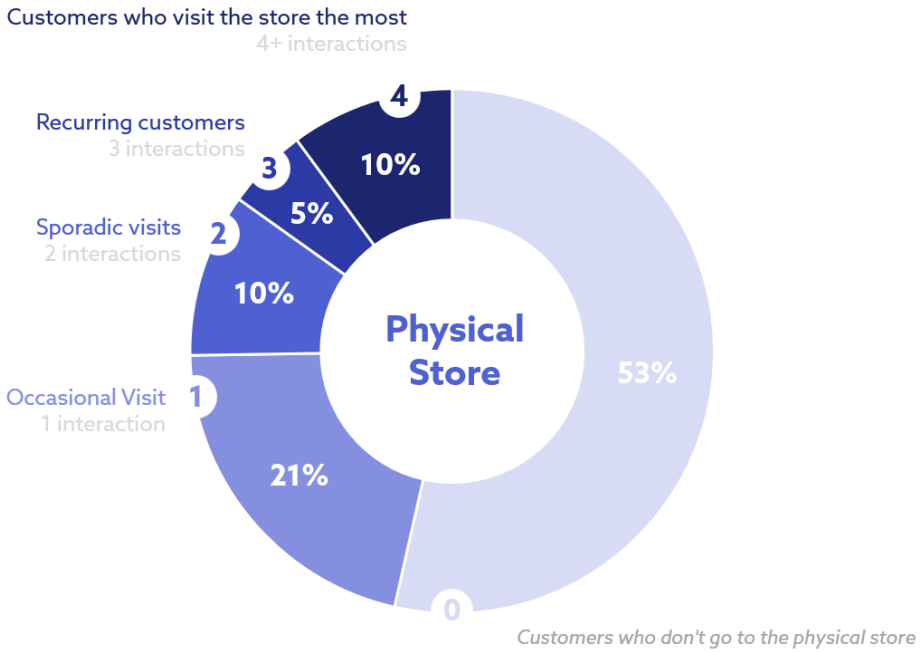


Figure D. 3 Scoring Model | Distribution of customers by channel, Physical Store

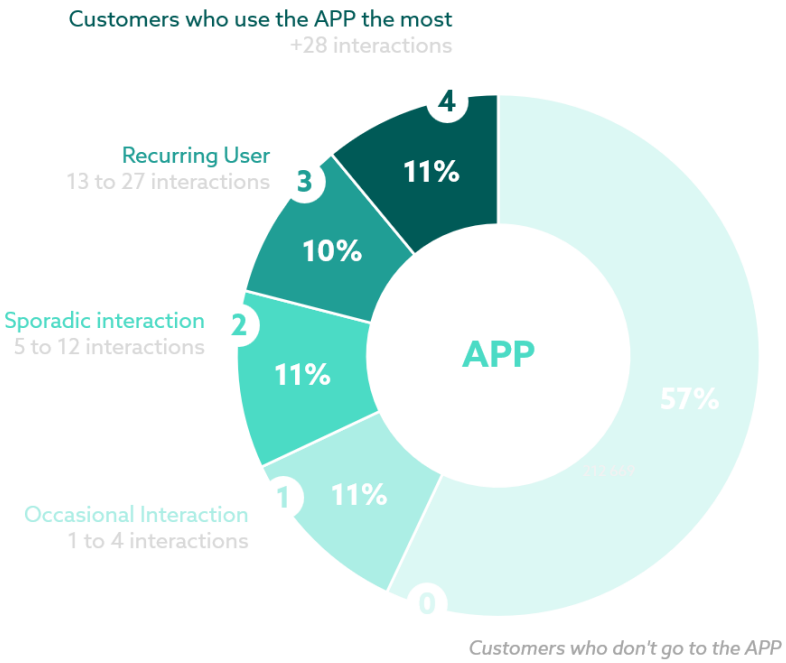


Figure D. 4 Scoring Model | Distribution of customers by channel, APP

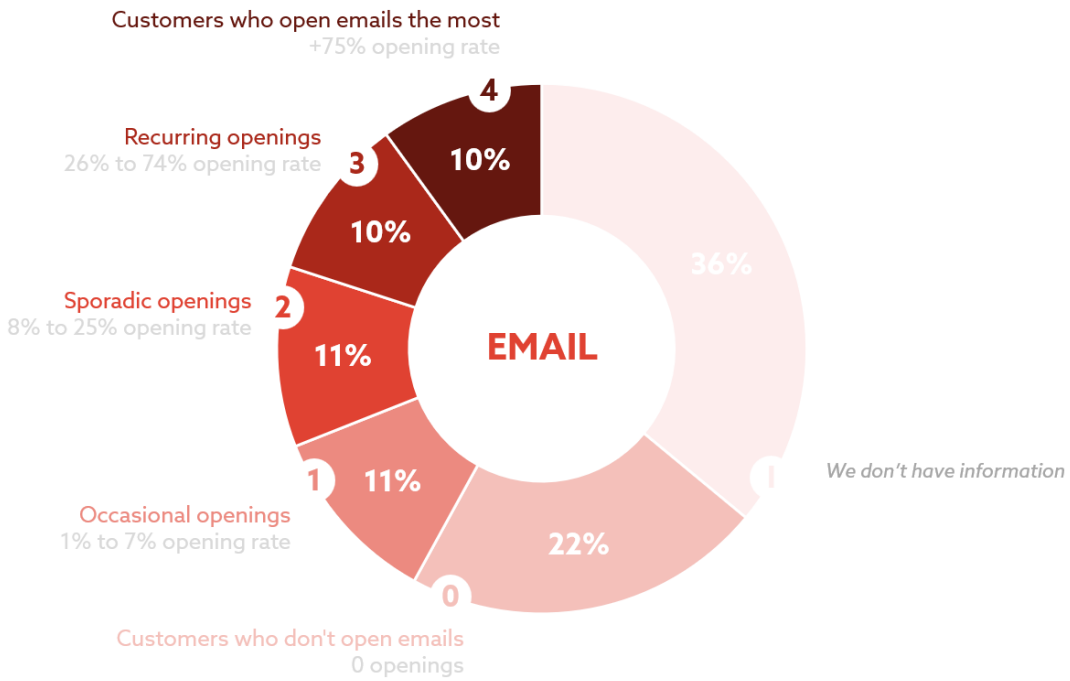


Figure D. 5 Scoring Model | Distribution of customers by channel, Email

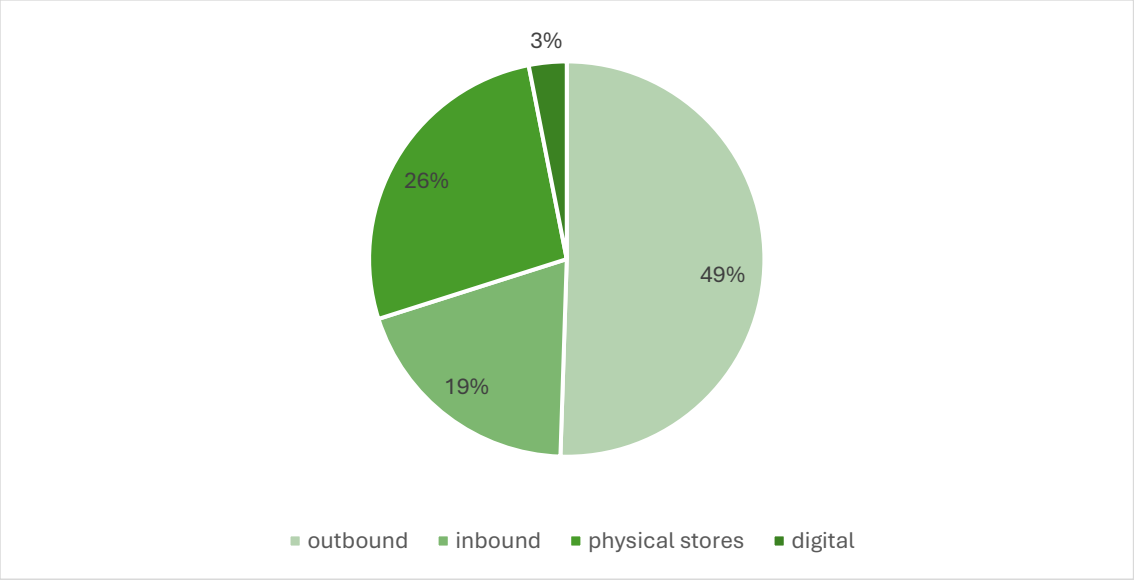


Figure D. 6 Sales Interaction Analysis by Channel

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