The Intentional Nudge: AI, Customer Intent Analysis, and Competitive Advantage in the Portuguese Telecommunications Sector

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Abstract

Title: The Intentional Nudge: AI, Customer Intent Analysis, and Competitive Advantage in the Portuguese Telecommunications Sector

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This thesis investigates how AI-driven intent parsing and nudging mechanisms can create new forms of strategic control within digital ecosystems, using Vodafone Portugal as a case study. While existing literature defines control points primarily around access to infrastructure or proprietary data, this study introduces the concept of second-order strategic control points—dynamic capabilities enabled by AI that interpret customer intent in real-time and influence decision-making through context-aware interventions. Through a mixed-methods approach combining in-depth interviews with Vodafone professionals and a consumer survey, the study uncovers both organizational barriers and consumer expectations surrounding AI personalization. Findings reveal that while Vodafone possesses large volumes of proprietary data, its current AI systems remain limited to rules-based automation and lack the cognitive capacity to parse customer intent dynamically. Consumers were open to proactive technical nudges but viewed commercial ones more critically, emphasizing the need for relevance and trust. The study concludes that leveraging AI to identify, interpret, and act on customer intent requires data integration, cross-functional collaboration, and the deployment of adaptive AI agents. By operationalizing intent as a strategic capability, telecom firms can evolve from reactive service to anticipatory engagement—redefining customer interaction as a source of long-term competitive advantage.

Keywords: Artificial Intelligence, AI Agents, Customer Intent Parsing, Digital Nudging, Strategic Control Points, Generative AI, Telecommunications, Personalization, Second-Order Control Points

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Abstrato

Título: O “Nudge” Intencional: IA, Análise da Intenção do Cliente e Vantagem Competitiva no Setor das Telecomunicações em Portugal

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Esta dissertação investiga como mecanismos de análise de intenção do cliente e nudging, baseados em Inteligência Artificial (IA), podem originar novas formas de controlo estratégico dentro de ecossistemas digitais, com foco no caso da Vodafone Portugal. Embora a literatura existente relacione os pontos de controlo com a posse de infraestrutura ou dados proprietários, este estudo propõe o conceito de pontos de controlo estratégicos de segunda ordem—capacidades dinâmicas viabilizadas por IA capazes de interpretar a intenção do cliente em tempo real e influenciar decisões através de intervenções contextualmente relevantes. Através de uma abordagem mista — entrevistas com profissionais da Vodafone e um inquérito a consumidores — a investigação revela barreiras organizacionais e perceções dos consumidores sobre a personalização com IA. Apesar do vasto volume de dados, os sistemas atuais da Vodafone ainda operam com lógica baseada em regras, sem capacidade cognitiva para interpretar intenções dinâmicas. Os consumidores demonstraram aceitação relativamente a nudges técnicos proativos, mas foram mais céticos em relação aos nudges comerciais, destacando a importância da relevância e confiança. Conclui-se que a operacionalização da intenção do cliente como uma capacidade estratégica requer integração de dados, colaboração transversal e agentes de IA adaptativos. Esta evolução permite às telecomunicações passarem de um modelo reativo para um serviço antecipatório, redefinindo a interação com o cliente como uma vantagem competitiva sustentada.

Palavras-chave: Inteligência Artificial, Agentes de IA, Análise da Intenção do Cliente, Nudging Digital, Pontos de Controlo Estratégicos, IA Generativa, Telecomunicações, Personalização, Pontos de Controlo de Segunda Ordem

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Preface

This thesis marks the end of a long academic journey, one that would not have been possible without the support, patience, and generosity of those around me.

First and foremost, I would like to thank my parents, Mariza Alves and Cláudio Faria, whose unconditional support and patience over the years gave me the strength and encouragement to complete this thesis. To my sister Joana Faria, thank you for always being present and cheering me.

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This thesis is not only mine; it belongs to all of you.

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1) Introduction

The telecommunications industry in Portugal is currently characterized by a fierce price-based rivalry, especially with the rise of low-budget competitors like DIGi. Given that the services provided by the major players - Vodafone, MEO, and NOS - have achieved similar levels of quality and dependability, price has surged as the primary determinant in customer choices. However, this heightened price sensitivity diminishes these companies' capacity to set themselves apart and cultivate lasting customer loyalty. Consequently, these businesses, or at least Vodafone, are progressively seeking out alternative approaches like improving customer service, combining services, and leveraging cutting-edge technologies to establish a competitive edge. This strategic shift towards technology-driven differentiation is intrinsically linked to the rise and importance of digital business ecosystems**.** Digital business ecosystems are evolving, and the concept of control points – strategic positions determining value creation and capture – is being fundamentally reshaped by disruptive technologies (Bohnsack et al., 2024) like Artificial Intelligence (AI).

In particular, the emergence of Generative AI and AI agents, capable of analyzing vast datasets to discern customer intent, presents both unprecedented opportunities and significant challenges (Iansiti & Lakhani, 2020).

As the industry evolves, understanding not just what customers do, but why they do it, becomes critical (Chung et al., 2021). This brings us to the concept of customer intent—a central theme in this thesis. This research focuses on how AI technologies - especially Generative AI and AI agents - can derive customer intent from data and consequently act upon it, enabling strategic value creation for firms like Vodafone. As Chaudhary & Penn (2024) compellingly state, "The intention economy will treat your motivations as currency" (p.1). This highlights the increasing value and strategic importance of understanding and acting upon customer intent. This data can act as a key tool for coming up with strategies, helping companies to figure out and reconsider their connections with products, markets, and rivals (Yoo et al., 2024). And, if ethically and legally leveraged, holds the potential to become a novel and powerful control point within the telecommunication firm's digital ecosystem. However, effectively establishing and utilizing this

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control point requires careful navigation of complex ethical considerations and strict regulatory frameworks like the GDPR (Iansiti & Lakhani, 2020) and the EU AI Act.

The central challenge for Vodafone, and the telecommunications industry at large, is to understand to what extent and how they can ethically and legally harness AI-driven analysis of customer intent data to create personalized, value-based service offerings. Such offerings aim to 'nudge' customers towards increased loyalty and spur new customer acquisition, thereby transforming the competitive landscape and establishing a sustainable advantage in an era defined by data-driven ecosystems and AI innovation.

As a result, this thesis aims to respond to the following questions:

1. To what extent and in what ways can Vodafone leverage customer intent data, parsed and analyzed by AI, to enable the delivery of personalized, value-based service offerings that 'nudge' customers towards increased loyalty and, potentially, new customer acquisition?

2. How can Vodafone ethically and legally leverage customer intent data, analyzed by AI, to set a control point within its digital ecosystem, while adhering to the GDPR and the EU AI Act?

This thesis is structured as follows: Section 2 reviews the literature on digital ecosystems, control points, data as a strategic asset, generative AI and AI Agents. Section 3 outlines the methodology, including qualitative interviews and a quantitative survey. Section 4 presents the findings, while Section 5 discusses the implications. Section 6 concludes with recommendations and directions for future research.

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2) Literature Review

2.1) Digital Ecosystems in Telecommunications

The telecommunications industry is going through significant changes driven by digital technologies and ever-changing customer expectations (Feizi et al., 2023). Historically, this sector has mainly been characterized by providing essential connectivity through voice and data. Nonetheless, the digital age has steered the market in a significant transformation, manifested by the increasing presence and influence of technology companies (KPMG, 2024). These technology companies, such as Google, which initially focused on software, hardware, and internet-based services, are now offering solutions that directly compete with the traditional services of telecommunications firms, which are now obliged to embrace digital transformation if they want to remain competitive and meet customer demands (Feizi et al., 2023).

In order to analyze the spectrum within which telecommunication companies are set, one first needs to understand its context in today's digital world - the context of digital ecosystems.
A digital business ecosystem is defined as a sociotechnical network of individuals, organizations, and technologies that collectively co-create value" (Senyo et al., 2019). This concept goes beyond traditional business ecosystems by incorporating digital technologies as integral parts of value creation (Bohnsack et al.,2024). Digital business ecosystems are characterized by the vast number of heterogeneous participants and the constant increase of competitors from different industries with separate business models and always-changing customer preferences (Bröring et al., 2006). In today's context, they involve interconnected networks of actors in systems where value is created through automated, data-driven, and virtual business processes (Hanelt et al., 2021).

The telecommunications sector is no exception. It functions as a complex digital ecosystem where many organizations, individuals, and technologies are interconnected to create and exchange value (Gawer and Cusumano, 2014). Within this environment, for telecom operators to thrive, it is imperative to have a clear understanding of the ecosystem dynamics to foster innovation and create a sustainable competitive advantage.

Interactions within digital ecosystems are key enablers of innovation and service diversification in the telecommunications industry (Rao & Jimenez, 2011). For instance, through

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the adoption of open innovation and partnerships with third-party developers and startups, telecommunications firms can quicken the development of new services and applications, as demonstrated by the current advances in 5G technologies (Tatipamula, 2024). An example, not with a startup, but with a digital incumbent, is Amazon, with their AWS Telco Network Builder, providing a range of services specifically tailored for the telecommunications industry by simplifying the deployment and management of telecom networks in the cloud (Amazon Web Services, n.d.). They offer solutions intended to assist telecom companies with network modernization, business operations, enhancing customer experience, and fostering growth initiatives. (Amazon Web Services, n.d.).

This collaborative approach enables telecommunications firms to diversify their offerings from traditional communication services to strategic new areas such as cloud computing, smart home solutions, and IoT-based applications (Kübel & Zarnekow, 2014), thus improving customer experience and revealing new revenue streams (Feizi et al., 2023; Grineisen & Rehme, 2019).

The facilitation of cloud-based services enables telecommunications operators to transform their infrastructure and operational processes, which could potentially lead to the reduction of network costs and more agility (KPMG, 2024). Furthermore, they enable faster development and deployment of new services, helping traditional telecommunication companies to move towards becoming digital service providers, also known as the "Telco to Techco" transformation (KPMG, 2024).

The emergence of digital ecosystems has therefore brought about a fundamental change in the strategic posture of telecom operators who have evolved from telecommunication companies to being called technology companies (Feizi et al., 2023) or, in other words, "Techco's" (KPMG, 2024). This change implies the integration of digital technologies, the adoption of new agile business strategies, and the development of a customer-oriented organization (Feizi et al., 2023; Grineisen & Rehme, 2019). In addition, digital ecosystems have prompted the adoption of platform business models in the telecommunications sector (Kübel & Zarnekow, 2014; Hoelck & Ballon, 2015). Hence, as an example, telecommunications firms such as AT&T, can and have already developed cloud and smart home services platforms to offer value-added services to customers and develop new revenue streams (Kübel & Zarnekow, 2014). Nevertheless, for these models to

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be effective, telecommunication companies depend on the proper control of complementary innovations and quality assurance (Kübel & Zarnekow, 2014; Viljainen & Kauppinen, 2011).

Competition in the telecommunications industry has been increasing with the growth of digital ecosystems (Hoelck and Ballon, 2015). Telecommunications firms are now competing against not only traditional rivals, but also with technology companies moving into the telecoms space (Farooq & Raju, 2019) as diversifying entrants (Bohnsack et al., 2024). Take the example of Google's Fiber, which has expanded its reach across the U.S., offering high-speed internet services and directly challenging traditional internet service providers (ISPs), further intensifying competition.

One of the first examples of technology companies competing directly with telecommunications firms within digital ecosystems can be seen with the impact of Over-the-Top (OTT) services (Farooq & Raju, 2019). Where telecom operators once dominated the connectivity space by providing core communication services, platforms such as WhatsApp, Signal, and Facebook began offering similar services independently of traditional network providers, shifting value creation and customer interaction away from telecom firms (Farooq & Raju, 2019). These companies reach customers directly by using the infrastructure built by cellular companies and offering services like messaging, voice calls, and video calls, which were traditionally key revenue streams for telecom companies (Farooq & Raju, 2019). Another example is Microsoft with "Teams Phone", where the company provides voice communication solutions that directly rival Voice over Internet Protocol (VoIP) and landline phone systems (Gartner, 2024). Google Fiber challenging traditional internet service providers (ISPs), Microsoft Teams Phone competing with Voice over Internet Protocol (VoIP) systems, and even AWS providing cloud-based telecom infrastructure, underscore this increasing competition present in today's digital context.

As Farooq & Raju (2019, pg. 187) state, "This new competitive landscape forces telecom companies to either evolve into digital partners themselves or risk being relegated to the role of mere "dumb pipes". For telecommunications firms, navigating this ecosystem requires a strategic understanding of their position and the opportunities available for differentiation and competitive advantage.

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2.2) Control Points in Digital Business Ecosystems

One of the key concepts that can help to understand how telecommunications companies build a sustainable competitive advantage in the digital age is the concept of control points in digital business ecosystems. Control points were first used to analyze the commercial advantages in the telecommunications sector (Trossen, 2005) and are critical nodes within a value network of a firm that enables the firm to control the flow of value and other resources and thereby steer the ecosystem to its advantage (Teece, 2007).

The success and value of a firm are fundamentally shaped by its ability to create and capture value (Iansiti & Lakhani, 2020). Needless to say, this also applies to a firm's performance in its digital ecosystem (Iansiti & Lakhani, 2020). Value creation refers to generating utility for customers, often achieved by leveraging digital resources, organizing collaborations, and innovating through technologies like AI (Bharadwaj, 2013; Åström & Parida 2022). Value capture is the process by which a firm seizes a share of this created value, using mechanisms such as pricing, data control, or strategic positioning to secure competitive advantage (Iansiti & Lakhani, 2020; Pagani, 2013). While traditional models focused on physical assets and direct transactions, digital transformation has introduced new ways for firms to both create and capture value, especially through control points that shape resource flows and access within the ecosystem (Bharadwaj, 2013; Bohnsack et al., 2024).

Control points are strategic or technical positions within digital ecosystems that determine a firm's ability to create value (innovate products and services) and capture value (monetize or retain competitive advantage) (Bohnsack et al., 2024). These points act as gatekeepers, influencing resource flows and bargaining power (Iansiti & Lakhani, 2020). In simple terms, they are like "checkpoints" in a game that stop others from moving forward until they beat certain obstacles.

Strategic control points are assets from the firm's strategic positioning, including the firm's strong brand, deep industry knowledge, established customer relationships, and effective networking within the ecosystem (Bohnsack et al., 2024). In a more concrete example, within the Portuguese telecommunications sector, incumbents like Vodafone, NOS, and MEO, together with their

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combined market share, have a strong customer network and brand reputation, cultivated over many years, fostering customer loyalty and significant switching costs. This perceived value that customers have in these incumbents can act as a barrier for entrants like DIGi, who will face challenges in capturing both market share and the perception of value without having to incur significant costs for brand building and customer acquisition.

Technical control points include the use of digital components, technical infrastructure, data capabilities, scalability, and interoperability. For example, a unique software solution or a strong digital platform that provides seamless connectivity in a business ecosystem is a technical control point. (Bohnsack et al., 2024). The control over data can provide a significant competitive edge. As noted in the context of AI adoption, firms with business models that rely on rich customer data possess a crucial advantage (Jacobides et al., 2021). The appropriation of data can lead to powerful network externalities, further solidifying the position of data-rich entities (Jacobides et al., 2021).

In addition to the data collected directly from customers and their in-person interactions with a company, data is gathered from physical devices and sensors and flows through connectivity layers, such as mobile networks, Wi-Fi, and data transmission protocols, which serve as the infrastructure enabling communication between devices and digital platforms (Atzori et al., 2010). In other words, connectivity layers act as a data highway that moves information from where it is first generated to where it is processed in real time. This data is then used in analytics (such as AI) and digital services; thus, managing data collection, accessing it, and analyzing it effectively becomes a tactical advantage (Bohnsack et al., 2024).

Yoo et al. (2024, pg. 1516) argue that the abundance of data that we have access to nowadays through means such as those described above, "renders possible the exploration of a much wider spectrum of conditions in and around organizations that, due to the lack of data, were previously
virtually impossible. The availability of data thus expands the range of events that organizations can attend to and provides the means for mapping and, eventually, rethinking relationships to products/markets, value chain networks, and competitors." This makes data a critical strategic

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asset in today's business ecosystems and a valuable resource for the establishment of control points, not only through the proprietary ownership and use of data (technical control point), but also by leveraging that data to create new strategic conditions for coordinating interactions, shaping participation structures, and setting behavioral expectations.

2.3) Data as a Strategic Asset and Potential Control Point in the Telecommunications Industry

Telecommunication companies possess large volumes and varieties of data spreading beyond traditional call records. Data in the telecom industry encompasses a wide range of information, including customer profiles, call records, network logs, location data, social media interactions (Sadiku et al, 2024) behavioral data, billing and payment data, and much more.

Within this vast data panorama, telecommunication companies usually start their customer data collection with basic *personal information* such as: the name and address for account setup and billing operations; date of birth to verify age and deliver personalized services; and government-issued IDs, including national ID numbers or passport information to satisfy legal requirements and fraud prevention needs. (Rahimi et al., 2023). Demographic information is therefore the first step as an input for machine learning models that telecommunications companies might use to predict customer behavioral patterns and preferences. A study by Saha et al. (2022) shows that demographic backgrounds maintain a vital connection with customer behavioral needs, which enables companies to create personalized service offerings and tariff plans. These demographic profiles enable telecom companies to categorize their customer base into distinct segments with similar characteristics, such as age, where one can target "Young Adults" (18-25) with mobile data-heavy plans and streaming service bundles, versus "Seniors" (65+) who might be offered simpler voice plans and better dedicated customer support. This segmentation enables a more targeted communication approach, improving marketing service delivery strategies (Anderson, 2024).

Telecommunication companies also gather detailed *geographic and location data* from their customers. This data can include both the residential and professional addresses of customers, as well as their mobile network-based real-time location tracking and service coverage regions.

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Geographic data allows companies to improve their network infrastructure and service delivery while revealing customer movement behaviors and lifestyle characteristics (Wang et al., 2024).

Telecommunication firms furthermore keep precise records of their customers' *billing and payment information*. The system stores an extensive payment record that shows all previous transactions together with payment options. There is subscription information, which includes the service plan type and contract period, along with any additional services that customers receive. The data serves multiple critical purposes because it not only enables precise billing statements and revenue control, but it also helps companies understand customer preferences between bundle packages (Li et al., 2006). The research of Li et al. (2006) shows that billing and payment data analysis helps companies maintain customer retention through the identification of churn-related patterns. According to CSG (2024), payment history information also serves as a valuable resource for credit underwriting when customers lack established credit profiles.

Most customer service interactions that telecommunications companies track result in complete *communication records*. In the Portuguese sector, these records can only be stored for up to 6 months (CNPD, 2000). These records span multiple channels, including recorded contact center conversations, together with chat transcripts, email exchanges, chat-bot interactions, and social media communications (Kalogiannidis et al., 2022).

These customer interactions include the specific nature of complaints, their respective resolution methods, work resolution time duration, customer satisfaction with their respective outcomes, and any follow-up actions. Complaint data serves as a valuable indicator of service pain points and customer frustration levels. Customer sentiment and satisfaction metrics are systematically collected through various mechanisms, including post-interaction surveys, Net Promoter Score (NPS) measurements, satisfaction ratings, and sentiment analysis of communications (Anderson, 2024), among other metrics. With the emergence of AI, telecommunications companies started to use “customer sentiment” as a key predictor in the churn analysis model (Anderson, 2024).

This sentiment data helps companies estimate the emotional state of their customer relationships and identify potential detractors before they churn.

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Behavioral data in the telecommunications industry captures how customers interact with services, applications, and digital platforms. It provides dynamic, real-time insights into customer preferences, needs, and potential dissatisfaction triggers.

Key categories of behavioral data include:

- **Call and SMS Patterns**: Telecoms collect detailed records on the frequency, duration, and timing of customer calls and messages (Anderson, 2024). These patterns help construct user profiles, identify highly connected individuals, and forecast churn risks based on declining communication volumes.

- **Browsing Habits and App Usage**: Monitoring website visits, app interactions, and overall data consumption enables telecoms to map online behaviors and preferences (Wang, 2024). Wang et al. (2024) demonstrate how "mining app usage patterns" predicts future behavior, helping firms tailor service offerings.

- **Service Usage Trends**: Patterns in data usage, voice minutes, and ancillary service subscriptions can reveal shifts in customer needs. As Begam (2024) highlights, analyzing usage behavior supports segmentation strategies and the design of personalized plans to boost engagement and retention.

- **Digital Footprints and Navigation Paths**: Digital interactions—such as website clicks, in-app navigation paths, and platform searches—offer detailed insights into customer intent (Savas & Ergen, 2023). Savas & Ergen (2023) emphasize the importance of tracking these digital trails to create predictive behavioral models.

- **Content Viewing Habits**: Internet Protocol Television (IPTV) systems generate billions of viewing records, capturing information about preferred genres, binge-watching behaviors, and ad engagement (Chang & Chiu, 2023). Such insights allow telecoms to customize content bundles and better address advertising strategies.

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- **Ad Engagement**: Telecoms can assess advertisement effectiveness by measuring which ads are watched, skipped, or ignored, thus tailoring marketing efforts based on content resonance (Pongiannan, 2012).

- **Social Media Activity and Integration**: When customers connect their social media accounts, telecoms can analyze content preferences, network affiliations, and sentiment patterns (Mansour et al., 2024). Social data enriches customer profiles, providing early signals of dissatisfaction or new interests.

This extremely detailed behavioral profile, together with demographic information and transactional and interaction data, provides substantial value to telecommunication companies. However, the vast potential of this information remains locked because of the amount of complex data existing across multiple different systems and formats. The process of organizing, managing, and operationalizing all this data presents a major challenge. This is where Generative AI and AI Agents enter the scene. They function as powerful enablers to address this situation, as this technology supports telecommunication companies with essential tools through their natural language processing (NLP) capabilities. They have the power to analyze extensive datasets through pattern recognition and automate tasks, which in turn can enable these companies to convert extensive customer data into strategic business intelligence.

In KPMG's (2024) "From Telco to Techco," one of the key points on how telecommunications companies should navigate today's digital ecosystem is by emphasizing customer centricity - focusing on what the customer actually wants. The report highlights that traditional telecommunication companies are often constrained by legacy (outdated) systems, resulting in services that do not meet modern customer expectations. By effectively leveraging behavioral insights, firms have the opportunity to transition from reactive service providers to proactive service providers.

Following the line of thought that leveraging data by using AI for data analysis can establish new strategic conditions around an organization (Yoo et al., 2024), the ability to derive customer intent from this analysis becomes a critical manifestation of such a strategic condition. It is also

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important to distinguish intent parsing from similar analytical methods, such as sentiment analysis or behavioral analytics. Whereas sentiment analysis captures emotional tone and behavioral analytics tracks past actions (Jayawardena et al., 2022), intent parsing seeks to discover the underlying future wants and needs driving customer behavior (Alhasan et al., 2025). This way of predicting future behavior enables firms to be more incisive not only when intervention is needed, but also being able to nudge customers at the right time, with context-specific offers. This difference is what potentiates the transformation of a technical capability into what I term a "second-order strategic control point" in this thesis.With AI's ability to aggregate multiple data sources and parse intent from that, it positions the company to steer customer behavior proactively, thereby reacting to demand as well as configuring the pathways through which demand unfolds in the ecosystem.

While the information derived from intent parsing is based on public emotions and standard usage data, it is also generated through the combination of Vodafone's proprietary integration of scattered datasets (service usage, app interaction, etc) with the AI systems embedded in its customer infrastructure. Competitors that do not possess access to the same nature of data cannot easily replicate the derived insights nor the timing of these incisive interventions. Therefore, AI-driven intent parsing enables not only the anticipation of churn and the personalization of journeys, but also the sustainable reinforcement of competitive position, turning a technical strength into a strategic barrier.

In the next section, I will discuss how the analysis of the data previously presented, leveraged by generative AI and AI agents, can better help in the formulation of customer intent analysis, enabling telecommunications companies to navigate and cater to the ever-changing needs of their customers.

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2.4) Generative AI, AI Agents, and Customer Intent Analysis

Artificial intelligence (AI) plays a transformative role in digital ecosystems by converting raw customer data into actionable insights (Iansiti & Lakhani, 2020).

Data by itself serves as a technical control point. Jacobides et al. (2021) highlight that control over proprietary data can create barriers to entry, particularly when such data is used to personalize services or gatekeep access to network innovation. However, the interpretation and application of that data, such as detecting intent, personalizing interactions, or automating nudges, could create a new second-order strategic control point through the influencing of customer behavior, redefining engagement, and the strengthening of customer dependence —essentially locking in customer access. In what follows, I take a closer look at the AI systems that are the drivers behind the kind of data parsing and analytics that make it possible to detect intent and deliver nudges based on intent data.

Generative Artificial Intelligence (GenAI) is often described as a subset of machine learning that enables models, such as large language models (LLMs) and related architectures, that learn from extensive datasets to produce a vast amount of content such as human-like text, audio and other forms of output (Creasy et al., 2024). The widespread diffusion of this technology with examples such as Perplexity, GPT-4, and Gemini is currently revolutionizing the way we work and communicate with each other (Feuerriegel et al,. 2024). Generative AI systems can be used for artistic purposes to generate new content, and they can also assist humans as intelligent question-answering systems (Feuerriegel et al,. 2024). Another usage for GenAI is the analysis of data. Unlike traditional predictive models that classify or regress on known outputs, generative models synthesize outputs by acquiring statistical patterns from historical data through learning, which enables them to generate logical responses to prompts, thus assisting with the analysis of understanding the underlying structure of the data (Wiesinger et al., 2024). In various sectors, including telecommunications, GenAI has the capacity to process a wide range of customer data, including structured billing records, behavioral logs, and unstructured text from service transcripts. Coupling this data together GenAI can help infer customer needs and generate personalized responses or product recommendations. This set of capabilities moves beyond simple analytics,

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enabling real-time, context-aware decision-making that supports customer intent prediction and service optimization (Gamboa-Cruzado et al., 2025).

AI Agents extend the above-mentioned Gen AI capabilities, amongst others, by aggregating content generation with autonomous decision-making and systems integrations. AI agents can be defined as autonomous systems designed to perceive their environment, process inputs make decisions and take actions to achieve predefined goals without direct human intervention (Liu et al., 2025). In the context of customer service and intent prediction, AI agents can actively seek information, trigger system responses, learn from past interactions, and continuously update their strategies in real time (Galileo, 2025). Unlike traditional automation tools, they do not just generate outputs; they begin actions, such as resolving a complaint or proposing an optimized service plan. By integrating the logical outputs of large language models into workflow and decision processes, AI agents operationalize advanced AI capabilities (Wiesinger et al., 2024).

In telecommunications, AI agents are already deployed as chatbots, voice assistants, and service automation engines (Gamboa-Cruzado et al., 2025). These systems enable proactive interventions, predictive service adjustments, and intent-driven nudging. As defined by Thaler and Sunstein (2008, p. 6), a nudge is "any aspect of the choice architecture that alters people's behavior predictably without forbidding any options or significantly changing their economic incentives."

Understanding how AI agents act on customer intent is fundamental to their strategic value. According to Chaudhary and Penn (2024), intent is described as a purposeful, directed state behind an action, which means having an aim or a particular plan when doing something. They assert that this concept is often associated with the concept of planning and deliberation of future actions. They also argue that intent can be a quantifiable and computable aspect of human behavior. The authors assert that digital interactions can reveal indications of what people might want or even plan to want. They propose that our activities online, such as search queries or social media posts, can provide hints to people's underlying desires or goals, whether as mundane as choosing a movie or something more significant, like political choices. For the latter, the Facebook-Cambridge Analytica data scandal provides a good example, where the consulting firm Cambridge Analytica

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used Facebook users' data as quantifiable indications of psychological traits and political inclinations. They computerized this data into profiles, and then acted purposefully by micro-targeting users with political campaigns and ads influencing their voting decisions (Hu, 2020).

It is also essential to differentiate between sentiment analysis, which assesses the emotional tone behind customer interaction (Katragadda, 2024) and intent parsing, which aims to uncover the underlying goals or purposes behind those interactions (Farshidi et al., 2024). While sentiment analysis, based on the tone of a chatbot interaction or a support call transcript, may help discovering that a customer is frustrated, intent parsing determines whether the customer is likely to cancel a service, inquire about a bill, or request a technical fix. For instance, if a customer types, "I am sick of this slow connection (…)", a sentiment derived analysis would classify the message as negative, while intent parsing would detect a likely service cancellation intent and trigger a proactive retention offer. Both are often used alongside one another within AI systems but they serve distinct functions in customer engagement.

By combining perception (data intake), cognition (intent parsing), and action (nudging or system execution), AI agents symbolize a new class of digital workforce, one that can independently mediate between company objectives and customer experiences. This ability to continuously parse customer intention is crucial to their strategic usefulness, which, in turn, transitions data from a technical control point to a strategic one, by creating a barrier that is difficult for competitors to replicate. Through intent parsing, firms obtain proprietary behavioral data that competitors may find difficult to duplicate, especially since this data is connected to internal systems. As previously discussed, telecommunications firms collect and integrate a wide array of data types, including billing records, service logs, app usage patterns, sentiment analysis chatbot transcripts, network performance data, among other. When combined, these different data points enable AI agents to create dynamic, real-time profiles of customer intent. For example, if a customer's data shows reduced engagement, frequent technical complaints, and browsing of cancellation pages in the FAQ (Frequent Asked Questions), the system can infer a high likelihood of churn and trigger a personalized retention strategy. The development of AI systems that understand and execute intent demands extensive financial investment across data pipeline development, model training, and operational workflow integration (Galilei, 2025), which extends

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the time needed to replicate. As this system interacts over time with customers, they continuously improve, forming a continuous feedback loop that improves personalization and performance (Liu et al., 2025), hence enlarging the competitive gap. Improving over time, delivering personalized, proactive, and context-aware experiences, one can logically assume this customer experience increases customer satisfaction, hence reducing churn, locking customers into an environment that is difficult to match. Thus, intent parsing via AI agents becomes not just a technological capability but a strategic control point protected by proprietary data, algorithmic intelligence, and adaptive learning that reshapes competitive dynamics in digital ecosystems.

Let us take the example of T-Mobile's collaboration with OpenAI. Together they established IntentCX, an "intent-driven AI decisioning platform" that ingests billions of interaction records to identify the Next Best Action (NBA) in real-time (T-Mobile, 2024). Its primary goal is to fundamentally revolutionize the customer experience by discerning customer intent and sentiment in real-time. IntentCX exemplifies a control point: by embedding AI agents within CRM and network systems, T-Mobile can pre-emptively resolve issues, upsell personalized offers, and automate complex service tasks—actions that competitors without similar platforms cannot easily replicate.

Once intent is identified, AI agents can deliver specific and personalized "nudges", which can be described as subtle, data-driven interventions designed to influence customer decisions without constraining their choice (Kumari & Raj, 2024).

Examples include and are not limited to:

- Retention Nudges: Real-time personalized offers taking into consideration live detected pain points such as temporary data boosts when low usage suggests dissatisfaction (Lunn, 2013)
- Acquisition Nudges: The system shows customer features of interest through customized onboarding sequences that match their predicted preferences. For example, subtly propose 5G gaming plans for high-bandwidth users (Lunn, 2024)
- Continuous Optimization: The system conducts A/B testing - controlled experiments comparing different versions of messages or timings - to optimize key metrics (retention rate, customer lifetime value) through agent-driven feedback loops (Kohavi et al., 2009; Indigo.ai,

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2025). The system enhances its nudging methods automatically through key performance indicators.

These individual nudging mechanisms operate within a broader AI-driven architecture that links customer data, intent interpretation, and adaptive orchestration. Figure 1 illustrates this conceptual model.

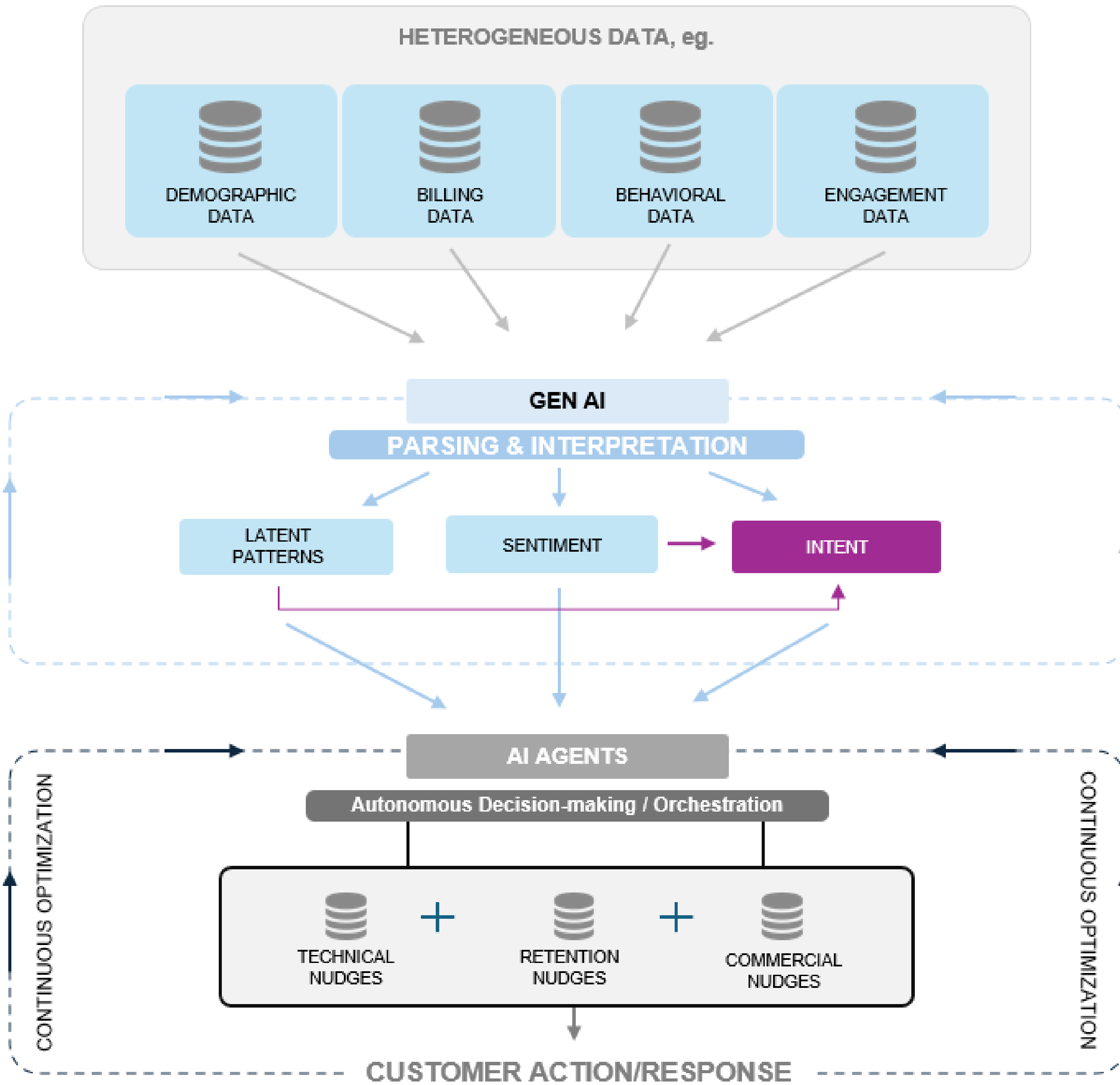

Figure 1 - Conceptual model illustrating the interaction between heterogeneous data, generative AI, and AI agents in enabling intent-based nudging and adaptive customer engagement

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The analysis demonstrates that AI-driven customer intent analysis goes beyond functioning as a technical capability; it can be leveraged as a second-order strategic control point within digital ecosystems. In Vodafone's case, the deployment of AI agents capable of parsing intent and generating adaptive nudges represents more than a technical capability, it resembles to what Alhasan et al. (2025) describe as *affordance perception*: the ability to detect which actions a customer is most likely to want or do next, given their current context and behavioral cues. Instead of treating customer intent as a fixed or pre-determined state, the AI system creates a flexible view of what the customer might want to do next, based on both their past behavior and their current context. As customers interact with the system, the system learns from their responses and becomes better at predicting and guiding future actions. This creates a feedback loop, where data increasingly helps the AI understand customers better. Consequently, that understanding drives decisions, and the results of those decisions create new data for learning, forming a self-reinforcing learning system.

Through this ongoing process, where data informs interpretation, interpretation informs action, and action reshapes future data, it elevates the control point beyond the static possession and use of data. It could even be argued that this algorithmic data-driven feedback loop becomes generative. According to Zittrain (2006, p. 1980), the concept of generativity relates to "a technology's overall capacity to produce unprompted change driven by large, varied, and uncoordinated audiences." AI systems enable data generativity by combining and interpreting heterogeneous data in ways that reveal new affordances and produce interactions that were never anticipated at the time of collection. In the case of intent parsing, they draw on varied data sources, learn from context, and gradually form a probabilistic sense of what a customer is likely to want or do. In this way, they can also help set a second-order control point —one that was not possible before AI's ability to work across vast, heterogeneous data sources.

The insights outlined in the above will guide the investigation on answering this thesis's research questions as to what extent, and how Vodafone can apply AI-driven intent analysis and nudging to gain a competitive advantage and establish a strategic control point, while remaining compliant with ethical and legal boundaries. To explore this, the next section outlines a mixed-

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methods research approach involving interviews with Vodafone professionals and a survey of Portuguese telecom consumers.

3) Methodology

To address the research questions on how Vodafone can ethically and effectively leverage AI-driven customer intent analysis as a strategic control point, this study adopts a *mixed methods approach* (Molina-Azorin, 2011). This combines qualitative interviews with Vodafone professionals and a quantitative public survey, enabling both deepness and coverage of insight. The mixed methods design augments the validity and rationality of the findings by capturing both expert perspectives and the general public's points of view (Dawadi & Shrestha, 2021). It aims to explore AI-driven customer intent analysis from multiple angles: strategic, operational, and ethical. A qualitative analysis allows for exploration of organizational intentions and assumptions, while the quantitative analysis tests the importance of those insights with real customer perceptions.

All participants were informed of the study's purpose, provided consent, and were assured of anonymity and confidentiality. The research design was guided by GDPR and ethical research standards, particularly regarding the handling of sensitive personal and professional data.

3.1) Qualitative Interviews with Vodafone Professionals

The reasoning behind choosing the interviews was to gain in-depth, context-rich insights into how AI-driven customer intent analysis is perceived, implemented, and challenged within Vodafone. Interviewing professionals from diverse departments (e.g., Data Science, Operations, Customer Experience, Privacy) ensured a complete understanding of the technical, strategic, and ethical dimensions (Young et al., 2018).

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Participants were selected by sampling ten Vodafone employees, who were specifically selected based on specific characteristics relevant to the research question in order to ensure representation from all relevant business areas (see Appendix for roles) (Palinkas et al., 2015). This sample size is consistent with qualitative research best practices, balancing depth of insight with feasibility (Saunders & Townsend, 2016).

Interviews followed a semi-structured format, with approximately 80% of the core questions asked to all participants and 20% tailored to departmental expertise (Rubin & Rubin, 2005). Central themes included:

- Understanding and challenges of customer intent analysis
- Opportunities and risks of AI for intent detection
- Use of data and technical infrastructure
- The concept and application of "nudging"
- Ethical and legal considerations (GDPR, EU AI Act)
- Strategic implications for control points and Vodafone's competitive positioning
- Department-specific impacts and collaboration needs

(See Appendix A for the full set of questions)

These questions were directly derived from the research questions, ensuring alignment with the study's aims: exploring how customer intent analysis can be a control point, and what ethical, legal, and operational factors must be considered.

Interview transcripts were analyzed using the Gioia Methodology. This theoretical approach involves systematic coding of first-order (informant-centric) concepts, aggregation into second-order (theory-centric) themes, and development of predominant dimensions (Gioia at al., 2012). This method is well-suited for theory-building in management research and enables the emergence of new conceptual insights grounded in participant experience (Gioia at al., 2012).

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3.2) Quantitative Public Survey

The rationale behind the public survey was to complement the qualitative insights derived from industry interviews. The goal was to capture the perspectives, concerns, and expectations of telecom customers in Portugal regarding AI-driven personalization, data use, and nudging. Surveys are ideal for accessing a broad, diverse population and quantifying attitudes and trends that complement the depth of the interviews (GOV.UK, 2021)

The survey was distributed online to Portuguese residents over 18 who subscribe to telecom services. It included:

- Demographics and provider usage
- Satisfaction and trust in providers
- Attitudes toward AI, personalization, and automated systems
- Comfort with different types of data collection
- Reactions to "nudging" and proactive engagement scenarios
- Data privacy awareness and preferences

(See Appendix A for the full questionnaire.)

Questions were designed to map directly onto the research questions, especially regarding public acceptance of AI-driven intent analysis, perceived value, nudging and ethical boundaries.

Survey data were analyzed using SPSS. Descriptive statistics (frequencies, means, cross-tabulations) were used to summarize the distribution of key attitudes, comfort levels, and demographic characteristics, while inferential statistics (e.g., t-tests and correlations) explored relationships between variables such as age, provider, and attitudes toward AI and nudging. This approach ensures rigorous, replicable quantitative analysis (Rahman & Muktadir, 2021).

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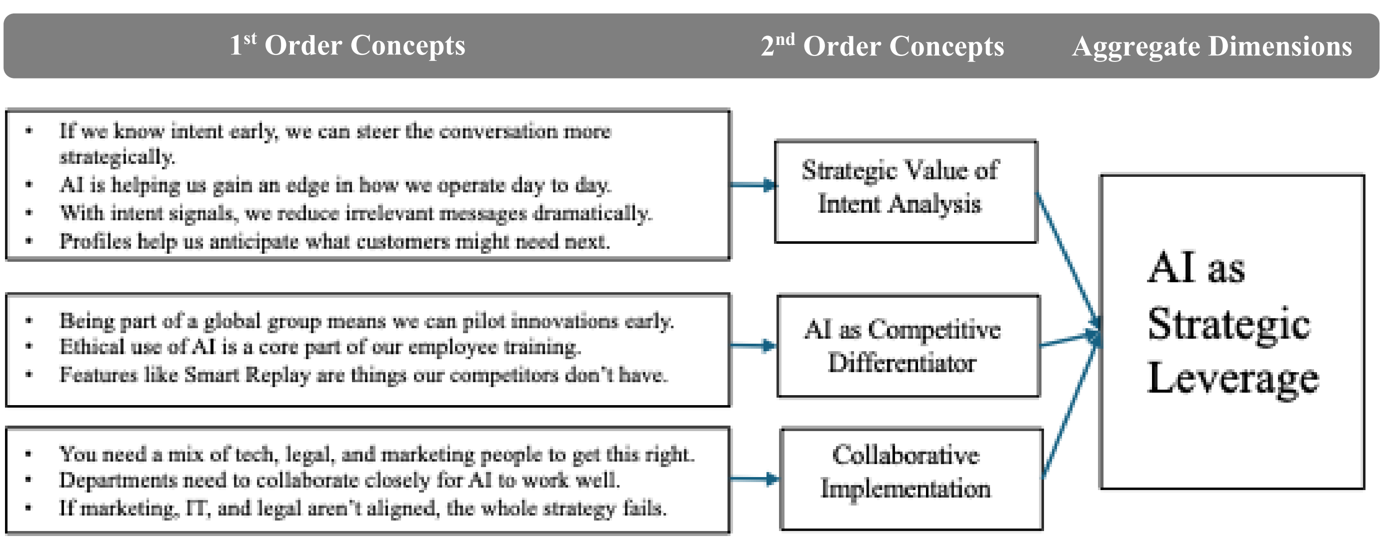
4) Findings

4.1) Qualitative Findings: Gioia Method Analysis

To deeply understand how AI-driven customer intent analysis and nudging are perceived and operationalized within Vodafone, I applied the Gioia Method to ten semi-structured interviews with professionals from across the organization. Coding was conducted using Atlas.ti software. There were a total of 6 rounds to refine categories within the concepts. Due to a lack of initial knowledge to code, more rounds were needed than 3 in order to achieve an Aggregate Dimension. All the rounds were conducted to ensure consistency across transcripts and to confirm the emergence of stable second-order themes and aggregate dimensions.

The analysis resulted into five aggregate dimensions, each emerging from clusters of second-order themes and grounded in participants' statements. Together, these dimensions offer a structured view of how AI capabilities combine with organizational strategy, technical limitations, and customer engagement. The table below depicts the analysis of the semi-structured interviews using the Gioia Method:



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1st Order Concepts	2nd Order Concepts	Aggregate Dimensions
• Customers are fine with personalization—if it's genuinely useful to them. • When we segment by behavior, the acceptance of our suggestions goes up. • If someone watches sports, we suggest the sports package—it's that simple.	Effective Personalization Tactics	Behavioral Response to Nudging
• We've seen some sorts of nudging actually help form new user habits over time. • We would offer plans based on how people actually use their devices. • Understanding mood beforehand helps tailor the support response.	Proactive Behavioral Shaping	Behavioral Response to Nudging
• If an ad its not liked, it's quickly rejected by the viewer. • Sending irrelevant campaigns just breaks trust with the customer. • People are tired of constant, irrelevant marketing messages	Personalization vs. Intrusion	Behavioral Response to Nudging
• We always make sure to strip out identifying data. • We don't touch customer data unless they've clearly given permission. • Even when data is anonymous, there's still a risk it can be linked back.	Data Ethics & Consent	Ethical and Legal Compliance
• Being open about the usage of AI will help maintaining customer trust. • We should tell users explicitly when they're interacting with AI. • If we don't understand how the AI works, we can't explain it or fix issues	Transparency & Explainability	Ethical and Legal Compliance
• Our privacy teams are actively training on new AI concepts. • We have mandatory refreshers to stay updated on compliance issues. • Our strategy is always changing to meet legal standards. • Deploying without fully grasping AI implications is too risky.	Organizational AI Readiness	Ethical and Legal Compliance
• If a customer switches customer support channels and has to repeat everything, it's frustrating. • TOBi handles basic stuff well, but it lacks on the tricky ones. • AI just doesn't get emotion the way a human can—yet. • Old systems don't always connect well with new tools.	Service Channel Fragmentation	Operational & Technical Challenges
• Our systems don't always talk to each other, which creates blind spots. • Data silos make it hard to get a full picture of the customer. • Some of our core infrastructure is just outdated	Systemic Integration Gaps	Operational & Technical Challenges
• We have to treat repeat detractors with extra care and attention. • Most complaints are about billing issues and network performance. • When we predict problems in advance, we lower our support volume.	Customer Risk Management	Operational & Technical Challenges

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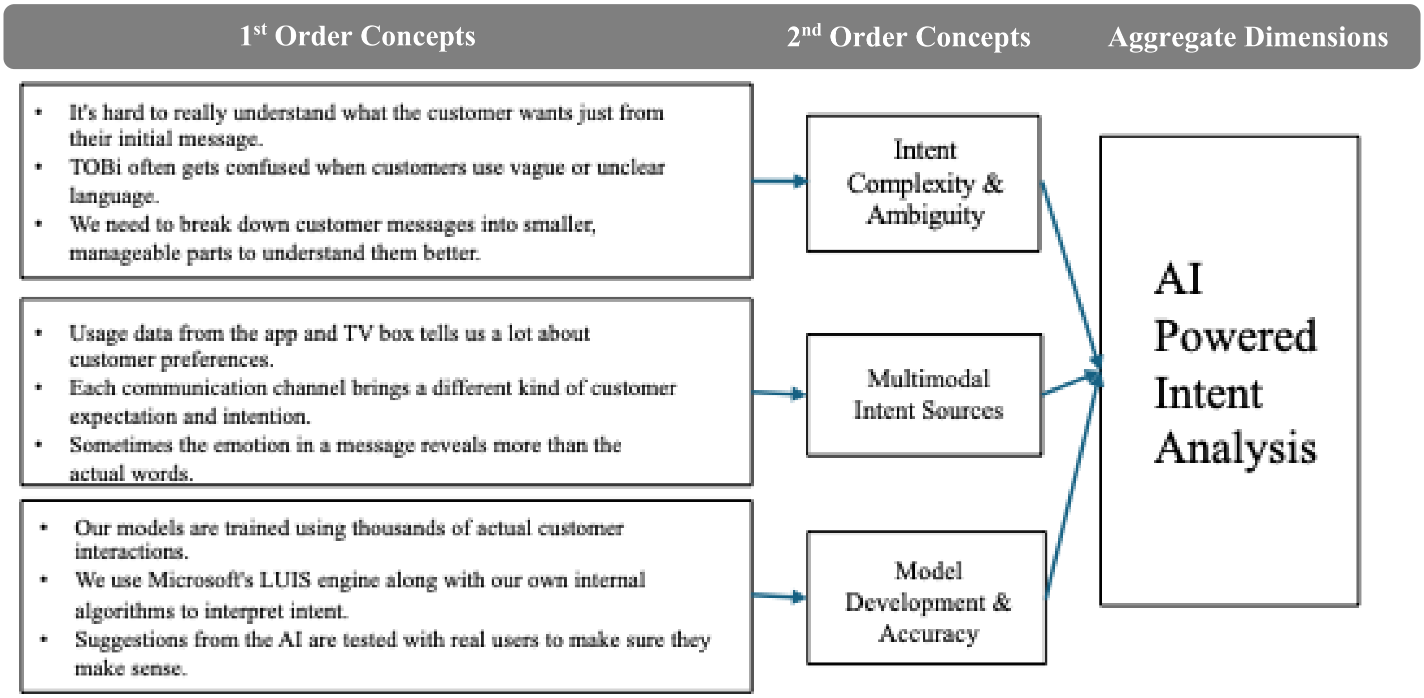

Figure 2 – Data Structure based on the Gioia Method

Data Structure and Coding Process

The analysis proceeded in three stages. First, interview transcripts were reviewed line-by-line to identify informant terms and expressions related to how AI is used to understand customer intent, automate personalization, address ethical concerns, and generate strategic business value. These informant-centric excerpts were grouped into initial first-order concepts that reflected participants' own language and framing. In cases where overlapping or recurring statements appeared across roles (e.g., data science, privacy), these concepts were merged to preserve distinctiveness without inflating the codebook. Notes were taken throughout this stage to track potential links between emerging ideas. In the second stage, I reviewed the first-order concepts for underlying patterns and began developing second-order themes that captured broader organizational or strategic meanings, particularly around AI's role in personalization and its implications for customer engagement, data infrastructure, and organizational readiness. These themes were repeatedly refined considering theoretical constructs from the literature on strategic control points and predictive personalization. Finally, I organized these second-order themes into

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aggregate dimensions that structure the findings in relation to the study's research questions and the strategic positioning of AI within Vodafone's digital ecosystem. The coding process was conducted using Atlas.ti, which supported me in systematic tagging, clustering, and visualization of concepts across interviews, helping to ensure conceptual clarity and comprehensive thematic development across the data set.

The first dimension, *AI-powered intent analysis*, reflects the challenge of interpreting customer intent when input is vague, emotionally difficult to parse, or distributed across channels. One participant stated that the current AI systems often struggle to interpret messages that are ambiguous or spoken with strong emotion, such as frustration, urgency, or dissatisfaction, where the intent is implied rather than explicitly stated. While Vodafone leverages tools like Microsoft's LUIS, a Machine Learning model for text processing, alongside proprietary models, the accuracy of these systems remains a work in progress. Several interviewees emphasized the importance of training AI on diverse data streams such as app usage, chatbot logs, and service call transcripts, in order to better capture intent. With this convergence of different data streams, interviewees' initial assessment was that these AI systems are positioned to evolve into strategic assets, capable of anticipating customer needs and enabling Vodafone to respond more effectively within its digital ecosystem.

The second dimension, *behavioral response to nudging*, revealed how Vodafone could use AI not only to understand intent but also to act on it. Participants described a growing focus on personalized, context-aware nudges such as recommending TV packages based on past viewing habits or detecting churn risk before it materializes. One respondent shared, "We've seen nudging actually help form new user habits over time." However, this strategy depends heavily on relevance. "Customers accept personalization when it's genuinely useful," one interviewee stated, suggesting that behavioral segmentation, rather than static demographic profiles, will drive success.

The third dimension, *ethical and legal compliance*, assesses the role of regulation as both constraint and strategic must. Professionals across departments stressed the importance of consent and transparency, with one stating, "We don't touch customer data unless they've clearly given

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permission." While Vodafone anonymizes most datasets, there was an awareness that "even anonymized data carries risk.". There was a clear consensus that trust is built not just through compliance with GDPR and the EU AI Act, but also through active transparency. "We should tell users explicitly when they're interacting with AI," participants explained.

The fourth dimension, *operational and technical challenges*, examines the organizational reality of implementing intent-based AI at scale. Participants described major ongoing struggles with channel fragmentation, data silos, and difficulty in system integration. "Our systems don't always talk to each other, which creates blind spots," one said. Legacy infrastructure continues to pose a barrier, especially in terms of aligning AI systems with existing CRM and billing platforms. These operational gaps limit the strategic potential of AI unless they are addressed through cross-functional coordination and modernization efforts, which according to some participants its already in motion.

The final dimension, *AI as strategic leverage*, summarizes Vodafone's potential motivation to turn AI-driven intent analysis into a competitive differentiator. Several professionals described intent parsing as a potential "emerging control point," allowing the company to personalize interactions, reduce churn, and optimize service delivery in real time. As one participant stated, "AI is helping us gain an edge in how we operate day-to-day." By integrating AI systems with behavioral prediction and customer journey mapping, Vodafone aims to evolve beyond traditional telco positioning, toward a more proactive, tech-enabled service provider.

4.2) Quantitative Findings: Survey Results

To complement the qualitative interviews, a public survey was conducted with Portuguese telecom consumers to assess their views on AI-driven personalization, data usage, and nudging. The survey received 100 valid responses and included 26 closed-ended questions. Of these, 18 used a five-point Likert scale (e.g., 1 = Very Uncomfortable / Strongly Disagree to 5 = Very Comfortable / Strongly Agree) to measure comfort, trust, transparency, and ethical concerns. Additionally, one question used a ranking format to analyze why they choose a particular telecom provider (e.g., price, service quality, customer service, etc.), while the remaining items were

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multiple choice or binary (yes/no) questions, covering demographics, service usage, and past experiences with automation. This mixed-question design allowed for an inclusive examination of both attitudes and behaviors across a representative customer base.

Trust and Data Comfort

In general, respondents reported moderate satisfaction with their current telecom providers (M = 3.9/5 for mobile services and M = 3.6/5 for home services). However, trust in providers to use customer data ethically was considerably lower, with a mean of 2.6 out of 5, indicating sector-wide distrust. This aligns with the concerns raised in interviews, where professionals emphasized the importance of transparency and data consent in building trust.

Comfort with data collection was moderate to mostly low throughout different data types. Participants were most comfortable sharing basic account information (M = 3.3/5) while showing low comfort with location data (M = 2.36/5), browsing activity (M = 2.1/5), and call/message history (M = 2.1/5). These values reflect a broader public sensitivity around behavioral and contextual data, reflecting Vodafone professionals' concerns about the limits of anonymization and the ethical risks associated with it. Interestingly, TV viewing data was viewed more neutrally (M = 2.7/5). This neutrality towards TV viewing data could be explained by several factors. TV consumption is often a shared, social activity, and consumers might perceive their viewing habits as less private than, for instance, their browsing history or private SMSs. Furthermore, the number of today's recommendation engines, like those used by Netflix, has accustomed users to a degree of personalization based on viewing patterns. Customers might see this as a valuable characteristic rather than an intrusion, especially if it leads to discovering relevant content (Romero Meza & D'Urso, 2024).

	N	Minimum	Maximum	Mean	Std Deviation
Q4 – Mobile Satisfaction	100	1.00	5.00	3.8700	1.06035
Q5 – Home Satisfaction	100	1.00	5.00	3.6224	1.03062
Q6 – Telecom Trust Customer Over Profit	100	1.00	5.00	1.7300	1.08110
Q11 – AI Customer Service Experience	87	1.00	4.00	2.2874	1.04445
Q12 – Comfort with AI Data Use	100	1	5	3.29	1.018

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Q13 – AI Understanding	100	1.00	5.00	2.6700	1.25573
Q14 – Personalized Offers Comfort Past Usage	100	1	5	3.19	1.012
Q15 – Provider Trust Data	100	1	5	2.59	1.111
Q16 – Data Rights Awareness	100	1	5	2.92	1.269
Q17_1 – Comfort Collection Account Info	100	1.00	5.00	3.3100	1.37580
Q17_2 – Comfort Collection Location Data	100	1.00	4.00	2.3600	1.16792
Q17_3 – Comfort Collection Call History	100	1.00	5.00	2.0700	1.29689
Q17_4 – Comfort Collection Browsing Data	100	1.00	5.00	2.0600	1.26985
Q17_5 – Comfort Collection TV Viewing Data	100	1.00	5.00	2.6800	1.33242
Q19 – Data Driven Suggestions	100	1	5	2.96	1.171
Q20_1 – AI Transparency	100	1.00	5.00	4.4300	.93479
Q21_1 – Info Fix Over Sell	100	2.00	5.00	4.3300	.86521
Q22_1 – Help Over Sales	100	3.00	5.00	4.4600	.70238
Q23 – Proactive Plan Suggestion Perception	100	1	4	2.59	1.248
Q24 – Proactive Tech Checkup Perception	100	1	4	1.37	.928
Q25 – Proactive Bill Savings Popup Perception	100	1	4	1.52	.810
Q26 – Proactive Discount Offer Usage Perception	100	1	5	1.79	1.157
Q27_1 – Data Driven Offers Seen As Help	100	1.00	5.00	1.9700	.94767
Q27_2 – Data Driven Offers Seen As Manipulation	100	1.00	5.00	3.6700	.92174
Valid N (listwise)	85				

Table 1 - Descriptive Statistics

AI Personalization and Nudging

Respondents displayed a neutral view towards AI-driven personalization averaging 3.1/5 on a Likert scale. Acceptance of personalized offers based on past usage (M = 3.2) and data-driven suggestions (M = 3.0) displayed a similar pattern. These attitudes do not differ significantly throughout age groups, indicating that relevance and value of the interaction likely matter more than generational differences, which were closely aligned in the interviews, where one participant noted, "Customers accept personalization when it's genuinely useful."

When accessing proactive nudging scenarios, there were important contrasts. Technical nudges, such as alerts about service disruptions, were well received among providers and age groups with 84% of respondents finding them helpful. In contrast, only 31% of respondents found commercial nudges appreciable (e.g., plan upgrades), and 22% found them intrusive, having a bigger incidence

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on younger generations and non-Vodafone customers. These results add another layer of sustenance to the qualitative insight that nudging must be context-aware and respectful of customer preferences to be effective. As Vodafone professionals asserted, “Poorly targeted campaigns breaks trust.”

		18-24	25-34	35-44	45-54	65+	Total
Helpful	Count	7	40	26	10	1	84
	% within Q56_AgeGroup	87.5%	87.0%	74.3%	100.0%	100.0%	84.0%
Indifferent	Count	0	2	3	0	0	5
	% within Q56_AgeGroup	0.0%	4.3%	8.6%	0.0%	0.0%	5.0%
Intrusive	Count	1	0	0	0	0	1
	% within Q56_AgeGroup	12.5%	0.0%	0.0%	0.0%	0.0%	1.0%
Depends on the offer	Count	0	4	6	0	0	10
	% within Q56_AgeGroup	0.0%	8.7%	17.1%	0.0%	0.0%	10.0%
Total	Count	8	46	35	10	1	100
	% within Q56_AgeGroup	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Table 2 – Proactive Technical Checkup Perception by Age Group

		18-24	25-34	35-44	45-54	65+	Total
Helpful	Count	0	19	7	4	1	31
	% within Q56_AgeGroup	0.0%	41.3%	20.0%	40.0%	100.0%	31.0%
Indifferent	Count	0	6	7	0	0	13
	% within Q56_AgeGroup	0.0%	13.0%	20.0%	0.0%	0.0%	13.0%
Intrusive	Count	6	9	5	2	0	22
	% within Q56_AgeGroup	75.0%	19.6%	14.3%	20.0%	0.0%	22.0%
Depends on the offer	Count	2	12	16	4	0	34
	% within Q56_AgeGroup	25.0%	26.1%	45.7%	40.0%	0.0%	34.0%
Total	Count	8	46	35	10	1	100
	% within Q56_AgeGroup	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Table 3 – Proactive Plan Suggestion Perception by Group

Transparency and Regulatory Awareness

Transparency materialized as a dominant theme and consistent throughout demographics. In correlation with the qualitative findings, 87% of respondents of the survey rated it as important or very important to be informed when AI is used in personalization. Awareness of privacy rights

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was lower, showing a mean of 2.9/5 (Table 1), which could suggest a knowledge gap between expectations of transparency and actual regulatory literacy.

		18-24	25-34	35-44	45-54	65+	Total
Strongly disagree	Count	0	0	2	0	0	2
	% within Q20_1_AI_Transparency	0.0%	0.0%	100.0%	0.0%	0.0%	100.0%
Somewhat disagree	Count	0	2	0	0	0	2
	% within Q20_1_AI_Transparency	0.0%	100.0%	0.0%	0.0%	0.0%	100.0%
Neither agree nor disagree	Count	0	9	2	2	0	13
	% within Q20_1_AI_Transparency	0.0%	69.2%	15.4%	15.4%	0.0%	100.0%
Somewhat agree	Count	1	9	6	1	0	17
	% within Q20_1_AI_Transparency	5.9%	52.9%	35.3%	5.9%	0.0%	100.0%
Strongly agree	Count	7	26	25	7	1	66
	% within Q20_1_AI_Transparency	10.6%	39.4%	37.9%	10.6%	1.5%	100.0%
Total	Count	8	46	35	10	1	100
	% within Q20_1_AI_Transparency	8.0%	46.0%	35.0%	10.0%	1.0%	100.0%

Table 4 – AI Transparency by Age Group

Cross-tabulation revealed that Vodafone customers showed slightly higher trust in their provider compared to others, but overall trust remained neutral across all operators. While transparency is inherently difficult to market or quantify, this marginally higher trust in Vodafone may be attributed to its recent handling of a 2022 cyberattack. Unlike competitors who may have delayed or deflected responsibility, Vodafone responded with immediate, proactive communication. By openly addressing the issue rather than waiting for external disclosure or attempting to downplay it, Vodafone demonstrated a commitment to accountability and customer respect (Caçador, 2022). Behaviors that can subtly reinforce brand trust even in adverse situations.

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		Vodafone	MEO	NOS	DIGi	Other, please specify	Total
Strongly disagree	Count	12	4	3	0	2	21
	% within Q15_ProviderTrust_Data	57.1%	19.0%	14.3%	0.0%	9.5%	100.0%
Somewhat disagree	Count	8	6	8	0	3	25
	% within Q15_ProviderTrust_Data	32.0%	24.0%	32.0%	0.0%	12.0%	100.0%
Neither agree nor disagree	Count	9	7	12	1	1	30
	% within Q15_ProviderTrust_Data	30.0%	23.3%	40.0%	3.3%	3.3%	100.0%
Somewhat agree	Count	16	0	5	0	1	22
	% within Q15_ProviderTrust_Data	72.7%	0.0%	22.7%	0.0%	4.5%	100.0%
Strongly agree	Count	0	0	2	0	0	2
	% within Q15_ProviderTrust_Data	0.0%	0.0%	100.0%	0.0%	0.0%	100.0%
Total	Count	45	17	30	1	7	100
	% within Q15_ProviderTrust_Data	45.0%	17.0%	30.0%	1.0%	7.0%	100.0%

Table 5 – Provider Trust Data by Provider

Awareness of new market entrants like DIGi was higher among younger respondents and Vodafone customers, although overall awareness remained moderate, reflecting the evolving competitive landscape.

		18-24	25-34	35-44	45-54	65+	Total
Not at all aware	Count	1	6	11	5	0	23
	% within Q9_DIGi_Awareness	4.3%	26.1%	47.8%	21.7%	0.0%	100.0%
Slightly aware	Count	0	12	8	1	0	21
	% within Q9_DIGi_Awareness	0.0%	57.1%	38.1%	4.8%	0.0%	100.0%
Somewhat aware	Count	1	5	5	3	0	14
	% within Q9_DIGi_Awareness	7.1%	35.7%	35.7%	21.4%	0.0%	100.0%
Moderately aware	Count	3	12	5	1	1	22
	% within Q9_DIGi_Awareness	13.6%	54.5%	22.7%	4.5%	4.5%	100.0%
Fully aware	Count	3	11	6	0	0	20
	% within Q9_DIGi_Awareness	15.0%	55.0%	30.0%	0.0%	0.0%	100.0%
Total	Count	8	46	35	10	1	100
	% within Q9_DIGi_Awareness	8.0%	46.0%	35.0%	10.0%	1.0%	100.0%

Table 6 – DIGi Awareness by Age Group

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Integrated System Limitations

Internal scattered data due to system fragmentation means that customer information is dispersed across multiple platforms, limiting the ability of current AI systems like TOBi to form a unified, real-time understanding of customer needs. Vodafone professionals noted that "different channels reflect different intentions," but without integrated systems, these insights remain isolated and underutilized. This limitation is observable on the customer side, where survey data reveals clear dissatisfaction with AI chatbots. Customers are frustrated by interactions that feel disconnected or unhelpful—an outcome that stems directly from the AI's inability to access and synthesize the full range of relevant customer information. When data is scattered, AI tools cannot retrieve the right context at the right time, leading to responses that are misaligned with the customer's intent.

Theme	Qualitative Analysis (Interviews)	Quantitative Support (Survey)	Alignment
Trust & Data Ethics	Trust depends on consent, transparency, and data minimization ("We don't touch data without permission.")	Trust in data usage averaged 2.6/5; 87% want to be informed when AI is used.	Strong alignment
Comfort with Personalization	Customers accept personalization when relevant and behavior-based, not demographic.	Comfort with AI personalization = 3.1/5; no major age-based variation, suggesting behavioral relevance is key.	Strong alignment
Technical vs. Commercial Nudging	Technical nudges (e.g., preemptive support) seen as useful; commercial nudges risk being intrusive.	77% found technical nudges helpful vs. 42% for commercial nudges; 31% found commercial nudges intrusive.	Strong alignment

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Theme	Qualitative Analysis (Interviews)	Quantitative Support (Survey)	Alignment
System Limitations	Operational silos and fragmented systems limit AI's effectiveness.	Customers frequently cited poor past experiences with automated systems; satisfaction with chatbots was low.	Partial alignment

Table 7 - Summary of Thematic Alignment Between Qualitative and Quantitative Findings

5) Discussion

5.1. Leveraging AI for Customer Intent: Capabilities and Customer Perceptions

Understanding customer intent is central to the value Vodafone could unlock from its AI capabilities, but the findings reveal that the company is not yet positioned to do so. Internal stakeholders described AI tools such as TOBi or Microsoft LUIS as useful tools for automating basic service workflows but acknowledged their limitations when it comes to understanding what customers actually want. The scattered, non-integrated data from different source points also does not help with the cause of accessing intention.

Right now, there is proprietary data - customer profiles, network logs, location data, social media interactions (Sadiku et al, 2024) behavioral data, billing and payment data - serving as a *(first-order)* technical control point (Jacobides et al., 2021), but real strategic potential happens when firms can interpret and act on that data in real time with appropriate intention. As Chaudhary and Penn (2024) argue, intent is not a static label but a computable, goal-directed cognitive state, one that requires interpretation of behavioral and linguistic signals within a particular context. When messages are ambiguous or emotionally charged, fragmented AI systems that rely on predefined categories often fail to understand underlying intent, illustrating how Vodafone's current tools fall short in moving from surface-level input to actionable knowledge.

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Vodafone professionals consistently described personalization as more effective when it is based on technical approaches vs commercial approaches. This view was especially evident in discussions around nudging, where the interviewees described the ideal approach as offering proactive support or relevant recommendations before the customer initiates contact with Vodafone. This aligns with survey results: 77% of respondents welcomed proactive technical nudges (e.g., notifications about service issues), whereas only 42% appreciated commercial nudges, and 31% found them intrusive. These findings suggest that if Vodafone wants to use nudging effectively, particularly for commercial purposes, it must maintain a strong imbalance in favor of technical over commercial nudges. In other words, commercial nudging is an option, but the customer must perceive it as secondary to, and justified by, valuable assistance. As nudging is most effective when it is context-aware, driven by real-time intent, and continuously refined through feedback loops (Kumari & Raj, 2024; Indigo.ai, 2025), without the ability to parse intent accurately, nudging risks being irrelevant or excessive, consequently damaging customer trust.

Right now, as it stands, Vodafone does not have the kind of AI intelligence required for intent-driven systems. Tools like TOBi help automate workflows, but they do not function as AI agents, autonomously perceiving, interpreting, and acting on customer needs across contexts (Liu et al., 2025). The adoption of Microsoft LUIS signals an initial step toward understanding user intent from unstructured text, rather than simply tagging inputs. However, Vodafone professionals noted that systems capable of integrating and analyzing data across all relevant channels are not yet in place, mentioning that without data integration it is impossible to go forward. Existing nudging strategies still depend on predefined rules rather than real-time, behavioral deductions. In theoretical terms, as for now, this means Vodafone lacks the core cognition layer required for AI to transition from basic automation to anticipatory engagement, and with it, from a functional capability to a true strategic control point. As one participant stated, “without integration, we can’t move forward”, pointing to the fragmented data landscape as a main hindrance. Systems capable of analyzing behavior across channels in real time are still missing, and nudging efforts continue to rely on static rules. To transition from basic automation to preemptive engagement, Vodafone has to build a unified data structure, invest in real-time processing capabilities, and shift toward AI agents, which will learn and evolve through customer interaction. Only then Vodafone can

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begin to develop the core cognition layer needed to transform AI into a second-order strategic control point.

5.2. AI-Driven Intent Analysis as a Second-Order Strategic Control Point

As previously mentioned, this thesis brings a novel theoretical contribution to the digital ecosystem: the concept of a second-order strategic control point facilitated by AI's unique capabilities to aggregate heterogeneous data sets and derive and interpret meaning from natural language, particularly as used during interactions with chatbots and customer-facing services. Earlier literature has shown that control points in digital ecosystems are often tied, for example, to things like control over infrastructure access or the possession of proprietary data (Jabobides et al,. 2021; Bohnsack et al., 2024). These are points in the digital ecosystem that are intrinsically difficult for other companies to replicate.

Circling back to Yoo et al.'s (2024) assertion that the abundance of data in modern ecosystems, conjoined with the novel capabilities of technologies like generative AI and agentic systems, now allows organizations to explore scenarios and behaviors that were previously unattainable, we could argue that data transitions from being a more passive technical asset, a resource used intentionally in value creation and value capture, to becoming a dynamic strategic tool. This transition is driven by the generative potential of AI to extract new forms of value from existing data, recombining it in ways that open up previously unrecognized patterns, relationships, and possibilities for strategic intervention. In this expanded role, data contributes directly to the establishment of novel control points within digital ecosystems.

Second-order control points, such as the one proposed in this thesis, therefore present a more dynamic form of strategic advantage. These emerge when firms move beyond the sole ownership of data and deploy integrated, multimodal AI systems that, following Alhasan et al. (2025), leverage affordance perception—the ability to detect which actions a customer is most likely to take given contextual cues. By interpreting customer behavior in real time and parsing intent, these systems enable adaptive, feedback-driven engagement (continuous) loops. Through

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ongoing interaction with digital services, new and often unanticipated sources of value emerge (Yoo et al., 2012). As these systems continuously learn and evolve, they do not merely respond to customer behavior—they begin to shape it, configuring demand and redefining service pathways across the ecosystem. This represents a shift from infrastructure-based control to cognition-based planning, and from reactive service delivery to proactive, context-aware intervention.

The mixture of AI capabilities with deep customer understanding, ethically and legally managed, can indeed establish a powerful second-order strategic control point for Vodafone. As interviewees suggested, AI-driven customer intent analysis is perceived internally as a possible "emerging control point that allows Vodafone to anticipate and proactively meet customer needs”. This shifts the consideration that data is just a technical asset to data, leveraged by AI to derive relevant insights, as a strategic must for customer understanding and value capture.

To broadly sum up, this second-order control point occurs from the proprietary combination of: (1) vast and varied customer data encompassing demographic, geographic, billing, interaction, and crucially, behavioral information; (2) sophisticated AI capabilities (GenAI and AI Agents) that parse this data to infer intent, predict needs, and generate personalized responses or nudges; and (3) integrated operational workflows that enable real-time action across customer touchpoints.

The strategic value of this novel control point is expressed in three keyways. First, *differentiation*, where Vodafone can deliver proactive and personalized customer experiences that are difficult for competitors to replicate, particularly those constrained by legacy systems and fragmented data. As one Vodafone professional noted, “AI is a new operational advantage.” Second, *customer lock-in* emerges when preemptive service is tailored to individual needs increases switching costs, as customers grow accustomed to a level of responsiveness unavailable from other providers. Third, *barriers to competitors***,** where the resources required for large-scale data integration, AI training, deployment, and compliance form a substantial barrier to entry. Furthermore, the learning loops of AI systems create cumulative advantages that intensify over time.

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The detailed evaluation of customer service interactions, together with account management patterns, galvanizes this control point. While a simple customer query to analyze a standard monthly bill might seem a mundane activity, its true power is revealed when GenAI parses its underlying intent by combining it with other behavioral data, such as app usage, competitor site browsing, and service call patterns showing a decline in usage, changes in service history, etc.). As an example, a customer who systematically maintained similar levels of data usage begins to frequently check their data consumption via the app towards the end of the billing cycle, coupled with a recent customer service interaction in which there was an overage charge, subsequently diminishing the usage of premium add-on services. This could potentially indicate the customer is becoming budget-conscious and value-conscious. Combining AI's ability to connect these scattered signals - app interactions, specific service call content, and subtle changes in service consumption - to parse a universal "intent profile" transforms previously minor data points into a highly valuable, actionable insight. Using Agentic AI for this newly derived multi-faceted intent understanding creates a stronger control point than any individual data stream. The system can deliver customized nudges that perform a "plan health check" to verify customers who have the most affordable tariff for their usage patterns and identify unused bundled services alongside suitable alternative plans. The company demonstrates financial concern awareness through cost optimization assistance, which builds customer trust and minimizes the risk of customers switching to cheaper but less suitable competitor services.

To illustrate the distinction between technical and strategic control points, and the role of AI systems in enabling the latter, Figure 2 maps the layered progression from data proprietorship to real-time, intent-aware orchestration.

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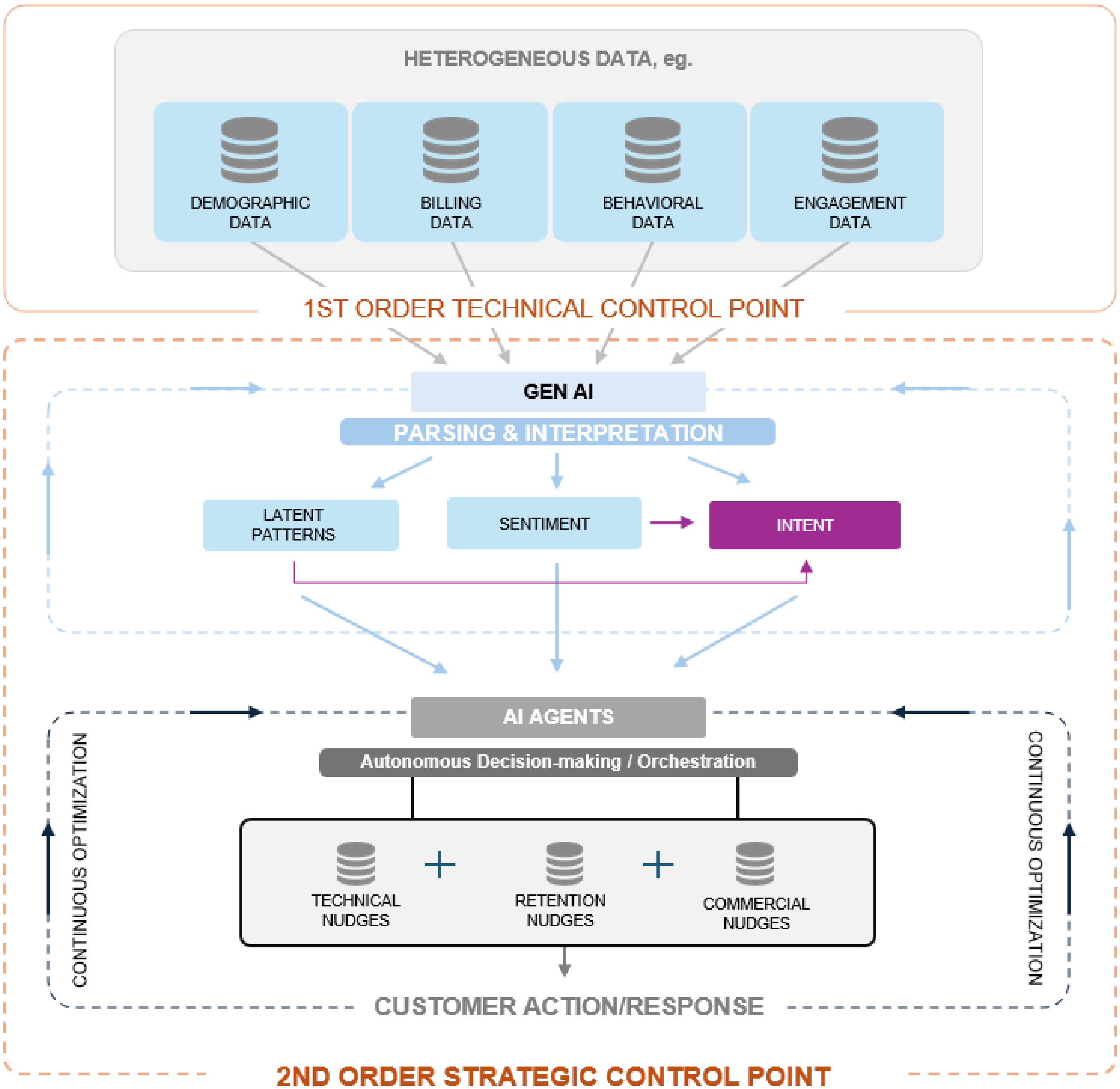

Figure 3 - AI-Driven Progression from (First-Order) Technical Control Points to Second-Order Strategic Control Points

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5.3. Ethical and Legal Requirements: Navigating GDPR and the EU AI Act

Parsing customer intent through AI analysis in order to enhance personalization and create strategic advantages are compelling. However, leveraging such potent tools can only raise crucial questions: How ethical is the deployment
of these technologies? What are the legal limitations that must be observed, especially concerning customer data and automated decision-making? These considerations are not insignificant; they are extremely important to the sustainable and responsible application of AI. Therefore, this section explores into the strict ethical and legal frameworks that govern this domain, particularly the General Data Protection Regulation (GDPR) and the EU AI Act, which are vital in shaping Vodafone's approach.

The pursuit of AI-driven customer intent analysis for establishing a control point is utterly linked to strict ethical and legal considerations. As emphasized by Vodafone professionals, "ethical and legal compliance are highly prioritized in every Al-driven interaction". This is not observed out of pure lawfully needed adherence, but also about building and maintaining customer trust, a trait that, as seen in the quantitative analysis, is scarce, with data showing low overall trust in providers to use customer data ethically (average 2.6/5).

The qualitative findings strongly align with consumer expectations: "Transparency builds trust". Vodafone professionals stressed that "customers must know when Al is used", and that "black-box models create risk". This is supported by the survey, where 87% of respondents rated it as important or very important to be informed when AI is being used for personalization. The principle of "only use consented data" is a non-negotiable, even if the "risk" associated with anonymized data is recognized internally at Vodafone.

While AI-powered intent analysis offers a potential second-order control point, the General Data Protection Regulation (GDPR) and the EU Artificial Intelligence (AI) Act deeply shape its viability. Compliance is "no longer optional but a determinant of strategic viability". Regulation, in this context, is more than a constraint; it acts as a strategic force shaping the digital business ecosystem. As Bohnsack et al. (2024) emphasize, institutional boundaries, which include regulations like GDPR and the EU AI Act, moderate how technical and strategic control points are

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formed and leveraged. These regulations set the "rules of the game," influencing data access, processing methodologies, and the types of AI applications that are acceptable. They can dismantle existing control points reliant on unregulated data use or, conversely, trigger innovation towards new, compliant control points.

The GDPR directly impacts how customer data can be utilized. GDPR compliance can be perceived as weakening AI-based control points in several ways. Article 5(1)(b) under the *purpose limitation* principle, mentions that data collected for one specific purpose, such as billing, cannot be arbitrarily repurposed for intent prediction without a clear, compatible lawful basis (European Parliamentary Research Service, 2020), potentially limiting the scope of data available for AI models. For this repurposing to be lawful, the new purpose must either “be compatible with the original purpose” or “be based on a new legal basis, such as explicit consent from the user”. Therefore, prior consent is non-negotiable. However, regarding consent, another challenge lies under the *consent complexity* principle, where valid consent must be "freely given, specific, informed, and unambiguous" (European Parliamentary Research Service, 2020). In other words, nudging based on inferred intent, which may predict future behaviors not explicitly consented to, is an obstruction for this endeavor. Furthermore, under *Article 22*, automated decision-making and profiling necessitate human oversight mechanisms, adding complexity and cost to fully automated AI nudging systems (European Parliamentary Research Service, 2020). Finally, *transparency requirements* assert that firms must provide "meaningful information" about the logic involved in AI decision-making, which might be difficult to satisfy without oversimplifying AI’s opaqueness, also characterized as a black box problem. This lack of transparency and explainability in how these systems arrive at their conclusions makes it difficult to understand their decision-making processes (Hu, 2020). These requirements restrict data reusability and impose transparency, directly affecting the foundation of data-driven control points.

The EU AI Act introduces a risk-tiered framework (Bird & Bird, 2024). It's crucial to note that not all telecom AI systems will automatically be deemed high-risk. However, AI systems that significantly influence customer access to essential services, play a critical role in billing, or guide substantial service experiences may be classified as high-risk, particularly if they involve profiling with significant effects or employ "nudging" techniques that could significantly alter behavior,

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especially concerning essential services (Bird & Bird, 2024). The Act also explicitly bans AI systems using subliminal techniques that materially distort behavior, ensuring nudges respect user autonomy (Deloitte, 2024). If an AI system for intent-based nudging falls into a high-risk category, it would trigger extensive compliance requirements, including risk management systems, data governance, extensive technical documentation, human oversight, and potential external conformity assessments (ECIIA, 2024). Curiously, Vodafone professionals and the public's mindfulness towards AI transparency perfectly intertwines with the EU AI Act, which states that there is an obligation that systems must disclose AI interactions (e.g., chatbots, recommendation engines) and differentiate AI-generated content (ECIIA, 2024).

Paradoxically, the high compliance costs associated with high-risk AI systems under the EU AI Act could concentrate control points among incumbent firms like Vodafone or T-Mobile, which possess the resources to meet all these regulatory burdens. It is also important to consider that this concentration could have broader market implications, potentially raising antitrust concerns if it significantly prevents competition from smaller players or new entrants who cannot endure such extensive compliance operational costs (De Boiscuille, 2024).

However, regulation can also be a catalyst for innovation and a source of competitive advantage (Bohnsack et al, 2024). Firms that are the first to proactively engage in "Ethical AI" and embed in their culture a compliance mindset into their core strategy, can differentiate themselves as "trustworthy AI providers", taking advantage as early movers. Findings from the survey suggest that Vodafone may already hold some sorts of a trust advantage compared to other telecommunication firms in Portugal. Overall trust in telecom providers using customer data ethically was neutral (M = 2.6/5), however, Vodafone customers reported slightly higher levels of data management trust compared to customers of other providers. This perception, although very subtle, could represent a strategic foundation on which to build a stronger compliance-driven brand identity within the evolving AI regulatory landscape.

Mastering these complex regulatory landscapes can itself become a strategic asset, turning compliance from an obligation into a brand differentiator that reinforces customer loyalty, thus reducing churn risk (Bird & Park, 2017).

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6) Conclusion

This thesis has argued that AI-driven intent analysis, particularly when deployed through Generative AI and autonomous agents, offers Vodafone the opportunity to establish a second-order strategic control point—one that goes beyond data ownership to the active shaping of customer behavior through real-time, context-aware interaction.

The findings demonstrate that while Vodafone currently possesses the technical foundations (e.g., proprietary data, intent detection tools like TOBi and Microsoft LUIS), its systems are still limited by fragmented operational infrastructure. Nonetheless, both internal interviews and consumer surveys reveal strong potential: when nudges are technically relevant and behaviorally substantiated, customers respond positively. This emphasizes that personalization is most effective not when based on demographic segmentation, but when driven by real-time behavioral insights.

Building on existing theories of strategic control, digital affordances, and ecosystem dynamics, the thesis introduced the notion of second-order control points. As proposed in this thesis, second-order control points emerge when AI systems leverage affordance perception and enable data generativity, allowing firms to move beyond static data ownership toward adaptive influence over customer behavior and interaction patterns. These concepts reflect AI's capacity not just to interpret static data, but to continuously reconfigure the firm's relationship with customers and the ecosystem by producing new, emergent forms of value. Rather than controlling infrastructure, firms begin to control interactional flows and decision contexts, shifting from technical to cognitive forms of influence.

However, the strategic potential of such control points is inextricable from ethical and legal constraints. GDPR and the EU AI Act do not merely limit data usage, they actively shape how AI can be deployed and trusted. Vodafone's relative strength in compliance, transparency, and customer trust can become a competitive differentiator, provided these principles are embedded deeply into AI system design and governance.

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In sum, the thesis proposes that the competitive advantage of intent-aware AI lies not simply in automation, but in its ability to generate, adapt, and respond to evolving behavioral signals, thus creating a generative loop between data, action, and learning. If Vodafone can align its technological capabilities with ethical design and regulatory anticipation, it can move from reactive service provider to anticipatory digital orchestrator, turning customer understanding into a defensible strategic asset.

Limitations

This study is not without its limitations. The qualitative sample was drawn entirely from Vodafone professionals, which may lead to internal bias and limit the variety of organizational perspectives. The quantitative survey focused exclusively on Portuguese telecom consumers, which limits the generalizability of the findings to broader or more diverse markets. Moreover, the technological and regulatory landscapes are evolving rapidly; conclusions drawn today may require reassessment soon as AI capabilities and laws continue to develop.

Nonetheless, despite these limitations, the research shows that intent-driven AI, if deployed responsibly, can redefine how telecoms engage customers, not just by reacting to needs, but by anticipating and shaping them. Vodafone's ability to align AI innovation with legal, ethical, and organizational promptness will determine whether customer intent becomes a true second-order control point, or a missed opportunity.

Recommendations for Future Research

Future research could explore several paths. One auspicious direction is conducting longitudinal impact studies to track the long-term effects of AI-driven nudging on customer behavior and trust. Another involves cross-sector benchmarking, examining how AI intent analysis is implemented in industries such as finance or retail to identify transferable strategies and best practices. Finally, further work is needed on operationalizing ethical AI by developing practical frameworks that embed ethical principles into everyday decision-making and system design.

Future research could explore several promising directions. One is the implementation of longitudinal impact studies to track how AI-driven nudging affects customer behavior, trust, and

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engagement over time. This would help measure if the projected advantages of intent-aware systems are indeed sustained or diminished through continued applications.

Another valuable opportunity is cross-sector benchmarking. By analyzing how industries like finance or retail deploy AI-driven intent parsing and nudging, researchers can identify conveyable strategies that telecom providers might adapt. Comparative analysis can reveal both common challenges and innovation opportunities that surpass industry boundaries.

Moreover, there is a growing need to operationalize ethical AI. Future studies should explore how organizations can embed ethical guidelines, such as transparency, freedom of choice, and fairness, into the design, deployment, and governance of AI agents. Practical frameworks are needed to translate ethical theory into managerial practice.

In addition, future research should deepen and extend the concept of second-order strategic control points introduced in this thesis. Scholars could explore how such control points emerge in different ecosystem settings, and whether the framework holds when applied to decentralized platforms or B2B contexts. Quantitative validation and comparative case studies could further refine the construct's applicability and theoretical contribution.

Finally, for telecom managers and decision-makers in other industries, this study offers a clear message: intent-aware AI systems are not passive tools, they have transformative capabilities with wide-ranging consequences for ecosystems and individuals. Firms that succeed in integrating behavioral data, parsing intent, and acting in real time will be able to proactively steer customer journeys, foster trust, and build defensible positions in their ecosystems. Strategic investment in data integration, cross-functional collaboration, and adaptive AI is not optional—it is the next edge in digital value creation and customer experience management.

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Appendix A - Quantitative Analysis Survey

Introduction & Consent:

- Purpose: Academic research for a Master's thesis on the Portuguese telecom market. **Please only complete this survey if you are over 18 years of age, currently residing in Portugal, and personally subscribe to or pay for mobile phone, home internet, or TV services in Portugal.**
- Anonymity: Responses are anonymous and confidential.
- Voluntary Participation: You can stop at any time.
- Data Use: Data will be used in aggregate for the thesis only.
- Estimated Time: Approx. [Insert realistic estimate, e.g., 5-7] minutes.
- Contact Info: Daniel Bento de Faria. [email address removed]
- Consent Checkbox: "I meet the criteria described above, have read the information, and agree to participate in this survey."

Section 1: General Telecom Experience:

- **Multiple Choice:** Which company is your **primary provider** for **mobile phone** services?
    - (Options: Vodafone, MEO, NOS, DiGi, Other [Specify], Don't have mobile service)

- **Multiple Choice:** Which company is your **primary provider** for **home internet/TV** services?
    - (Options: Vodafone, MEO, NOS, DiGi, Other [Specify], Don't have home service)

- **Likert Scale:** Overall, how satisfied are you with your primary **mobile phone service** provider?
    - (Scale: Very Dissatisfied to Very Satisfied)

- **Likert Scale:** Overall, how satisfied are you with your primary **home internet/TV** service provider?
    - (Scale: Very Dissatisfied to Very Satisfied)

- ***Control Question - Likert Scale:***
  "I believe telecom companies generally prioritize their customers' best interests, even when it might reduce their profits."

    - *(Scale: Strongly Disagree to Strongly Agree)*

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- **Ranking Question**: Please rank the following factors in order of importance when choosing or staying with a telecom provider (1 = most important, 5 = least important):

    - Monthly price
    - Network quality (speed, coverage)
    - Customer service quality
    - Variety of services/packages offered
    - Brand reputation

- **Likert Scale**: How aware are you of the telecom provider **DiGi** operating in Portugal?
    - (Scale: Not at all Aware to Very Aware)

Section 2: AI & Personalization:

- Have you interacted with automated customer service systems (like chatbots or automated voice responses) when contacting a company?

    - (Yes/No/Unsure)

- **Likert Scale:** If yes, how was your experience generally?

    - (Scale: Very Negative to Very Positive)

- **Likert Scale:** How comfortable would you be with your telecom provider using technology (like Artificial Intelligence - AI) to understand your needs and preferences based on how you use their services (e.g., data usage, types of TV channels watched)?

    - (Scale: Very Uncomfortable to Very Comfortable)

- ***Control Question - Likert Scale):*** **"I feel I have a good understanding of how companies use Artificial Intelligence (AI) in their services."**
    - *(Scale: Strongly Disagree to Strongly Agree)*

- **Likert Scale:** How do you feel about receiving personalized offers or recommendations from your telecom provider based on your past usage or preferences?

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- (Scale: Strongly Dislike to Strongly Like)

- ***Control Question Likert Scale:***
  "I trust my telecom provider to do the right thing with my data."

  - *(Strongly Disagree to Strongly Agree)*

Section 3: Data Privacy:

- **Matrix**: Telecom companies collect various types of data. How comfortable are you with your provider collecting the following?

  - (Scale: Very Uncomfortable to Very Comfortable for each)
    - Your basic account information (name, address)
    - Your location data (based on mobile network)
    - Your call and message history (numbers called/texted, duration - *not* content)
    - Your internet browsing activity (websites visited, apps used)
    - Your TV viewing habits (channels watched, programs recorded)

- **Likert Scale**: How aware are you of your data protection rights (like GDPR) regarding how companies use your personal information?

  - (Scale: Not at all Aware to Very Aware)

- ***Control Question - Likert Scale:***
  "I always read the terms and conditions carefully before agreeing to a new service."

  - *(Scale: Strongly Disagree to Strongly Agree)*

Section 4: 'Nudging' & Proactive Engagement:

- *(Likert Scale):* "How comfortable are you with your telecom provider using your data (like usage patterns or call history) to proactively suggest new services or products you might like?"
  - (Scale: Very Uncomfortable to Very Comfortable)

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- *(Likert Scale):* "It's important for companies to be transparent and explicitly state when they are using AI or my data to make proactive suggestions or offers."
    - (Scale: Strongly Disagree to Strongly Agree)
- *(Likert Scale):* "Companies should use customer information primarily to fix problems rather than to sell more services."
    - (Scale: Strongly Disagree to Strongly Agree)
- *(Likert Scale):* "Receiving proactive help from my provider (like fixing issues before I notice them) is more valuable to me than receiving proactive sales offers."
    - (Scale: Strongly Disagree to Strongly Agree)
- *(Scenario 1):* Imagine your telecom provider notices your mobile data usage pattern. They proactively send you a message suggesting a different plan based on this usage pattern. How would you view this?
    - (Options: Helpful, Intrusive, Indifferent, Depends on the offer)
- *(Scenario 2):* Imagine your provider's system detects a potential technical issue with your home internet service. They contact you preemptively to offer a technical check-up. How would you view this?
    - (Options: Helpful, Intrusive, Indifferent, Unnecessary)
- *(Scenario 3):* Imagine you visit your provider's website to check your bill. A pop-up message appears offering help with understanding your charges or suggesting ways to save money based on your current plan and usage. How would you perceive this interaction?
    - (Options: Helpful and convenient, Slightly intrusive but potentially useful, Intrusive and annoying, I would likely ignore it)

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- *(Multiple Choice):* "If a telecom provider proactively offered you a discount on a service upgrade based on your usage, what would be your main reaction?"
    - (Options: Appreciative of the potential savings, Suspicious of their motives, Indifferent, Annoyed by the unsolicited contact, Concerned about how they knew to offer it)
- *(Likert Scale):* "To what extent do you agree with this statement: 'When companies proactively contact me with suggestions or offers based on my data, they are usually trying to help me.'"
    - (Scale: Strongly Disagree to Strongly Agree)
- *(Likert Scale):* "To what extent do you agree with this statement: 'When companies proactively contact me with suggestions or offers based on my data, they are usually trying to manipulate me into spending more."
    - (Scale: Strongly Disagree to Strongly Agree)
- "Do you believe you can usually tell when a company is trying to subtly influence ('nudge') your choices through their communications or app/website design?"
    - *(Yes/No/Unsure)*

Section 5: Demographics:

- What is your age group?
    - (e.g., 18-24, 25-34, 35-44, 45-54, 55-64, 65+)

Conclusion:

- "Thank you for taking the time to complete this survey. Your input is valuable for this research."

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