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AI-Driven Personalization and Customer Loyalty in Swedish E-Commerce

Exploring the Effectiveness of AI as a Strategic CRM Practice

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Abstract

The digital landscape is evolving rapidly, where Artificial Intelligence (AI) emerges as a key driver in the development of technological applications aiming to facilitate personalized content. This technological shift not only fosters the adoption of more innovative approaches, but also fundamentally redefines the ways in which organizations engage with customers.

This thesis investigates how personalization driven by AI impacts customer loyalty, also addressing challenges associated with its implementation. With the purpose of exploring how different industries within the Swedish e-commerce value chain perceive the relationship between AI-driven personalization and customer loyalty, a multiple case study has been conducted. Through interviews with industry professionals from ten large companies operating in the Swedish e-commerce value chain, the study provides a comprehensive analysis that contextualizes the phenomenon within specific sector and market dynamics.

The empirical findings reveal that there is no definite positive relationship between AI-driven personalization and customer loyalty. Concerns regarding inadequate personalization, transparency, and effectively scaling AI strategies, present challenges affecting organization's ability to increase customer loyalty through personalization efforts. Though the lasting effectiveness of customer loyalty is challenged by these concerns, AI-driven personalization still holds potential in increasing loyalty through highly accurate personalized content that exceeds customer expectations. Through the adoption of a customer-centric approach, which prioritizes relevance, openness, and value-creation, AI-driven personalization could realize this potential.

Keywords: Artificial Intelligence, Customer Loyalty, Customer Relationship Management, E-Commerce, Personalization

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Sincerely,

Axelina Edberg

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List of Abbreviations

AI……………………………………………………………………...Artificial Intelligence
CRM…………………………………………………..Customer Relationship Management
DOI……………………………………………………………Diffusion of Innovation
GDPR…………………………………………………General Data Protection Regulation
TAM……………………………………………………...Technology Acceptance Model
TOE…………………………………………………Technology, Organization, Environment
UTAUT………………………………Unified Theory of Acceptance and Use of Technology
UTAUT2…………………...Extended Unified Theory of Acceptance and Use of Technology

1. Introduction

The following chapter introduces the objectives and context of the study, which focuses on how customer loyalty in Swedish e-commerce is influenced by personalization driven by Artificial Intelligence (AI). Initially, the background of the thesis is introduced, followed by a problem discussion of the research field. Thenceforth, the research purpose and research questions are presented, after which the disposition is outlined, constituting an overview guiding the reader though the thesis.

1.1 Background

The digital landscape is evolving rapidly, with AI playing an increasingly crucial role in shaping consumer experience (Raji et al., 2024). According to Wiles (2023), 30% of new applications are expected to use AI, driving personalized user interfaces. Moreover, the relationship between AI and Customer Relationship Management (CRM) connects technological advancement to the management of customer relations (Venkateswaran, 2023), presenting a promising area of exploration. CRM is defined as a business strategy managing customer relationships to promote customer loyalty, aiming to optimize revenue and profitability (Gartner, n.d.). As reported by Harvard Business Review (Reichheld, Schefter, & Rigby, 2002), CRM works as a provider of customized products and services, which influences customer loyalty over time. The loyalty relationship is built upon aligning business processes with customer strategies, focusing on bundling customer strategy and processes (Reichheld, Schefter, & Rigby, 2002).

There are several types of CRM focusing on different business processes, where organizations orient between one or more of these management forms. Though multiple CRM types can be addressed within an organization, the part targeting customer loyalty essentially refers to strategic CRM, specified by strategy development process and
the value creation process (Iriana & Buttle, 2007). With CRM's purpose of increasing revenue, strategic CRM focuses on achieving profitability through strategies creating value superior to competitors, ultimately gaining and maintaining customers (Ismaili, 2015). Hence, strategic CRM encompasses the enhancement of customer value, aiming to achieve increased customer loyalty (Mack, Mayo, & Khare, 2005). The Cambridge Dictionary (N.d.) defines the term customer loyalty as *"the fact of a customer buying products or services from the*

same company over a long period of time (...)". However, there is a wide spectrum of customer behaviors and lifetime values that correspond to customer loyalty, moving beyond the span of repurchase. Other vital customer behavior aspects determining the degree of loyalty are commitment, apostle-like behavior, and ownership. The mere definition of customer loyalty is hence complemented by core apostles and owners bringing superior lifetime value for companies (Heskett, 2022).

In parallel with the digital transformation over the past years, consumer behavior has undergone significant changes, giving rise to evolving patterns of customer loyalty (Huang, 2020). Thus, the role of AI in personalization strategies has evolved as a crucial component in shaping customer interactions. AI-driven personalization represents a versatile approach, referring to the use of machine learning and advanced algorithms. These techniques aim to tailor recommendations, content, and user experience to align with individual preferences. Not only has the relationship of loyalty between companies and customers changed as a response to AI, but also how e-commerce platforms engage individual consumer preferences. Though some usage of AI, such as chatbots and virtual assistants, have shown a glance into the future of data-driven personalization, the topic remains an evolving phenomenon. These techniques are reshaping e-commerce, influencing consumer behavior and market trends such as predictive analytics in optimizing inventory management, and the adoption of data-driven strategies for personalized recommendations. Hence, there are indications suggesting that businesses must leverage these technologies to remain competitive and adapt to the evolving demands of customers (Raji et al., 2024).

1.2 Problem Discussion

Notably, the implications on customer loyalty resulting from AI-driven personalization remains complex. Though AI has shown its potential in enhancing customer experiences, there is still an ongoing debate regarding its actual effectiveness in fostering long-term loyalty, as well as the challenges associated with its implementation. With this being stated, previous research has demonstrated a successful impact of AI-driven personalization on customer loyalty (e.g. Ifekanandu et al., 2023; Patil, 2024). Furthermore, some studies have also highlighted a positive influence of this relationship on the e-commerce sector (e.g. Arora et al., 2024; Zed, Kartini, & Purnamasari, 2024). However, there are some studies who have found the opposite effect of AI driven-personalization on customer loyalty, indicating that some strategies within AI personalization have a negative effect on customer loyalty (e.g. Draws et al., 2021; Obiegbu & Larsen, 2024). While a growing amount of research has explored the relationship between AI-driven personalization and customer loyalty, there remains a notable gap in understanding how this relationship manifests specifically within the e-commerce sector.

Though previous research on this topic has recently been published, the fast-paced evolution of AI-driven personalization necessitates the need for continuous research on its contribution to customer loyalty. Moreover, much of the existing literature focuses on general outcomes or broader geographic contexts, often overlooking market-specific factors that may influence results. Researchers (e.g. Arora et al., 2024; Obiegbu & Larsen, 2024) emphasize the need for future research to explore how the relationship between AI-driven personalization and customer loyalty manifests within specific markets or industry sectors, as such contextual investigations can offer valuable contributions to the existing body of literature. As Swedish e-commerce businesses increasingly adopt AI solutions (Global Innovation Index, 2024), understanding how these technologies influence customer loyalty within this particular market is both relevant and valuable. Moreover, factors such as integration, regulations, and initial costs in adopting AI-based systems could shape different outcomes compared to findings from other regions (Kaveh, 2025). Other researchers have also underscored the importance of further investigating the challenges inherent in the relationship between AI-driven personalization and customer loyalty, particularly emphasizing issues of trust and transparency (e.g. Raji et al., 2024; Zed, Kartini, & Purnamasari, 2024). In light of this, this study aims to contribute to existing research by examining these challenges within specific market contexts, thereby offering nuanced insights into how such factors may influence this relationship.

By examining these dynamics, this study seeks to provide insights for businesses looking to implement effective AI-driven personalization strategies while navigating the challenges of maintaining consumer trust and fostering enduring loyalty. The findings from this research could offer practical guidance for actors within e-commerce and their value chain in Sweden, and potentially inform best practices for similar markets globally.

1.3 Purpose and Research Questions

The purpose of this master thesis is to explore how AI-driven personalization impacts customer loyalty, analyzing how large companies in the Swedish e-commerce market perceive its response to customers. The objective is to understand how companies operating in different industries within the value chain of the e-commerce sector perceive changes in consumer behavior as a response to personalized experiences given by AI. By pursuing a multiple case study, the thesis seeks to offer insights into the investigated phenomenon, providing a comprehensive analysis derived from qualitative data. Hence, this study aims to contribute to existing literature on technology by offering an analysis of how AI-driven personalization is implemented and perceived within a specific market context. In doing so, it extends the applicability of the Technology-Organization-Environment (TOE) framework proposed by Tornatzky and Fleischer (1990), particularly in relation to the organizational and environmental contexts. Furthermore, the study seeks to elevate the literature on customer loyalty by investigating how AI-driven strategies influence both behavioral and attitudinal loyalty, thereby building on the framework established by Dick and Basu (1994). In addition to its theoretical contributions, the study offers practical implications on the studied phenomenon for firms operating within the Swedish e-commerce sector.

Keeping the above purpose in mind, the following main research question has been formulated:

> *RQ: How is customer loyalty in Swedish e-commerce influenced by AI-driven personalization?*

To provide a comprehensive understanding of the main research question, it is necessary to address the following sub-questions, which explores key components upon which the broader inquiry depends:

> *Sub-Question 1: What are the key challenges faced by Swedish e-commerce businesses in implementing AI-driven personalization?*

> *Sub-Question 2: How might these challenges affect customer loyalty?*

1.4 Disposition

Following the introduction, the chosen literature is presented under the theory chapter. This chapter introduces a justification of the chosen theoretical frameworks followed by a presentation of the four chosen theories, ultimately summarizing an operationalization of theoretical concepts. Thenceforth, the method is outlined under the methodology chapter, consisting of five sections explaining the approach applied to derive the finalized report. Furthermore, the result chapter presents collected data from interviews through the multiple case study. The results are followed by the analysis chapter, linking secondary and primary data to present a comprehensive discussion of the research. Finally, the conclusion is put forward, initially answering the research questions and subsequently presenting implications and suggestions for future research.

2. Theory and Literature Review

This chapter summarizes different theories that form the foundation for analyzing the research questions concerning the impact of AI on customer loyalty. The starting point for this chapter is the *Technology-Organization-Environment* (*TOE)* framework, which examines how the context of firms affects the implementation and adoption of technological innovation. Moreover, the *Unified Theory of Acceptance and Use of Technology* (*UTAUT)* explains a firm's acceptance towards, and use of, technology, where *UTAUT2* adapts the model for a consumer context. While the TOE framework emphasizes the macro-level of innovation, the UTAUT and UTAUT2 aims to discuss the micro-level, focusing on the innovation adoption of firms and customers. Furthermore, the *Two-Dimensional Framework on Customer Loyalty* provides a framework in understanding how CRM strategies influence the engagement and retention of customers, aiming to cover the area of customer loyalty addressed in this study. Lastly, the *Process Framework for E-Commerce Personalization* examines how personalization strategies impact online vendors, followed by a presentation of previous research bridging the gap of personalization in relation to AI and customer loyalty. At the end of the chapter, an *Operationalization of Theoretical Concepts* is presented, connecting the theories to the empirical contributions and research questions of the study.

Together, these frameworks constitute a funnel, progressing from the broader contextual factors influencing innovation adoption to firm and customer level engagement. Complementing the theories on technology, the framework on customer loyalty connects to the strategic CRM that is addressed in the study. By incorporating perspectives on both technology adoption and customer loyalty, the final theoretical framework directly connects these concepts to the specific area of investigation, namely AI-driven personalization and its impact on customer loyalty.

2.1 The TOE Framework

The *Technology-Organization-Environment (TOE)* framework is a framework that explains how the context of firms influences the implementation and adoption of innovation. The framework was presented by Tornatzky and Fleischer (1990) as one of the phases in the process of technological innovation. Another theory examining innovation adoption is the *Diffusion of Innovation* (DOI) theory, which explains how new technologies spread within a social system, emphasizing factors such as relative advantage, compatibility, and observability (Rogers, 1962). While DOI provides valuable insights into the adoption process, it primarily focuses on individual and social influences rather than the structural and environmental factors that shape adoption at an organizational level. In contrast, the TOE framework offers a more comprehensive perspective by considering not only technological factors, but also organizational capabilities and external environmental influences. Given that this study investigates how large Swedish e-commerce firms perceive and adapt to AI technologies in relation to customer loyalty, they are subject to complex organizational structures. Therefore, TOE is the chosen theory for this study as it better aligns with the focus on macro-level technology adoption. According to Tornatzky and Fleischer (1990), technological innovation within the TOE framework is influenced by the *technological, organizational* and *environmental context*, all three constituting critical elements both constraining and promoting adoption decisions.

2.1.1 The Technological Context

The first element of the innovation adoption process is the *technological context*, including existing technology available within the firm, as well as all external technologies available at the market, even though not implemented by the focal firm. Existing technologies within a firm play a crucial role in the adoption process, as they establish the overall boundaries on the extent and speed of technological change the firm can pursue (Collins, Hage, & Hull, 1988). While existing technology within the firm sets the limit and scope for adoption, innovation not yet adapted by the firm determines the limits of possibilities, as well showcasing the technological outcomes that innovation enables.

Existing innovation outside the firm can be categorized into three types: incremental, synthetic, and discontinuous (Tushman & Nadler, 1986). Incremental innovations involve minor enhancements, such as upgrading existing systems, which most often present minimal risk and disruption. Synthetic innovations combine existing technologies in novel ways, exemplified by online course delivery. Discontinuous innovations, often termed radical, signify significant shifts in technologies or processes, such as the transition to cloud computing or the introduction of bar-code scanning (Ettlie, Bridges, & O'Keefe, 1984). Discontinuous innovations may be either competence-enhancing, building on existing expertise, or competence-destroying, rendering prior competencies obsolete (Tushman &

Anderson, 1986). For instance, Radio Frequency Identification (RFID) adoption enhances existing asset-tracking skills, while cloud computing may disrupt IT expertise. Organizations must carefully evaluate the technological implications of innovations, balancing risks and opportunities to maintain competitiveness.

2.1.2 The Organizational Context

The *organizational context* represents the second element of innovation adoption, referring to the resources and characteristics of the firm (Tushman & Nadler, 1986). The authors mention several factors that shape an organizations' ability to adopt and implement new technologies. These include the degree of centralization, quality of internal communication, management support, and size of the organization.

Tushman and Nadler (1986) distinguish between organic/decentralized structures, and mechanistic structures in terms of innovation phases. Organizations with organic and decentralized structures tend to have fluid responsibility amongst employees, promote lateral communication, and emphasize teams. Researchers highlight that this structure is associated with the adoption phase of the innovation process (Burns & Stalker 1962; Daft & Becker, 1978), while organizations with a mechanistic structure rather emphasize the implementation phase of the innovation process (Zaltman, Duncan, & Holbeck, 1973). Moreover, the mechanistic structure differs from the decentralized, as it promotes centralized decision-making, clearly defined employee roles, and formal reporting.

Moreover, the communication processes within an organization significantly impact innovation, which could either promote or hinder innovation. According to Tushman and Nadler (1986), top management plays a crucial role in fostering a culture that embraces change, promoting innovative practices. Leadership behaviors, such as emphasizing innovation's strategic importance and rewarding creative efforts, are argued to enhance innovation potential. The founders of the TOE framework thus emphasize the importance of not only qualitative internal communication, but also management support for innovation (Tornatzky & Fleischer, 1990).

The relationship between innovation and size is often discussed as an influential link, as larger firms more often adopt innovations (Cyert & March, 1963). Tornatzky and Fleischer, 1990 argue that larger organizations tend to have better infrastructure and more resources to support innovative change. However, they also mention how these organizations might be more bureaucratic and resistant to change. Oppositely, though smaller firms might lack necessary resources, their ability to be flexible towards change might make their adoption process smoother (Tornatzky & Fleischer, 1990). Nevertheless, Kimberly (1976) underscores that size alone remains insufficient in analyzing a firm's ability to adopt and implement new technologies, as resource availability and other structural elements are more meaningful determinants.

2.1.3 The Environmental Context

Representing the last element of the innovation adoption process, the *environmental context* encompasses the regulatory environment, technology service providers, and the fundamental structure of the industry (Mansfield, 1968). The inventors of the TOE framework, Tornatzky and Fleischer (1990), often refer to the industry life cycle when discussing the environmental context. The maturity of the firm is argued to matter when analyzing the likelihood to innovate, as mature firms tend to be slower in implementing innovative practices than those in rapidly growing industries. Furthermore, a firm's support infrastructure for technology is another critical aspect of the environmental context in adopting innovation. While some firms are rather compelled to innovate through labor-saving innovations, firms with existing skilled labor or skilled technology services fosters innovation (Rees, Briggs, & Hicks, 1984). Lastly, government regulation can both promote and hinder innovation, depending on the constraints imposed. Mandates such as pollution-control requirements can drive innovation, while stringent safety and testing regulations in industries like construction and agriculture increase costs and slow progress. Similarly, privacy laws in banking may restrict the development of new customer services, highlighting the dual impact of regulation on innovation (Baker, 2011).

Together, the technological, organizational, and environmental context constitute the three elements affecting the implementation and adoption of technological innovation, presenting both opportunities to innovate, as well as obstacles hindering innovation (Tornatzky & Fleischer, 1990). This multidimensional perspective makes the TOE framework particularly suitable for this study, as it enables a structured analysis of how large firms respond to innovation not only through their internal capabilities and technological readiness, but also in light of broader environmental influences. Thus, by focusing on large Swedish firms, this study is enhanced by the incorporation of a macro-level perspective that enables an examination of how these contexts interact to influence the adoption of AI-driven personalization and its impact on customer loyalty.

2.2 The UTAUT

In 2003, Venkatesh and his colleagues developed the *Unified Theory of Acceptance and Use of Technology* (UTAUT), a theory explaining a firm's acceptance towards, and use of, technology. UTAUT can often be compared to the *Technology Acceptance Model* (TAM), which is a widely used framework for explaining technology adoption, focusing on how perceived usefulness and ease of use influence user acceptance (Davis, 1989). While TAM shares similarities with UTAUT in predicting adoption behavior, it lacks key features of the consumer context that the extension of the original UTAUT model provides. The rationale for selecting UTAUT and UTAUT2 over TAM will be further elaborated in section 2.2.1.

The extent of technology acceptance and use in this theory is determined by four main influences; *facilitating conditions, social influence, performance expectancy* and *effort expectancy* (Marikyan & Papagiannidis, 2023). *Facilitating conditions* refer to an individual's belief that the technical and organizational infrastructure exist to support the use of the system, being measured to a certain degree of belief. Moreover, *social influence* involves the extent to which individuals perceive that other, important individuals, believe that they should use the new system. Lastly, *performance expectancy* and *effort expectancy* represent to which extent individuals believe that the new system will help them obtain prosperity in work performance, as well as ease associated with the use of the system, respectively (Venkatesh et al. 2003). However, Venkatesh, Thong, and Xu, (2012) extended UTAUT about ten years later, incorporating three constructs into the theory*; hedonic motivation, price value*, and *experience and habit*.

2.2.1 The UTAUT2

The development of the extended UTAUT, referred to as *UTAUT2*, adapts the framework for a consumer context, widening the organizational context of the model. According to Venkatesh, Thong, and Xu (2012), the constructs *hedonic motivation, price value*, and *experience and habit*, are expected to constitute key predictors of consumer behavior. While

TAM provides a foundational understanding of technology adoption through core constructs such as perceived usefulness and perceived ease of use, its primary focus lies within organizational settings (Davis, 1989). Given that the TOE framework already offers a comprehensive perspective on organizational-level adoption, UTAUT2 is deemed appropriate over TAM for this objective, as it introduces consumer-specific constructs to the theoretical framework. Thus, the constructs presented by Venkatesh, Thong, and Xu (2012) offer a valuable analytical foundation for examining how and why consumers respond to technological change, thereby aligning with the study's purpose of understanding the effects of AI-driven personalization on customer loyalty.

The first construct, *hedonic motivation*, has shown to be an important determinator in the technology use and acceptance. According to Venkatesh, Thong, and Xu (2012), this construct represents a valid predictor of behavioral intention of technology. Hedonic motivation refers to the individual's pleasure arising from the usage of the new technology, which affects the acceptance towards the innovation as well as use of it. This not only refers to employees' acceptance and usage of new technology, but is also directly related to consumers' behavioral intention to use a technology (Brown & Venkatesh, 2005). Moreover, Venkatesh, Thong, and Xu (2012) emphasize that experience can be used as a moderator to analyze the effect on hedonic motivation over time, indicating that the impact of hedonic motivation of technology use decreases as experience increases.

Moreover, the *price value* plays a crucial role in determining the consumer's tradeoff between perceived benefits from the new technology, and the monetary cost of its usage (Dodds, Monroe, & Grewal, 1991). Hence, this construct represents cost tradeoffs that consumers perceive, which employees do not, differentiating the consumer use setting from the organizational use setting (Chan et al. 2008). In contrast to hedonic motivation, this construct directly translates to the perceived usefulness amongst consumers, excluding perspectives given by employees on an organizational level. According to Venkatesh and colleagues (2012), price value is seen as a predictor of behavioral intention of technology usage as it refers to consumers' cognitive tradeoff. In practice, price value is positive in cases where the benefits of technology exceed the monetary cost of using it, making such price value positive on intention for technology use.

Lastly, *experience and habit* contribute as the final constructs, being highly related yet distinct in their definitions. *Experience* refers to a user's prior interaction with technology that shapes their perceptions over time, while *habit* is the automatic, learned behavior that directly influences continued technology use (Kim, Malhotra, & Narasimhan, 2005). Experience is thus measured through the passage of time from an individual's initial usage of a certain technology. Moreover, habit can be operationalized in two different ways. The first refers to the construct being measured through prior behavior (Kim & Malhotra, 2005), and the second to the extent of which an individual believes the behavior to be automatic (Limayem, Hirt, & Cheung, 2007). As presented by Venkatesh, Thong, and Xu (2012), these constructs represent predictors of technological use behavior. Considering these constructs, there are two important differences to be mentioned. First, while experience is required for a habit to develop, it alone does not guarantee that a habit will form. Second, although the accumulation of experience over time can contribute to habit formation, the strength of the resulting habit depends on the degree of interaction and familiarity an individual develops with the specific technology (Limayem, Hirt, & Cheung, 2007). As the constructs are distinct definitions, habit can be measured through experience as a moderator, where habit becomes a stronger predictor of technology use as experience increases, according to Venkatesh, Thong, and Xu (2012).

Together, these constructs are influenced by individual differences, incorporating the moderating effects of age, gender, and experience into the understanding of behavioral intention and technology use (Venkatesh, Thong, & Xu, 2012). However, while these moderating effects could offer valuable insights into the relationship, they are not all addressed within this theoretical framework, as this study does not focus on examining these specific influences. The decision to solely include experience as a moderating effect is based on its direct relevance to the research questions and its expected influence on customers' interaction with AI-driven personalization. Moreover, the three constructs presented by UTAUT2 provide a comprehensive theory explaining the acceptance and use of new technology from a consumer perspective. Hence, the examination of constructs alone is considered being both sufficient and effective in explaining user adoption across diverse technologies and contexts (Venkatesh, Thong, & Xu, 2012).

2.3 The Two-Dimensional Framework of Customer Loyalty

As of today, business success is highly dependent on customer loyalty, representing a critical component influencing long term profitability. Given this, Dick and Basu (1994) presented a two-dimensional framework with the aim of exploring key success factors of customer loyalty. In their research, they distinguished between two different dimensions, namely *behavioral loyalty* and *attitudinal loyalty*. According to the researchers, behavioral loyalty contributes to the framework as it refers to the actual repeat of purchase behavior, whereas attitudinal loyalty represents the psychological commitment to the brand. Together, the dimensions provide a framework with a robust foundation in understanding how CRM strategies influence the engagement and retention of customers.

Before delving into the components of the framework explaining customer loyalty, Dick and Basu (1994) emphasizes the importance of thoroughly understanding the actual definition of the phenomenon before it can be analyzed. The concept of customer loyalty is often referred to as a notion covered by marketing literature, as it analyses the rate of retention and devotion of customers. To assess the perspectives already given by prior research, Dick and Basu (1994) combine the theories given by Kim, Morris, and Swait (2008) and Day (1969). Kim and colleagues (2008) claim that true loyalty involves a conscious decision to prefer a brand over another, while Day (1969) distinguishes between true loyalty, based on attitudinal commitment, and spurious loyalty, driven by external constraints. Dick and Basu (1994) further expands these perspectives by integrating the behavioral and attitudinal dimensions into the framework, emphasizing the importance of considering both frequent purchases and a strong brand reputation.

2.3.1 The Loyalty Relationship

The loyalty relationship represents a framework of factors shaping behavioral and attitudinal loyalty, ultimately developing consequences (Dick & Basu, 1994). The figure below illustrates how the dimensions relate to each other, and how they are shaped, together constituting a framework for customer loyalty.

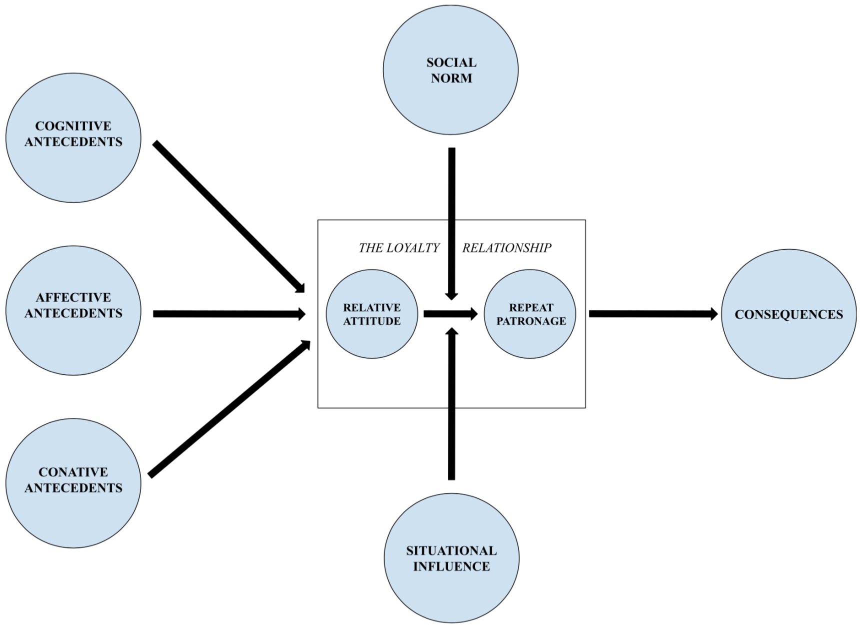

Figure 1. The Customer Loyalty Relationship Framework

(Source: Author's elaboration, based on Dick & Basu, 1994)

The attitudinal dimension refers to the *relative attitude* towards a brand, shaping the preferences by cognitive, affective, and conative factors. These factors, or antecedents, are shaped by different attitudinal drivers. Accessibility, centrality, confidence, and clarity are drivers affecting the cognitive antecedents, while the affective antecedents are shaped by emotions, satisfaction and mood. Lastly, the conative antecedents are rather intentional, focusing on switching- and sunk costs, as well as expectations. On the other hand, the behavioral dimension relates to the *repeat patronage* behavior, which refers to the purchasing patterns exhibited by customers. It is the social norms and situational influences that mediate the relationship between the relative attitude and repeat patronage, either strengthening or weakening the relationship between customers' attitude towards the brand and their purchasing patterns (Dick & Basu, 1994). While the situational factors serve as externalities impacting a customer's willingness to purchase, such as competition, time, and availability, the social norms represent social influences shaping consumer behavior, which are guiding the decision behind purchasing intentions based on group acceptance (Ziliani & Ieva, 2019). As a result, while the behavioral loyalty can be measured in terms of repurchase rate, the attitudinal loyalty is rooted in a deeper emotional engagement towards a brand (Dick & Basu, 1994).

Moreover, the interaction between the attitudinal and behavioral dimension results in four classifications of loyalty; true loyalty, latent loyalty, spurious loyalty, and no loyalty. True loyalty is achieved when both the relative attitude and repeat patronage are high, whereas no loyalty occurs when both dimensions are low. However, if the relative attitude is high, but the repeat patronage is low, latent loyalty will take place, meaning that the commitment to the brand remains high, even though the repeatment of purchase is low. Oppositely, when the customer has a high purchase retention rate, but a low commitment towards the brand, spurious loyalty will occur. These classifications highlight that not all repeat purchases indicate genuine loyalty, but that businesses must cultivate both behavioral and attitudinal loyalty to achieve sustainable customer retention (Dick & Basu, 1994).

Ultimately, Dick and Basu (1994) highlight that the outcomes of customer loyalty manifest in several key consequences. They emphasize the importance of outcomes related to search motivation, resistance to counter persuasion, and word-of-mouth. The search motivation is satisfied when consumers are loyal to the extent of which they exhibit a lower tendency or need to seek alternative brands from competitors. Moreover, they become more resistant to persuasive attempts from other brands, as they've developed a strong psychological barrier against switching to competitive brands. Lastly, positive word-of-mouth is argued to be the most valuable outcome, as satisfied consumers are more likely to share their positive experiences with others.

2.3.2 CRM Strategies and Their Impact on Loyalty

CRM is a strategic approach aimed at managing customer interactions to foster stronger relationships and improve loyalty. Effective CRM strategies address the antecedents of relative attitude and repeat patronage behavior by enhancing cognitive, affective, and conative factors, as well as the social norms and situational influence affecting their relationship (Dick & Basu, 1994).

CRM Strategies Enhancing Cognitive, Affective, and Conative Antecedents

According to Dick and Basu (1994), *cognitive antecedents* refer to a customer's belief system regarding a brand's attributes, quality, and value proposition. These are components that are all affected by the presence of CRM strategies, present to enhance customer perception. One effective strategy within CRM enhancing customers' cognitive antecedents are personalization strategies. As stated by Kumar and Reinartz (2018), perceived relevance and value of a brand has a tendency to increase as a company adopts customized product recommendations and marketing practices based on consumer preferences. In addition to personalization strategies, data-driven insights are also drivers of brand loyalty connected to personalization, where relevant information and tailored solutions improve brand perceptions through usage of customer data (Peppers & Rogers, 2016). However, Kang, Shin, and Gong (2016) emphasizes the importance of transparency and trust, as a clear communication regarding use of personal information, policies, and pricing, is a critical element of cognitive commitment.

Shifting focus to the *affective antecedents*, alternative CRM practices are shown to be effective in enhancing emotional connections to the brand. To reinforce positive emotions associated with the brand, loyalty programs serve as a successful CRM strategy, offering exclusive deals, personalized incentives and unique rewards (Kumar & Reinartz, 2018). Additionally, storytelling as a CRM strategy can be utilized by using customer data to create personalized narratives that strengthen emotional connections, serving a highly important aspect of the emotional connection given by affective antecedents (Ziliani & Ieva, 2019).

Finally, *conative antecedents* reflect a customer's intention to repurchase and advocate for a brand (Dick & Basu, 1994). Customer advocacy programs is one of many CRM strategies that encourages this commitment, supporting user-generated content and testimonials, serving as an act where customers promote a brand, product or service to others, signifying a higher level of loyalty engagement (Ziliani & Ieva, 2020).

CRM Strategies Enhancing Social Norms and Situational Influence

As *social norms* shape consumer behavior, CRM systems can leverage these influences by fostering a sense of social validation to increase customer loyalty. An example of a strategy within CRM to enhance social norms is social proof integration, which works as an approach seamlessly blending ratings, recommendations, and reviews into the customer purchase journey. Practically, the social proof features are displaying reviews or popularity of certain items, ultimately creating a sense of community towards the brand (Roethke et al., 2020). Moreover, referral programs represent an additional CRM strategy capitalizing social norms, as it encourages recommendation in exchange for rewards or discounts. Through such a program, organizations can both offer personalized incentives and track customer referrals through CRM platforms, rewarding customers for driving new businesses (Schmitt, Skiera, & Van den Bulte, 2011).

Despite a consumer's positive attitude toward a brand, *situational influences* may face limitations that can hinder purchase decisions. Factors such as price increases, supply chain disruptions, and the availability of more accessible alternatives can reduce the perceived benefits of a product, leading consumers to adjust their behavior accordingly (Foxall & Yani-de-Soriano, 2005). CRM strategies can mitigate the effects of these situational factors by addressing the obstacles that limit customers' purchasing ability (Kumar & Shah, 2004). One key CRM practice for managing situational factors is dynamic pricing, which could play an essential role in overcoming barriers of purchase. CRM systems can provide customized pricing plans that maximize sales by gathering real-time data on market trends, rival pricing, and consumer behavior. As a result, customers feel they are getting the greatest bargain due to this real-time flexibility, which increases their propensity to purchase and fosters loyalty (Gailey & Lundstrom, 2005). Moreover, an important CRM practice for handling situational influences, such as time restrictions, is targeted marketing automation. CRM systems are able to offer time-sensitive promotions or reminders that stimulate purchases at the most favorable times by studying the preferences and habits of their customers (Blattberg et al., 2008).

Through an effective integration of CRM systems with these strategies, companies can improve social norms and handle situational influences to increase customer loyalty. CRM systems enable for a seamless gathering and analysis of client data, allowing for tailored experiences that adapt to social influences and external conditions. Thus, CRM strategies give firms a strong tool to handle these complications and increase enduring client loyalty because of its capacity to handle real-time data and automate personalized interactions.

2.4 Process Framework for E-Commerce Personalization

In modern business strategies, the role of personalization in e-commerce has emerged as a valuable strategy for many online vendors (Kaptein & Parvinen, 2015). According to Schneider (1980), personalization emerge as an important strategy to enhance, attract, and maintain customers, stating that:

"*What is surprising is that (1) researchers and businessmen have concentrated far more on how to attract consumers to products and services than on how to retain those customers, (2) there is almost no published research on the retention of service consumers, and (3) consumer evaluation of products or services has rarely been used as a criterion or index of organizational effectiveness.*" (p. 54)

As discussed by Kaptein and Parvinen (2015), personalization efforts can be understood by examining content used for customization, as well as their technological abilities. To assess this relationship, the authors present a *Process Framework for E-Commerce Personalization*, building on Consumer Behavior Assumptions and Technological Requirements, illustrated by the figure below.

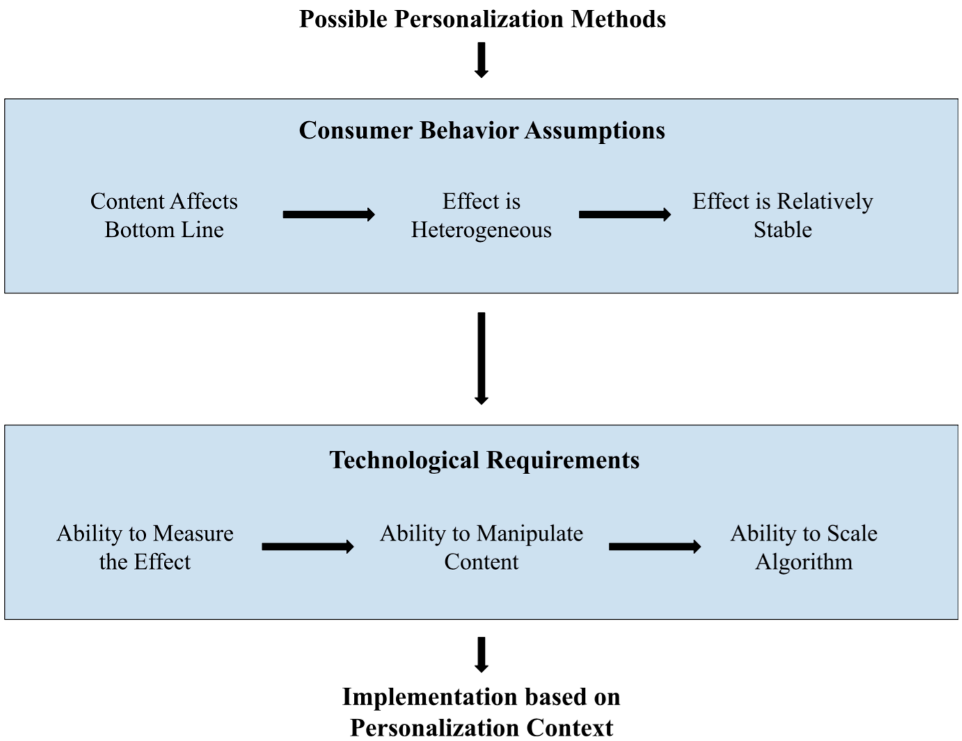

Figure 2. Process Framework for E-Commerce Personalization

(Source: Author's elaboration, based on Kaptein & Parvinen, 2015)

To achieve effective personalization, the possible personalization methods must adhere to certain assumptions regarding the consumer behavior. These assumptions are; *1) content affects bottom line, 2) effect is heterogeneous,* and *3) effect is relatively stable*. The first assumption refers to content, such as price and type of promotion, leading to measurable financial benefits. Moreover, the content's positive effect on the bottom line should also have an heterogeneous effect, indicating that personalization must not always be necessary. When content can be promoted in different ways depending on the traits of the customer, personalization is needed. However, the authors suggest that some content, for example a "buy now" button on the website, is not only subject to certain inferred properties of customers, but should rather be visible for all. Lastly, the effects of the content should be relatively stable within individuals. While heterogeneity is only useful when individual-level effects can be estimated in subsequent interactions with the customer, the effects of content need to have some stability within people to select optimal content for each individual (Kaptein & Parvinen, 2015).

Besides adhering to these assumptions, Kaptein and Parvinen (2015) describe that successful personalization depends on three technological requirements: *1) ability to measure the effect, 2) ability to manipulate content,* and *3) ability to scale algorithm*. The first requirement involves ensuring that one can measure or assess the effect of certain content on individual customers. Moreover, the technology must be able to alter the content without hampering the user experience. As a final requirement, companies that are subject to these personalization strategies must ensure that the computational processes, such as machine learning and estimation of models, that enable the link between content and customer properties, are scalable.

Given this theory, previous literature bridging e-commerce personalization in relation to AI and customer loyalty is deemed relevant for the purpose of this study. Thus, to provide a comprehensive understanding of the studied phenomenon, a combination of four papers will be presented. Zed, Kartini, and Purnamasari (2024) focus on the relationship between AI-driven personalization and emotional connections and satisfaction with a brand, while Arora et al. (2024) explore the effectiveness of AI-driven personalization on customer trust. Thus, both studies analyze the relationship between AI-driven personalization and customer loyalty, although through different metrics. Furthermore, Patil (2024) discusses the ethical considerations of AI, including bias and transparency, which are critical to building trust and long-term loyalty. Finally, Karami, Shemshaki, and Ghazanfar (2024) delve into the ethical implications, emphasizing how bias and transparency impact consumer perceptions and loyalty.

2.4.1 AI-Driven Personalization Literature

As presented in their study, Kaptein and Parvinen (2015) explain how companies can benefit from the usage of certain personalization strategies. Moreover, Zed, Kartini, and Purnamasari (2024) continue to underscore the importance of personalization, being highly relevant in building customer loyalty. According to recent studies, the role of customization has a growing significance in e-commerce, whereas AI plays a crucial role in fostering personalization strategies (Arora et al., 2024; Patil, 2024). As stated by Zed and colleagues (2024), innovative personalization strategies do not only possess potential to enhance intention for repurchase, but also brand advocacy and emotional connections between the customer and e-commerce platform. As to this, weight is put towards identifying customer patterns to understand consumer demographics, with the purpose of developing effective personalization strategies (Zed, Kartini, & Purnamasari, 2024).

AI technologies, such as personalized content, predictive analysis, and recommendation systems, are allowing companies to offer hyper-personalized offers, engaging customers on a higher level compared to traditional marketing approaches. Leveraging consumer data not only creates opportunities to meet immediate consumer needs, but also anticipate needs evolving in the future. The anticipation of future consumer demand can possibly foster an emotional bond, making customers more likely to return to purchase from a specific brand. Moreover, moving beyond transaction frequency, AI-driven personalization can play a significant role in building brand advocacy through positive word-of-mouth. There is a higher probability for customers to actively recommend a brand based on the personalized value they’ve received (Zed, Kartini, & Purnamasari, 2024).

Furthermore, Arora and colleagues (2024) examine the impact of AI-driven personalization on customer loyalty, whereas customer loyalty is referred to as customer trust. These results are based on the effectiveness of AI applications in the e-commerce sector using five evaluation parameters: *overall impact, personalized recommendations, dynamic pricing strategies, customer satisfaction, and trust & transparency*. As the dependent variable for customer loyalty in their study is customer trust, the last evaluation parameter, i.e. trust and transparency, will be replaced by openness in the table below. Arora and colleagues (2024) also emphasize the concept of openness in their paper rather than trust and transparency, making the variables easier to interpret. This study adopts the same approach, as examining the effect of trust in isolation does not offer a comprehensive understanding of the phenomenon under investigation. Table 1 below showcases the effects on these evaluation parameters given AI-driven customization in e-commerce.

Evaluation Parameter	Mean Effect Size	Standard Deviation	95% Confidence Interval
Overall Impact	0.75	0.16	0.65
Personalized Recommendations	0.66	0.11	0.63
Dynamic Pricing Strategies	0.71	0.20	0.68
Customer Satisfaction	0.70	0.15	0.66
Openness	0.73	0.14	0.67

Table 1. Impact of AI Applications in E-Commerce
(Source: Author's elaboration, based on Arora et al., 2024)

The meta-analysis reveals that AI-driven personalization yields a strong positive effect across all parameters, with the highest mean effect size observed for overall impact and the lowest for personalized recommendations. The overall impact represents the general effectiveness of AI-driven personalization in improving e-commerce, while personalized recommendations assess the influence of AI-based recommendations on user engagement and purchasing behavior. Furthermore, Arora et al. (2024) also suggest that AI-based customization enhances customer trust through improved satisfaction and openness. The emphasis on openness, replacing trust and transparency, underscores that trust is built through honest data practices and open algorithms, while customer satisfaction reflects the extent to which AI-driven personalization enhances user experience and meets customer expectations. Lastly, dynamic pricing strategies further indicate that AI-driven pricing in optimizing sales and consumer response can positively influence consumer perceptions. To conclude, Arora et al. (2024) refer to AI systems as a transformable effort that enhance the customer experience by analyzing vast amounts of data to deliver personalized recommendations and pricing plans tailored to individual preferences. The authors state that this level of customization ensures that products and services align closely with customer needs, leading to greater customer trust and therefore a stronger customer loyalty. Patil (2024) agrees that AI has revolutionized the view of customer loyalty in terms of consistently providing personalized interactions. However, in terms of trust and transparency, as well as openness, Patil (2024) highlights that businesses must adapt to ethical considerations to maintain consumer trust, creating a tradeoff between effective automation strategies and qualitative human interaction.

2.4.2 Ethical AI-Driven Personalization

Though AI-driven personalization strategies present numerous positive effects on customer loyalty, it also encompasses obstacles, primarily due to ethical concerns raised by its implementation. There is no doubt that in order to attain sustainable customer relationships, businesses must ensure trust from, and transparency towards, customers. Excessive automation presents risk, which might lead to ethical dilemmas due to misuse of data-driven decision making. While Patil (2024) highlights *Bias* and *Transparency* as the main concerns given by AI-personalization, Karami, Shemshaki, and Ghazanfar (2024) complements this view by adding three areas of contributions, namely *Privacy and Data Security*, *Consumer Manipulation*, and *Economic and Social Repercussions,* tapping into the discussion of openness addressed by Arora et al. (2024).

According to Patil (2024), it is mainly the presence of bias, and the lack of transparency, that creates incentives for businesses to implement clear data protection measures and ethical AI practices, ensuring a safe environment for customers. The author highlights how *Bias*, and in particular algorithmic bias, i.e. bias arising from AI systems' reinforcement of stereotypical or discriminatory behavior, occurs as a result of biased training data. This presents a major risk for businesses, as they must adhere to principles ensuring diverse datasets, making sure AI-driven models remain fair and inclusive. Moreover, *Transparency* concerns must be addressed through clear communication, ensuring transparent information on how AI-driven personalization operates. Karami, Shemshaki, and Ghazanfar (2024) continues to stress the importance of both transparency and accountability, understanding how decisions are made and assessing the ethical implications through accountability mechanisms. Furthermore, *Privacy and Data Security* represent a significant consideration that businesses must take into account. Compliance with privacy regulations and robust data protection are considered extremely important in AI-powered personalization, as it fosters trust by securing personal data. Karami and colleagues (2024) highlight the need for businesses to comply with the General Data Protection Regulation (GDPR), presenting a crucial component in adhering to concerns regarding privacy and data security. Though GDPR is present across the whole European Union (EU) and European Economic Area (EEA), it also has a broad international impact amongst all countries that handle personal data of citizens within these markets (European Commission, n.d.; Datafisher, 2024). Countries must carefully adhere to principles given by GDPR, while complying to their unique governing body. Sweden, as one such country, exemplifies the nuanced challenge of aligning domestic regulations with data protection standards (Datafisher, 2024). As to this, *Consumer Manipulation* remains a central considerable aspect, protecting customer's autonomy and agency by ensuring that no manipulation of their decisions are being present. Lastly, *Economic and Social Repercussions* addresses social implications of AI in the long term. Businesses gain trust from customers by ensuring that AI benefits are distributed equitably, not exacerbating any social inequalities. To conclude, AI automation remains a significant ethical consideration when analyzing the effect of AI-driven personalization on customer loyalty (Karami, Shemshaki, & Ghazanfar, 2024).

2.5 Operationalization of Theoretical Concepts

To ensure that there remains a clear link between the theoretical frameworks and the empirical data, key concepts of the literature are operationalized in relation to emerging themes from the interview guide. The table below summarizes the main theoretical constructs relevant to answering the research questions, indicating how these concepts are reflected in the empirical themes. Thus, this operationalization ensures that the theoretical foundation systematically connects to the empirical results of the study.

Author & Theory	**Key Concept**	**Theme**	**Purpose for Data Collection/Analysis**
Tornatzky and Fleischer (1990) *TOE framework*	How technological, organizational, and environmental context of firms influences the implementation and adoption of innovation	AI-Driven Personalization in E-Commerce	To identify factors influencing the organizational adoption and implementation of AI-driven personalization

Venkatesh, Morris, Davis, and Davis, (2003); Venkatesh, Thong, and Xu, (2012) *UTAUT/UTAUT2*	A firm's acceptance and use of technology, adapted for a consumer context in UTAUT2	AI-Driven Personalization in E-Commerce; AI's Impact on Customer Loyalty	To explore how key factors influencing consumer acceptance affect the adoption of AI-driven personalization
Dick and Basu (1994) *Two-Dimensional Framework of Customer Loyalty*	Understanding how CRM strategies influence the engagement and retention of customers through attitudinal and behavioral aspects	AI's Impact on Customer Loyalty; Customer Perception and Trust	To understand how AI-driven personalization impacts both the attitudinal and behavioral aspects of customer loyalty
Kaptein and Parvinen (2015) *Process Framework for E-Commerce Personalization*	How personalization strategies impact online vendors based on consumer behavior assumptions and technological requirements	AI-Driven Personalization in E-Commerce; AI's Impact on Customer Loyalty	To identify consumer behavior and technological requirements impacting AI-driven personalization in e-commerce
Arora et al. (2024); Karami, Shemshaki, and Ghazanfar (2024); Patil (2024); Zed, Kartini, and Purnamasari (2024) *AI-Driven Personalization Literature*	Previous literature bridging personalization in relation to AI and customer loyalty, also assessing ethical implications	AI's Impact on Customer Loyalty; Customer Perception and Trust; Future of AI and its Impact on Customer Loyalty	To achieve a comprehensive understanding of how AI-driven personalization efforts impact customer loyalty in Swedish e-commerce, and challenges associated with its implementation

Table 2. Operationalization of Theoretical Concepts

(Source: Author's elaboration)

3. Methodology

The following chapter outlines a systematic explanation of the research approach and procedures used to investigate the study's objectives. It begins with an overview of the research strategy, explaining the choice behind the qualitative nature of the study and the abductive approach. This is followed by the research design, outlining the case study that has been applied. Furthermore, the data collection and thematic analysis are being described, followed by reflections. This includes the criteria for assessing the quality of academic research, as well as ethical considerations. Lastly, the limitations of the study are discussed, including selection of organizations, participants, and sample size. These elements collectively guide the research process and ensure rigor throughout the study.

3.1 Research Strategy

3.1.1 Qualitative Study

This study adopted a qualitative approach with the aim of exploring how AI-driven personalization impacts customer loyalty within Swedish e-commerce. The purpose behind the decision to conduct a qualitative study was to gain a deep understanding of the research phenomenon, by reaching nuanced and multifaceted descriptions of how different actors within e-commerce experience the effect of AI-driven personalization on customer loyalty. According to Bell, Harley, and Bryman (2022), qualitative research focuses on interpreting social phenomena through rich, detailed insights rather than numerical analysis. Given the complexity of AI as a personalization strategy, a qualitative approach allowed for a nuanced exploration of professionals' perspectives regarding its effect on customers. Moreover, data of qualitative characteristics is considered being analytical, interpretable, and with consideration of external and social contexts. Hence, this study aimed to be objective towards analysis, as well as allowing room for further interpretation (Bell, Harley, & Bryman, 2022). To answer the study's research questions and reconnect to the purpose of the study, multiple interviews with actors linked to the e-commerce value chain, operating in different industries, contributed to a broad perspective of the study's research area.

Furthermore, by adopting a qualitative approach, the study emphasized the understanding of social contexts through individuals' subjective experiences, as the fundamentality behind qualitative research aligns with an interpretivist epistemology (Bell, Harley, & Bryman, 2022). For this specific study, such an emphasis was considered relevant since perceptions, as well as implementations, of AI-driven personalization in CRM cannot alone be fully captured by a quantitative approach. Moreover, the flexible and exploratory nature behind a qualitative approach justified the choice of method used. As the implementation of AI personalization affecting customer loyalty remains an evolving phenomenon, the qualitative nature was considered suitable as it enabled adaptability for interpretation. In turn, this allowed for a deeper understanding of the organizational opportunities and challenges that firms face (Bell, Harley, & Bryman, 2022). This methodological approach thus provided a comprehensive and contextualized understanding of how customer loyalty is affected by AI-driven personalization within Swedish e-commerce.

3.1.2 Abductive Approach

Abduction was the adopted approach to this study, which is characterized by its iterative nature. The abductive approach was considered suitable for this study as it explored a complex and evolving phenomena, representing a bridge between deductive reasoning, going from theory to data, and inductive reasoning, going from data to theory. Thus, this approach allowed the author to iteratively move between theoretical insights and empirical observations (Bell, Harley, & Bryman, 2022). Abduction allowed for a flexible way of action, as well as a structured one, to develop a deep understanding of the study's dynamic interaction.

The approach towards abduction involves formulating a hypothetical pattern as an explanatory model, based on previous individual cases. Furthermore, the hypothesis or theory should be tested on new cases, which can lead to new views that may affect the conclusions drawn. Unlike deduction, which tests pre-existing theories, or induction, which builds theories solely from data, abduction allows for the refinement of conceptual frameworks by incorporating empirical findings into existing theoretical models (Bell, Harley, & Bryman, 2022). This was reflected in the study as theories were being replaced, with the aim of finding suitable frameworks as explanatory models for the specific purpose. This approach was deemed appropriate for this study because it facilitated a deeper exploration of e-commerce professionals' experiences with AI and customer loyalty, while remaining open to emerging patterns and insights that may not have been initially anticipated. Upon completion of the analysis and conclusion, it could be noted that the starting point for the study was not the same as the final version, as new insights had continuously emerged.

The process of this study consisted of a continual interplay between theoretical constructs and empirical findings, laying the foundation of the abductive approach. As interviews were completed, and further analyzed, patterns on the field of study could be identified. The insights given from these patterns were henceforth evaluated in relation to the prior collected literature, allowing for a dynamic process involving both theoretical refinement and elaboration (Bell, Harley, & Bryman, 2022). This iterative process ensured that the study remained responsive to the complexities of contemporary research, while maintaining a strong connection to relevant established theoretical frameworks. Two practical examples of the abductive process in this study occurred after conducting the first four interviews. At this stage, it became evident that one theoretical contribution from Arora et al. (2024) did not align well with the emerging empirical patterns. Consequently, that section was replaced with another, more relevant contribution of AI-driven personalization given by Arora et al. (2024), which offered a better conceptual fit with the observed data. Furthermore, following the completion of all interviews, an alternative theory within relationship marketing was deemed irrelevant to the study. Thus, this theory was replaced by a more suitable framework that aligns more closely with the study's purpose and research questions, namely the Process Framework for E-Commerce Personalization proposed by Kaptein and Parvinen (2015). These adjustments exemplifies the iterative and flexible nature of the abductive approach, where theoretical frameworks were not fixed, but rather refined in response to empirical findings.

The interpretivist epistemology underlying this study also aligned with the abductive approach given by the method. The mentioned emphasis on experiences given by the qualitative study, supported the abductive approach in reaching a thorough and contextual interpretation of the studied phenomenon. Moving beyond simple and objective descriptions by engaging in theory development, a more nuanced and comprehensive understanding of the research problem could be reached through the adoption of an abductive approach (Bell, Harley, & Bryman, 2022). In summary, the abductive approach provided the methodological flexibility needed to explore how customer loyalty is affected by AI-driven personalization. By iteratively linking empirical observations with theoretical perspectives, this study ensured a rich and contextually grounded analysis of the studied phenomenon.

3.2 Research Design

This study compared different companies across industries, therefore, the multiple case study was chosen as research design. It enabled for the conduction of a comparative analysis and adopt broader generalizability, while still providing in-depth exploration (Bell, Harley, & Bryman, 2022). Hence, a multiple case study allowed for identification of patterns across organizations, and simultaneously acknowledging unique firm contexts.

As the study adopted both a qualitative and abductive approach, the multiple case study was deemed relevant as it allowed to explore complex problems while maintaining contextual depth (Bell, Harley, & Bryman, 2022). In the case of this research, the combination of shared trends and firms specific variations benefited the analysis of the study by contrasting several implementations of AI strategies affecting customer loyalty. Relating the case study with the nature of qualitative research constitutes a distinct alignment with the purpose of understanding social phenomena through detailed insights, rather than relying on numerical generalizations (Bell, Harley, & Bryman, 2022).

Moreover, case studies are often referred to as preferable research designs when aiming to answer questions including "how" and/or "why" (Bell, Harley, & Bryman, 2022). Hence, to address the research questions, a case study methodology was an appropriate research design, as the study explored *how* customer loyalty in Swedish e-commerce is influenced by AI-driven personalization, as well as *how* challenges associated with this relationship might affect customer loyalty. Additionally, the choice to proceed a multiple case study was supported by the abductive approach, due to the allowance of iterative refinement on emerging empirical findings.

3.3 Methods and Means

3.3.1 Data Collection

It is crucial to present the data collection process in qualitative studies to ensure that the findings are reliable, relevant, and rich (Bell, Harley, & Bryman, 2022). Initially, this section outlines the process and criteria set to collect data from secondary sources, presented under the *Secondary Data Selection Process*. Moreover, to confirm the study's relevance and rigor, the data selection process is addressed under the *Primary Data Selection Process*. Onwards, the section presenting the *Interview Process* describes how the interviews were structured to facilitate open discussions while maintaining a consistent framework for comparison across different cases.

Secondary Data Selection Process

The secondary data is referred to as already existing data, from sources such as questionnaires, articles, books, and databases (Bell, Harley, & Bryman, 2022). For this study, the initial collection of data began by conducting a systematic literature review, however being complemented during the research process as an abductive approach was adopted. According to Bell, Harley, and Bryman (2022), it can be preferred to collect some of the data beforehand, as it gets easier for the observer to trace the actions taken by the author. A summary of the inclusion criteria for secondary data is showcased in the table below.

Format of Secondary Sources	Peer-reviewed journal articles, academic books, website publications, reports
Language	English
Year of Publication	1962-2025
Databases	Gothenburg university library, google scholar, scopus, web of science
Keywords	“AI-personalization”, “strategic CRM”, “strategic CRM framework”, “innovation strategies”, “customer loyalty”, “customer loyalty framework”, “personalization in e-commerce”

Table 3. Inclusion Criteria for Secondary Data

Peer-reviewed journal articles and academic books were selected carefully to ensure high relevance to the research field, as well as maintaining high quality of the sources included as theoretical framework. Through this selection process, reliability and validity were obtained (Creswell, 2014). Moreover, some of the secondary data was collected from website publications and reports, with the aim of understanding and explaining the fundamental definitions of certain concepts in this study field, mainly presented in the introduction chapter. A combination of recent and older sources were included to both obtain fundamental definitions and background of theories, as well as updated knowledge about the impact of recent studies, where the range spanned between sources from 1962 to 2025. The inclusion criteria focused on articles, website publications, and books written in English to ensure consistency through all sources, as well as being directly related to knowledge about customer loyalty and AI-driven personalization strategies. Moreover, the research process involved a comprehensive review of academic literature by reviewing sources though four different databases: Google Scholar, Scopus, Gothenburg University Library, and Web of Science. To ensure alignment with the purpose and research questions of this study, specific keywords were identified and applied as part of the inclusion criteria. These keywords, including "AI-personalization", "innovation strategies", and "customer loyalty framework", guided the selection process, where sources were initially screened by systematically evaluating their titles and abstracts against the established criteria. Books and peer-reviewed journal articles considered relevant underwent a thorough review to confirm their consistency with the study's objectives. Moreover, a snowball sampling approach was used, consistent with methodologies employed in other qualitative studies (Bell, Harley, & Bryman, 2022). This process involved reviewing the reference lists of secondary data sources that met the established inclusion criteria. Newly identified sources were then assessed using the same criteria to determine their relevance to the study. The key findings, themes, and conclusions from these sources were then categorized and analyzed in depth to strengthen their connection to the theoretical framework. Nevertheless, certain limitations should be acknowledged, such as the exclusive reliance on English-language studies, which may have resulted in the omission of valuable contributions published in other languages (Creswell, 2014).

Primary Data Selection Process

According to Bell, Harley, and Bryman (2022), the objective to obtain rich, relevant, and reliable findings are fundamental in guiding the data selection process. Thus, to find suitable companies and professionals to interview, a purposive sampling strategy was employed, where participants were intentionally selected based on specific characteristics or qualities relevant to the study (Bell, Harley, & Bryman, 2022). Through this strategy, the study could assure an inclusion criteria composed by participants with direct experience and knowledge in the specific field of study. Therefore, the first step of the selection process was to identify firms within the targeted sector meeting the established inclusion criteria. For this study, the inclusion criteria was set according to sector, market presence, expertise, and relevance to the research topic, as showcased in the table below.

Sector	E-Commerce Value Chain
Market Presence	Large Companies in Sweden
Expertise	Executives, Managers, and Seniors
Relevance to Research Topic	Either 1. *Knowledge and Involvement in Understanding Customer Loyalty as an Effect of AI-Driven Personalization,* or 2. *Knowledge and Involvement in the Process of Integrating AI-Driven Personalization affecting Customer Loyalty*

Table 4. Inclusion Criteria for Primary Data

Based on the inclusion criteria, potential interview candidates were identified through professional networks, company websites, and LinkedIn. Initially, potential participants were contacted through LinkedIn or via email, where the research subject, research questions, and purpose of the study were presented. Alongside the initial invitation to participate as interview candidate to the study, a snowball sampling was incorporated to the selection process. This means that the initially contacted interview participants were asked to recommend additional relevant participants to the study, if they did not have the possibility to participate themselves, or expertise relevant to the study (Bell, Harley, & Bryman, 2022). This approach ensured access to key informants who might not have been initially considered, but possessed valuable insights. By applying these selection criteria, the study ensured that the collected data was both relevant and comprehensive, facilitating a robust analysis of the research topic. Below follows a table summarizing information about the ten respondents who have participated in this study.

Respondent	Industry	Professional Title	Primary Competence*	Date and Time
A	Beauty	Consumer Centric and Data Driven E-Commerce Key Account Manager	AI, CRM, E-commerce	21/2-2025 40 minutes
B	Distribution Services	Transport and Logistics Manager	AI, CRM	26/2-2025 45 minutes
C	Pharmaceuticals	AI/ML Tech Lead	AI, E-commerce	27/2-2025 50 minutes
D	Retail Construction Materials	Consumer Behavior Expert and Business Developer	AI, CRM	27/2-2025 55 minutes
E	Retail Construction Materials	E-Commerce Manager	AI, CRM, E-commerce	28/2-2025 45 minutes
F	Furniture	Market Analyst	CRM, E-Commerce	7/3-2025 45 minutes
G	Betting and Gambling	Chief of Innovation and Future Affairs	AI, CRM, E-Commerce	7/3-2025 60 minutes
H	Sports	Analyst and E-Commerce Sales Manager	AI, CRM, E-Commerce	14/3-2025 45 minutes
I	Sports	Head of Marketing	CRM, AI	2/4-2025 45 minutes
J	Fashion	CRM Manager	CRM, E-Commerce	11/4-2025 40 minutes

Table 5. Summary of Interview Respondents

**Primary competence related to this study*

Interview Process

The conducted interviews followed a semi-structured format (Bell, Harley, & Bryman, 2022), where each interview consisted of conversations lasting approximately 40-60 minutes. The semi-structured interviews were covered by an open dialogue between the author and the respondents, where all meetings were held digitally. As the interviews followed a semi-structured format, prepared interview questions were combined with spontaneous follow-up questions, jointly representing the structure of the interview with the aim of answering the research questions in a comprehensive and detailed way. According to Bell, Harley, and Bryman (2022), such an approach can be characterized by an interview guide, where the respondent is left with room for interpretation, as well as an opportunity to guide the interview. As for the author, the interview guide enabled for adjustments of the questions, as well as refinement of them, according to the respondents' answers.

The preparations for the interviews were above all based on the creation of the interview guide, which can be found under appendix A. Here, pre-prepared questions were put forward, based on themes that have been identified as relevant for the analysis. The themes on which the structure of all interviews was based followed a chronological order, with the *Background* of the respondent's work position and insights on the studied phenomenon as a starting point. Furthermore, the interviews focused on *AI-Driven Personalization in E-Commerce,* which dived into the actual usage of AI connected to customer experience within the specific company. This was followed by a theme called *AI's Impact on Customer Loyalty*, where the focus was on gaining an understanding of the actual effects on customer loyalty given by AI. This theme was then followed by *Customer Perception and Trust*, which intended to provide insights into the customer's point of view resulting from AI implementation. Thenceforth, the *Future of AI and its Impact on Customer Loyalty* was discussed to gain a long term perspective of the studied phenomenon. Finally, *Final Thoughts* were concluding the interview guide, where space was left for the respondent to add further insights and comments. These six main themes set up the structure of the interviews and the interview guide, but at the same time left room for further reflections and follow-up questions, which followed the structure of a semi-structured interview (Bell, Harley, & Bryman, 2022).

3.3.2 Thematic Analysis

A thematic analysis was applied to this study when analyzing the collected data, which was made through identifying, organizing, and interpreting patterns or themes within the data. The thematic analysis has a great theoretical freedom according to Braun and Clarke (2006), resulting in a flexible approach that can be modified for different needs in different studies. This provides a rich and detailed, yet complex, presentation of the data. Another advantage of thematic analysis is its efficacy in examining the perspectives of diverse research participants, allowing for the identification of both commonalities and divergences. This process can yield unanticipated insights, thereby enriching the depth and complexity of the analysis (Braun & Clarke, 2006). Furthermore, this approach is useful for the purpose of summarizing key features of a large data set, in conjunction with the structured approach to manage the collected data (Braun & Clarke, 2006; King, 2004). Adopting a thematic analysis was particularly useful for this study as it allowed for the identification of recurring patterns and insights across multiple organizations within the e-commerce sector, providing both a structured and flexible approach to analyzing how AI affects customer loyalty while capturing the nuanced perspectives of industry professionals. The thematic analysis documented by Braun and Clarke (2006) consists of six phases, which are as follows: *familiarizing yourself with your data, generating initial codes, searching for themes, reviewing themes, defining and naming themes*, and *drafting the report.*

Though the thematic analysis could be presented in a linear manner, it is actually a dynamic, iterative, and reflective process that evolves continuously. This means that movement between different phases is ongoing rather than strictly sequential (Nowell et al., 2017). One way in which the thematic analysis applied to this study is in processing interview data. After each interview, responses from different participants were compared, where commonalities and differences were identified. This developed a deeper understanding of the data, aligning with the first phase of the thematic analysis. During transcription, key responses were highlighted to facilitate the creation of initial codes and themes, corresponding to the second, third, and fourth phases of the thematic analysis. Empirical examples, codes, and themes can be found in the coding scheme, visualized under appendix B. As the process progressed, the themes were refined and synthesized to ensure that they were effectively represented in the report, in accordance with the fifth phase. Some recurring themes included *Perceived Usefulness of New Technology Among Customers, AI-driven Personalization Strategies*, and *Perception of Customer Loyalty*. Since the approach was highly reflective, the author frequently revisited earlier phases to refine findings before finalizing the report, aligning with the sixth phase. By applying these phases of thematic analysis, the report author could distill key insights from a substantial amount of data, allowing for a structured and coherent presentation of findings from the ten interviews.

3.4 Reflections

3.4.1 Criteria for Assessing Qualitative Research Quality

Under this chapter, four criteria in qualitative study are being discussed; *credibility, transferability*, *dependability*, and *confirmability*. Together, these criteria helped ensure trustworthiness of a qualitative study, allowing to establish the validity of their findings and the extent to which they can be applied to other contexts.

Credibility

The concept of credibility refers to the reliability of the presented findings (Bell, Harley, & Bryman, 2022). According to the authors, *respondent validation* represents a typical technique that researchers adopt to ensure credibility throughout their work. The respondent validation for a qualitative study is achieved by confirming the findings with respondents for a study, which, for this particular study, was made by confirming results with interviewees. When empirical results were finalized, the most important findings, including citations, were sent to interview participants to ensure that all information was correctly interpreted. This process was facilitated through the use of a structured coding scheme, incorporating recurrent themes and supporting citations, thereby ensuring that only the most relevant information from the coding and results were shared with the interviewees.

Transferability

Transferability refers to the extent of which the findings of a qualitative study can be transferred, i.e. applied to other contexts (Bell, Harley, & Bryman, 2022). For this study, the transferability was ensured by providing detailed descriptions of the research context, such as providing transparency about the interview procedures, respondents's backgrounds, and analyzing decisions. Furthermore, the author assured transferability by thoroughly documenting the research process and illustrating themes with direct quotations. Thus, this study enabled readers to evaluate the relevance of the results to their own contexts. While the findings were not intended to be universally applicable, the depth and transparency of the analysis allowed for meaningful comparisons across similar research areas. Additionally, transferability was supported by the alignment of this study's methodology with established qualitative research principles. The thematic analysis approach ensured that data is interpreted systematically, making it possible for researchers in related fields to assess whether similar methods could yield comparable insights in their respective studies. As a result, through these strategies, the reader can easily apply the findings given by this study to various contextual settings.

Dependability

The third criteria assessed to ensure trustworthiness in this qualitative study is dependability. According to Bell, Harley, and Bryman (2022), dependability refers to the aspect of time, which parallels the reliability criteria. The time aspects measures to which extent the findings of the study can be applied at other times. This study achieved dependability by ensuring that records from all phases of the research process are maintained. These records not only included transcriptions, coding, and interview guides, but also rough drafts, notes, and brainstorming documents. Thus, the entire research process, i.e. from problem formulation and brainstorming, to concluding thoughts, can be reviewed by peers upon request (Bell, Harley, & Bryman, 2022).

Confirmability

By systematically documenting each stage, from data collection to thematic analysis, this study established transparency, which is crucial to ensure confirmability. Confirmability relates to the findings being shaped by the collected data, rather than assumptions, researcher bias, personal interpretation, or any other subjective contribution. Beyond achieving objectivity, the study also established auditability, a strategy that is employed to strengthen the confirmability through openness for external scrutiny (Bell, Harley, & Bryman, 2022). Through the semi-structured interviews, participants were given the opportunity to guide the conversation, question the direction of the inquiry, and contribute additional insights that were not initially considered within the scope of the research. Furthermore, participants were invited to review drafts of the study, providing them with an overview of the research findings thus far, and allowing them to offer further perspectives or suggest additional areas of exploration that may have been overlooked. By allowing participants to guide the interviews, review drafts, and offer additional insights, the study ensured confirmability by minimizing researcher bias and fostering a collaborative process that grounded the findings in the perspectives of the participants rather than subjective interpretation.

3.4.2 Ethical Considerations

To make sure that the interviews followed the ethical rules required by an academic report, the study took into account four key ethical principles outlined by Bell, Harley, and Bryman (2022). According to the authors, a researcher should adhere to the following ethics; *informed consent, harm to participants, privacy and confidentiality,* and *preventing deception.*

The first principle, *informed consent*, refers to the ensurement that participants understand the research purpose, their role for the study, and their right to withdraw at any point of time. When invitations to participate as interview candidates were sent out, all these criterias were included to ensure that the participants were aware of their contributions to the study. Once the respondents agreed to participate in an interview, joint discussions between the report author and the interviewee were prepared and carried out. In this dialogue, all other necessary information was provided to give the respondent a clear insight into the work, such as ensuring that no reputational harm for the respondent or company will occur, according to the second principle, *harm to participants.* Furthermore, *privacy and confidentiality* were assured in connection with the initial invitation to participants, where they were informed about their personal and the companies' anonymity and protection of personal data. Moreover, external anonymity was applied, which means that outsiders were not given information about which respondents have participated. In addition to the external anonymity, the respondents were also internally anonymous, as no employees within their organization, nor competitors, were given permission to identify who provided specific information (Bell, Harley, & Bryman, 2022). The initial invitation also ensured transparency, informing participants about the exact purpose of the study and their contribution to it, alongside with informing that all recordings and transcriptions will be deleted as the study is finalized, satisfying the fourth and last principle, *preventing deception*.

3.5 Limitations

3.5.1 Selection of Organizations

This study adopted an exclusive focus on actors within the e-commerce value chain that are present in the Swedish business market. To make the selection of organizations relevant for the research purpose, companies were either an important actor of the e-commerce value chain, or offering products and services through their e-commerce platform. Though this inclusion criteria aligned with the objective of the study, it also introduced certain limitations, possibly affecting the generalizability of the findings.

Organizations were chosen upon their relevance to identified themes, following a purposeful sampling approach (Coyne, 1997). However, the variability became limited by such an approach, as it excluded companies that were either outside the Swedish market, or outside the e-commerce value chain. Hence, though additional companies adopt AI-personalization strategies to enhance customer loyalty, they were excluded from this study as they were not active in Sweden or within e-commerce. According to Coyne (1997) a theoretical sampling method could possibly have provided a broader perspective, including a dynamic selection based on emerging patterns.

Furthermore, selective sampling could lead to biased conclusions if the study exclusively includes successful or visible organizations (Denrell & Kovács, 2008). By only incorporating companies that have implemented AI-driven personalization, this study did not capture organizations that have avoided AI-incentives. Consequently, the findings could have overestimated the effectiveness of AI in e-commerce by excluding cases where AI adoption did not finalize its implementation. However, by incorporating companies at different stages of their AI implementation, the study captured a diverse range of adoption levels. Lastly, by solely focusing on Swedish actors within e-commerce, conclusions were drawn by country specific digital infrastructure, regulations, and consumer behavior. This limitation presented a risk, as valuable insights from companies established in other countries were being excluded.

By acknowledging these sampling limitations, this study did not claim universal applicability but rather offered context-specific insights into the Swedish e-commerce sector. Future research could adopt a theoretical sampling approach (Coyne, 1997) to compare AI adoption across different sectors, markets, and adoption levels, thereby mitigating potential selection biases and broadening the study's applicability.

3.5.2 Selection of Participants

The selection of interview participants for this study was established by a specific inclusion criteria based on participant's expertise and experiences. To ensure that all participants were relevant contributors to this study, the selection of interviewees were limited to candidates with prior experience in either AI-driven personalization strategies adopted by the organization, or knowledge about the effects on customer loyalty. Moreover, an inclusion criterion was set to exclusively incorporate participants in senior, managerial, or executive positions to ensure valuable perspectives on the research topic as they possessed strategic insights and decision-making responsibilities in the organization. While these criteria ensured the relevance of the data collected, they also introduced certain limitations.

One of the primary limitations resulting from the selection of interview participants was the exclusion of certain potential participants who, despite working in a relevant organization, were not in senior, managerial, or executive positions. As a result, this decision may have caused omission of valuable perspectives from employees on an operational level, who potentially could have provided relevant insights of more practical implementation decisions of AI-driven personalization strategies, or effects on customer loyalty as a result. As discussed by Dahal et al. (2024), qualitative research should carefully balance between specificity and inclusivity to both maintain a deep yet broad understanding. Through the focus on solely including professionals with higher positions, this study may have limited the diversity of certain aspects, and thus constrained the viewpoints given by bottom-up processes. However, Subedi (2023) highlights the importance of carefully selecting participants to enhance the robustness and credibility of qualitative studies, which was the aim of the selection process for this study.

Furthermore, though efforts were made to include participants with diverse organizational backgrounds and expertise, one must mention that the final sample was highly influenced by participant's willingness to participate, and accessibility to be contacted. Dahal and Bhandari (2023) emphasize the importance of diversity in qualitative research to enhance the richness of data. However, the final interview selection may not fully have represented the broader spectrum of perspectives within the research field, as some reliance on purposive sampling were adopted. In addition to this, there were several other factors that possibly could have affected the responses or generalizability, such as cultural backgrounds, gender, or sector-specific experiences.

Despite these limitations, the targeted selection of interviewees ensured that the insights gathered were highly relevant to the research questions, as they provided firsthand knowledge of strategic decision-making and organizational approaches to AI-personalization and effects on customer loyalty. Future research could address these constraints by incorporating a more varied sample, including employees on an operational level, or by employing additional data collection methods such as surveys to capture a broader range of perspectives. By acknowledging these limitations, this study remains transparent in its methodological approach while highlighting potential avenues for future inquiry.

3.5.3 Sample Size

The sample size for this study was set in alignment with the principles given by qualitative research methods, which specifically drew from the concept of *data saturation* and *information power (*Dworkin, 2012; Malterud, Siersma, & Guassora, 2016). The final number of conducted interviews resulted in a total of ten, following the principle that the sufficiency of the sample in qualitative research is not exclusively determined by the quantity, but also by the relevance of the data collected.

The concept of *information power* was introduced by Malterud, Siersma, and Guassora (2016), explaining the concept as a guiding principle to determine the appropriate sample size in qualitative research. According to the authors, the more substantial and relevant the collected data is relative to the research field, the fewer participants are required to contribute. Given that this study targeted participants in senior, managerial, and executive roles with direct experience in AI-driven personalization strategies or customer loyalty, the data obtained from these participants held high information power, thus justifying the selected sample size.

Moreover, Dworkin (2012) highlights how sample size relates to the concept of *data saturation* in qualitative research. The concept emphasizes the importance of meaningful thematic saturation, which can be achieved with as few as six to twelve interviews in homogenous study groups. This study achieved saturation within the ten conducted interviews, as recurring patterns and themes emerged regarding the implementation of AI-driven personalization, as well as its effects on customer loyalty. Furthermore, the key theme emergence across participants strengthened the selected sample size.

However, despite justification of the chosen sample size, there are some limitations that may be acknowledged. While the amount of ten interviews in total remains sufficient as sample size, a higher number of interviews could possibly have captured a broader range of perspectives, particularly from more diverse organizational contexts. These constraints could be assessed by future research by expanding the pool of participants, or incorporate supplementary data collection procedures to enhance generalizability. Nonetheless, within the scope of this study, the selected sample size was deemed appropriate to ensure a robust and insightful exploration of the research topic.

4. Results

The results chapter presents the empirical findings of the study, derived from a total of ten interviews with industry professionals. Based on the themes identified and covered by the interview guide, which can be found under appendix A, the results chapter is structured accordingly. The outline of the chapter follows the structure of the themes presented in the interview guide, initially covering the perception, adoption, and practical implementations of AI-driven personalization. Thenceforth, the companies' view of customer loyalty is covered, followed by the impact of AI-driven personalization on customer loyalty. Lastly, a final section is added to this relationship, covering challenges of the studied phenomenon.

In the methodology chapter, under section 3.3.1, a summary of the interviewees can be found in table 5, including their respective industry and professional title. The respondents presented in the table represent professionals from a wide range of industries, though all being important actors of the e-commerce value chain. While some of the chosen companies exclusively target customers through their e-commerce platform, some are also active within physical stores. However, the empirical findings in this study solely focuses on their insights and experiences of AI-driven personalization and customer loyalty through their online platforms. Empirical examples, codes and themes identified through these interviews can be found in the coding scheme under appendix B.

4.1 Perception and Adoption of AI-Driven Personalization

The empirical findings reveal a significant difference in the extent to which companies have progressed in implementing AI-driven personalization. While some companies emphasize their efforts to keep pace with the rapid advancements in AI-driven personalization strategies, others highlight the substantial progress they have made in its implementation. Though there remains a disparity between the extent to which companies have progressed in implementing AI as a personalization strategy, they all emphasize the importance of keeping up with this particular technological change. Respondent B believes that there is great potential for AI-personalization strategies to play a crucial role in how their business creates value for customers, however, there remains a gap between this potential and what they actually do. Moreover, respondent E explains that, even though they offer products both through their e-commerce platform and in physical stores, their traffic online has seen a significant increase over the past few years. She continues to stress that no matter if the customer buys the product through their online or physical platform, personalization through e-commerce remains essential, as many customers will browse the supply of goods before actual purchase. Respondent F confirms this view, stating that despite the fact that customers of furniture most likely want to see and try their item before purchasing it, a vast majority will still initially find their wanted items through their website, making AI a central component in delivering personalized offers. Moreover, respondent J agrees that AI has a huge potential in enhancing customer loyalty through personalization efforts, however, he also notes that their organization has encountered instances where AI-driven personalization strategies did not yield the desired outcomes. He continues:

> *"We have an approach where we believe AI is the future, but we will not implement something in the long-term just because it is AI. We need to have faith in it, thus we will buy an AI-tool to test it, use it, and evaluate it".*

He further explains that some AI initiatives have fallen short in delivering personalized offers, as the tools lack the capabilities of human personnel in crafting and delivering tailored content. That said, he notes that the organization remains actively engaged in exploring AI-driven personalization tools that may prove effective in the future. Nonetheless, he emphasizes that, at present, human efforts continue to yield better personalized results.

Though respondents agree on the importance of keeping up with AI, they also highlight that such an implementation can take some time, as organizations need to adapt to new technologies. However, respondent G underscores that even though it might be scary to be a first mover in such a technological change, businesses must be prepared to challenge themselves. He states:

> *"We were very quick in implementing AI, as we had already manifested its effects through our journey of change".*

Moreover, he underscores that the reason they could be so fast in implementing AI-driven personalization is due to their proficiency, but also luck to some extent. The respondent continues:

> *"Proficiency is also linked to some extent of luck. Businesses have to expose themselves to luck too"*.

Another respondent who explains their progress in implementing AI-driven personalization on their e-commerce platform is respondent I, who agrees that businesses must adapt to the technological advancements that follow with AI to remain competitive. He explains that AI is entering all business areas, therefore it's important to keep up with its implementation to not lag behind competitors. He continues by stating that early adopters of AI have a competitive advantage to those with similar assortments, making them more relevant. However, both respondent G and respondent I state that there might be a disparity between to which extent small versus large companies can implement AI-driven personalization. Respondent I explains that large companies often have well-established systems, which may facilitate the integration of AI into their existing infrastructure. In contrast, smaller companies may possess greater flexibility in adapting to AI, as they have fewer structural components to modify. However, the respondent further argues that if smaller firms adopt a passive approach to AI-driven personalization, they may still benefit from reduced implementation costs and the opportunity to replicate successful strategies developed by others. This point is also emphasized by respondent J, who underscores the complex trade-off between being a first-mover and a later adopter of technology. Organizations must carefully evaluate and determine which approach aligns best with their strategic objectives and long-term benefits.

As previously mentioned, respondents have a somewhat similar view towards the importance of integrating AI as a personalization system, however, one of the respondents is skeptical towards the perception of AI, and how it's commonly referred to as of today. Moreover, the respondent, respondent D, highlights that there is a risk that AI overshadows what's important in this case, namely the consumer behavior. She states that:

> *"AI is similar to what we called digitalization five to ten years ago, it was as revolutionizing as AI is now. And then we were talking about the importance of businesses digitizing, but what do we do with the opportunities? That's what's important"*.

Thus, she emphasizes that businesses should question what they want to do with the technological possibilities, rather than how the technology should be implemented, because the technology will solve itself. Although the respondent questions the view of AI, she still underscores that businesses must keep up with technological advancement, something that respondent C agrees with. Respondent C acknowledges that AI dominates the discussion of delivering personalized offers to consumers, but highlights that some extent of human interaction must still be present to both maintain creativity within the organization, but also to deliver value to customers. He continues to underscore that even though they have seen AI as efficient in creating personalized content, it must still be controlled to some degree by a human. Respondent D and respondent A both agree that human interaction will not be fully replaced by AI-driven initiatives, instead, it will continue to play a central role within customer engagement strategies.

Respondent A refers to internal and external efficiency as he discusses AI-driven personalization, underscoring that they choose to perceive AI personalization as valuable in streamlining internal practices and delivering quality through external practices. He continues by stating that there is still much to do in the progress of integrating AI-driven personalization into their organization, but that they've already seen a positive effect both in terms of internal and external efficiency. Respondent H agrees that while progress has been made, there is still significant work to be done in fully integrating AI-driven personalization within their organization. She acknowledges the potential for further improvements in above all capturing and understanding future consumers through AI-driven personalization, emphasizing that ongoing refinement and adaptation will be key to maximizing AI's benefits. Respondent B reinforces the perspectives shared by respondent A and respondent H, emphasizing the necessity for businesses to continuously adapt to advancements in AI. He highlights that as AI continues to evolve, it plays a crucial role in shaping how companies engage with their customers.

4.1.2 Practical Implementation and Usage of Personalization Strategies Driven by AI

Regarding the practical implementation of AI-driven personalization, the interviewed companies report a diverse range of approaches, reflecting varying stages of progress in their adoption of these technologies. Respondent B is transparent in explaining that, despite the ongoing process of integrating more advanced systems to offer personalized content though AI, their current personalization is limited to generating text through generative AI.

Furtheron, he explains that generative AI helps them to provide customized emails according to segmentation that has been made through traditional technologies. According to Respondent F, current personalization efforts within their e-commerce operations are primarily driven by traditional technologies, as AI has not yet seen successful results in delivering customized content within their organization. Though he further explains that he believes AI could benefit the company in terms of engaging the customers, he acknowledges that significant progress is still required in its implementation. Moreover, respondent H mentions how traditional technologies serve as their current foundation in creating personalized content, mainly through analytic metrics such as Google Analytics 4, Microsoft Clarity, and Net Promoter Score. While these tools measure customer satisfaction and how the customer acts on their website, AI could serve as a crucial tool in understanding what customers demand today and in the future. Today, the company solely uses AI in their post-purchase phase, using customer data to deliver product recommendations through the e-commerce platform. However, as previously mentioned, she emphasizes that AI has huge potential in foreseeing how future customers will act. Considering this, she continues by explaining that their organization is ongoing a major project with a management consultancy firm, investigating how the implementation of AI-driven personalization could affect consumer behavior through their e-commerce platform.

In contrast to respondent B and respondent H, who are straightforward in mediating their need to adapt further to advancements in AI-driven personalization, respondent G presents several examples on how AI has already been implemented as a personalization strategy into their organization. In terms of personalization, he highlights that they utilize generative AI in three ways. The first way in which they use AI is through algorithms at the website. Respondent G underscores that they have been skilled in foreseeing future technological change, which resulted in them being early adopters of AI, mainly through a voice control project they had been working on. This has changed how they can tailor customized experiences through their website, creating seamless and personalized practices through voice command. Second, AI is used to create personalized content generation, mainly through email. Third, and most importantly according to the respondent, they have implemented an AI assistant. Through this tool, customers are assisted throughout the whole purchase journey, receiving both advice and practical guidance on the website. He states:

> *"AI assistants are the highest degree of personalization I would say. And I think it is a very important part of the future interface between the buyer and the e-commerce company"*.

Respondent J asserts that AI assistants, along with various online navigation and support tools, are increasingly central to contemporary personalization strategies. He explains that, although the organization has not yet fully implemented AI across its operations, they are currently using AI-driven personalization to collect behavioral data about customers, which are used to build clusters that enable personalization. According to three parameters: how recently you've placed an order, how often you place an order, and to which monetary amount you order, the organization can segment customers. He continues by underscoring that through these three parameters, they can create personalized newsletters, emails, and other customized content. Moreover, respondent A describes that AI has shown effectiveness in enhancing their marketing strategy, mainly through developing marketing automation emails, customized for different segments of customers. He outlines the following:

> *"AI is essential for us not only to create individualized content and enhance internal efficiency, but also to generate customized materials visually, such as images, which creates a buzz to enhance our external efficiency"*.

He continues by underscoring that these marketing strategies not only help the company to offer personalized content, but also to identify high-intent customers, and do proper segmentations, which is also mentioned by respondent H and respondent I. Furthermore, respondent C highlights that, in terms of personalization, AI helps them to deliver seamless and customized recommendations to customers directly through their online platform. He describes that they are using AI to find similar products to the ones the customer is currently browsing, or products that could complement what they initially seek. Thus, the company applies AI to directly meet the needs of customers, also utilizing historic data, which makes the post-purchase phase important to create personalized content.

However, respondent D discusses to which extent companies themselves can choose to implement AI or not. She underscores this by stating:

"AI can be viewed as a competitive tool that is accessible for everyone. In the vast majority of cases it is the suppliers who, in purely practical terms, ensure that we can use AI technology more. If we have a search function on our site that is outsourced, it is the supplier that makes sure that AI is introduced to our e-commerce website to make content more personalized. It kind of makes you jump on the trend whether you do it actively or not".

Respondent I and respondent J also note the benefits derived from collaboration with large purchasing platforms, emphasizing the indirect advantages gained through the AI-driven personalization strategies employed by these external actors. Though respondent E states that they are internally developing AI-driven personalization, she states that the search function is an important aspect for its implementation. Making an integrated search engine that provides customized recommendations based on patterns is an AI strategy developed by their company, according to respondent E. Beyond searching for patterns and historic data, the AI supported search engine enables them to deliver personalized content through segmenting different target groups. However, the respondent believes that the company has potential to expand their usage of AI to develop their personalization beyond marketing strategies and simple search engines, as they are investigating the opportunity to implement AI assistants to drive sales online. Another respondent who underscores the importance of AI on their online platform to provide a personalized search function is respondent I. He continues by describing how this function, together with personalized product recommendations, remain the most prominent strategy for AI-driven personalization in their organization. Nevertheless, similarly to other respondents, he emphasizes the necessity for their organization to continuously enhance AI-driven personalization.

4.2 Perception of Customer Loyalty

Regarding customer loyalty, the respondents express varying perspectives and employ different approaches to its definition and measurement. Though all respondents present different insights into customer loyalty, they all agree that it begins with some kind of engagement or commitment from customers, creating a robust foundation of the loyalty relationship. Respondent D adopts an analytical approach towards the definition of customer loyalty. She states that a large proportion of individuals today associate the concept with repurchase, which she believes is not a direct translation to customer loyalty. The respondent expresses that:

> "*Loyalty is a feeling felt by the customer, and a motivation to do some kind of sacrifice. It can be based on economic, social, or even temporal aspects. However, to have an exchange where a customer returns to buy a product or service from a company, is called repurchase rate. And that's a huge difference*".

She further explains that the core essence of loyalty is rooted in customers' perceptions of a brand, emphasizing that these perceptions play a crucial role in fostering long-term loyalty. Respondent J agrees that loyalty is a complex estimate, arguing that it is a feeling rather than something you can measure. The respondent characterizes loyalty as a buzzword, emphasizing that individuals tend not to exhibit loyalty toward specific brands, but rather direct their loyalty toward personal relationships, such as those with friends and family. He further explains that while a brand may be appreciated by customers, achieving genuine loyalty remains a distinct and more challenging objective. However, other respondents argue that the degree of repurchase can be an indicator for loyalty, in combination with other metrics. Respondent G explains that they estimate customer loyalty through a customer's retention rate, together with the customer's potential to consume other products from their website. Other than this conversion, as a betting and gambling company, they also estimate loyalty in terms of a customer's total "gaming wallet". Though it's a complex estimate, it indicates how large a proportion of a customer's total gaming wallet that is spent on their website. Respondent J also refers to a customer's retention rate when discussing whether being an appreciated brand or not, using transactional KPI's, Net Promoter Score (NPS), and customer reviews as measurements.

Moreover, respondent H explains that customer loyalty is assessed through various metrics in their organization, including satisfaction rates measured by the NPS. Additionally, they utilize other loyalty indicators within their membership program, analyzing the frequency of customer purchases over the course of a year. She further elaborates that Customer Lifetime Value (CLV) serves as a key metric for understanding customer loyalty and identifying potential strategies to encourage increased future purchases. Respondent I also discusses how CLV serves as a crucial indicator of customer loyalty, as it incorporates a wide range of parameters useful for product recommendations. Although CLV accounts for multiple factors, he further emphasizes that its primary function is to estimate the rate of repurchase over time. However, respondent D is questioning whether purchases over time might be a vague indicator of customer loyalty, stating:

> *"If a customer completes a purchase with us ten times a year, we would want to claim it's a loyal customer. But if they also purchase twenty times a year at our competitor's, we can't say anything about that customer being loyal or not".*

Hence, she means that it's almost impossible for companies to actually measure whether a customer is loyal or not, she continues:

> *"It has very little to do with loyalty, in particular attitudinal loyalty. Whether a customer is loyal or not is up to the customer, it's not something we can decide as a company".*

She suggests that simple factors, such as accessibility and convenience, may serve as drivers of repurchase behavior, rather than indicators of genuine customer loyalty. This statement is supported by respondent I, who, despite describing how their organization measures loyalty, remains skeptical about its accuracy, as a valuable customer for them could also be a valuable customer for a competitor.

Representatives from two different industries, respondent A and respondent B, refers to customer loyalty as a feeling felt by customers, rather than something companies can measure. Although, respondent B indicates that companies can make some kind of estimation regarding if the customer is loyal or not, such as satisfaction and repurchase. Furthermore, respondent C emphasizes that the reason they've succeeded in attaining loyalty is due to their high concern about customers, building a strong brand reputation and relation to the consumers. Yet, he describes that it is a challenge for e-commerce companies to develop strong customer loyalty, as the loyalty that retailers can build from human interaction in physical stores are more likely to give effects on the customers. While physical stores can more easily build connections and understand that a customer is loyal as they return, it is more complex for e-commerce retailers to distinguish between convenience and loyalty. Respondent D confirms this dilemma, underscoring that:

"*A customer might purchase from us simply out of convenience, just because we happen to offer the cheapest product at the right time*".

Respondent E frequently emphasizes that customer loyalty is most effectively measured during the post-purchase phase, as it allows companies to assess whether customers return. Respondent D also highlights how the post-purchase phase remains a highly important aspect for companies to consider, arguing that this phase presents the greatest opportunity for companies to influence customers, either by encouraging repeat purchases or fostering long-term loyalty. However, respondent E acknowledges that measuring loyalty remains complex, as multiple indicators influence its extent, making precise estimation challenging. Respondent D continues on this track by showcasing how loyalty also can be hard to measure the other way around:

"If someone buys a specific product from a company each ten years, then the repurchase doesn't happen very often. However, this customer could still be loyal to this company, because they would never buy this specific product from any other competitors".

Respondent F has a similar perception of customer loyalty, stating that it's potentially more complex for the industry he operates in, i.e. retail of furniture, than for example grocery stores, to estimate customer loyalty in terms of repurchase rate.

4.3 The Relationship Between Customer Loyalty and AI-Driven Personalization

Given the respondents' varying experiences with AI-driven personalization in their organizations, and their differing perceptions of customer loyalty, they provide diverse insights into how AI-driven personalization influences customer loyalty. While some respondents report positive effects of AI-driven personalization on customer loyalty, others express a more cautious perspective on its impact. According to respondent F, this relationship originates with the emergence of CRM, which enables companies to recognize that profitability is achieved by nurturing and retaining customers. He continues:

> *"My point is that the basis has always been that the more we know about our customers, the more we can personalize and be relevant, which in turn leads to customer loyalty. What's happening now is that AI has revolutionized how companies interact with customers, sharpening the model of personalization which, per definition, should generate higher customer loyalty".*

However, he also questions this view by stating that AI could possibly damage loyalty in the long run. He argues that as customers become increasingly aware of AI's influence on their experiences, they may develop higher expectations for AI-driven personalization, which could, in turn, pose challenges for maintaining loyalty. He continues by stating that younger users tend to place higher expectations for what AI should deliver, as they are more integrated with technological advancements in their daily life. This statement resonates with the answers given by respondent H and respondent J, who believes that consumers, in particular the younger generation, will place higher demands on companies as AI becomes more accessible for everyone. However, respondent H highlights that they've already seen a positive impact on how traditional personalization strategies have positively affected customer loyalty, which she believes will only be strengthened by AI. By facilitating a seamless online purchasing experience, companies can enhance customer satisfaction, which may, in turn, foster greater customer loyalty.

Considering that respondent G reports positive outcomes from the implementation of their AI assistant, he further explains how AI in personalization is expected to have different impacts on loyalty in the short versus long term. Keeping all other things equal, the customer loyalty should logically increase in the short term, in response to AI offering enjoyable purchase experiences and customized offers. However, he continues by stating that in a couple of years a competitive dynamic will likely emerge between AI assistants integrated into company websites and customers' own AI-driven tools. If the AI assistant effectively delivers what customers seek, it is likely to strengthen customer loyalty. However, if the AI assistant fails to accurately meet customer demands, customers may turn to their own AI-driven solutions to identify suitable offerings. Fundamentally, this dilemma is associated with customers' growing adaptation to AI technologies, which in turn elevates their expectations regarding the quality and personalization of services provided by companies. This shift could result in companies losing direct engagement with their customers, potentially driving them toward competitors. Respondent G is not the only respondent mentioning the battle between company-offered AI assistants and customer's personal AI-driven tools. Moreover, respondent D mentions how the importance of AI-assistants offered on a specific website will likely diminish over time, as customers have accessibility to use their own AI-assistants. This enables the consumer to collectively compare offers from different websites, making it harder for companies to ensure some kind of loyalty amongst customers. However, respondent E yet has a positive attitude towards the relationship between AI-driven assistants in e-commerce and customer loyalty. She states:

> *"What's important in achieving customer loyalty is to find the relevance. And to find the relevance it remains crucial to personalize in a correct manner, which we believe will be done through integrating a well-developed AI-selling assistant"*.

She continues by underscoring the importance of companies offering a seamless purchase-journey, making it easy for customers to find their demanded products online, ultimately resulting in customer loyalty. Beyond AI assistants, respondent I describes the positive impact of AI-driven personalization on customer loyalty, primarily through their well-established search function and recommendation system. These tools have demonstrated favorable outcomes when analyzing both member engagement and CLV over time.

Respondent C adopts a more skeptical perspective on the impact of AI-driven personalization on customer loyalty, as he personally believes that AI advancements could actually reduce customer loyalty. He further states that as companies implement AI-driven personalization tools, customers' own AI-assistants, used to compare prices, quality, and overall experiences across different companies, are developing at a similar pace. He continues:

> *"With the increasing usage of AI amongst companies and customers, the consumer behavior shifts focus towards being more focused on trying to find the best solution for themselves, rather than staying loyal to a specific brand"*.

Moreover, he states that some AI-driven personalization strategies could even worsen customer loyalty, where chatbots constitute one of them. The respondent continues by expressing that chatbots are AI-driven tools providing generalized solutions for customers, rather than customized ones, possibly driving frustration amongst consumers. Subsequently, he underscores the importance of thoroughly understanding what actually drives loyalty before assuming AI's positive effect through personalization strategies, as some might not provide successful results. This statement is supported by respondent I, who shares insights from previous experiences where AI-driven personalization generated algorithms based on clicks rather than genuine customer interest. He explains that certain products may attract clicks out of curiosity rather than a true intent to purchase. Moreover, respondent B provides similar reasoning, carefully stating that there is no given positive relationship between AI-driven personalization and customer loyalty, but rather refers to the relationship as dynamic and situation-based. There is a fine line between providing valuable customized content through AI, and overdoing the personalization so that it gives the opposite effect. This tradeoff is also argued by respondent A, who states:

> *"I believe the effect of AI-driven personalization on customer loyalty is a relationship moving backwards and forward at the same time"*.

While he acknowledges that customer engagement most likely increases as AI-powered recommendation makes the shopping experience more enjoyable and fun, he also expresses that inaccurate recommendation can damage its novelty. Hence, he believes companies must be careful in how they use AI as a personalization strategy to make sure it gives a positive effect on the customer, rather than making it intrusive. This perspective is supported by respondent J, who emphasizes that the integration of AI should not be pursued solely for its innovative appeal, but rather for its potential to enhance the customer experience. He consistently highlights that organizations should not adopt AI-driven personalization strategies if their existing approaches provide better results. Nonetheless, he acknowledges the considerable potential of AI to improve customer experience when implemented effectively, particularly through seamless website navigation, enhanced support functions, and the delivery of customized offers. He summarizes this by stating:

> "*Together with AI, the future holds potential in communicating the right message, at the right time, to the right customer"*.

4.3.1 Challenges

All of the respondents present different challenges associated with the implementation of AI-driven personalization, addressing both internal factors from the organization's perspective and external issues related to the customer experience. From an organizational point of view, respondent B and respondent J highlights that companies face a challenge in ensuring that all employees are ready for technological change. Respondent J stresses the importance of top management to embrace all the consequences followed by AI-implementation, making sure that all employees are informed and convinced of its benefits. Moreover, respondent B describes that the management team historically has encountered some resistant employees who have expressed concerns about AI's impact. These employees worry about how AI might affect their jobs internally, while also questioning its potential positive effects externally. Subsequently, he emphasizes that for the successful implementation of an AI-driven personalization system, it is essential that employees at all levels perceive the system as beneficial, both for their individual roles and for the organization as a whole. Respondent D adopts the same reasoning, but continues by underscoring that some employees might be questioning whether relying on AI will inhibit internal creativity, something that leaders must actively prove wrong to reinforce positive feelings associated with AI-driven personalization. She personally believes that advancements in AI-driven customization will enhance employees' ability to concentrate on creative aspects of their work, as increasing efficiency in processes is expected to reduce routine tasks. In practice, respondent G explains that the company has implemented an AI Center of Excellence, consisting of employees from different units building a cross-functional change management organization. With this structure, the company has dedicated time and devotion to not only get different perspectives on different AI incentives, but also to create an organizational manifestation. Throughout the process of adapting to these technological advancements, the company has sought to overcome internal challenges, ensuring that all employees align with and support the transition.

While Respondent G emphasizes that challenges related to organizational readiness for change have been addressed through their AI Center of Excellence, regulatory issues surrounding AI-driven personalization continue to pose significant challenges. Given their involvement in the betting and gambling industry, they must adhere to specific regulatory requirements that govern their operations. Another industry that faces challenges in complying with regulations in their AI-driven personalization is the retail of pharmaceutical products, according to respondent C. Regarding recommendations and personalized offers, he states that AI can only generate suggestions for consumers that exclude any sensitive products. Moreover, he explains:

"We do not want to train any model, any machine learning or any AI-driven approach based on data that is sensitive. (...). Prescriptive data is never used to train any personalized approach based on consumer behavior, as we are also cautious to recommend certain types of products".

Although not active in the pharmaceutical or gaming industries, respondent I also emphasizes that these industries face greater regulatory challenges than many others regarding AI-driven personalization. The interviews revealed that certain industries, such as the pharmaceutical and gaming industries, face some challenges in implementing AI-driven personalization due to the necessity of complying with regulatory frameworks, which may slow the pace of innovation.

Beyond the organizational challenges associated with implementing AI-driven personalization, the respondents highlight potential obstacles from the customer perspective. All of the interviewed companies are mentioning ethical aspects as crucial to consider when using personal data in AI to offer customized content. While ethical aspects are essential to consider, the respondents highlight that AI-driven personalization presents certain ambiguity in terms of ethical boundaries. Respondent A mentions the existence of a significant grey zone regarding the ethical implications of AI-driven personalization, emphasizing the role of GDPR in defining its boundaries. Moreover, in terms of ethical issues, respondent E describes:

"*It's important that the company is consistently transparent about what is reality and what is not, both internally and towards the end consumer*".

Respondent F also comments on how the importance of ethical issues will continue to grow as AI-driven personalization does. He emphasizes:

"For every step we take towards integrating more AI-driven personalization, the more personal data we need to have about the customer. Given existing regulations on data management, such as GDPR, companies must exercise caution in how they utilize this information. Once data is collected and processed by AI systems capable of

> *autonomous decision-making, a new level of risk emerges, as current models lack clear boundaries regarding ethical and regulatory limits”.*

In addition to the ethical concerns that arise when implementing AI-driven personalization, respondent H describes how GDPR hinders the pace of executing innovation in their organization. She explains that due to the company’s strong emphasis on ethical considerations, their adoption of AI-driven personalization may progress more slowly than the industry average. The ethical boundaries set by GDPR is a concern mentioned by all respondents, highlighting organizations’ need to adhere to these principles. In summary, the respondents' insights indicate that the implementation of AI-driven personalization presents several challenges, impacting both the internal organization and the customer experience.

5. Analysis

This chapter analyzes the empirical results in relation to the theoretical framework presented in this study. The aim of the analysis is to provide a thorough understanding of the research phenomenon by discussing the insights given by industry professionals in relation to the presented theoretical framework. The analysis begins with an examination of how organizational contexts influence the implementation, adoption, and use of AI-driven personalization, followed by an exploration of the consumer context. Subsequently, the concept of customer loyalty is addressed, drawing on respondent discussions and relevant theoretical perspectives from the literature. The final section analyzes the impact of AI on customer loyalty, concluding with a critical examination of the complexities surrounding this relationship.

5.1 Implementation, Adoption, and Use of AI-Driven Personalization

As discussed by Tornatzky and Fleischer (1990), the implementation and adoption of technological innovation can either be constrained or boosted by broader contextual factors. This perspective is reflected in the varying degrees of AI-driven personalization adoption among the respondents, where some companies emphasize rapid integration while others acknowledge a gap between AI's potential and its current usage. Moreover, this view is complemented by the acceptance and usage of innovation, emphasizing the firm's and customer's attitude towards technology as drivers of technological success (Venkatesh, Thong, & Xu, 2012). The empirical findings present different perceptions of this diffusion, as respondents underscore both the necessity of keeping up with AI advancements and the challenges posed by customer expectations, ethical considerations, and organizational readiness. While some organizations embrace AI as a means to enhance efficiency and customer engagement, others remain cautious, emphasizing the need for strategic implementation rather than mere adoption of new technologies. The following sections under chapter 5.1 outlines how both the organization and the customers navigate these complexities, highlighting the key factors influencing the adoption and implementation of AI-driven personalization.

5.1.1 Organizational Readiness and Technological Adaptation

Tornatzky and Fleischer (1990) introduces a framework explaining how the context of firms affects their ability to implement innovation, consisting of three influential elements. In accordance with the first element, the technological context, several respondents highlight how firms face a huge challenge in keeping up with rapid technological advancements shaping the ever evolving business landscape. Respondents continue to stress that as AI drives digital transformation, firms risk losing their relevance if they lag in its implementation and adoption. However, though smaller firms might gain from flexibility and imitating early adopters of innovation, large firms often have the resources and capabilities to drive innovation themselves. This is supported by literature, stating that large firms are more likely to adopt innovation, creating an influential link between innovation and organizational size (Cyert & March, 1963). Moreover, the respondents explain that even though this early adoption might benefit companies in terms of competitive advantage, it also presents drawbacks. Not only does the implementation of AI present high costs for early adopters in terms of initial investment, but also time and devotion, as the opportunity to imitate and learn from others are limited. This resonates well with what Tornatzky and Fleischer (1990) discusses, explaining that large firms tend to be more bureaucratic, while smaller firms are more flexible and open to change. The respondents' insights also touches upon what Tushman and Nadler (1986) describes with regards to the technological context of innovation adoption. The authors emphasize the advantage firms may receive from external technologies, as innovation not yet implemented by the firm showcases the outcomes possibly resulting from certain innovation incentives. Although all participating organizations are large companies, some have yet to implement AI-driven personalization, aligning with prior research suggesting that while organizational size may facilitate adoption, it is not a sufficient condition on its own (Kimberly, 1976; Tornatzky & Fleischer, 1990).

From the discussion with interview participants, it seems that most companies are either adopting their organization to technological change through continuous improvements or combining existing technologies in a novel way. According to Ettlie, Bridges, and O'Keefe (1984), such innovations are termed incremental and synthetic, respectively. While respondents who are early adopters of innovation provide examples of how they've integrated existing technology for AI-driven personalization, the later majority describe how they continuously upgrade their existing systems to move towards AI-driven personalization.

Although some companies acknowledge that they are lagging in adopting AI for personalization strategies, the majority are actively planning to implement greater synthetic innovation within their organizations to remain competitive in the era of rapid technological advancement. Nevertheless, some respondents also highlight how firms can gain from collaborating with external actors, indirectly benefiting from their usage of AI-driven personalization. This type of innovation could also be associated with the synthetic characteristics described by Ettlie, Bridges, and O'Keefe (1984), as it involves leveraging external technological advancements.

In relation to the organizational context, referred to as the second element of innovation adoption by Tomatzky and Fleischer (1990), several respondents highlight the importance of organizational readiness towards innovation by adding insights from their experience on AI-implementation processes. For instance, respondent B explains that employees have historically been sceptical towards the contributions of AI into the organization, making it highly important to engage them in the adoption phase to reach successful outcomes. This aligns with the concepts of performance expectancy and effort expectancy outlined by Venkatesh et al. (2003), which refer to the extent to which employees perceive the new system as beneficial to their individual work performance and the degree of ease associated with its use. The skepticism towards AI implementation mentioned by respondent B suggests that organizations with more mechanistic structures, characterized by centralized decision-making and clearly defined roles (Zaltman, Duncan, & Holbeck, 1973), may face greater resistance in the adoption phase. This resistance reinforces the notion that decentralized and organic structures, which promote lateral communication and team collaboration (Burns & Stalker, 1962; Daft & Becker, 1978), are more conducive to early-stage innovation adoption. Several respondents agree with the statement presented by respondent B, underscoring the importance of top management ensuring that all employees are ready for technological change, which corresponds with Tushman and Nadler's (1986) argument that leaders play a crucial role in fostering a culture of innovation. By actively engaging employees and emphasizing the strategic importance of AI, leaders can mitigate skepticism and facilitate a smoother transition into AI-driven processes. This perspective is further supported by literature, as organizational size influences adoption but is not sufficient in isolation (Kimberly, 1976; Tomatzky & Fleischer, 1990). The respondents' experiences suggest that beyond structural and resource-based considerations, fostering an organizational mindset that embraces technological change is critical for successful AI implementation.

Moreover, Venkatesh et al. (2003) explains that there are several components influencing an individual's acceptance towards technology, stressing that social influence remains a central aspect for a successful implementation. The authors emphasize that for an individual to develop a positive attitude towards a new technology, other important individuals must show significant belief and faith towards this innovation. One practical example of how social influence can drive technology acceptance is the implementation of the AI Center of Excellence discussed by respondent G. By bringing together employees from different units to form a cross-functional change management organization, the company has created a group of influential individuals who can champion AI adoption across the organization. Furthermore, by dedicating time and resources to gather diverse perspectives on AI initiatives and create an organizational manifestation, the company is effectively using social influence to overcome internal challenges and ensure widespread support for the technological transition. This perspective, emphasizing the integration of employees at all levels into the technological transition posed by AI-driven personalization, is supported by multiple respondents. As discussed previously, interviewed industry professionals believe that they play a crucial role in mediating how technological advancements will serve as a beneficial tool for both the employees and the final customer. This pertains not only to the concept of social influence discussed by Venkatesh et al. (2003) in their UTAUT model, but also to facilitating conditions, as organizations must assure employees that the necessary technical and organizational infrastructure is in place to support the system's implementation. These factors contribute to employees' belief in the system's usability and effectiveness.

Beyond ensuring readiness to change among employees, several respondents highlight the regulatory environment as a highly significant aspect to take into account when preparing the organization for technological transformation, aligning with the role of the environmental context shaping the innovation adoption (Tornatzky & Fleischer, 1990). All of the respondents highlight GDPR as a privacy risk, while some of the respondents also mean that the implementation of AI-driven personalization strategies into their organizations have been met by greater regulatory obstacles, somewhat hindering a fast and smooth adoption procedure. Similarly, Mansfield (1968) emphasizes how external constraints shape the pace of technological diffusion. Respondents describe how compliance with regulations affects the implementation of AI into their organization, posing a challenge in striking a balance between leveraging AI for personalization and adhering to regulatory requirements. This dynamic underscores the need for a nuanced, industry-specific approach to AI implementation that considers both the technological possibilities and the regulatory realities. Moreover, some respondents highlight that organizations with existing technological expertise find it easier to balance regulatory compliance while still leveraging AI's potential, reinforcing the importance of internal capabilities in overcoming environmental constraints, as discussed by Rees and colleagues (1984). This implies that organizations should carefully navigate these constraints to successfully implement AI-driven personalization strategies while ensuring compliance with relevant regulations. The figure below showcases empirical validations of the TOE framework on the implementation and adoption of AI-driven personalization.

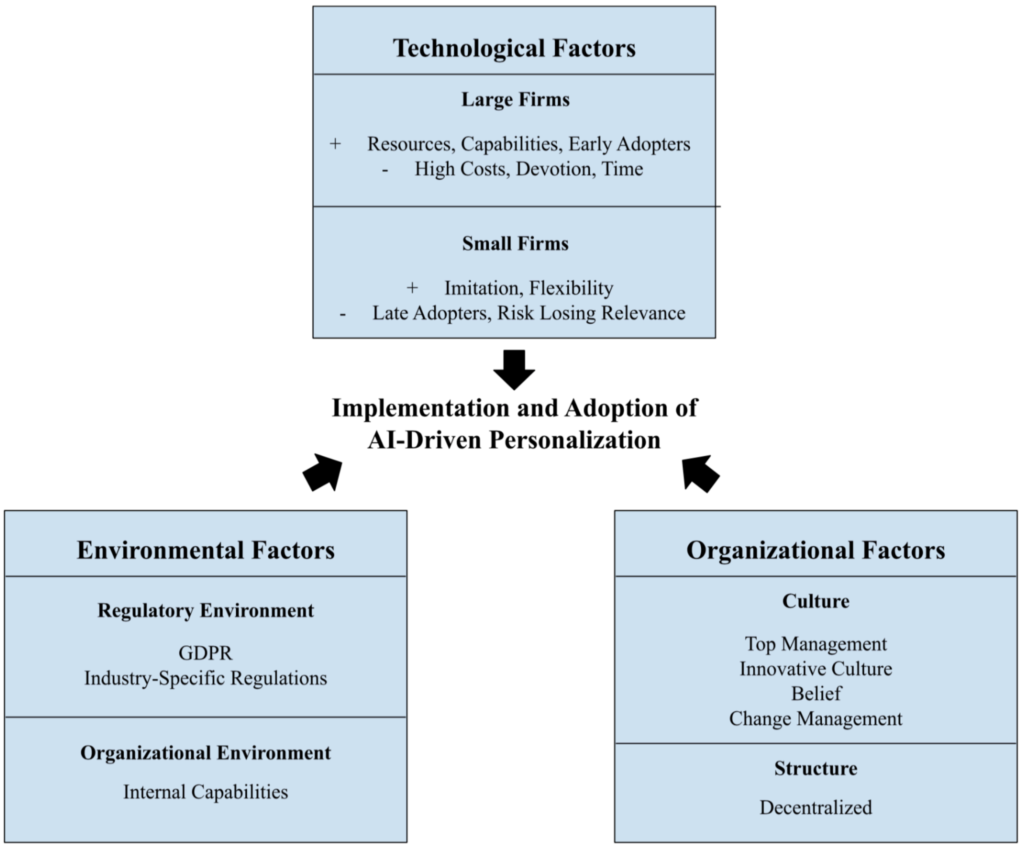

Figure 3. Empirical Validations of the TOE-Framework

(Source: Author's elaboration, based on Tornatzky & Fleischer, 1990)

5.1.2 Customer Perception and Acceptance of Technological Diffusion

To ensure a successful implementation of AI-driven personalization impacting customer loyalty, the acceptance towards the new technology from customers perspective is crucial.

Prior to this, the analysis has discussed how professionals within e-commerce perceive that employees, and the organization as a whole, cope with new technology implementation. Complementing this view, the analysis will shift focus towards the perception from customers towards new technology, which Venkatesh, Thong, and Xu (2012) applies to UTAUT2 by examining behavioral intention and technology use.

The pleasure arising from customers when using a system with new technology refers to hedonic motivation (Brown & Venkatesh, 2005), which emerges as a key factor for several respondents when discussing the effects on customers by AI-driven personalization. Some respondents emphasize how AI can provide a seamless shopping journey that enhances the experience for customers. However, this is not universally shared by all respondents, as some experienced professionals means that hedonic motivation alone does not ensure a successful technology adoption. Interestingly, answers provided from respondent C even indicate that hedonic motivation could decrease as a result of implementing AI-driven personalization. He suggests that certain tools may lead to customer skepticism regarding the use of AI, potentially acting as a source of frustration rather than facilitating effective personalization. This notion is reinforced by several respondents, who are presenting potential drawbacks on customer perception given by AI-driven personalization. This critique introduces an important counterpoint to the idea that technology adoption is affected by the enjoyment or excitement it generates. In the context of AI-driven personalization, it seems like the novelty effect can wear off quickly, especially if the technology fails to meet customers' expectations. Subsequently, respondent A further emphasizes this point, suggesting that while customers may initially find AI-driven personalization exciting, its impact diminishes when recommendations are perceived as inaccurate or irrelevant. This statement aligns closely with the findings of Venkatesh, Thong, and Xu (2012), stating that the impact of hedonic motivation decreases as experience increases. Several respondents address this concept, emphasizing that the relationship between AI and customer loyalty is not inherently positive, but rather a dynamic and contingent one influenced by multiple contextual factors. This dynamic highlights the need for businesses to ensure that the long-term benefits of AI-driven personalization extend beyond initial novelty and enjoyment. It suggests that while hedonic motivation might drive initial adoption, the sustained success of AI tools depends on their ability to deliver consistent, accurate, and meaningful personalization over time.

The extent of experience affecting hedonic motivation differs from its effect on habit, according to Kim and colleagues (2005). In contrast to hedonic innovation, habit becomes a stronger predictor of technology use as experience increases (Venkatesh, Thong, & Xu, 2012). The results show that several of the respondents mean that once customers become accustomed to AI-driven recommendations, they expect a seamless experience across all touchpoints, which, according to Venkatesh and colleagues (2012), can be explained by repeated exposure of technology, often resulting in automatic behavior. Although expectations might increase as a result of extended habit of use, some of the respondents' answers indicate that continuous adaptation is required to maintain habitual use. For instance, respondent G describes that if AI recommendations fail to adjust to changing preferences, users may disengage and revert to their own AI-assistants. Hence, the results suggest that organizations must consider sustained system performance in order to obtain successful effects on customers. This realization draws attention to a paradox in the application of AI for personalization, while habit may promote consistent engagement, it also increases system performance demands on businesses. Customers' tolerance for subpar AI-driven interactions declines as they grow more used to personalized experiences, which could eventually cause them to become frustrated.

There are both opportunities and challenges to implementing AI-driven personalization, especially when considering ethical concerns. The empirical results support the theoretical framework's central components of transparency, bias, privacy, consumer manipulation, and wider socioeconomic impacts (Karami, Shemshaki, & Ghazanfar, 2024; Patil, 2024). This is especially evident when considering regulatory restrictions and corporate responsibility. The ethical ambiguity around AI-driven personalization is one of the main issues brought up by the respondents, which supports Patil's (2024) claim that bias and transparency are significant hazards in AI applications. Current AI models run the risk of inadvertently reinforcing biases due to their unclear ethical bounds, which could erode consumer trust. Several respondents emphasize the necessity of maintaining ethical integrity, particularly in ensuring that customers are aware of how AI personalizes content, and where the line between automated and human-driven interactions lies. Karami, Shemshaki, and Ghazanfar (2024) stress the importance of transparency and accountability in mitigating these risks, which aligns with the call from respondents for greater corporate responsibility in ethical AI practices.

Moreover, privacy and data security concerns are also a prevalent subject raised by respondents, connecting to Karami, Shemshaki, and Chazanfar's (2024) emphasis on compliance with regulations, often referred to as GDPR by respondents. While AI-driven personalization can enhance customer experiences, it also necessitates extensive data collection, which introduces ethical and regulatory complexities. The respondents note that while data-driven decision-making allows for enhanced personalization, it also increases the potential for, what Karami, Shemshaki, and Ghazantar (2024) refer to as, consumer manipulation. This reflects the author's concern that excessive automation may lead to ethical dilemmas regarding customer autonomy. Additionally, the findings highlight how regulatory constraints, such as GDPR, can slow innovation, aligning with Karami, Shemshaki, and Ghazanfar's (2024) discussion on economic and social repercussions. While compliance ensures data security, it may also hinder businesses' ability to fully leverage AI capabilities. Striking a balance between regulatory adherence and innovation remains a key challenge. Ultimately, the balance between AI automation and human interaction emerges as a crucial ethical consideration highlighted by several respondents. While AI-driven personalization offers efficiency, excessive reliance on automation risks creating impersonal and potentially untrustworthy experiences, which is argued by several respondents. Patil (2024) and Karami, Shemshaki, and Ghazanfar (2024) suggest that businesses must integrate ethical AI practices while ensuring that human oversight remains a core element of customer interaction, fostering trust and long-term customer relationships. The figure below showcases empirical validations of UTAUT2 on customers' acceptance and use of AI-driven personalization.

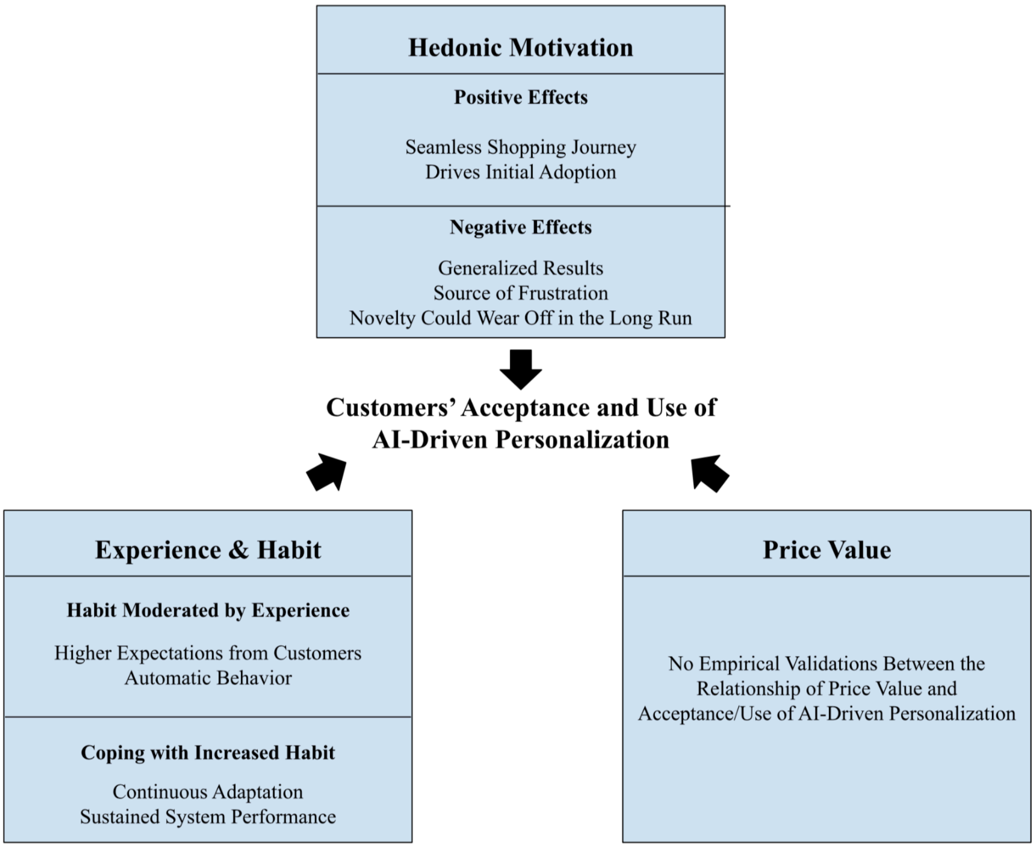

Figure 4. Empirical Validations of UTAUT2

(Source: Author's elaboration, based on Venkatesh, Thong, & Xu, 2012)

5.2 Customer Loyalty in Strategic CRM

The theoretical framework presented in this study outlines customer loyalty as a key component in establishing long-term business success, making it a crucial element of strategic management of customer relationships (Disk & Basu, 1994). To analyze the effects given by AI-personalization on customer loyalty, it is essential to explore how companies view these loyalty relationships, and how they are part of their strategic CRM practices. The empirical findings reveal varying perspectives on the definition and measurement of customer loyalty, with respondents acknowledging both the challenges and opportunities AI-driven personalization presents for cultivating loyalty. The following sections under chapter 5.2 explore how industry professionals approach customer loyalty, focusing on the diverse methods companies employ to measure loyalty and the implications of these perceptions.

5.2.1 Defining Customer Loyalty

According to respondent D, customers' perceptions of a brand is essential in building robust customer loyalty. Moreover, multiple respondents relate to this statement, meaning that companies face a challenge in today's digital transformation, where a tradeoff between efficient procedures and personal interaction take place. Respondents are continuously discussing how the role of technology can possibly damage customer loyalty if not executed correctly. Hence, respondents indicate that it is vital for companies to build a strong brand reputation to attract and retain customer loyalty, aligning with customers' psychological commitment to a brand shaping attitudinal loyalty (Dick & Basu, 1994).

Though almost all respondents discuss influences of customer loyalty, and its effect of AI, some respondents also present a critical approach towards the definition itself. For instance, respondent D questions the actual meaning behind customer loyalty, stating that a large proportion of individuals today associate the concept with repurchase, which is not considered a direct translation to customer loyalty. The respondent expresses that customer loyalty extends beyond mere repurchase behavior, and that it rather encompasses a deeper emotional connection and willingness to make sacrifices for a brand, something that is agreed upon from several of the interviewed companies. This sentiment can be rooted in economic, social, or temporal factors, while repurchase rate simply measures repeat transactions. While often conflated, loyalty and repurchase rate are distinct concepts with significant differences in their implications for customer relationships and business strategies. This aligns with Dick and Basu's (1994) definition of customer loyalty, emphasizing that the devotion of customers lays as much foundation to the concept as the actual retention rate does. Though respondents present varying insights into the definition and measurements of customer loyalty, they all highlight different types of engagement and commitment towards a brand as important pillars of loyalty. This indicates that latent loyalty, as discussed by Dick and Basu (1994), remains the most important indicator of loyalty. Moreover, the discussions regarding this attitudinal loyalty is approached differently among respondents, targeting both the cognitive, affective, and conative antecedents (Dick & Basu, 1994). Some respondents highlight how marketing strategies serve as crucial in delivering personalized content, enhancing perceived brand relevance by ensuring that recommendations are aligned with individual preferences. This aligns with the findings of Kumar and Reinartz (2018), arguing that personalization can enhance cognitive loyalty by improving customer perception. Complementing this view, respondents also explain that in their experience, customers engage more when they feel that the website and/or offers are truly tailored to their shopping habits or personal needs, which relates to the affective antecedents discussed by Dick and Basu (1994). Moreover, the respondents mention that through these personalization strategies, it's easier to identify high-intent customers, offering incentives at the right moment. This observation resonates with the conative antecedents presented by Ziliani and Ieva (2020), arguing that several CRM practices encourage brand promotion and purchase intentions.

However, some respondents continue being critical towards the measurement of customer loyalty, especially the attitudinal one. Amongst others, respondent D discusses the validity of purchase frequency as an indicator of customer loyalty, arguing that true loyalty, particularly attitudinal loyalty, is determined by the customer rather than the company. She highlights that a customer who frequently buys from a company may also purchase even more from a competitor, making loyalty difficult to define from a business perspective. Several other respondents provide discussions that relate to this exact dilemma, questioning how companies should assess the degree of loyalty amongst customers. The respondents' answers indicate that the behavioral loyalty, as discussed by Dick and Basu (1994), pose easier measurements compared to the attitudinal loyalty, as it reflects the repurchase rate through repeat patronage and purchasing habits. Interestingly, several respondents identify repurchase rate as a significant indicator of customer loyalty, however, there is a shared recognition that it does not fully capture the complexity of the concept. Furthermore, respondents explain that as customers become more aware of the possibilities given by AI, they put higher demands on the accessibility, navigation, and pricing on the website, in accordance with the situational factors of behavioral loyalty discussed by Gailey and Lundstrom (2005). This is a source of strengthened repurchase behavior, together with the social norms given by peer recommendations and community engagement according to Ziliani and Ieva (2019).

5.2.2 The Loyalty Relationship

Though many respondents have shown positive attitudes towards strategies strengthening customer loyalty through repurchase, Dick and Basu (1994) highlight that not all repeat purchases are indicators of true loyalty. Moreover, respondents express some difficulty in determining the reasoning behind why some customers decide to repurchase and some do not. Among others, respondent I reinforces this dilemma by highlighting that customers may purchase based on convenience, while simultaneously continuing to engage with competing brands. This resonates with what Dick and Basu (1994) explains as spurious loyalty, where customers repeatedly purchase due to habit rather than genuine commitment. This habit can be dependent on several factors, where respondents mention factors such as convenience and accessibility. Moreover, several respondents keep discussing the complexity of measuring loyalty, noting that infrequent purchases do not necessarily indicate a lack of loyalty. A customer who buys a specific product rarely over time may still be loyal if they consistently choose the same company over competitors. Oppositely, this refers to latent loyalty, where the commitment towards a brand remains high, even though the repurchase rate is low (Dick & Basu, 1994).

Interestingly, some of the respondents' answers still resemble spurious loyalty when discussing the loyalty relationship, which puts more focus on the relative attitude towards a brand according to Dick and Basu (1994). This resemblance can be seen as many respondents, though still questioning repurchase as a solely significant measure, still refer to purchase retention rate as an estimation of customer loyalty. Many of the respondents actually mentions repurchases to some extent when discussing loyalty, indicating that spurious loyalty still remains important when studying its relation to AI-driven personalization. Although, one should mention that some answers given by the respondents indicate that there is a risk that customer loyalty reduces in pace with today's technological advancements, which could possibly result in what Dick and Basu (1994) refer to as no loyalty. For instance, respondent C continues by stating that these technological advancements, such as AI, makes it easier for customers to compare products or services offered by different companies, which eliminates their incentives to remain loyal towards a specific brand. Moreover, respondents explain that it’s vital for companies to work on strategies not worsening the customer loyalty, putting emphasis on prevention strategies, such as enhancing the consumer experience online. The main concepts derived from the empirical results in relation to the theory given on customer loyalty are presented in figure 5. To showcase the empirical validations of the two-dimensional framework on customers’ attitudinal and behavioral loyalty regarding AI-driven personalization, the below figure has been made.

Figure 5. Empirical Validations of The Two-Dimensional Framework
(Source: Author's elaboration, based on Dick & Basu, 1994)

5.3 The Impact of AI on Customer Loyalty

Just as Schneider (1980) highlights, personalization emerges as a key strategy to enhance, attract, and maintain customers. Moreover, Kaptein and Parvinen (2015) discuss how personalization in e-commerce has evolved as a valuable strategy in modern business. The role of AI-driven personalization can be applied to the framework on e-commerce personalization, focusing on how Swedish companies within the e-commerce value chain adhere to these strategies, ultimately affecting customer loyalty (Kaptein & Parvinen, 2015). In the following sections under chapter 5.3, the respondents' insights on AI personalization and customer loyalty within their organization is applied to the theory of e-commerce personalization, in conjunction with the four papers complementing the theoretical framework on AI-driven personalization.

5.3.1 The Post Purchase Journey

As stated by Schneider (1980), though the approaches of enhancing, attracting, and maintaining customers, are all central personalization efforts, the research on consumer evaluation as a criterion on organizational effectiveness has been rare. However, in relation to the contemporary corporate landscape, the insights provided by the respondents in this study indicate that industry professionals actually place significant emphasis on the post-purchase experience. Interestingly, respondents put much emphasis on the post-purchase phase, which several professionals believe is the key usage of AI-driven personalization in enhancing the customer experience. The emphasis put towards this phase resonates with the discussion presented by Zed, Kartini, and Purnamasari (2024), describing how personalized content, but also predictive analysis, can engage customers after the initial purchase. However, though respondents underscore the importance of understanding the customer's needs after the initial purchase, they highlight the need to ensure that this stage does not feel intrusive or overly promotional, but instead, for instance, serves as a subtle reminder of complementary products that may enhance the customer's previous purchase. As stated by Zed, Kartini, and Purnamasari (2024), recommendation systems serve as an important pillar in engaging customers, which connects to the respondents insights given on understanding the customer's needs after the initial purchase, promoting products that they truly need.

Moreover, the empirical findings support several key aspects with regards to the post-purchase journey addressed in the Process Framework for E-Commerce Personalization, especially with regards to the technological requirements (Kaptein & Parvinen, 2015). The respondents emphasize the importance of having proper knowledge about the customers, ensuring that the information is relevant in terms of personalization. After an initial purchase, this stage becomes both easier to assess and interpret, which aligns closely with the first technological requirement presented by Kaptein and Parvinen (2015). This requirement, i.e. the ability to measure the effect, suggests that companies must ensure their ability to measure or assess the effect of certain content on individual customers. The empirical findings further underscore the complexity online vendors face in implementing personalization strategies, particularly when compared to physical stores, where personalization may occur more naturally. Several participants noted that, unlike in physical stores where staff can directly observe and respond to customer behavior in real time, online vendors must rely on data-driven inferences, making personalization a more technologically demanding and less straightforward process. Thus, e-commerce platforms must ensure that the computational processes that enable the link between content and customer properties are scalable, according to the third requirement presented by Kaptein and Parvinen (2015).

5.3.2 Seamless Integration of AI and its Effect on Customer Loyalty

A recurrent theme that respondents thoroughly mention in their interviews is the importance of personalized recommendations in building a robust customer loyalty. Respondents highlight that, if companies succeed in utilizing AI to create personalized recommendations, they are likely to increase customer loyalty. Though this relationship is highly significant in Arora et al's (2024) study, the effect of personalized recommendations on customer loyalty remains the lowest out of the five evaluation parameters. Moreover, similarly to what the respondents highlight in their answers, Arora et al. (2024) explain how the parameter is assessed through increased user engagement and purchase behavior. Respondents continuously mention that personalized recommendations could strengthen the shopping experience, also targeting the fourth evaluation parameter presented by Arora et al. (2024), customer satisfaction. With regard to practical AI-driven strategies, respondents highlight various parameters that facilitate product recommendations, with several specifically referencing CLV. By leveraging CLV, respondents suggest they are able to both identify and gain deeper insights into high-value customers, thereby enabling more personalized and targeted product recommendations aligned with individual needs. Although several of the respondents present similar reasoning to the relationship between customer loyalty and the evaluation parameters presented by Arora et al. (2024), they emphasize a different understanding of customer loyalty. While Arora et al. (2024) evaluate customer loyalty as customer trust, respondents tend to perceive loyalty more in terms of repeat purchases and long-term engagement rather than trust alone. Though trust remains an important pillar of customer loyalty amongst respondents, they indicate that other measures should be considered in conjunction with trust. This divergence suggests that, while trust may contribute to loyalty, respondents also view indicators such as frequent purchases and emotional commitment with the brand as strong signals of customer loyalty, representing the behavioral and attitudinal loyalty presented by Dick and Basu (1994), respectively.

The empirical results touch upon what Zed, Kartini, and Purnamasari (2024) describe as hyper-personalization, enabling companies to engage customers on a higher level than possible with traditional marketing practices. While there is considerable variation in the extent to which the companies have progressed in implementing AI assistants within their organizations, they collectively acknowledge the crucial role of this form of personalization in generating tailored content. Several respondents mention how they believe AI-assistant will be an important personalization tool in the future, as they provide real-time support and guidance through the customer journey. This is highly supported by Zed, Kartini, and Purnamasari (2024), asserting that hyper-personalization fosters an emotional bond between consumers and brands, as the AI assistant offers individualized recommendations and assistance, creating a seamless and engaging purchasing experience. For instance, one of the respondents highlights how he believes that AI assistants pose the highest degree of personalization, directly reflecting the argument presented by Zed, Kartini, and Purnamasari (2024), indicating that AI-driven personalization extends beyond transactional interactions.

The AI assistant, by offering tailored guidance and proactive support, becomes a key component in deepening customer relationships according to several interviewed companies. This supports the claim that AI-enabled personalization has the potential to go beyond increasing transaction frequency; it can also drive brand advocacy by delivering a highly individualized experience that customers appreciate and trust (Zed, Kartini, & Purnamasari, 2024). In contrast to the measurement of customer loyalty presented by Arora et al. (2024), Zed, Kartini, and Purnamasari (2024) measure loyalty through emotional connections and satisfaction with a brand. Respondents' answers suggest a stronger alignment with this conceptualization of loyalty, as it encompasses both repurchase intentions and brand advocacy, thereby offering a more comprehensive perspective on its definition.

5.3.3 Addressing Complexities of the Relationship between AI-Driven Personalization and Customer Loyalty

The empirical results indicate that while companies recognize the importance of AI-driven personalization in enhancing customer engagement, their implementation strategies and perceptions of its impact on customer loyalty vary. The general implications given by respondents suggests that AI-based personalization can, if carried out successfully, improve customer experience, aligning with the finding of Arora et al. (2024), emphasizing the positive impacts of AI-driven personalization on customer loyalty. However, respondents' answers reveal complexities that Arora et al. (2024) does not fully capture, challenging the fundamental view of the relationship between AI-driven personalization and customer loyalty. One central theme that emerges amongst participants is the disparity in the level of AI adoption across organizations. While some companies have already integrated AI-driven personalization into their strategies, others remain in the early stages, relying primarily on traditional technologies. This variation underscores the reality that while AI offers substantial potential, practical implementation is often hindered by internal capabilities, resource constraints, and the need for gradual adaptation. According to Arora et al. (2024), AI-driven personalization is positioned as a transformative force in e-commerce, yet in practice, companies face obstacles in optimizing and scaling their AI strategies.

The respondents continuously mention the risk of AI-driven personalization merely being about technological advancements, shadowing the importance of ethical implications. Some respondents emphasize that businesses must be transparent about their AI practices and ensure that AI-driven recommendations genuinely add value rather than being perceived as intrusive. Others point out that AI's success in personalization depends on how well it aligns with consumer expectations and how openly businesses communicate their use of AI in shaping customer experiences. With regards to consumer expectations, and the importance of delivering truly personalized results, respondents acknowledge Kaptein and Parvinen's (2015) requirement on ability to manipulate content, underscoring that the technology must be able to alter the content without hampering the user experience. Moreover, Arora et al. (2024) discusses how AI applications' effect on openness helps build trust through open algorithms and honest data practices, which is partly, however not completely, supported by the respondents. While the respondents encompassess the importance of transparency in AI-driven personalization strategies, they also discuss how some customers will, to some extent, remain critical towards AI providing generalized content rather than personalized. Hence, respondents acknowledge Arora et al.'s (2024) argument that open algorithms and transparent data practices contribute to building trust in AI-driven initiatives. However, they remain critical of the inherent limitations of AI in achieving genuinely personalized experiences, as well as the broader ethical implications associated with AI-driven decision-making. To summarize, the key takeaways on the impact of AI on customer loyalty are presented in the figure below.

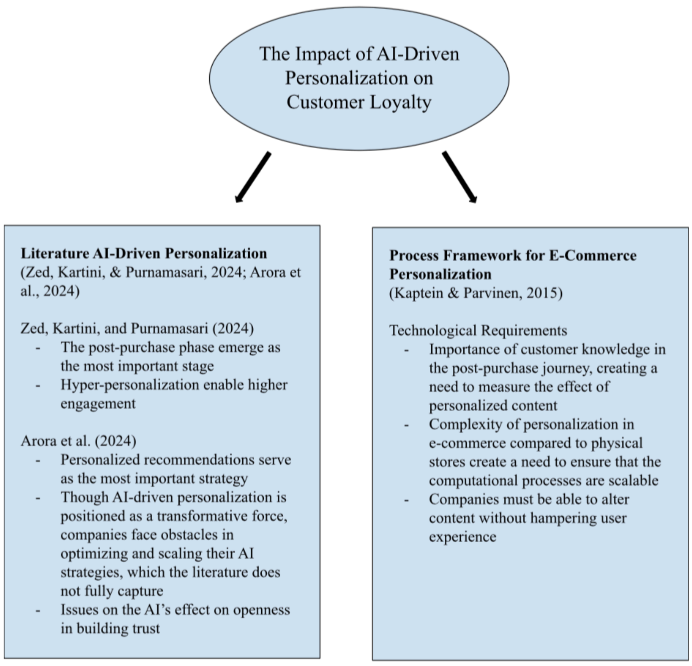

Figure 6. Empirical Validations of Literature about the Impact of AI-Driven Personalization on Customer Loyalty

(Source: Author's elaboration)

6. Conclusion

In this chapter, the research questions are answered in the first section. Subsequently, practical and theoretical implications are discussed, followed by suggestions for future research constituting the final part of this study.

6.1 Answering the Research Questions

This thesis is set out to explore how AI-driven personalization shapes customer loyalty, aiming to understand shifts in consumer behavior as a response to the technological change. Focusing on large companies within the Swedish e-commerce value chain, the study seeks to achieve insights of how these companies address customer loyalty with response to AI-driven personalization. To achieve this objective, the main research question, followed by the two sub-questions, will be answered.

> *RQ: How is customer loyalty in Swedish e-commerce influenced by AI-driven personalization?*

It is evident that both the conceptualization of customer loyalty, and the degree of advancement in implementing AI-driven personalization, differ considerably among companies. While some assess customer loyalty primarily in terms of repurchase frequency, most place greater emphasis on a customer's propensity to choose their brand over competitors. Given this distinction, it can be concluded that customer perceptions and emotions toward a brand are crucial determinants of loyalty, as engagement and commitment appear as essential foundational factors across companies. As a result, attitudinal loyalty emerges as the most crucial determinator in establishing long term customer loyalty. Moreover, the disparity in adoption of AI-driven personalization both affects the precision of customer engagement, but also influences the overall customer perception and loyalty toward the brand. Although larger companies are generally perceived to possess greater technological capabilities for implementing AI-driven personalization, many continue to face challenges in effectively integrating these technologies. With some companies leveraging advanced AI strategies to deliver highly tailored customer experiences, while others remain in the early stages of integration, those at the forefront of AI adoption are likely to foster deeper engagement and commitment through more personalized interactions. Given these distinctions, there are two key dimensions to the relationship between AI-driven personalization and customer loyalty. The first dimension is that no definite positive relationship can be established between AI-driven personalization and customer loyalty. Instead, a delicate balance exists between AI-driven strategies that may become intrusive and damage customer loyalty, and strategies that oppositely enhance customer loyalty through increased customer satisfaction. AI efforts that fail to deliver accurate and precise personalization risk becoming generalized, thereby harming customer loyalty by decreasing commitment. Similarly, intrusive AI practices can erode trust, weakening customer loyalty consequently. The second dimension is that when AI effectively delivers accurate and highly personalized content that exceeds customer expectations, it will enhance customer loyalty. In such cases, personalization functions not only as a tool for improving short term customer experience, but also a driver of long-term engagement and commitment. Companies that succeed in aligning customer demands with AI-driven personalization are positioned to foster loyalty. Thus, a customer-centric approach is essential to maintain customer loyalty through AI-driven personalization, where relevance, openness, and value-creation are prioritized.

Sub-Question 1: What are the key challenges faced by Swedish e-commerce businesses in implementing AI-driven personalization?

Sub-Question 2: How might these challenges affect customer loyalty?

For companies within the e-commerce value chain utilizing or transitioning to AI-driven personalization, three key challenges emerge related to its implementation and the resulting impact on customer loyalty. First, organizational factors regarding optimizing and scaling AI strategies require substantial resources, technical expertise, and internal capabilities. When organizations lack these, they may implement AI-driven personalization strategies that are either underdeveloped, or that fail to be successfully implemented by the organization, delivering personalization below expectations. If these solutions fail to enhance customer experience compared to traditional methods, they can lead to consumer frustration, unmet expectations, and a perception of poor value. Over time, this erodes satisfaction and weakens both the engagement and commitment towards the brand, as customers may seek more responsive competitors. Second, issues of openness and transparency assess environmental factors presenting ethical concerns. A lack of clear boundaries around data use and algorithmic decision-making will lead to biased outputs and reduced transparency. If customers perceive that their data is being misused, or if AI strategies are biased, trust becomes compromised. Though trust alone does not solely determine the degree of customer loyalty, it remains an important contributor, whereas issues of openness and transparency increase the likelihood of customers switching to more ethical and trustworthy brands. Third, the risk of inadequate personalization providing generalized results remains significant. Examples include chatbots that fail to understand specific customer needs, or recommendation systems that suggest irrelevant products. As a result, a sense of disconnect between the brand and the consumer arises, ultimately eroding engagement. Impersonal AI-driven personalization strategies reduce the emotional connection towards a brand, both decreasing the advocacy and likelihood of repurchase. Together, these challenges highlight the importance of a strategically grounded, ethically responsible, and technically capable implementation of AI-driven personalization to foster and sustain customer loyalty in the Swedish e-commerce value chain.

6.2 Practical Implications

The shift to AI-driven personalization necessitates a careful balance between maintaining trust through fair, transparent, and non-intrusive processes, and leveraging customer data to improve relevance in personalization. Companies must attentively prioritize their personalization efforts to strike this balance, informed by a thorough comprehension of how AI-driven interactions affect customer loyalty. This calls for top management to encourage an innovative culture, supported by a decentralized structure that encourages a positive employee attitude toward technological change. Although the effective application of AI-driven personalization depends heavily on the organizational structure, how users engage with the system ultimately determines how it affects customer loyalty. Companies must evaluate the effect of AI-driven personalization on the consumer's hedonic motivation, i.e. enjoyment of use, in fostering true loyalty. Ultimately, while basic metrics like repurchase rates may serve as initial indicators of customer loyalty, it is necessary to explore the deeper emotional effects of AI-driven personalization to foster lasting engagement and commitment.

6.3 Theoretical Implications

This thesis presents theoretical contributions regarding how AI-driven personalization is implemented and perceived within a specific market context. By focusing on the Swedish e-commerce value chain, the research addresses an evident gap in current literature by offering market-specific perspectives on AI-driven personalization, and how it affects customer loyalty. Through this reinforcement, suggestions for future research from previous studies in this field have been addressed. Moreover, the findings extend the TOE framework (Tornatzky & Fleischer, 1990) by illustrating how firm size shapes technological factors, how regulatory constraints inform environmental factors, and how culture and structure influence the organizational factors shaping the implementation, adoption, and use of AI-driven personalization. It also adds to the conceptual framework by Dick and Basu (1994), demonstrating how AI-driven personalization can influence not only repurchase behavior but also deeper emotional commitment. Overall, this research enriches the theoretical discourse by bridging technology adoption and customer relationship literature, offering a thorough understanding of how personalization strategies operate within a specific market context.

6.4 Future Research

To achieve a more nuanced and comprehensive understanding of how customer loyalty in Swedish e-commerce is influenced by AI-driven personalization, alongside with its challenges, future research could address both consumers' and professionals' perspective on the studied phenomenon. By integrating another angle given by consumers into the study, a deeper understanding would likely occur with regards to analyzing customer loyalty as a response to AI-driven personalization. Furthermore, future research could contribute to the studied phenomenon by conducting similar research in other market contexts or sectors, to provide a broader body of literature on the effects of AI-driven personalization within specific contexts. Results from such research could reveal findings both similar to, and differing from, the findings presented in this study. Finally, future research could further explore how organizations cope with specific identified challenges related to the effect of AI-driven personalization on customer loyalty.

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Appendix

Appendix A: Interview Guide

Theme	Question
Background	● Can you briefly introduce your role at *XX* and your experience with AI-driven personalization? ● How is AI currently being used in *XX*'s CRM strategy?
AI-Driven Personalization in E-Commerce	● What types of AI-driven personalization techniques does *XX* use to enhance the customer experience? (e.g., recommendation systems, dynamic pricing, chatbots, personalized emails, etc). ● How do you ensure that AI-driven personalization is both effective and ethical in e-commerce?
AI's Impact on Customer Loyalty	● Do you think AI-driven personalization has a direct impact on customer loyalty? Are there any specific methods or strategies that *XX* uses to build long-term relationships with customers through AI? ● In your experience, how does AI-driven personalization influence customer loyalty at *XX*? ● Have you seen any measurable improvements in customer engagement, repeat purchases, or customer lifetime value due to AI-driven personalization?
Customer Perception and Trust	● What are the main challenges of implementing AI-driven personalization in e-commerce? ● How do customers perceive AI-driven personalization? Are there any concerns about its implementation? ● What measures does *XX* take to ensure that AI-driven personalization remains relevant and not intrusive?
Future of AI and its Impact on Customer Loyalty	● How do you see AI-driven personalization impacting customer loyalty evolving in the e-commerce industry over the next few years? ● What advancements in AI do you think will further enhance customer loyalty in e-commerce?
Final Thoughts	● Is there anything else you believe is important to consider when studying the relationship between AI-driven personalization and customer loyalty?

	• If I have any follow-up questions, would it be okay for me to reach out?

Appendix B: Coding Scheme

Empirical Examples	**Observed Codes**	**Theme**
So that the whole establishment of the change journey with Center of Excellence in some kind of organizational manifestation.	Structured Change Process	Introduction and Adoption of AI within the Organization
Historically, we have encountered some employees that are sceptical towards the integration of AI.	Organizational Adaptation Challenges	
You need to make sure that you adhere to all possible regulations that might be affected by the implementation of AI-driven personalization.	Ethical Concerns	
One of the most important things to consider when implementing AI is to make sure that the whole organization is ready for technological change.	Organizational Readiness	
AI-driven personalization could, if used correctly, enhance customer engagement by making the shopping journey more enjoyable and relevant.	Positive Associations	Perceived Usefulness of New Technology Among Customers
Often, companies integrate AI personalization tools, such as ChatBots, to make more efficient procedures, making the outcome generalized rather than personalized for the customer.	Generalized vs Personalized Results given by AI	
Customers demand more from companies today, 10 years ago you searched one way, five years ago another way, and today you expect to get an answer to your exact question.	Customers Increasing their Standards	
We are currently in the process of integrating more AI-driven personalization associated with our website.	Early Stage in Implementing AI	

We were early in implementing AI-driven personalization into our organization, mainly because we were skilled in foreseeing its potential in the future.	Early Adopters of Technology	AI-driven Personalization Strategies
In the future, we believe AI assistants will be the most important tool within e-commerce to provide highly personalized content.	Foreseeing Future Usage of AI	
Loyalty is a feeling felt by the customer, and a motivation to do some kind of sacrifice.	Definition of Loyalty	Perception of Customer Loyalty
Sometimes the loyalty can be easier to estimate at a total level rather than an individual level, as we cannot know how much each customer spends at our competitors.	Loyalty as a Complex Estimate	
There are several parameters that should be considered, but one of them is of course repurchase.	Repurchase Rate	
What's happening now is that AI has revolutionized how companies interact with customers, sharpening the model of personalization which, per definition, should generate higher customer loyalty.	Positive Relationship	AI's Impact of Customer Loyalty
I believe we should focus more on the post-purchase journey, analyzing what the customer wants and using AI to provide customized offers, which could lead to loyalty if executed correctly.	Post-Purchase Journey	
There is a risk that AI could damage customer loyalty if it becomes intrusive of personal data, or fail to provide personalized content that the customer expects.	Negative Relationship	