LEVERAGING AI-ENABLED PERSONALIZATION IN CUSTOMER RELATIONSHIP MANAGEMENT

Jyväskylä University
School of Business and Economics

Master's Thesis

2024

Author: Vili Karppanen
Subject: Marketing
Supervisors: Outi Niininen and Juha Munnukka

JYVÄSKYLÄN YLIOPISTO
UNIVERSITY OF JYVÄSKYLÄ

(This page may be intentionally left blank in order to start the main text from an odd page, here from page 7. If you don't have a list of tables and figures or the table of contents requires two pages, for example, this page can be omitted.)

ABSTRACT

Author Vili Karppanen	
Title Leveraging AI-enabled personalization in customer relationship management	
Subject Marketing	Type of work Master's Thesis
Date 2024	Number of pages 69 + appendices

Abstract

Customer relationship management (CRM) became an important topic in both research and companies due to technological advancements such as the World Wide Web and innovations in customer database and data warehouse technologies. In today's competitive business landscape, where companies are seeking new ways to differentiate themselves from competitors, one strategy is to implement an individualized CRM strategy that treats customers as unique individuals and relies on effective personalization. This thesis explores the role of personalization in CRM and how AI can enhance personalization. Especially generative AI's effect on customer acquisition through creation of personalized content will be examined. Using the Stimulus-Organism-Response (SOR) framework, it is hypothesized that generative AI-personalized content (stimulus) influences perceived personalization, perceived value, and satisfaction (organisms), which then lead to purchase intentions (response). A quantitative methodology was adopted, collecting data from 65 participants through an online survey administered in Finnish. The findings indicate that generative AI-personalized content has a stronger impact on perceived personalization compared to non-personalized content, implying that generative AI can effectively be used in the personalization of marketing communications. Moreover, results suggest that perceived personalization enhances perceived value of the content, which in turn, positively affects customer satisfaction. Lastly, the results indicate that customer satisfaction has a positive relationship with purchase intentions. The study also identifies the role of involvement as a control variable influencing purchase intention. Based on this study, leveraging AI for personalization process can facilitate customer relationship initiation.

Key words
Customer relationship management, CRM, personalization, AI, Generative AI

Place of storage
Jyväskylä University Library

TIIVISTELMÄ

Tekijä Vili Karppanen	
Työn nimi Leveraging AI-enabled personalization in customer relationship management	
Oppiaine Markkinointi	Työn laji Pro gradu
Päivämäärä 2024	Sivumäärä 69 + liitteet
Tiivistelmä Asiakkuudenhallinta (CRM) nousi merkittävään asemaan sekä tutkimuksessa että yrityksissä teknologisten innovaatioiden, kuten World Wide Webin sekä tietokantojen ja -varastojen kehittymisen myötä. Nykypäivän liiketoimintaympäristön intensiivisen kilpailun keskellä yritykset etsivät jatkuvasti uusia keinoja erottautua kilpailijoistaan. Yksi keino on yksilöidyn CRM- strategian käyttöönotto, jossa asiakkaita kohdellaan uniikkeina yksilöinä hyödyntämällä tehokasta personointia. Tämän tutkielman tarkoituksena on tarkastella personoinnin roolia CRM:ssä ja kuinka tekoälyä voidaan hyödyntää personoinnissa. Erityisesti markkinointisisällön personointi luovalla tekoälyllä ja sen vaikutukset asiakashankintaan ovat tarkastelun kohteena. Stimulus-Organism-Response (SOR) -mallin pohjalta tehtiin hypoteesit, että luovalla tekoälyllä luotu personoitu sisältö (ärsyke) vaikuttaa koettuun personointiin ja arvoon sekä tyytyväisyyteen (organismit), joka lopulta johtaa ostoaikomukseen (reaktio). Tutkimusmenetelmänä käytettiin määrällistä eli kvantitatiivista menetelmää. Suomeksi toteutettuun verkkokyselyyn osallistui 65 vastaajaa. Tuloksista voidaan päätellä, että luovalla tekoälyllä personoitu sisältö vaikuttaa voimakkaammin koettuun personointiin kuin personoimaton sisältö, mikä viittaa siihen, että luovaa tekoälyä on mahdollista hyödyntää markkinointiviestinnän personoinnin tehostamisessa. Lisäksi tulokset viittaavat siihen, että koettu personointi lisää asiakkaiden kokemaa arvoa sisällöstä, mikä puolestaan vaikuttaa positiivisesti asiakastyytyväisyyteen. Lopuksi tulokset osoittavat, että asiakastyytyväisyydellä on positiivinen vaikutus ostoaikomukseen. Tutkimuksessa tunnistetaan myös tuotesitoutumisen vaikutus ostoaikomukseen kontrollimuuttujana. Tämän tutkielman perusteella tekoälyllä on mahdollista tehostaa personointiprosessia asiakassuhteiden aloittamisessa.	
Asiasanat Asiakassuhdehallinta, CRM, personointi, tekoäly, AI	
Säilytyspaikka Jyväskylä University Library	

CONTENTS

LIST OF TABLES AND FIGURES

FIGURES

TABLES

1 INTRODUCTION

1.1 Research background

"Just as electricity transformed almost everything 100 years ago, today I actually have a hard time thinking of an industry that I don't think AI will transform in the next several years."

- Andrew Ng (Lynch, 2017)

Over the years, we have transitioned from a production economy focused on increasing returns through higher output to an exchange economy that emphasizes interactions between companies and customers. Currently, we are in a knowledge economy where information is the currency, and increasing returns to knowledge are the primary performance indicator (Kumar et al., 2019). In this evolving landscape, customer relationship management (CRM) has become an important aspect of business, with customer knowledge playing a pivotal role. At the heart of CRM is the task of identifying which customers to serve and to what extent, aiming to allocate resources based on the customer's value to the company (Ramani and Kumar, 2008; Chen and Popovich, 2003). This strategy not only enhances value creation for the company but also benefits customers through better interactions. Due to intense competition among products and services, companies started to utilize differentiation strategies to initiate and maintain customer relationships (Kwon and Kim, 2012). One such strategy is individualized CRM (Frow and Payne, 2009), which can be operationalized through the personalization of marketing outputs such as pricing or promotions.

Personalization enables companies to create unique, relevant, and meaningful interactions with customers, facilitating engagement and reducing information overload (Fan and Poole, 2006; Tam and Ho, 2006; Kwon and Kim, 2012; Kumar et al., 2021). This can be implemented both digitally and non-digitally. For example, Amazon tailors product suggestions based on user behavior and preferences. Additionally, companies can use insights from customer data analysis to improve personal selling non-digitally. The importance of personalization in contemporary business is highlighted by the fact that in 2021, it was estimated that the global revenue for the industry specializing in customer experience personalization and optimization software and services reached $7.6 billion, with expectations to rise to $11.6 billion by 2026 (Statista, 2023a). Additionally, a 2023 survey conducted worldwide found that 70% of business leaders were boosting their investment in personalization technologies (Statista, 2024). The same survey indicated positive impact of personalization in CRM as 80% of the business leaders surveyed acknowledged an increase in consumer spending due to personalized experiences, and 62% highlighted its positive effects on customer retention (Statista, 2024).

In addition to spending and retention, literature suggests that implementing personalization can provide various other benefits for both customers and companies. For customers, these include improved communication, service, and better preference matching, while for companies, it includes differentiation, satisfied customers, and better response rates (Vesanen, 2007). However, personalization can also cause costs for both customers and companies. For customers, these could include privacy risks and additional fees, while for companies, they might involve investments in technology and the risk of irritating customers (Vesanen, 2007).

Technological advancements such as World Wide Web and customer data solutions have provided new possibilities for companies to enhance their personalization efforts. For instance, these advancements have improved companies' ability to personalize on a broader scale, more quickly, and more effectively (Fan and Poole, 2006). In recent years, Artificial Intelligence (AI) has emerged as a pivotal technology for enhancing personalization operations (e.g., Salonen and Karjaluoto, 2016; Kaplan and Haenlein, 2019; Kumar et al., 2019). For example, generative AI is increasingly used to produce personalized advertisements for potential consumers (Fui-Hoon Nah et al., 2023). A 2023 survey involving marketers across the United States revealed that 73% of the participants were utilizing generative AI technologies, including chatbots, into their company's operational strategies (Statista, 2023b). Additionally, Libai et al. (2020) proposed that AI can be leveraged in personalization to enhance the performance of companies' CRM processes.

As previously mentioned, statistics suggest that both personalization and AI are currently relevant topics. Therefore, this thesis will explore personalization within CRM and the utilization of AI in this context. The examination of AI in personalization will be conducted using the personalization process framework developed by Vesanen and Raulas (2006), which includes the four operations of interaction, process, customization, and delivery. Additionally, the empirical section will assess the impact of generative AI on personalized content on customer acquisition subprocess of CRM, developed by Reinartz et al. (2004).

The effect of generative AI-personalized content on customer acquisition will be examined through the Stimulus-Organism-Response (SOR) framework. This framework suggests that a stimulus, such as personalized content, can influence a customer's internal states, "organism," which in turn leads to specific responses such as purchase intention (Chang et al., 2011). The organisms proposed in this study are perceived personalization, perceived value, and satisfaction. The expected response is purchase intention, and as behavioral intentions are seen to lead to actual behavior (Morwitz and Schmittlein, 1992), it is assumed that purchase intention can lead to customer acquisition. Next, the research questions and objectives are discussed in more detail.

1.2 Research questions and objectives

The need to research the use of AI in personalization to improve CRM has become increasingly relevant during the recent years. Marketers are recognizing that customers desire to feel unique yet also want to belong to a group (Chandra et al., 2022), which increases the need for personalization tactics. This transformation accompanied with development of AI technology has created a need for exploration of how AI can be utilized to enhance these personalized experiences, ensuring that CRM strategies remain effective and relevant in a dynamic market. Moreover, advancements in AI such as in the field of generative AI creates a need for new researches. This technology has potential to revolutionize personalization yet remains underexplored due to its novelty, indicating a significant research opportunity. Additionally, Boulding et al. (2005) and Zeynep Ata and Toker (2012) suggests that research should focus towards understanding the interaction in CRM subprocesses rather than viewing CRM as a macro-level process. This approach will allow for a more nuanced understanding of different marketing activities' impact towards CRM's components.

Therefore, the aim of this thesis is to explore the role of AI in enhancing personalization within CRM, specifically in the customer acquisition subprocess within relationship initiation stage of CRM process. This study investigates how generative AI-enabled personalization can impact B2C customer acquisition by analyzing its relationship between perceived personalization, perceived value, customer satisfaction, and purchase intention. The goal is to offer actionable recommendations for both practitioners and researchers on implementing AI in the personalization process to effectively initiate customer relationships. Thus, the research questions of this thesis are the following:

RQ1. *What is the role of personalization in CRM, and can AI be leveraged to improve the personalization process?*
RQ2. *Can generative AI be used to increase customers' perceived personalization?*
RQ3. *Does generative AI-personalized marketing content have an effect on customer acquisition through perceived personalization, perceived value, customer satisfaction and purchase intention?*

The quantitative approach has been chosen for this explanatory research due to its capacity to uncover causal relationships through the systematic collection of extensive data (Hirsjärvi et al., 2005). The survey for this study is conducted using a structured online questionnaire, which does not include open-ended questions. The questionnaire was created using the Webropol 3.0 survey software. Data collection involves distributing the online questionnaire to students at Jyväskylä University. Subsequently, the collected data is analyzed using IBM Statistical Package for the Social Sciences 28.0 and SmartPLS 4.

1.3 Theoretical framework

This thesis' theoretical framework includes the focal concepts of CRM, personalization, and AI. The key concepts of this study and their relationships are depicted in Figure 1. Sin et al. (2005, 1266) define CRM as "a comprehensive strategy and process that enables an organization to identify, acquire, retain, and nurture profitable customers by building and maintaining long-term relationships with them." Payne and Frow (2005, 168), define CRM as a "strategic approach that is concerned with creating improved shareholder value through the development of appropriate relationships with key customers and customer segments." Richards and Jones (2008, 121) emphasize technology in their definition in which they define CRM as "a set of business activities supported by both technology and processes that is directed by strategy and is designed to improve business performance in an area of customer management." Reinartz et al. (2004, 294) define CRM as "a systematic process to manage customer relationship initiation, maintenance, and termination across all customer contact points to maximize the value of the relationship portfolio." This systematic process-based view of CRM is adopted for this study.

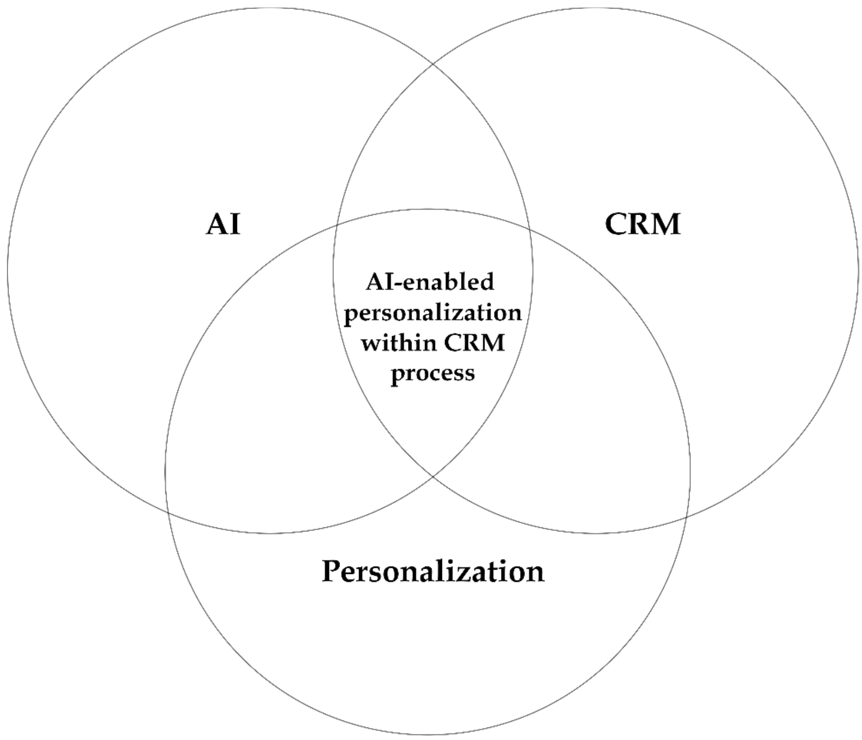

Figure 1. The theoretical framework of this thesis

The concept of personalization encompasses numerous terms and applications, ranging from profiling, segmentation, and targeting to filtering, tailoring, customization, mass customization, mass personalization, and one-to-one marketing (Vesanen and Raulas, 2006). However, Aksoy et al. (2023, 271) define personalization as "as an essential activity of the marketing strategy that plays a vital role in today's data-driven business world and that aims to provide value based on personal information obtained from the first contact with customers". Similarly, Kwon and Kim (2012, 102) define it as "a process that alters the entire marketing mix, including the core product or service, website, and communication methods, to increase its relevance to an individual". Furthermore, Maslowska et al. (2016, 74) define personalization as "a communication strategy that involves incorporating elements in a message that refer to each individual recipient and are based on the recipient's personal characteristics, such as name, gender, residence, occupation, and past behaviors".

Definitions of AI in marketing literature share similarities with each other even though they may be articulated differently. Kaplan and Haenlein (2019, 17) define AI as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation". Paschen et al. (2020, 405crm) conceptualize AI as "information systems that act rationally based on the information available to them in order to solve problems".

1.4 Research structure

This thesis is divided into six distinct chapters, as shown in Figure 2. It begins with an introductory chapter followed by a literature review. In chapter two CRM and the role of personalization within it is explored. After that in chapter three the use of AI in personalization processes is discussed. In this chapter, hypotheses for empirical research on generative AI-enabled personalization's impact on customer acquisition are also formulated, and a research model is developed. Chapter four details the data and methodology used to study these hypotheses. In chapter five the results of the empirical research and their analysis are presented. The final chapter, chapter six, covers the theoretical and managerial implications, outlines the research limitations, and offers suggestions for future research.

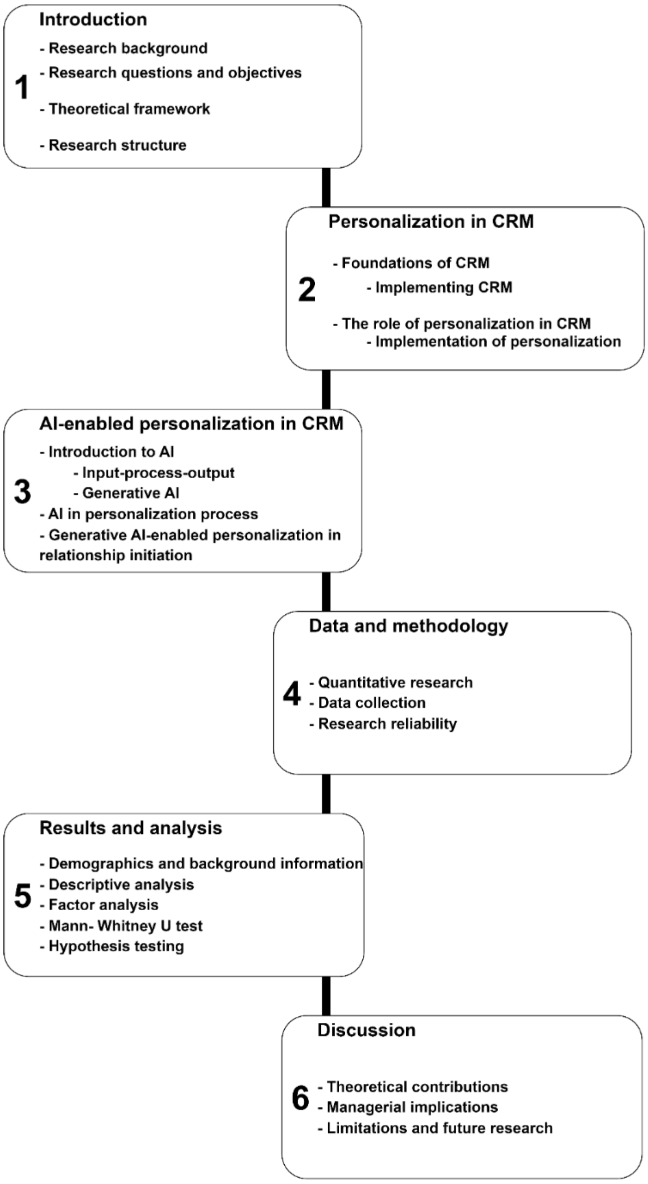

Figure 2. The structure of this thesis

2 PERSONALIZATION IN CRM

This chapter explores two of the central theoretical concepts of this thesis. These concepts are CRM and personalization. The purpose of this chapter is to identify relationships between these concepts and how they are implemented in companies to generate value. This chapter begins with CRM, then moves to personalization, and combines these two together.

2.1 Foundations of CRM

Literature suggests that businesses have always practiced CRM to some extent. Before the Industrial Revolution, sellers knew their customers, often by name, and generally understood their needs (Chen and Popovich, 2003). However, due to mass production, where the goal was to find customers for standardized products, buyers and sellers became more distanced from each other. Mass marketing and mass production were successful as long as standardized products satisfied customers, but as more companies entered the market, mass marketing techniques began to lose its effectiveness since competitors could easily imitate them over a short period of time (Chen and Popovich, 2003; Nguyen and Mutum, 2012). This led to a shift for companies towards a more relational-based approach (Nguyen and Mutum, 2012).

This shift towards relational-based approach can be seen as a basis for CRM. Boulding et al. (2005) suggest that evolution of CRM began in the 1970s with marketers emphasizing the exchange process of dual perceived value, meaning an approach where the goal is to provide value to both parties of the exchange. Then in the 1980s the focus shifted to company-customer relationships, which ultimately lead to the concept of relationship-building expanded across various domains (Boulding et al., 2005). Similarly, Payne and Frow (2006) argue that relationship marketing, which is considered as the philosophical predecessor of CRM (Zeynep Ata and Toker, 2012), came out from work in the 1980s in industrial marketing, studies of interaction, relationships and networks by IMP and services marketing.

Relationship marketing differentiates itself from the transaction-oriented marketing approach by emphasizing the process of maintaining and enhancing on-going relationships with customers as well as identifying and establishing new ones (Chen and Popovich, 2003; Zeynep Ata and Toker, 2012). Relationship marketing was developed on the idea that customers vary in their needs, preferences, buying behavior, and price sensitivity (Chen and Popovich, 2003). Thus, for companies to maximize the overall value of their customer portfolios, they can use information about customer drivers and profitability to better tailor their offerings (Chen and Popovich, 2003).

Literature for CRM have developed parallel with the relationship marketing literature, and some authors discuss these concepts collectively (Zeynep Ata and Toker, 2012). However, based on literature there are varying points on how these two concepts differentiate. For instance, relationship marketing is management of relationships with all relevant stakeholders, while CRM is strategic management of relationships with customers that involves appropriate use of technology (Frow and Payne, 2009). In addition, CRM can be considered more managerial, focusing on how management can make efforts in attracting, maintaining, and enhancing customer relationships (Sin et al., 2005). Thus, CRM can be seen as managerial level concept that focuses solely on management of customer relationships and is connected to technology utilization.

In addition to literature on capabilities of companies to manage relationships, there were other areas of work that formed CRM. Boulding et al. (2005) suggest that brand equity work recognized that equity is in the minds of consumers, which shifted the focus of attention from brands and products to customers. They highlight that this lead to an evolution from product or brand management to customer management and from product portfolio management to customer portfolio management. Additionally, target marketing (or segmentation) shifted a company's focus to adjusting products and marketing efforts to fit customer requirements (Chen and Popovich, 2003).

Despite having its roots in the 1970s, it was two decades later when CRM term emerged. The term appeared in the information technology vendor community and practitioner community in the mid-1990s, and it was often used to describe technology-based customer solutions, such as sales force automation (Payne and Frow, 2005). However, as literature suggests, CRM technology is not equal to CRM (Chen and Popovich, 2003; Payne and Frow, 2005; Frow and Payne, 2009).

Nevertheless, it is due to technological advancements that sets present day CRM apart from the past. Research in marketing has for a long time been focused on relationships and building partnerships, but it was not until technology became available to support managers in building relationships that CRM became an important part of this research (Richards and Jones, 2008). Companies today have more opportunities to utilize technology and manage one-to-one relationships with large amount of customers than couple decades ago. Technology-enabled CRM created a shift from product- and brand-centric marketing to a more customer-centric approach (Reinartz et al., 2004). Additionally, customer relationships have gained much attraction from organizations since the World Wide Web was invented due to the fact that the web provides wider opportunities for developing relationships, by allowing organizations to respond directly to customers' requests and provide highly interactive and personalized customer experiences (Winer, 2001). Thus, it can be said that the present-day CRM is formed from paradigmatic shift from transaction-based selling to relation-based selling, and technological developments.

The reason behind the shift towards CRM can be seen to be the benefits that it provides both to the companies and customers. Reimann et al. (2010) suggest that a significant advantage of CRM is its potential to help companies understand customer behavior and needs more extensively. Understanding customers' needs can help companies to sell more proactively and consistently for improved customer retention and loyalty (Chen and Popovich, 2003) and adapt their offerings to meet the needs of its customers better than its competitors (Reimann et al., 2010). Salespeople now have the ability to target the most profitable customers and manage customer relationships more effectively, due to direct online access to large volumes of data and the accurate knowledge of customers' preferences (Fraccastoro et al., 2021). In addition, companies can gain other valuable measures and information, such as customers' lifetime value or acquisition and retention costs, which can be utilized in the value creation process (Nguyen and Mutum, 2012). Richards and Jones (2008) suggests that there are seven core benefits that serve as value drivers for CRM. These are 1) improved ability to target profitable customers; 2) integrated offerings across channels; 3) improved sales force efficiency and effectiveness; 4) individualized marketing messages; 5) customized products and services; 6) improved customer service efficiency and effectiveness; and 7) improved pricing.

Past studies have also shown positive relationship between CRM and business performance. Reimann et al. (2010) study indicate that CRM creates value by enhancing the business strategies of the company, which in turn drive performance. The results of Zeynep Ata and Toker (2012) show that CRM adoption has a significant positive effect on organizational marketing performance.

Sharing customer data throughout the organization may also result in various benefits. Chen and Popovich (2003) suggest that it can derive superior levels of customer service, opportunities for cross-selling and up-selling, vast information about customers' habits and preferences, integrated and complete view of the customer, improved targeting to segments and individual customers, and efficient call centers/service centers. CRM utilization might aid in customer data sharing since it increases the perceived levels of internal collaboration (Rodriguez and Honeycutt Jr., 2011).

2.1.1 Implementing CRM

Implementation of CRM and relationship marketing techniques require focus on individual customers and for the company to be organized around the customer, rather than the product (Chen and Popovich, 2003). Integration of CRM and its activities into overall operations of the company also require assessment of capabilities because different companies have different core capabilities. Thus, CRM activities have a differential effect depending on the context of where and when they are implemented. (Boulding et al., 2005). Despite the differences, investments in CRM technology and processes should be made to support strategic marketing initiatives (Richards and Jones, 2008).

Effective implementation of CRM can be seen to require a holistic understanding and integration of technology, processes, and people within an organization (Chen and Popovich, 2003). From a technological standpoint, companies have a vast amount of tools that they can utilize, including database, data mart, and data warehouse technologies, as well as CRM applications, to collect, analyze, and utilize vast amounts of customer data (Payne and Frow, 2006). CRM systems enable organizations to gain insights into individual customer behavior and generate valuable data from it (Zeynep Ata and Toker, 2012). Enterprise Resource Planning (ERP) systems act as a robust foundation, integrating back-office functions, while CRM's purpose is to link front and back-office applications, addressing fragmented customer data (Chen and Popovich, 2003).

The positive effects of CRM initiative are enhanced when the company has the CRM processes in place (Zeynep Ata and Toker, 2012). This involves integrating customer-facing processes, such as order handling, complaint resolution, and pre/post-sales activities.) Organizations must adopt a customer-centric approach, redesigning core business processes from the customer's perspective, while involving customer feedback (Chen and Popovich, 2003).

One important process is the allocation of resources based on the value that different customers bring to the company. Through customer knowledge, organizations can manage customers' journeys by allocating more resources to the most valuable customers and fewer resources for marginal customers (Winer, 2001). Additionally, customer data analysis enables a company to identify the customers it does not want to serve at all (Chen and Popovich, 2003). Thus, companies should develop the practice of matching the resources spent on customers with the revenues or profits those customers generate (Ramani and Kumar, 2008).

Revenues that customers generate can be assessed by calculating the customer lifetime value (CLV) of different segments (Payne and Frow, 2005). CLV can be defined as "the net present value of a single customer's value" (Richards and Jones, 2008, 122). Based on individual CLVs, marketers can decide the extent of the relationship and whether to provide customized offerings (Sin et al., 2005). CLV metric helps companies plan suitable marketing and communication channel mixes and provide time- and product-based cross-selling and up-selling recommendations for individual customers (Ramani and Kumar, 2008).

CLV can be used in the calculation process for customer equity (CE) thus, CE is tied to a metric measuring the return on marketing efforts. Richards and Jones (2008, 122) define CE as "the discounted sum of each customer's CLV less any on-going investments required to maintain customer relationships" therefore, it means that CE purpose is to identify value of a customer to the selling company. They suggest that three types of equity have been described as antecedents to customer equity: value equity, brand equity, and relationship equity.

Value equity is customer's evaluation of the brand based on its utility, brand equity is more concerned with image and meaning rather than rational evaluation of price, quality and convenience, and relationship equity is measured by customer's evaluation of loyalty programs, affinity programs, community-building programs, and knowledge-building efforts (e.g., personal selling relationships) (Richards and Jones, 2008). Companies must first focus on building value equity and then they are able to enhance that with brand equity and cement the relationship with relationship equity, because when value equity is missing for a consumer, it is very difficult for brand and relationship equity to maintain a long-term relationship (Richards and Jones, 2008).

Finally, the people dimension underscores the importance of organizational commitment, employee performance, and top management support in CRM initiatives (Zeynep Ata and Toker, 2012; Chen and Popovich, 2003). Individual employees are responsible for implementing CRM, which makes them even more crucial than technology and business processes. Therefore, every employee must understand CRM's purpose and the changes it will create (Chen and Popovich, 2003). Employee engagement and change management are identified as essential factors in CRM implementation, and top management intervention is often required to address objections and disagreements among functional departments (Payne and Frow, 2005; Chen and Popovich, 2003).

In order to successfully implement CRM, companies should also consider it from a more holistic and strategic point of view. Recognizing CRM as a pivotal strategic initiative, it becomes important to evaluate it as carefully as other strategic decisions a company might encounter (Boulding et al., 2005). This involves questioning whether CRM can provide a sustainable competitive advantage. Furthermore, the strategic implementation of CRM plays a crucial role not only in attracting new customers but also in the development and retention of existing customer bases (Chen and Popovich, 2003).

When considering CRM strategy it can be seen as important to determine what are the activities that are included in CRM process. Reinartz et al. (2004) provide a framework for the implementation of CRM processes outlining three critical activities: relationship initiation, relationship maintenance, and relationship termination (Figure 3). Within this framework, they identify specific subdimensions for each primary activity. Firstly, customer evaluation serves as the foundational subdimension across all activities, with acquisition and recovery management being part of the initiation stage. During the maintenance phase, emphasis shifts to retention, up-selling/cross-selling, and referral management to strengthen and expand the customer relationship. The termination stage focuses on exit management.

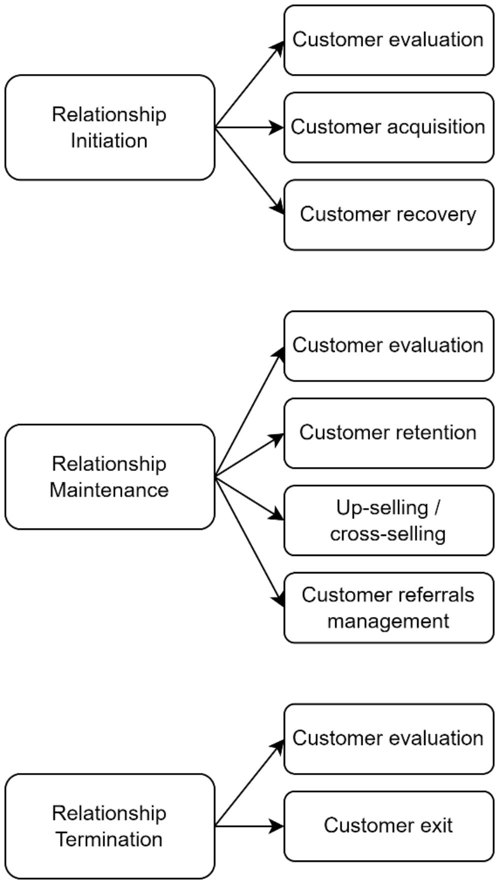

Figure 3. CRM process (adapted from Reinartz et al., 2004)

In addition to outlining the CRM process stages, it can be seen as important for companies to identify their current CRM strategy and where they want to be. The CRM strategy framework developed by Payne and Frow (2009) introduces a classification of customer relationships into four types: product-based selling, managed service and support, customer-based marketing, and individualized CRM (Figure 4). This classification is determined by the level of completeness of customer information available and the degree of individualization in the customer approach. Differences between these types are significant, with individualized CRM standing out for its reliance on extensive data and the use of advanced technology to tailor services and interactions to the unique needs of each customer. Despite the advantages that can emerge from moving towards more individualized CRM strategies, in the past numerous companies continued to focus primarily on product-centric models (Payne and Frow, 2009). This was often caused by organizational cultures and processes that act as barriers to adopting a more customer-centric focus (Payne and Frow, 2009). This insight highlights the challenges businesses face in transitioning towards CRM approaches that fully leverage customer information, such as personalization, for enhanced relationship management and underscores the need for organizational change to harness the full potential of CRM.

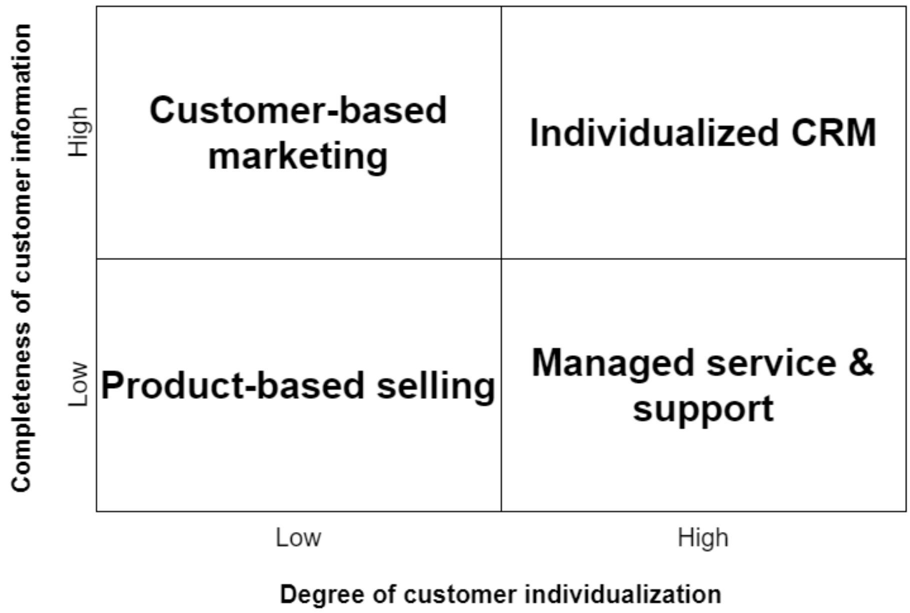

Figure 4. CMR strategy framework (Frow and Payne, 2009, 17)

The framework suggests that companies harness detailed customer data to create personalized experiences tailored specifically to their customers' individual needs to create more value in individualized CRM strategy. Subsequent chapters will explore personalization as part of CRM. Particularly, the focus is on the customer acquisition subprocess of CRM.

2.2 The role of personalization in CRM

Personalized marketing is not a novel concept as it traces back to the 1870s and gained significance in discussions around segmenting and targeting in the 1970s (Vesanen and Raulas, 2006). This evolution is closely linked with customers' growing expectations for personalized offerings, signaling a paradigm shift from product-dominant (P-D) logic, where goods are the primary exchange medium, to service-dominant (S-D) logic, which sees value as solely customer-determined (Vargo and Lusch, 2004; Grönroos, 2006; Alimamy and Gnoth, 2022). Advancements of information and communication technologies revolutionized the way customer data is collected and analyzed, enabling more personalized communication with customers (Vesanen and Raulas, 2006). The capacity for differentiation was historically limited by companies' operational abilities to produce and deliver a variety of options until technological advancements allowed for mass customization (Miceli et al., 2007). Despite its benefits, mass customization can lead to customer confusion due to the overwhelming variety of options. Customers often lack the necessary knowledge and capability to accurately define their preferences, resulting in choices that do not fully satisfy their needs. To reduce the challenges caused by mass customization and prevent customer disorientation, one-to-one marketing solutions gained popularity by offering a more focused approach to customer care (Miceli et al., 2007).

An increasing number of marketers are turning to personalization to enhance their marketing efforts, motivated by the anticipated benefits of one-to-one marketing and CRM (Vesanen and Raulas, 2006). In the contemporary business environment, which is increasingly driven by knowledge, personalization is seen as crucial for gaining a competitive edge (Aksoy et al., 2021). They argue that its significance extends across multiple disciplines, attributed to its ability to impact human choice. The commercial aim behind personalization is to excel in business metrics such as increasing customer value and achieving lower churn rates (Zanker et al., 2019). The decision of a company to adopt personalization may depend on various factors including the size of its customer base, the depth of customer information available, customer loyalty, the costs associated with personalization, and the level of similarity among customers (Murthi and Sakar, 2003).

Nevertheless, personalization have been proven effective in both digital and nondigital settings, as evidenced by the success stories across various platforms and industries (Kumar et al., 2019). In the digital realm, classic examples of personalization are seen in the "recommended for you" sections on websites like Amazon, Pandora, and Netflix, which tailor suggestions based on user behavior and preferences (Kumar et al., 2019). Additionally, an example from the nondigital sphere, Sprint employs predictive analytics for personalized marketing strategies to customers identified as being at risk of churning, showcasing the adaptability of personalization techniques (Kumar et al., 2019).

Insights from cognitive psychology reinforce the effectiveness of personalization by suggesting that individuals are more likely to recall information that is relevant to themselves or someone close to them, both more easily and accurately (Aksoy et al., 2021). Offers that are customized to match an individual customer's preferences are capable of delivering superior value, highlighting the importance of personalization (Kwon and Kim, 2012). Therefore, understanding key aspects that an individual values and priorities becomes crucial for crafting successful personalization practices, ensuring that tailored offerings resonate with the recipient (Aksoy et al., 2021).

The effort to define personalization has included numerous scholars, leading to vast amount of definitions across various fields (Vesanen, 2007). This diversity has created creative perspectives on the phenomenon, enriching the discourse surrounding personalization. However, it also complicated the development of a unified body of research, as the concept was interpreted differently across disciplines and among researchers who explore it (Fan and Poole, 2006). Computer scientists primarily focus on the technologies behind personalization, whereas marketers emphasize their application in managing customer relationships (Kwon and Kim, 2012). Consequently, personalization assumes various meanings depending on the field and the individuals within it (Fan and Poole, 2006). For architects, it means the creation of functional and inviting personal spaces; social scientists view it as a method to enhance social relationships and foster social networks; and for some computer scientists, personalization represents a set of technologies aimed at improving the Web experience through innovative graphic user interface design. However, there are differences in understanding even within these groups. (Fan and Poole, 2006.)

When trying to understand personalization it is also important to define the differences between relating concepts. The terms customization and personalization have been often used interchangeably (Fan and Poole, 2006; Aksoy et al., 2021). However, personalization is a concept initiated by companies, while customization is driven by the preferences and actions of customers (Aksoy et al., 2021). Similarly, Kumar et al. (2019) describe personalization as a process largely controlled by companies, utilizing customer-level data, while customization focuses on customer-driven design and delivery of offerings. Customization occurs when customers actively engage by specifying elements of their marketing mix, often selecting from a suite of template-driven options (Fan and Poole, 2006; Kwon and Kim (2012). This approach to customization offers advantages such as predictability and low intrusiveness. Additionally, customization can be positioned as a subfield within the broader umbrella of personalization (Aksoy et al., 2021) or a method for implementing personalization (Fan and Poole, 2006).

Literature suggests that the concept of personalization can be seen as central concept in CRM, by significantly influencing the way in which businesses and customers interact. As outlined in the CRM strategy framework by Frow and Payne (2009), the organization of customer relationships is determined by the extent of a company's knowledge about each customer and the individualization of their interactions. The more individualized the interaction and the greater the use of customer information, the more extensively personalization tactics are employed. Thus, personalization can be seen as an integral element of an individualized CRM strategy.

In addition, given that the essence of CRM is centered on focusing on individual customers (Chen and Popovich, 2003; Sin et al., 2005; Nguyen and Mutum, 2012) and providing unique customer experiences (Boulding et al., 2005; Chen and Popovich, 2003; Richard and Jones, 2008), the personalization process emerges as a key tactic to fulfill these objectives. Similarly, Sin et al. (2005) categorize CRM practices into four broad behavioral components: key customer focus, CRM organization, knowledge management, and technology-based CRM, where key customer focus encompasses personalization. Moreover, both CRM and personalization are focused on dual value creation (Boulding et al., 2005; Vesanen and Raulas, 2007).

2.2.1 Implementation of personalization

One of the goals of CRM is to enhance interactions with customers and gather the right data to make these personalized experiences possible (Micel et al., 2007). This approach aims to ensure that both the company and its customers find value in their relationship. However, it is important to note that while personalization can increase a company's value, it might sometimes do so at the expense of customer value, such as through personalized pricing or less attention to less profitable customers (Boulding et al., 2005). Therefore, precise assessment of specific customers value to company is important.

In addition, the implementation of personalization involves careful consideration of various dimensions of personalization. Fan and Poole (2006) outline three crucial dimensions: the aspect of the information system subject to manipulation for personalization (what is personalized), the target audience for personalization (to whom to personalize), and the entity conducting the personalization process (i.e., the user or the system). However, Kwon and Kim (2012) propose even broader approach of four key dimensions for effective personalization implementation: defining the object of personalization (what), determining the level of personalization (to whom), identifying the entity responsible for personalization (who), and selecting the method for learning customer preferences (how).

First dimension of implementing personalization is the aspect of what is personalized. Fan and Poole (2006) identify four distinct aspects within the information system that can be personalized: the content itself, the presentation of information through user interfaces, the channels or means through which information is delivered, and the functionality available to users. Similarly, Kwon and Kim (2012) delineate four layers of personalization objects, including product or service layers, website layers, communication layers, and price layers. Furthermore, Fan and Poole (2006) categorize four ideal types of personalization based on architectural, relational, instrumental, and commercial perspectives in the context of information systems, which provides insights into different approaches to personalization implementation.

The perspectives on personalization can be distinguished based on their orientation towards utilitarian or affective aspects (Fan and Poole, 2006). The instrumental and commercial perspectives prioritize task accomplishment and commercial transactions, thus are more towards utilitarian concerns. In contrast, the architectural and relational perspectives have more emphasis on users' emotional experiences, including aesthetic and socioemotional factors. Different design strategies cater to various user needs, but combining multiple approaches can better address diverse requirements. Designs that blend functionality with aesthetics and incorporate aspects of productivity, education, and entertainment are more likely to satisfy human needs effectively. (Fan and Poole, 2006.)

Additionally, while presenting personalized information, it is crucial to consider the surrounding environment of individuals, including factors such as their location and the current time (Aksoy et al., 2021). Predicting when a customer is likely to revisit, make a purchase, or leave a website is valuable for determining the optimal timing to offer promotions or incentives (Murthi and Sakar, 2003). Leveraging personalized content based on individuals' calendars is becoming increasingly feasible, as exemplified by Rentalcars.com's personalized emails referencing past rental experiences (Aksoy et al., 2021). Location-based personalization involves identifying an individual's location and delivering personalized information tailored to their current whereabouts, providing a tailored experience from the outset. With insights into users' anticipated whereabouts and timing, systems can offer personalized recommendations and even add new events to individuals' calendars, further enhancing the personalized experience. (Aksoy et al., 2021.)

Second dimension of personalization implementation is the level of personalization. Personalization operates across various levels, ranging from one-to-all, which includes standardization rather than personalization, to one-to-N, which covers micro-personalization and segment marketing, and finally, one-to-one (Kwon and Kim, 2012). Individuals often perceive themselves either as members of a social group or as unique individuals, depending on contextual social cues (Fan and Poole, 2006). At the individual level, personalization goes into specific information such as past digital behaviors, consumption patterns, attitudes, and preferences, gathered both from digital and real-world settings (Aksoy et al., 2021). This individual-level personalization aims to deliver goods, services, or information tailored uniquely to each individual (Fan and Poole, 2006). Platforms like Netflix effectively utilize personalization by tailoring recommendations based on users' past choices, showcasing the effectiveness of personalized approaches in modern media services (Aksoy et al., 2021).

The social group personalization approach involves targeting specific user categories, such as women, single-child families, or members of a club (Fan and Poole, 2006). People may react differently depending on whether they focus on their individual identity or their group membership, with motivations and decision-making processes differentiating accordingly (Fan and Poole, 2006). Businesses, particularly e-vendors, leverage information gathered from users' social networks to deliver effective personalized suggestions, recognizing the influence of social environments on individuals' preferences and behaviors (Aksoy et al., 2021). However, when individuals focus on category membership, their motivation is often driven by group norms and perceptions, which may lead to stereotyping (Fan and Poole, 2006). Despite the individual level personalization aims to capture the unique individuality of a person, its actual implementation may rely on categorical analysis. This involves defining an individual's uniqueness as the intersection of various categories representing their significant characteristics, such as gender, ethnicity, profession, location, age, family status, among others, and ensuring the utilization of a sufficient number of categories to distinctly define each individual (Fan and Poole, 2006).

Literature suggests that in certain scenarios, utilizing one-to-N level personalization may be more suitable approach over one-to-one personalization. Malthouse and Elsner (2006) advocate for the effectiveness of one-to-N personalization strategies. Similarly, Kwon and Kim (2012) propose that the significance of one-to-one content personalization could be downplayed, as it may not significantly enhance customer value compared to one-to-N content personalization. They suggests that if implementing one-to-one content personalization demands excessive time, cost, or effort, utilizing one-to-N content personalization, also known as 'segment marketing ', could be a better option.

To navigate these challenges companies can customize their customization based on the customer attributes. Miceli et al. (2007) recommend companies to tailor the level of customization to each customer by analyzing customer preferences concerning content and interaction. They suggest that content-based analysis should focus on the expected benefits, while interaction-based analysis should account for individual differences in ability, relational attitude, and motivation to engage with the company. This approach allows companies to customize their interactions and offerings effectively, even in the face of obstacles to individualization, by aligning their strategies with the varied preferences and capabilities of their customers.

The dimension of who does the personalization process focuses to differentiate whether the personalization is customer-initiated or system-initiated (Kwon and Kim, 2012). This differentiation aligns with the distinction between personalization and customization. According to Kwon and Kim (2012), this particular dimension significantly impacts how customers perceive the quality of the service or product, thus their overall satisfaction. Understanding whether the user or the system takes the lead in tailoring experiences is essential for businesses aiming to enhance customer satisfaction through personalized or customized interactions.

The last dimension of Kwon and Kim (2012) addresses the selection method for learning about customer preferences, emphasizing the extent to which personalization is automated and the entity which does it. This dimension is divided into explicit and implicit personalization, based on user involvement levels. Explicit personalization involves users actively providing choices or information, influencing the system's adaptation to their preferences, a process that can be initiated by directly collecting data from individuals (Fan and Poole, 2006; Aksoy et al., 2021). In contrast, implicit personalization allows the system to automatically adjust to users' needs without direct input, utilizing real-time behavior data to anticipate future needs (Aksoy et al., 2021). This includes the use of complex algorithms and machine learning to recognize and adapt to unique user interaction patterns (Fan and Poole, 2006). The number of different techniques highlights the dynamic balance between user control and system automation in crafting personalized experiences. Important to also note that even though preferences have been often seen as static, contextual factors like timing, location, and buying phases make preferences dynamic (Salonen and Karjaluoto, 2016).

In addition to personalization dimensions, it can be seen as crucial to establish the process that is required for an company to effectively implement personalization. Vesanen and Raulas (2006) identified four essential operations (interaction, processing, customization, and delivery) and four objects (customer, customer data, customer profile, and marketing output) within the personalization process (Figure 5). The operations explain the actions taken at different stages, while the objects are the essential elements required for executing these operations or the end results of them. This structured approach to personalization highlights the importance of a strategic, step-by-step process in creating personalized customer experiences, from data collection to the delivery of customized marketing efforts. In this study, the personalization process of Vesanen and Raulas (2006) will be used to examine use of AI-enabled personalization in CRM.

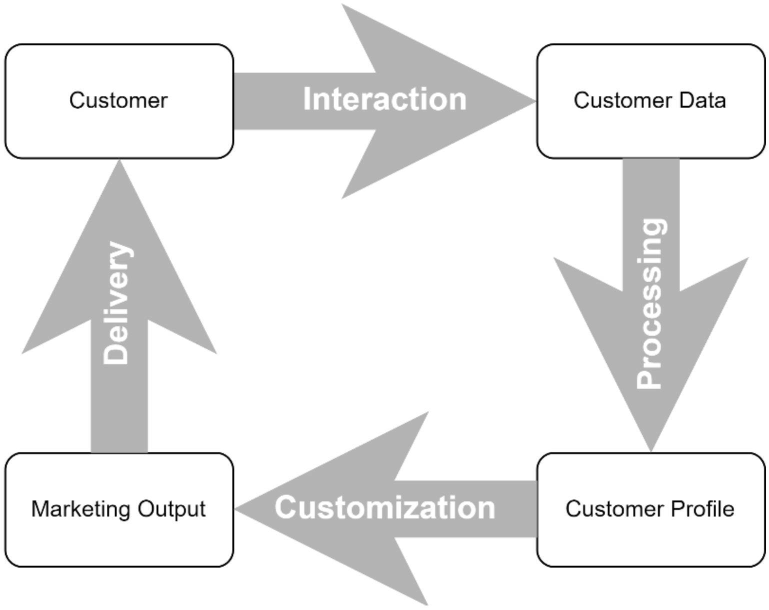

Figure 5. Personalization process (adapted from Vesanen and Raulas, 2006, 10)

Vesanen and Raulas (2006) describe the process of personalization as a continuous dynamic loop, emphasizing its ongoing and iterative nature. Vesanen (2007) elaborates on this by characterizing personalization as a process that builds and enhances relationship between customer and marketer through interaction by leveraging personalized marketing outputs. Personalization serves as a way to create value for customers by more accurately aligning the 4Ps of the marketing mix (product, price, place, and promotion) to their specific needs and preferences (Vesanen, 2007). Thus, personalized marketing output may encompass any single aspect of the marketing mix or integrate all of them together, offering a tailored approach to meet individual customer demands.

Vesanen and Raulas (2006) outline nine crucial requirements and potential pitfalls of each operation which are outlined in the Table 1. These include: 1) data collection and the necessity of obtaining direct marketing permissions, 2) database integration and efficient list management, 3) ensuring data correctness and regular data updating, 4) achieving segmentation success through accurate profiling, 5) targeted marketing strategies, 6) developing creative solutions and their production, 7) understanding and utilizing channel preferences, 8) achieving differentiation through timing, and 9) fostering interactivity. Each of these elements addresses one of the four operations involved in the personalization process emphasizing the importance of close attention to detail and strategic planning in each step to avoid common pitfalls and maximize the effectiveness of personalized marketing efforts.

TABLE 1. Personalization process (Vesanen and Raulas, 2006)

Operation	Purpose	Challenges
Interaction	Customer data collection	- Failure to record customer interactions - Learning about customer responses after the delivery of personalized marketing ouput
Process	Transforming data into customer profiles	- Maintaining the data to be up to date and accurate - Creating customer profiles and segmenting customers in alignment with business objectives
Customization	Tailoring marketing output to individual customer profiles	- Accurately identifying and presenting the most appropriate offer - Creating a creative marketing message
Delivery	Selecting communication channel, timing and the location of delivery based on customer preferences	- Utilizing delivery channels that align with the customer's preferences - Timing and differentiation of the delivery

The first operation of the personalization process is interaction with the customer. Vesanen and Raulas (2006) emphasize that recognizing differences in needs and preferences among customers is crucial for segmenting them effectively. Similarly, Peltier et al. (2003) suggest to develop unique and personalized 'conversations' with each customer company must gather and utilize a wide range of individual-level customer data from various sources. This approach enables companies to deeply understand and develop buyer/seller relationships. In the same way, Murthi and Sakar (2003) highlight the significance for companies to have access to data at an individual level to accurately grasp a customer's preferences and deliver effective personalization.

Customer data collection includes both interactions with customers and external data sources (Murthi and Sakar, 2003; Vesanen and Raulas, 2006). This data includes buying history, demographic, and psychographic information, deriving from three primary sources: customer interactions, changes, or opportunities in their status, external data sources, and the integration of external data with internal customer data (Vesanen and Raulas, 2006). The methods of collecting data through interactions range from direct inquiries through online surveys and registration forms to tracking customer interactions with the company's website (Murthi and Sakar, 2003). Website behavior, dialogues between marketers and customers, and purchasing events are crucial interactions that provide valuable data (Vesanen and Raulas, 2006). The importance of making the data collection process as easy and enjoyable as possible when gathering information directly from individuals, suggesting that a customer-centric approach not only enhances the quality of the data collected but also contributes to a positive customer experience (Aksoy et al., 2021).

Through tracking a customer's online interactions companies can gain different types of data that are valuable for personalizing customer experiences (Murthi and Sakar, 2003). The data types include (1) transaction data or point of sale data, which captures details about purchased items, their prices, purchase timing, and conditions at the time of transaction; (2) web and application server logs, which collect data such as the browser host's IP address, the date and time of interaction, requested page URLs, the referrer field, and a cookie field; and (3) cookies, small text files placed on the browser host's hard disk that help in identifying users within and across sessions, facilitating an understanding of their browsing behavior and tracking repeat visits (Murthi and Sakar, 2003). To tailor offerings more effectively, companies also require information on a customer's demographics and preferences (Murthi and Sakar, 2003), emphasizing the need for an extensive approach to data collection to better meet customer needs and preferences.

Vesanen and Raulas (2006) identify two challenges in the interaction operation that impact the effectiveness of personalized marketing. The first challenge is the failure to record customer interactions, resulting in a lack of data or inadequacy of data concerning customers' behaviors and interests. The second challenge involves learning about customer responses after the delivery of personalized marketing ouput. Understanding these responses enables marketers to answer to customers' needs in a more personalized and effective manner.

The second step of personalization is process of transforming data into customer profiles, which plays a crucial role in identifying, differentiating, and segmenting customers (Vesanen and Raulas, 2006). These profiles created through an analysis of customer data, behaviors, and interests, serve as a foundation for customization, allowing companies to address customer needs more accurately. Technology in analyzing customer behavior enables companies to recognize their best customers, tailor marketing efforts more effectively, and reward those with a higher probability to purchase (Chen and Popovich, 2003)

Personalization is often conducted at the segment level, based on collective preference functions, emphasizing the significance of identifying distinct segments and their specific needs for effective personalization (Murthi and Sakar, 2003). However, the evolving nature of customer needs and preferences requires the definition of increasingly finer market segments, indicating a shift towards more granular targeting strategies (Chen and Popovich, 2003). Techniques, such as data-mining, neural networks, and fuzzy logic can facilitate this more sophisticated segmentation (Vesanen and Raula, 2006). Nevertheless, even basic market segmentation within CRM through analyses of observed behaviors rather than simple demographics can offer benefits (Nguyen and Mutum, 2012).

Literature suggests that companies utilize a variety of methods to interpret customer preferences, purchase behaviors, and browsing habits. These interpretation tasks broadly fall into categories of prediction (of purchases, web visits, etc.), clustering and classification, and the understanding of preferences (Murthi and Sakar, 2003). To accomplish these tasks, traditional methods like regression analysis, discrete choice models, neural networks, Bayesian networks, and other AI techniques are employed, with the selection of a specific technique being influenced by factors such as scalability and the trade-offs between speed and sophistication (Murthi and Sakar, 2003).

Two relevevant challenges can be seen in customer data processing operations. The first challenge is maintaining the data to be up to date and accurate with changes in customers' status over time, as data correctness can be seen as crucial for successful segmentation. The second challenge is about company's capability to create customer profiles and segment customers in alignment with its business objectives. (Vesanen and Raulas, 2006.) In addition to these challenges, the complexity of combining segment-level preferences for certain attributes with individual preferences on other attributes to create a comprehensive preference function can create challenges (Murthi and Sakar, 2003). This complex integration process requires careful attention to ensure a complete understanding of customer preferences.

The third step of personalization process is customization, which refers to the production of personalized marketing outputs tailored to individual customer profiles, including any or all aspects of the marketing mix: promotion/communication, product/service, pricing, and delivery (Vesanen, 2007). For example in promotion, the use of self-reference type messages plays an important role in personalization by emphasizing relevance to the individual through specifically tailored wording (Aksoy et al., 2021). Personalization techniques provide companies with a cost-effective means to assess customer valuations, facilitating more defined price discrimination strategies (Murthi and Sakar, 2003).

Vesanen and Raulas (2006) highlight two significant challenges in the customization of marketing output that marketers need to consider. The first challenge is about the marketer's capability to accurately identify and present the most appropriate offer, including product or service, price, channel, and promotion, to the customer. The second challenge focuses on the importance of creativity in creating the marketing message. Even if the offer is well-targeted, it risks being ineffective if the message fails to capture the customer's attention due to lack of interest or creativity (Vesanen and Raulas, 2006).

Last step of the personalization process is delivery, which is a critical aspect of how personalized marketing outputs are transferred to the customer, including the selection of communication channel (e.g., mail or email) based on customer preferences, as well as considerations for timing and the location of delivery (Vesanen and Raulas, 2006). The delivery not only serves the purpose of reaching the customer but also triggers a response, marking the beginning of a new interaction that provides additional insights about the customer that can be used to refine and target customer profiles more accurately (Vesanen and Raulas, 2006). Consequently, the process of personalization is conceptualized as an evolving learning loop, where with each iteration, the approach becomes more tailored and effective.

In the delivery stage, Vesanen and Raulas (2006) highlight two main challenges that need to be addressed for optimal operation. The first challenge is about the utilization of delivery channels that align with the customer's preferences, highlighting the importance of choosing the right medium to ensure the marketing message is effectively received. The second challenge involves the timing and differentiation of the delivery, which are deemed crucial for the marketing message not only to capture the attention of the customer but also to meet their needs at the right moment (Vesanen and Raulas, 2006).

Optimal performance of personalization can be seen to require careful consideration of every aspect of the process. Vesanen and Raulas (2006) highlight that if only parts of the process are done or they are inadequately executed, it can lead to customer dissatisfaction or low return on investment (ROI). Furthermore, low ROI may also originate from heavy investments in resources necessary for personalized marketing, such as information systems, software, databases, analysis tools, and human skills, which are not utilized to their fullest capacity (Vesanen and Raulas, 2006). This highlights the importance of not only investing in the necessary tools and talents for personalization but also ensuring that these resources are optimally utilized across the entire process to avoid inefficiencies and maximize the impact of personalized marketing efforts.

Implementing personalization in CRM strategy can offer numerous benefits in creating customer value. For example, innovative CRM technology can be used in attracting both existing and potential customers through personalized communications (Chen and Popovich, 2003). In addition, messages aligned with processing goals facilitate deeper elaboration, thus emphasizing the importance of relevance in communication (Tam and Ho, 2006). Similarly, Kumar et al. (2020) emphasize the ability of personalization in initiating meaningful interactive marketing activities with customers that can foster engagement. Furthermore, personalized communications can decreases information overload and aid in decision-making processes (Tam and Ho, 2006). Personalization in advertising is widely embraced due to its perceived advantages, including deeper customer engagement, increased brand awareness, and satisfaction (Maslowska et al., 2016). In the next chapter, the use of AI in personalization process is discussed and what benefits it can bring to companies leveraging personalization.

3 AI-ENABLED PERSONALIZATION IN CRM

This chapter looks into AI, focusing on its application in personalization processes. It introduces the foundations of AI and generative AI and discusses their potential in addressing challenges at each stage of personalization. The chapter then employs the SOR framework to formulate hypotheses. Subsequently, a research model is developed based on these hypotheses.

3.1 Introduction to AI

AI has been a topic of discussion in literature for over half a century, tracing back to the seminal contributions of the computer scientist Alan Turing (Kaplan and Haenlein, 2019). The combination of AI's vast capabilities with the increasing availability of data has the ability to fundamentally transform the workforce, potentially exceeding the impact of the Industrial Revolution between 1820 and 1840 (Kaplan and Haenlein, 2019). Companies often are navigating between aiming for revenue growth or reducing costs, and while AI provides process efficiencies which reduce costs, companies are investing in AI with the expectation of future revenue gains, with marketing functions expected to have the most substantial impact by AI (Kumar et al., 2019). Similarly, Davenport et al. (2020) argue that in the future AI is likely to reshape marketing strategies, including business models, sales processes, customer service options, and even customer behaviors. This growing importance of AI in marketing is caused by increasing computing power, lower computing costs, the availability of big data, and the advancement of machine learning algorithms and models (Huang and Rust, 2021).

AI encompasses the broad concept that computers, utilizing software and algorithms, can emulate human thinking and perform tasks (Kumar et al., 2019). The first wave of AI applications, often categorized as artificial narrow intelligence (ANI), has become part of everyday life, enabling various tasks such as Facebook's facial recognition and tagging features, Siri's voice understanding capabilities, and the development of self-driving cars by companies like Tesla (Kaplan and Haenlein, 2019). These first-generation applications represent a focused approach to AI, which are targeting specific tasks. However, modern AI applications have evolved to cover problem-solving, reasoning, planning, learning, communication, perception, and action, facilitated by advanced data processing technologies that enable the utilization of large datasets (Rusthollkarhu et al., 2022).

In general terms, AI refers to algorithms, systems, and machines that demonstrate intelligence (Shankar, 2018). However, deciding whether something qualifies as AI based on its intelligence is linked to human perceptions of intelligence, leading to intelligence-based AI definitions being interpretative (Rusthollkarhu et al., 2022). Similarly, Paschen et al. (2020) suggest that the term "AI" could be misleading since it indicates the potential for computers to demonstrate human-like intelligence, which is not the case. They emphasize that rather than measuring AI systems' performance based on their resemblance to human intelligence, their effectiveness is evaluated in terms of rationality, where an AI system is considered intelligent if it makes decisions that lead to the best possible outcome or in uncertain scenarios to the best expected outcome.

Huang and Rust (2021) propose a multiple AI intelligence view, suggesting that rather than treating AI as a single thinking machine, it can be designed to include multiple intelligences same as humans, each suited for specific tasks. They outline three main types of AI: Mechanical AI, which is tailored for automating repetitive and routine tasks such as clustering algorithms; Thinking AI, designed to process data and derive new conclusions or decisions, exemplified by systems like IBM Watson and recommender systems; and Feeling AI, created for two-way interactions with humans and/or for analyzing human emotions, such as chatbots (Huang and Rust, 2021). Additionally, companies have the option to pursue various strategies leveraging AI capabilities, including a commodity strategy utilizing automated/robotic technology for efficiency, a relational strategy focused on cultivating customer lifetime value, a static personalization strategy employing cross-sectional big data analytics, or an adaptive personalization strategy utilizing longitudinal customer data for dynamic personalization over time (Huang and Rust, 2021).

According to Paschen et al. (2020), all AI systems can be explained through a common input-process-output model. In the first phase, which is input, data for the process phase is being fed to the system. Moradi and Dass (2022) highlight that in every AI model, including ML models, computer programs improve their capabilities by learning from datasets, commonly known as training datasets. They state that once the computer has gathered the necessary knowledge to generate correct outputs using specific datasets or variables, it goes through testing with a separate dataset to assess its proficiency.

Data inputs for AI can be categorized into two main forms: structured data and unstructured data. Structured data includes standardized datasets in numerical formats like demographics, web clicks, or transaction records, and unstructured data includes non-numerical and multifaceted information such as text, audio, or images, including comments, likes, reviews, inquiries, photos, and videos (Paschen et al., 2020). While numerous AI applications have begun analyzing unstructured data, they are frequently translated into numerical formats to facilitate analysis (Davenport et al., 2020).

According to Kumar et al. (2019), one of the key factors influencing the integration of AI into organizational operations is the level of data maturity. Ma and Sun (2020) further state that achieving success with AI-enabled personalization presents challenges due to limitations caused by the quantity and quality of customer data, the capacity of companies to derive insights from this data, and the effectiveness of implementation efforts. Kaplan and Haenlein (2019) highlight that since the fundamental mathematical principles underlying AI are generally accessible, companies can gain a competitive edge primarily through either faster hardware or more data.

After input data is fed into the system, the next critical step involves processing that information. AI systems, with their significant computing power, can efficiently process vast amounts of structured data, but as already stated, it is their capability to interpret unstructured data in ways that generate value which sets them apart from traditional information systems. This processing is enabled by ML (Paschen et al., 2020). According to Han et al. (2021) decision support systems and ML techniques stand out as two of the most notable technologies for businesses within AI. ML encompasses various methods, including artificial neural networks, decision trees, regression techniques, and random forests, often discussed within specific application areas like natural language processing (NLP) for written texts and image recognition for picture data (Rustholkarhu et al., 2022). Syam and Sharma (2018) suggest that significant advancements in business applications stem from rapid progress in NLP, which resides at the intersection of linguistics and machine learning, falling under the domain of computational linguistics.

Analyzing different data types is crucial for decision-making, but processing numerical data is notably simpler compared to other forms of data (Davenport et al., 2020). However, according to Syam and Sharma (2018) neural networks offer a powerful solution for handling complex and messy datasets that traditional methods struggle with. They argue that these networks work well in extracting patterns and trends that conventional computer programs and human perception cannot detect.

The initial step in AI's processing stage is preprocessing, where raw data is prepared for further analysis. According to Paschen et al. (2020) during this phase, AI can employ natural language understanding to interpret human language in both spoken and written forms, and computer vision to identify patterns and interpret still images, facial expressions, or gestures. They argue that these preprocessing steps, which include normalization, feature extraction, and selection, are crucial for transforming data into a format that can be analyzed more deeply. Once preprocessing is complete, the refined data goes through AI's three value creating main processes: problem-solving, reasoning, and ML (Paschen et al., 2020). The problem-solving and reasoning involve defining the problem AI aims to solve and determining the analytical approach. An example of this application is in marketing, where professionals want to identify prospects (problem to be solved) using a segmentation model that analyzes customers' web browsing history, email, telephone inquiries, and demographics (reasoning how to approach the analysis) (Paschen et al., 2020).

Lastly, outputs from AI systems serve as critical information stemming from value-creation processes, significantly impacting various business applications and decision-making strategies. According to Paschen et al. (2020), these outputs can range from simple compilations, like lists of frequently mentioned topics in competitors' news articles, to more complex tasks such as the generation of sales battle-cards by analysts using AI-derived insights. The autonomous operation of AI, including chatbots addressing customer queries or natural language generation systems crafting advertising content, highlights the breadth of AI's capability to produce outputs independently, revolutionizing traditional business operations and decision-making processes (Kaplan and Haenlein, 2019; Paschen et al., 2020).

3.1.1 Generative AI

Recent advances in AI, particularly with generative AI models, are transforming perceptions of creativity and automation in tasks traditionally viewed as uniquely human, such as writing, composing music, and designing fashion (Feuerriegel et al., 2024). Unlike other AI techniques focused on classification or prediction, generative AI learns to create entirely new content by analyzing patterns within data (Agrawal, 2023). Feuerriegel et al. (2024, 111) define generative AI as "computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data". Previous automation phases mainly addressed routine tasks, but with deep learning advancements, even creative activities that are complex to codify, like writing and image generation, are becoming automated (Noy and Zhang, 2023). This evolution in AI capabilities also enhances hybrid intelligence, integrating human and AI strengths to foster new ways of working and communicating, highlighted by innovations like Dall-E 2, GPT-4, and Copilot (Feuerriegel et al., 2024).

Feuerriegel et al. (2024) provide a framework for understanding generative AI, categorizing it into three distinct levels: model, system, and application. The model level encompasses machine learning architectures that utilize AI algorithms to generate new data instances based on patterns and relationships in the training data. At the system level, generative AI extends beyond just the model to include the supporting infrastructure, user-facing components, modality, and the associated data processing, such as for prompts. Finally, at the application level, these systems are integrated within organizations to create value by addressing specific business challenges and meeting stakeholder needs.

Fui-Hoon Nah et al. (2023) suggests that generative AI models are enhancing the efficiency of content creation significantly, similar way to how the industrial revolution harnessed steam power, internal combustion engines, and electricity to boost goods production. This comparison highlights a trend where the integration of generative AI into employee workflows is becoming essential for boosting productivity. Additionally, as the automation of content generation advances, innovative business models are emerging, notably personalized AI-generated content (AIGC) is being tailored to individual preferences, becoming a primary consumption source (Fui-Hoon Nah et al., 2023).

Generative AI has seen significant advancements due to two major breakthroughs. Firstly, transformers that were introduced by Google researchers in

2017, which allowed for the parallel processing of text rather than sequentially, enhancing the scaling capabilities of models through billions of parameters (Bughin, 2023). This development paved the way for Large Language Models (LLMs) that use transformer that learn from examples to predict the next word in a sequence and thus produce novel outputs (Ooi et al., 2023). Secondly, the introduction of Generative Adversarial Networks (GANs), which feature two competing neural network, a generator producing realistic data and a discriminator distinguishing between fake and real data, has pushed generative AI into a new era of innovation (Fui-Hoon Nah et al., 2023).

Feuerriegel et al. (2024) highlight the remarkable capabilities of large generative AI models, often referred to as foundation models, which demonstrate versatility and comprehensiveness in modeling outputs across diverse domains or data types. They suggest that these models exhibit two key properties: emergence, where they can manifest behaviors, such as generating calendar entries in .ical format without specific training, and homogenization, allowing a single model to support a wide array of systems and applications, including tasks like generating source code in multiple programming languages. Moreover, generative AI models can be categorized into two main groups: unimodal and multimodal. Unimodal models operate within the same input-output type (e.g., text), whereas multimodal models are capable of accepting inputs from various sources and generating outputs in different formats, showcasing their adaptability and flexibility in handling complex data structures and tasks (Feuerriegel et al., 2024).

LLMs have become integral to various applications, frequently utilized to generate content, find information, engage in conversations, and organize data (Ooi et al., 2023). These models can be utilized as chatbots for customer service, virtual assistants for completing specific tasks, and tools for carrying out accounting, human resource activities, and generating marketing content (Fui-Hoon Nah et al., 2023). Generative AI can integrate various datasets to provide concise summaries of major trends and craft detailed descriptions, enhancing content creation in areas like product descriptions, personalized recommendations, marketing messages, and user-tailored website layouts (Agrawal, 2023). Furthermore, generative AI tools such as Bard, ChatGPT, Synthesia, Claude, Cohere Generate, Github, Jasper, and others are developing a range of outputs including advertising content in text, pictures, videos, digital marketing strategies, chatbot-based solutions, blog posts, and sales training programs (Ooi et al., 2023).

Generative AI is transforming problem-solving by facilitating brainstorming and aiding in the generation or refinement of solutions (Fui-Hoon Nah et al., 2023). Generative AI has become a tool that can enhance management efficiency by improving decision-making and organizational productivity in real-time, facilitating strategic decision-making in fast-paced business environments (Agrawal, 2023). Even though it lacks decision-making authority in business and societal contexts, it stimulates human creativity by offering synthesized summaries from diverse viewpoints, often highlighting overlooked aspects (Agrawal, 2023). Overall, generative AI is expected to affect both society and businesses, particularly in terms of increasing productivity and efficiency as well as assisting the creation of new designs and product developments (Ooi et al., 2023).

ChatGPT (GPT is short for generative pre-trained transformer) represents a popular generative AI system that belongs to the family of LLMs (Feuerriegel et al., 2024). It is designed and fine-tuned for conversational purposes, leveraging its vast reservoir of information and knowledge to produce responses that resemble human interaction (Fui-Hoon Nah et al., 2023). Employing Reinforcement Learning from Human Feedback (RLHF), systems like ChatGPT undertake a three-step process: initially generating demonstration data for prompts, subsequently soliciting user feedback to rank output quality, and ultimately refining its output generation policy through reinforcement learning to consistently produce desirable responses (Feuerriegel et al., 2024).

ChatGPT's popularity’s main reason can be seen to be its user-friendly interface, making it accessible even to non-expert users (Feuerriegel et al., 2024). Noy and Zhang (2023) speculate on the transformative potential of powerful generative tools like ChatGPT, suggesting they could either displace or augment human labor. Their study demonstrates ChatGPT's ability to boost productivity across all proficiency levels among college-educated professionals engaged in midlevel writing tasks, thereby narrowing inequality while improving output quality and task efficiency. Moreover, ChatGPT serves as a versatile collaborator, capable of contributing to both internal and external projects or campaigns within various organizational contexts (Fui-Hoon Nah et al., 2023).

Despite Generative AI’s benefits it also introduces societal challenges that span ethical, technological, regulatory, and economic realms. Ethical issues include harmful content, bias, over-reliance, misuse, privacy, and digital divide; technological concerns cover data quality, explainability, authenticity, prompt engineering, and hallucination where LLMs like ChatGPT produce plausible yet potentially inaccurate responses due to flawed training data (Ooi et al., 2023; Fui-Hoon Nah et al., 2023); regulatory challenges address copyright and governance; and economic impacts involve labor market disruptions, industry transformations, and issues of income inequality and monopolies (Fui-Hoon Nah et al., 2023). Additionally, the management of private and public data, along with intellectual property rights, presents further issues in leveraging generative AI effectively (Ooi et al., 2023). The source of many of these challenges can be attributed to the neglect of sociotechnical issues and human needs and values (Fui-Hoon Nah et al., 2023).

3.2 AI in personalization process

While personalization has been an important part of marketing since the formation of modern marketing principles, it was with advancements in information technology and AI that elevated its significance, affecting various marketing endeavors (Salonen and Karjaluoto, 2016). AI is revolutionizing the way value is delivered to users, enabling a deeper and more effective personalization than previously possible (Kumar et al., 2019). Additionally, application of AI in marketing and sales for improved targeting and personalized communication has increased (Kaplan and Haenlein, 2019). The success of personalization efforts can be seen to depend on the volume and quality of customer data, the ability to derive insights from this data, and the proficient execution of these insights, in which the AI-powered solutions can be used to solve these issues (Kumar et al., 2019).

Internally AI enables a multitude of tasks to be executed faster, more efficiently, and at a reduced cost, while externally it reshapes the dynamics of relationships between companies and their customers, other businesses, and society at large, improving interactions and engagement (Kaplan and Haenlein, 2019). Companies are increasingly deploying AI to foster more effective, precise, and timely decision-making processes (Moradi and Dass, 2022). According to Kumar et al. (2019) the reduced cost of serving customers as a result of AI allows companies to offer personalized product recommendations and serve a broader spectrum of customers profitability. They argue that the transition to automation and intelligent systems marks a shift away from conventional CRM methods, which mostly relied on the cost differences in serving customers, as automation reduces the heterogeneity in service costs, moving companies towards a new era characterized by enhanced efficiency and personalized customer engagement.

Literature suggests that AI can enhance each step of the personalization process from interaction to delivery, as outlined in Table 2. In the first stage of personalization process, interaction, AI can be used to solve the hurdles of data collection, database integration, and learning about customer responses. The ability of AI to automate the processes involved in the collection, storage, management, and retrieval of data can help in the development and management of company offerings (Kumar et al., 2019). Similarly, the capabilities of mechanical AI in automating the gathering of comprehensive data regarding the market, the environment, the company, competitors, and customers, makes it simpler to track and monitor market data in our increasingly digital world (Huang and Rust, 2021). Furthermore, AI can harness the Internet of Things (IoT) by employing sensors, wearables, heat maps, video surveillance, and beacons to amass a wide array of individuals' data, both structured and unstructured (Soleymanian et al., 2019). This integration enables the collection of customer intelligence, such as data on consumer behaviors, activities, and environments, through connected devices, offering detailed insights into product usage and consumption experiences (Huang and Rust, 2021). Moreover, mechanical AI's application extends to conducting surveys or experimental data collection efforts, aimed at understanding consumer psychographics, opinions, and attitudes, showcasing AI's extensive potential in enhancing the precision and depth of market and customer intelligence (Huang and Rust, 2021).

TABLE 2. Benefits of AI in personalization process

Operation	Challenges (Vesanen and Raulas, 2006)	Benefits of AI
Interaction	- Failure to record customer interactions - Learning about customer responses after the delivery of personalized marketing ouput	- Automate the processes involved in the collection, storage, management, and retrieval of data (Kumar et al., 2019; Huang and Rust, 2021). - Integration with IOT (Soleymanian et al., 2019). - Conducting surveys or experimental data collection efforts (Huang and Rust, 2021). - Ability to recognize and monitor real-time customer reactions and emotions (Huang and Rust, 2021). - Refinement of predictive accuracy (Kumar et al., 2019).
Process	- Maintaining the data to be up to date and accurate - Creating customer profiles and segmenting customers in alignment with business objectives	Autonomously uncover patterns from vast amount of data (Huang and Rust, 2021) Improvements in predictive capability (Davenport et al., 2020; Moradi and Dass, 2022; Huang and Rust, 2021). Analysis of non-numeric data (Davenport et al., 2020; Syam and Sharma, 2018; Moradi and Dass, 2022).
Customization	- Accurately identifying and presenting the most appropriate offer - Creating a creative marketing message	Smart content curation through recommendation engines (Kumar et al., 2019; Aksoy et al., 2021; Hermann, 2022; Moradi and Dass, 2022; Huang and Rust, 2021). AI-generated content (Moradi and Dass, 2022; Huang and Rust, 2021; Ooi et al., 2021; Fui-Hoon Nah et al., 2023; Agrawal, 2023). Targeted advertising (Moradi and Dass, 2022). Pricing optimization (Kumar et al., 2019).
Delivery	- Utilizing delivery channels that align with the customer's preferences - Timing and differentiation of the delivery	Predict which channels and timing are most likely to be effective for specific segments (Kumar et al., 2019; Huang and Rust, 2021). AI voice interface delivery (Kumar et al., 2019). AI bots (Davenport et al., 2020).

AI tools can refine their predictive accuracy regarding customer preferences through learning from customer interactions, which in turn, augments the value delivered to customers across their relationship lifecycle with the company (Kumar et al., 2019). Huang and Rust (2021) discuss the use of feeling AI that can recognize the satisfaction levels of existing customers with a product and the reasons behind their sentiments. Similarly, for potential customers, feeling AI helps marketers grasp what these customers desire and why they might prefer competitors or other alternatives. Moreover, feeling AI has the ability to monitor real-time customer reactions to promotional content.

In the processing step, AI can be utilized especially in the segmentation and customer profile generation operations. Marketers no longer need to predetermine segmentation variables, as unsupervised machine learning can autonomously uncover patterns (Huang and Rust, 2021). Following segmentation, thinking AI can recommend the optimal segments to target, leveraging its predictive power to anticipate customers' diverse preferences. However, the thinking AI's decision-making process poses a challenge, as its recommendations may not always be transparent to human marketers, potentially leading to accountability issues if errors occur. (Huang and Rust, 2021.) Nevertheless, the personalization benefits generated by thinking AI, coming from its ability to discern patterns and predict market trends, offer valuable information for tailoring marketing outputs to target customers' preferences (Huang and Rust, 2021). Moreover, AI's capacity to analyze non-numeric data holds promise for enhancing company's understanding of customer needs and improving customer service, further underscoring the multifaceted potential of AI in revolutionizing marketing practices (Davenport et al., 2020).

In order to address the limitations inherent in conventional supplier segmentation approaches, fuzzy rules-based systems are anticipated to outperform traditional methods by incorporating fuzzy variables (Martínez-López and Casillas, 2013). One such model, proposed by Martínez-López and Casillas (2013), aims to aid sales personnel in identifying businesses within the market that are most likely to progress through the entire sales funnel—from prospects to leads and ultimately to becoming loyal, long-term customers. This innovative approach leverages fuzzy logic to provide nuanced insights into customer behavior and preferences, thereby enhancing the accuracy of sales predictions. Furthermore, the utilization of AI enables companies to predict what customers will buy more effectively, potentially leading to significant advancements in predictive capability (Davenport et al., 2020).

Predictive analytics, which is a key application of propensity modeling, which forecasts the probability of converting customers into value-added clients, estimates conversion prices, and identifies customers likely to engage in repeat purchases (Moradi and Dass, 2022). Lead scoring, another aspect of propensity modeling, assigns scores to leads, enabling sales teams to gauge lead quality and prioritize their efforts accordingly (Moradi and Dass, 2022). Additionally, leveraging machine learning and AI, such as NLP tools, aids in demand estimation and sales forecasting by analyzing target market data, including speech and email content, to predict consumer purchase probabilities (Syam and Sharma, 2018). Furthermore, AI's capacity to swiftly process unstructured data, including emails, phone conversations, and social media posts, enables the identification of trends and the identification of promising prospects, streamlining the lead generation process (Moradi and Dass, 2022).

In the third step of personalization process, customization, AI can be utilized in targeting and creating creative solutions. AI presents numerous opportunities for customer reach and acquisition through AI-generated content, smart content curation, and targeted advertising (Moradi and Dass, 2022). For example, Lexus car commercial utilized IBM’s AI Watson to create the script for the “Driven by Intuition” commercial (Huang and Rust, 2021). Kumar et al. (2019) highlight the transformative capability of AI's potential to deliver personalized content to users with minimal human intervention by handling vast amounts of data and generating valuable insights. This capacity for personalization, facilitated by modern thinking AI, represents a significant advancement in marketing, enabling the automatic analysis of big data to target individual customers effectively (Huang and Rust, 2021). For instance, the Bank of Montreal (BMO) leverages IBM Interact to analyze customer data across all channels and identify personalized product offerings, exemplifying the practical implementation of AI-driven personalization strategies (Davenport et al., 2020).

Generative AI can significantly facilitate the creation of personalized content. By utilizing data such as prospective customers' browsing histories, past purchases, and other digital footprints generative AI can help to achieve hyper-personalization, which allows for the delivery of customized advertisements and offers, tailored in real-time based on user engagement metrics such as views, likes, and comments (Agrawal, 2023; Fui-Hoon Nah et al., 2023; Ooi et al., 2023). Furthermore, generative AI empowers sales and marketing teams to deeply analyze extensive customer data sets, extracting valuable insights and recommendations that enable the sending of targeted product information and relevant promotional offers (Ooi et al., 2023). Additionally, generative AI supports a remarketing strategy that effectively reaches specific customers in a seamless and personalized manner, employing techniques such as the recency-frequency-monetary (RFM) matrix to enhance marketing precision (Ooi et al., 2023).

Additionally, AI empowers product curation on a scale that transcends human capabilities, enabling the automatic selection of products, prices, website content, and advertising messages tailored to individual customer preferences (Kumar et al., 2019). Recommendation engines are a popular application of machine learning used in curation, which utilize algorithms to link users with offerings based on their past preferences and potential future interests, effectively decreasing consumer cognitive load and shifting the responsibility of finding the best options to the platform or brand (Kumar et al., 2019). Through smart content curation, marketers can identify potential customers who have purchased products within specific categories and engage them with personalized content (Moradi and Dass, 2022). Thinking AI further enhances promotional content creation and personalization, enabling the generation of tailored ad or post content that can be optimized for different customer profiles (Huang and Rust, 2021). Additionally, AI facilitates website content customization, pricing optimization, and seamless customer interaction across various channels and devices, enhancing the overall customer experience (Kumar et al., 2019). Examples of AI-driven ad targeting strategies include video ads and real-time bidding, enabling marketers to reach customers with relevant advertisements based on their browsing behavior (Moradi and Dass, 2022).

The last step of personalization process is delivery in which AI can aid and improve differentiation and timing of the delivery of marketing output. For instance, AI algorithms can analyze vast amounts of data to predict which channels are most likely to be effective for specific segments of your target audience. Kumar et al. (2019) highlight the AI's ability to determine the type, timing, and purchase of preferred products and services. Similarly, Huang and Rust (2021) suggest that thinking AI can optimize delivery based on location, and time. AI can be utilized in delivering content trough voice interface applications that have been trained on extensive volumes of customer voices (Kumar et al., 2019). Additionally, AI bots have demonstrated effectiveness comparable to trained salespersons and four times greater than inexperienced ones (Davenport et al., 2020), which suggests that AI can be used in delivery is sales setting. However, revealing that a customer is interacting with an AI bot can lead to a significant drop in purchase rates by 75% (Davenport et al., 2020). In conclusion, AI can dynamically adjust the content and format of marketing messages based on real-time data, such as user location, device type, or browsing behavior, which improves the delivery of marketing output.

As the literature indicates, AI can enhance each stage of the personalization process. However, this study will focus only on generative AI in the empirical section. This focus is chosen because generative AI is still a relatively new technology and has not been extensively researched. Moreover, given its significance across various industries (Fui-Hoon Nah et al., 2023), it is crucial to explore its impact on customer responses and the subprocess of customer acquisition.

3.3 Generative AI-enabled personalization in relationship initiation

The aim of this chapter is to develop hypotheses and a research model based on the SOR framework. The focus is on understanding how generative AI-personalized marketing content can lead to customer acquisition. Based on personalization dimensions of Kwon and Kim (2012) the object of personalization is marketing text, level of personalization is one-to-N, entity responsible for personalization is system initiated, and method of learning in this hypothetical situation implicit. Generative AI used in this study is ChatGPT. The hypotheses involve the relationship between the content and perceived personalization, perceived value, customer satisfaction, and purchase intention. Past literature suggests that when measuring consumers' purchase behavior, intention to purchase has been widely used as a predictor for consumers' future purchasing (e.g., Morwitz and Schmittlein, 1992; Pena-García et al., 2020) Therefore, it is assumed that purchase intention can lead to customer acquisition.

The SOR framework provides a model for understanding how various aspects of an external environment, such as product features, serve as stimuli that influence individuals' internal states, or "organism," which in turn lead to specific responses (Chang et al., 2011). This model defines a stimulus as factors that impact the internal states of an individual, potentially altering their mental and cognitive conditions (Eroglu, Machleit, and Davis, 2001; Lin and Lo, 2016). According to Zhu et al. (2020) the response of an organism to external stimuli is not only a passive sequence from stimulus to response but it is an active engagement by the organism. Stimulus in the case of this study is marketing content that is personalized using generative AI.

The organismic state includes affective and cognitive states that reflect how an individual internally processes environmental cues, such as perceived value (Kim and Lennon, 2013). For example, this internal assessment can be influenced by the organism's perception of the product, leading to feelings of satisfaction or dissatisfaction (McKinney, 2004). In this study, explored organisms are cognitive state of customer's perceived personalization and perceived value of marketing output and affective state of satisfaction.

Literature suggests that actual personalization and perceived personalization are two distinct constructs. In actual personalization the personalization cues are included in the message, while in perceived personalization the message is subjectively felt as tailored by the recipient (De Groot, 2022; Li, 2016; Maslowska et al., 2016). Li (2016) further elaborates that a personalized message can be accidentally perceived as non-personalized, and a non-personalized message can be accidentally perceived as personalized.

Li (2016) highlights that users' perceptions of personalized messages do not always come from an actual personalization process but rather from how well the content aligns with their expectations. This perception of personalization does not necessarily correlate with the perceived relevance or involvement of the message, although these could be outcomes of perceived personalization (Maslowska et al., 2016). Perceived personalization can be defined as" a recognition that the message is personalized for the individual" (Maslowska et al., 2016, 77). Li (2016) emphasize that perceived personalization is the real diver of favorable personalization effects.

Maslowska et al. (2016) suggest that various personalization strategies can differentiate in their effectiveness, and the degree to which these strategies trigger perceived personalization can lead to different outcomes. Li (2016) points out that personalized messages are not universally more effective than generic ones.

This highlights that while perceived personalization can enhance the impact of a message, only the application of personalization techniques does not guarantee better results.

Although actual personalization and perceived personalization are different concepts, it can be argued that marketing content specifically tailored to the individual is often perceived as more personalized compared to generic content. Research by Maslowska et al. (2016) supports this, demonstrating a positive link between personalized advertising and its perception as personalized. Moreover, De Groot's (2022) study suggests that ads with high levels of personalization are perceived as more personalized than those with less personalization. Additionally, recent literature points out that generative AI tools can significantly aid in creating highly customized content (Ooi et al., 2023; Fui-Hoon Nah et al., 2023). These tools also have the capability to integrate diverse datasets to enhance the individualization of marketing messages (Agrawal, 2023). Based on these insights, the following hypothesis is proposed for this thesis:

H1: *Generative AI-personalized marketing content has a positive relationship with perceived personalization.*

Additionally, it can be seen that perceived personalization has a positive relationship with customer's perceived value of the personalized content. Eggert and Ulaga (2002) highlight the importance of assessing how value is perceived by customers complements the information needed for marketing decision making. Therefore, studying how perceived personalization affects perceived value can be seen as important. Tam and Ho (2006) suggest that content relevance through personalization is crucial for favorable user evaluations. Similarly, Homburg et al. (2011) argue that identifying and satisfying customer needs is essential for creating customer value. Thus, relevance and differentiation through personalization can be seen to enhance perceived value.

Eggert and Ulaga (2002) suggest that customer perceived value is a trade-off between the benefits and sacrifices experienced by customers when engaging with suppliers. The benefits of personalized marketing outputs could be meaningfulness and relevancy (Kumar et al., 2020; Kwon and Kim, 2012), and facilitation of deeper engagement while decreasing information overload (Tam and Ho, 2006). The sacrifices could relate to privacy or irritating issues of personalized content. Eggert and Ulaga (2002) also emphasize the subjective nature of value perception, and that different customer segments may have varying perceptions of value. This perspective proposes that value perception is dynamic and influenced by diverse factors, including customer segmentation. Therefore, personalization can be seen to affect customer's perceived value.

Richards and Jones (2008) highlight the crucial role of customized marketing messages in enhancing value equity through heightened perceived utility. They highlight the heightened impact of personalized information, especially during the initiation and maintenance phases of customer relationships, where tailored messages can foster and sustain customer engagement. Similarly, Kwon and Kim (2012) emphasize the superior value delivered by offers customized to individual preferences, stressing the importance of. Alimamy and Gnoth (2022) further emphasize the significance of personalized purchase experiences in shaping customers' perceptions of unique value. Additionally, in the context of advertising, perceived personalization has a positive relationship with perceived relevance (De Keyzer et al., 2022), which can be seen to be driver of perceived value. Together, literature emphasize the pivotal role of personalization in enhancing the perceived value. Thus, this study hypothesizes the following:

H2: *Perceived personalization of Generative AI-personalized marketing content has a positive relationship with perceived value.*

Delivering exceptional customer value is crucial for achieving a competitive advantage in the marketplace, as it significantly impacts customer satisfaction (Murali et al., 2016). Satisfaction relates to a psychological state that emerges from comparing expected and actual performance during a consumer experience (Santini et al., 2018). This feeling of satisfaction can develop from a single encounter or through a series of interactions (Hu et al., 2009). Satisfaction stems from both a cognitive process, where perceived performance is evaluated against set standards, and an affective state that reflects emotional responses (Eggert and Ulaga, 2002). Consequently, satisfaction encompasses both cognitive and affective components, though it is predominantly an affective reaction (Chiou and Droge). Research consistently shows that perceived value influences customer satisfaction. For instance, studies on service quality demonstrate that high perceived value leads to substantial customer satisfaction (Hu et al., 2019). This trend is also evident in the domains of blogging and social media marketing, where a positive correlation exists between perceived value and customer satisfaction. Other studies further confirm the direct link between perceived value and customer satisfaction (Cronin et al., 2000; Eggert and Ulaga, 2002; Kim et al., 2007). Based on this evidence, the third hypothesis of this study proposes the following:

H3: *Perceived value of Generative AI-personalized marketing content has a positive relationship with customer satisfaction.*

Ultimately, the response in the SOR model is the outcome of the organism's processing, representing final actions or decisions made by the consumer (Chang et al., 2011). This response can be either positive or negative (Mehrabian and Russell, 1974 as cited by Zhu et al., 2020). The SOR framework in marketing research has vastly documented how emotional responses generated by stimuli significantly predict consumer behaviors and intentions (Zhu et al., 2019; Zhu et al., 2020). This study focuses on the response of purchase intention, which represents the consumers' willingness to purchase a product (Dodds et al., 1991).

Similar to the SOR framework, various studies have demonstrated a direct correlation between organism such as customer satisfaction and response of behavioral intentions. For instance, research on digital brand interactions has shown that customer satisfaction significantly influences the purchase intention (Dash et al., 2021). Likewise, studies examining the effects of website quality on customer satisfaction and subsequent purchase intentions reveal that customer satisfaction positively impacts purchase intention (Hsu et al., 2012). This relationship is consistently supported by numerous other studies (e.g., Cronin et al., 2000; Kim et al., 2007; Hu et al., 2019). Based on these findings, the fourth hypothesis of this study is proposed as follows:

H4: *Customer satisfaction has a positive relationship with purchase intention.*

Figure 6 provides a detailed illustration of the research model and hypotheses for this study. In addition to these hypotheses, it is expected that involvement affects the purchase intention. Zaichowsky (1985, 342) define involvement as "a person's perceived relevance of the object based on inherent needs, values, and interests." As literature suggests, involvement has a direct effect on purchase intention (Lee et al., 2017). The following chapter will explore the study's methodology and data, discussing the rationale for the chosen methodology, its implementation, and the reliability of the research.

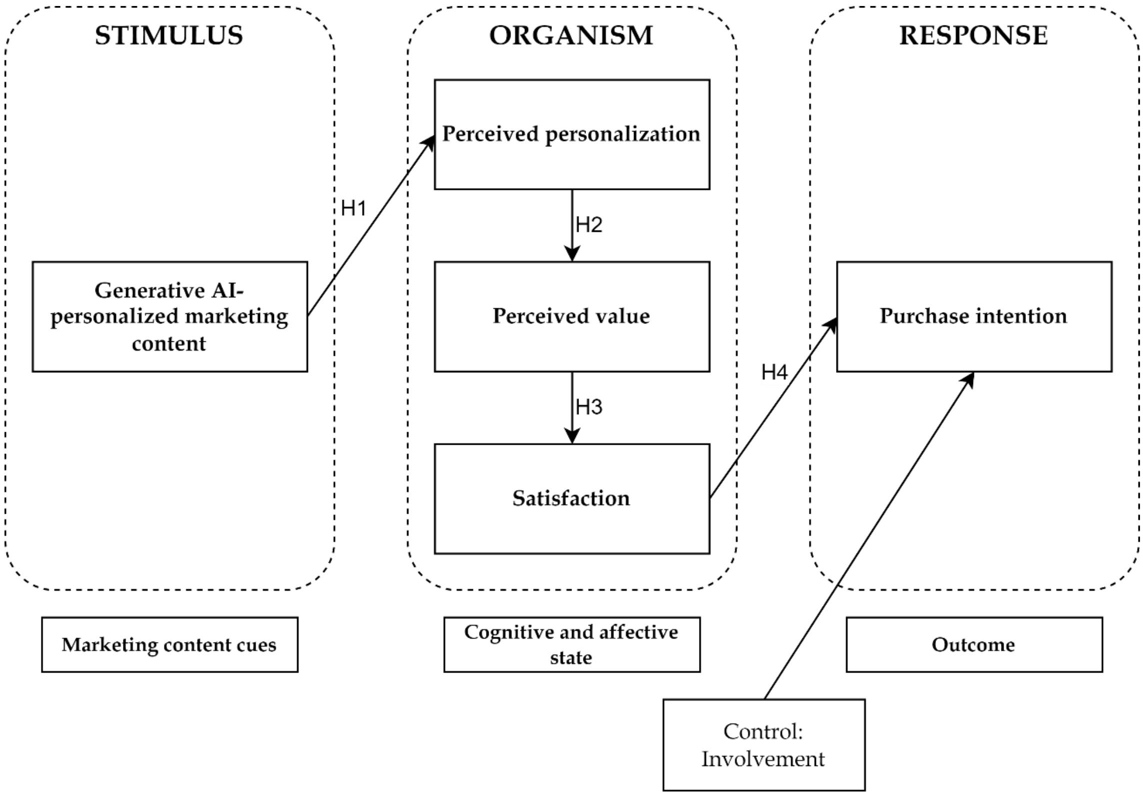

Figure 6. Research model

4 DATA AND METHODOLOGY

4.1 Quantitative research

Research can be conducted using either qualitative or quantitative methods. Quantitative and qualitative research can be hard to distinctly separate, and they can be seen as complementary approaches. Qualitative research can be used as a pilot study for quantitative research, or the methods can be used side by side. Although quantitative research deals with numbers and qualitative with meanings, numbers and meanings are interdependent. (Hirsjärvi, Remes & Sajavaara, 2007.)

The basis of qualitative research is the depiction of real life. It aims to examine phenomena as holistically as possible. Qualitative research favors using humans as the instrument of data collection rather than measuring instruments. Unlike in quantitative research, the target group is purposefully selected, not by using random sampling methods. (Hirsjärvi et al., 2007.) According to Metsämuuronen (2005), qualitative research is particularly suitable when interested in the detailed structures of events, the individual actors involved in events, and in studying natural situations.

Despite the complementarity of quantitative and qualitative research, the approaches differ significantly (Metsämuuronen, 2005). This study employs a quantitative research method. The choice of research method is influenced by testing hypotheses derived from previous theories and the formation of a new theory and model, which are characteristic features of quantitative research. Theory and model formation are considered invaluable in research. The purpose of the theory is to guide the search for new knowledge while organizing and systematizing collected data. In contrast, qualitative research focuses on a multifaceted and detailed examination of the data, not on testing theories or hypotheses (Hirsjärvi et al., 2007.) The benefits of hypotheses include their testability. A theory can be given a testable form and can be confirmed or rejected with the help of hypotheses. Another benefit of hypotheses is the objective approach to the research subject. Perfect objectivity is impossible, but hypotheses bring us closer to it (Metsämuuronen, 2005.)

The purpose of this research is explanatory. Explanatory research aims to find cause-and-effect relationships and identify causal chains. It is common practice to use hypotheses in explanatory research (Hirsjärvi et al., 2007). Next, the data collection method will be discussed in more detail.

4.2 Data collection

The research method chosen was survey research, which is traditional in quantitative research and is suitable for the purpose of this study (Hirsjärvi et al., 2007.) Survey research is an interview used in quantitative research in which structured questions are asked to a random sample. The data collected are used to answer the purpose of the study, i.e. to compare and explain a phenomenon (Hirsjärvi et al., 2007; Metsämuuronen, 2005).

The questionnaire in this study is conducted as a structured online questionnaire with no open-ended questions. The questionnaire was created using Webropol 3.0 survey software. The questions are multiple-choice and scale-based. All questions have been translated from the original English into Finnish by the questionnaire administrator. To ensure good fit of the items in this context, minor modifications in the wording were made. The scale-based questions are 7-point Likert scales. The 7-point scale was applied instead of the 5-point scale because it tends to be more reliable (Metsämuuronen, 2005). Multiple-choice questions were used at the end of the questionnaire for background information. Likert-scale questions measured perceived personalization, perceived value, satisfaction, and purchase intention. In addition, there were questions for a control variable that measured involvement.

The company used in the survey was a fictitious company "Q", which manufactures tablets. The questionnaire assumes a hypothetical situation where "Q", through processing data collected from customer interactions, has identified Finnish university students as an important customer profile and wants to tailor its marketing communications to target this profile. This personalization was created using the generative AI ChatGPT4 to customize a highly generic email marketing message. The prompt used to personalize the message was "personalize this text to university student".

At the beginning of the questionnaire, the respondent's month of birth was asked. This question was used to divide the respondents into two groups. Those who chose an odd month of birth were shown a generic non-personalized email marketing message and those who chose an even month of birth were shown a generative AI-personalized message. The purpose of the division is to collect data to compare AI-personalized and non-personalized marketing content. Respondents were asked to carefully review the message and then answer the questions on the next page. In addition, background questions at the end of the questionnaire asked respondents about their usage of a similar product, age and gender.

After the marketing message, four statements were presented to measure the respondent's perceived personalization, which were based on the peer-reviewed questionnaire of De Keyzer et al. (2022) (Table 3). After the statements measuring perceived personalization, respondents were presented with questions measuring perceived value, satisfaction, and purchase intention. The three items measuring perceived value are based on the questionnaire developed by

Zhang and Du (2020), satisfaction on the questionnaire developed by Gong and Yi (2018), and purchase intention on the questionnaire developed by Bues et al. (2017). Additionally, the control variable of involvement questions are from the Zaichowsky (1985) questionnaire.

TABLE 3. Survey Questions

Variables	Source
Perceived personalization (PER) PER1: This X is tailored to my situation. PER2: I believe this X is customized to my needs. PER3: I believe that this X is customized to my characteristics. PER4: This X was personalized according to my profile.	De Keyzer et al. (2022)
Perceived value (VAL) VAL1: very useful VAL2: very effective VAL3: of great help to me	Zhang and Du (2020)
Satisfaction (SAT) SAT1: Overall, I am satisfied with XYZ	Gong and Yi (2018)
Purchase intention (INT) INT1: Would the purchase of the promoted X be more likely or less likely given the information shown? INT2: Given the information shown, how probable is it that you would consider the purchase of the promoted X? INT3: How likely would you be to purchase the promoted X after reading the information? INT4: How likely is it that you would look out for the promoted X to purchase it?	Bues et al. (2017)
Involvement (INV) INV1: Means a lot to me INV2: Useful INV3: Interested INV4: Needed INV5: Important INV6: Valuable INV7: Exciting	Zaichowsky (1985)

The email marketing message in the survey is personalized for university students, thus the link to the survey was distributed with the cover letter to the

University of Jyväskylä students' email list. In addition, the same cover letter inviting students to respond was shared on Facebook in the "Jyväskylä Puskaradio"- group and on Instagram. The cover letter covered the information about the researcher, the subject of the study in brief, the importance of the responses for the success of the study and the confidentiality of the responses. The link to the questionnaire was distributed to the email list on 15.5.2024 and was active until 26.5.2024. In addition, the link was shared on Instagram on 30.5.2024 and on Facebook on 1.6.2024. A total of 65 people answered the questionnaire, 127 started to answer, and 359 opened it. The response rate of the survey was 18.1% of those who opened the questionnaire. The aim was to obtain a minimum of 100 responses and at least 50 respondents for both content types, in order to improve statistical reliability. The number of respondents was below the target. All questions were set as mandatory in order to avoid missing observations.

4.3 Research reliability

According to Metsämuuronen (2005), the reliability of a survey is directly related to the reliability of the measures used in the survey. Reliability is usually examined from two perspectives: reliability and validity. Reliability refers to the reproducibility of a study. The responses of a reliable measure are fairly similar even if the phenomenon was measured several times. Validity refers to whether the research measures what it is intended to measure (Metsämuuronen, 2005.)

Validity can be approached through external and internal validity. External validity refers to how generalizable a study is. It is influenced to a large extent by sampling issues. Internal validity can be divided into three different types: content validity, structural validity and criterion validity. Content validity examines the theoretical adequacy of the concepts of the measure and whether the concepts capture the phenomenon in a sufficiently broad way. It does not use mathematical tools but is more a conceptual or theoretical property of the measure. Structural validity, on the other hand, can be examined mathematically, for example by means of SEM analysis. SEM analysis calculates whether the variables measuring a concept are more systematically correlated with each other than with other variables. Criterion validity compares the value obtained by a measure with a value that already serves as a criterion for validity. Criterion validity can be assessed by calculating the validity coefficient, i.e. the correlation coefficient between the measure and the criterion variable. (Metsämuuronen, 2005.)

In this study, the measures were constructed on the basis of peer-reviewed questionnaires. In the original studies, internal validity has been tested through structural validity using SEM analysis. The questionnaires have also been used in various peer-reviewed scientific articles, which further reinforces the content validity. However, the content validity is slightly weakened by the fact that the measures have been translated from English into Finnish. However, the questionnaire was pre-tested with three test respondents to ensure that the English translation of the indicators was sufficiently clear. Criterion validity was checked using Pearson's correlation coefficient of the income moment. Pearson's correlation fits well with the interpretation of Likert-scale variables. The correlation coefficient can have values between -1 and 1. The closer the value is to zero, the less correlation there is between the variables (Metsämuuronen, 2005.) The correlation coefficients between all criterion variables and their measures were statistically significantly different ($p<0.01$). Correlation coefficients ranged from 0.448 to 0.843.

External validity can be assessed by interpreting the survey respondents. The respondents to the questionnaire were Finnish students. Therefore, the results cannot be fully generalized to all consumers globally. However, the results are indicative.

There are three different ways to calculate the reproducibility of a measurement, i.e. the reliability of a measurement: parallel measurement (using a different measure at the same time), repeated measurement (using the same measure at different times) or internal consistency of the measure (Metsämuuronen, 2005). In this study, reliability is calculated through internal consistency using both Cronbach's alpha and exploratory factorial analysis. Using Cronbach's alpha, internal consistency is measured by artificially dividing the measure into two parts. The correlation between these halves is a measure of reliability. The lowest acceptable value for the alpha is 0.60. (Metsämuuronen, 2005.) The alphas of the measures before factor analysis ranged from 0.875 to 0.917.

According to Metsämuuronen (2005), factor analysis is used to find a reliability measure of the factor structure. A sum variable constructed from factor loadings has the highest reliability if the assumptions of the factor model hold. Chapter 5.3 discusses the factor analysis used in this study in more detail. The reliability of the sum variables generated by factor analysis was further verified by Cronbach's alpha. The alpha calculated for the standardized variables measuring perceived personalization is 0.913, which exceeds the acceptable threshold. Perceived value calculated alpha is 0.900, purchase intention alpha is 0.903 and involvement alpha is 0.932. The results show that all the sum variables constructed are reliable.

5 RESULTS AND ANALYSIS

In this chapter, the results of the study are discussed. The data was analyzed using IBM Statistical Package for the Social Sciences 28.0, or SPSS software and SmartPLS 4. Firstly, the data was checked to locate insufficient responses. No insufficient responses existed. Next, the data and respondents' background information using direct distributions and statistical basic figures were examined. Then, the formation of sum variables through factor analysis is presented. These sum variables are used to compare the effects of respondents' background information to the personalized and non-personalized content with Mann-Whitney U test. Lastly, for hypothesis testing SmartPLS 4 was used to conduct SEM analysis. Based on the results of these analyses, an updated research model is then formed.

5.1 Demographic and background information

This study investigated the effects of two different types of content on perceived personalization- Therefore, the questionnaire is divided into two parts according to the month of birth. Those born in odd months answered the questions after seeing non-personalized content, while those born in even months answered personalized. Table 4 shows that the distribution between content types is relatively even (53.8% and 46.2%).

TABLE 4. Distribution of responses by content type

Marketing content	Frequency	Percent
Non-personalized	35	53,8 %
Generative AI Personalized	30	46,2 %
Total	65	100 %

The gender and age distribution of respondents is shown in Table 5. The majority of respondents were female (60,0%). Of the respondents, 35.4% were male, two were other than male or female (3,1%), and one didn’t want to say (1,5%). As expected, the age distribution of respondents was skewed between 18 and 34, as the sample consisted of university students. The highest proportion of respondents were aged 25-34 (50,8%), and the second highest were aged 18-24 (46,3%). Both the 35-44 and 45-54 age groups accounted for 1,5%. The under 18, 55-64, and 65 and over age groups accounted for 0% of respondents.

TABLE 5. Gender and age distribution of respondents

Gender	Frequency	Percent
Male	23	35,4
Female	39	60,0
Other	2	3,1
Don't want to say	1	1,5
Total	65	100
Age		
Under 18	-	-
18-24	30	46,2
25-34	33	50,8
35-44	1	1,5
45-54	1	1,5
55-64	-	-
65 or older	-	-
Total	65	100

Table 6 shows the frequency of respondents using a similar product than in the email marketing content presented in the survey. 18,5% of respondents use a similar product, while 81,5% do not. Thus, the majority of respondents do not use a similar product to the presented tablet.

TABLE 6. Usage of similar product

Usage of similar product	Frequency	Percent
Yes	12	18,5
No	53	81,5
Total	65	100

5.2 Descriptive analysis

Tables 7 and 8 present the means, medians and standard deviations of the independent, dependent, and control variables used in the hypotheses for respondents of both non-personalized and personalized surveys. The tables show the mean, median, and standard deviation of the answers. The mean is calculated by summing all the observation values and dividing the sum by the total number of observations. The median can be seen as a better measure of the weight of the ordinal scale data than mean. The median is the middle figure in the rank-ordered data. Above and below the median is 50% of the observations. The standard deviation is a dispersion figure that describes the variation of values around the mean (Metsämuuronen, 2005.) As expected for all variables standard deviation is close to one, since Likert scale was used.

TABLE 7. Means, medians and Std. deviations of non-personalized survey responses

Variable	Mean	Median	Std. Deviation	N
PER	3,70	3,75	1,35	35
VAL	3,63	3,33	1,42	35
SAT	4,24	4,00	1,50	34
INT	3,14	3,33	1,35	35
INV	4,23	4,33	1,38	35

TABLE 8. Means, medians and Std. deviations of personalized survey responses

Variable	Mean	Median	Std. Deviation	N
PER	4,78	5,13	1,70	30
VAL	4,14	4,00	1,52	30
SAT	4,37	5,00	1,47	30
INT	3,90	4,33	1,66	30
INV	4,27	4,08	1,62	30

5.3 Factor analysis

It is possible to summarize the data and create sub-measures of several variables for further analysis (e.g. regression analysis) using either principal component or factor analyses. Principal component analysis is suitable for a t-analysis where there is no underlying assumption about the theory. In this study, measures developed in previous studies have been used, therefore factor analysis was chosen. Factor analysis can be further divided into two types: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). In EFA, an explanatory model is sought among the variables, whereas in CFA, the existing model is examined to see whether the data support the model (Metsämuuronen, 2005.) Although the measures are from peer-reviewed studies, they are translated from English into Finnish, which justifies EFA. EFA is particularly suited to situations where the researcher has an idea of a theory linking the variables under study (Metsämuuronen, 2005). For these reasons, the decision was made to conduct EFA.

Before performing a factor analysis, it is necessary to check that all the required conditions are met. The analysis assumes that there are genuine correlations between the variables. In a factor analysis, the threshold value for correlation can be taken as 0,30. Additionally, the variables must be measured on an ordinal scale.

The correlation analysis shows that the correlations of involvement 7 and involvement 4 do not exceed the threshold of 0,30. The factor analysis also shows that involvement 7 loads on a different factor than the other involvement variables. Therefore, the involvement 7 variable is deleted. Otherwise, all correlations exceed the threshold value and are statistically significant by at least 5%. The Bartlett's skewness test and Kaiser's test performed with the factor analysis can be used to further examine whether the correlation matrix used is suitable for factor analysis. Bartlett's skewness test examines the hypothesis whether the correlation matrix values are zero, and if the Kaiser's test obtains a value greater than 0,6, the correlation matrix is suitable for factor analysis (Metsämuuronen, 2005.) The p-value of the Bartlett's test was less than 0,001, so the null hypothesis can be rejected. Kaiser's test was 0,894, so the correlation matrix is suitable for factor analysis.

The Unweighted Least Squares method was used to perform the factor analysis. This method is a good option if the data is limited (Metsämuuronen, 2005). The rotation method used was the rectangular Varimax rotation. The goodness of fit of a variable can be assessed by the sum of squares of the loadings on its different factors, i.e. the communality (Metsämuuronen, 2005). The threshold value for the communality can be taken as 0,5 (Yana et al., 2015). The extracted communality of the Intention 1 variable was below the threshold value (0,456), and as a result, it was removed. Otherwise the communality of the variables ranged from 0,579 to 0,884, suggesting that they reliably measure the factors.

Table 9 shows that the variables loaded strongly on the factors (0,561-0,854), which also reflects the goodness of fit of the variables. In factor analysis, variables loaded on four factors. Together, these factors explain 74,41% of the total variation in the variables. In other words, only 25,59% of the information is lost as a result of factorization. Based on the factor loadings, it can be argued that the sets of variables generated in the factor analysis can be summed to form the variables perceived personalization (PER), perceived value (VAL), purchase intention (INT) and involvement (INV).

TABLE 9. Factor analysis loadings

Items	Loadings
Perceived personalization	
PER1	0,743
PER2	0,795
PER3	0,690
PER4	0,776
Perceived value	
VAL1	0,735
VAL2	0,561
VAL3	0,640
Purchase intention	
INT2	0,639

INT3	0,817
INT4	0,595
Involvement	
INV1	0,854
INV2	0,757
INV3	0,705
INV4	0,814
INV5	0,844
INV6	0,715

5.4 Mann-Whitney U- test

When comparing more than two groups, a parametric analysis of variance (ANOVA) or a Kruskalin-Wallis test, the parameter-free equivalent of a one-way analysis of variance, can be used. The assumptions of ANOVA are that the measurement should be at least on a distance scale, there should be a sufficient number of samples (>100) and the variances of the groups should be equal in order to give reliable results. (Metsämuuronen, 2005.) This study does not meet these requirements, which is why the Kruskalin-Wallis test would be appropriate for comparing the groups. However, in the Kruskalin-Wallis test, the number of observations must exceed the threshold >5, thus only the age groups of 18-24 and 25-34 can be used for comparing age groups and male and female for comparing genders. For this reason, the Mann-Whitney U-test was chosen, which is more suitable for comparing the two groups.

The differences between the two means can be compared using a non-parametric Mann-Whitney U-test and a parametric t-test. As noted earlier, the non-parametric option is well suited to small sample sizes and when the measurement is performed with a measure that is less accurate than the interval scale. In a t-test, the variables should also be normally distributed (Metsämuuronen, 2005.) Since the conditions of the t-test are not met, the Mann-Whitney U-test was conducted in this study.

The Mann-Whitney U-test is very effective in the study of ordinal scaled variables. The test involves ranking the data in order of magnitude with respect to the variable under study and seeing how the findings are distributed. If the findings of the groups are distributed at different ends in order of magnitude, it can be concluded that there is a statistical difference between the groups (Metsämuuronen, 2005.) Table 10 shows that there is no statistically significant difference between the means of the age groups on any of the variables to be explained. There are also no statistically significant differences between genders on variables (Table 11). Similarly, there are also no statistically significant differences between usage of similar product on variables (Table 12).

TABLE 10. The effect of age

AGE	PER	VAL	SAT	INT
18-24				
Mean rank	35,83	36,50	35,23	33,23
25-34				
Mean rank	28,52	27,91	29,06	30,88
p- value	0,113	0,062	0,170	0,610
Mann-Whitney U	380,00	360,00	398,00	458,00

TABLE 11. The effect of gender

Gender	PER	VAL	SAT	INT
Male				
Mean rank	25,96	27,09	31,15	26,11
Female				
Mean rank	34,77	34,10	31,71	34,68
p- value	0,063	0,138	0,904	0,070
Mann-Whitney U	576,00	550,00	456,50	572,50

TABLE 12. The effect of using a similar product

Usage of similar product	PER	VAL	SAT	INT
Yes				
Mean rank	40,96	40,79	41,88	37,83
No				
Mean rank	31,20	31,24	30,99	31,91
p- value	0,106	0,113	0,064	0,325
Mann-Whitney U	222,50	224,50	211,50	260,00

In contrast, when comparing personalized content and non-personalized content, statistically significant differences can be found in perceived personalization and purchase intention (Table 13). By comparing the mean ranks, it is possible to determine which of the groups has a stronger effect on the variable to be explained. As can be seen from the table, the mean rank value for personalized content (39,60) was higher than for non-personalized content (27,34) when the explanatory variable is perceived personalization. Also, when the explanatory variable is purchase intention, the mean rank value for personalized content (38,20) was higher than for non-personalized content (28,54). The results indicate that content personalized with generative AI has a stronger impact on perceived personalization and purchase intention.

TABLE 13. Differences between content types

Non-personalized/ Personalized	PER	VAL	SAT	INT
Non-personalized				
Mean rank	**27,34**	29,56	32,61	**28,54**
Personalized				
Mean rank	**39,60**	37,02	33,45	**38,20**
p-value	**0,009**	0,112	0,855	**0,040**
Mann-Whitney U	723,00	645,50	538,50	681,00

5.5 Hypothesis testing

The hypotheses presented in Chapter 3 were tested by examining the internal model of the study. The evaluation of the internal model utilizes standardized path coefficients (β) and the model's explanatory power (R^2) at a statistically significant level. This was conducted in SmartPLS 4 using the Bootstrapping function with a sample size of 5000, taking into account all significance levels universally recognized as defined (p = 5%, T-value > 1,96) (Hair et al., 2011). Table 14 compiles both the path coefficients and the explanatory powers of the model. The explanatory powers can vary from 0-1, showing how much of the variation in each explained variable is accounted for by the entire model. Hair et al. (2011) suggest a general rule that an explanatory value of 0,75 is strong, 0,50 is moderate, and 0,25 is weak. Perceived personalization explained perceived value with a value of 0,529, meaning the construct accounts for 52,9% of the total variance of perceived value. Subsequently, perceived value also moderately explain satisfaction of the content (R^2 = 0,572). Similarly, satisfaction and involvement explained purchase intention moderately (R^2 = 0,495).

TABLE 14. Standardized path coefficients and their statistical significance

	β	t-value	p-value	Hypotheses
PER → VAL	0,732	15,910	<0,001	H2: supported
VAL → SAT	0,760	12,677	<0,001	H3: supported
SAT → INT	0,481	3,917	<0,001	H5: supported
INV → INT	0,356	3,140	0,002	

The impact of individual constructs is examined in more detail by looking at standardized path coefficients. These coefficients indicate the effects of latent variables on the explained variable, with particular attention paid to the strength indicated by the beta value and statistical significance (Hair et al., 2011). This study's second hypothesis, which suggested that perceived personalization impacts perceived value, was supported. The path coefficient between perceived personalization and perceived value was 0,732, with both t-value and p-values indicating significant statistical importance on this path. The third hypothesis, that perceived value has positive relationship with satisfaction was also supported. The path coefficient between these two variables was 0,760 and statistically significant with a t-value of 12,677 and a p-value of <0.001. The fourth hypothesis, proposing that increased satisfaction would positively affect purchase intention was supported. The path coefficient between satisfaction and purchase intention was 0,481 and statistical significance with a t-value of 3,917 and a p-value of <0,001. Additionally, the control variable of involvement with a path coefficient of 0,356, a t-value of 3,140, and a p-value of 0.002, suggests a positive effect of involvement on purchase intentions.

In the theoretical part of this thesis, four hypotheses were set for the study. All of these hypotheses are supported as the standardized path coefficients are positive and statistically significant, i.e. there is a positive correlation between the variables. Figure 7 shows the effects of the independent variables on the dependent variables to be explained using standardized path coefficients. In the next chapter the results of this thesis are discussed in more detail.

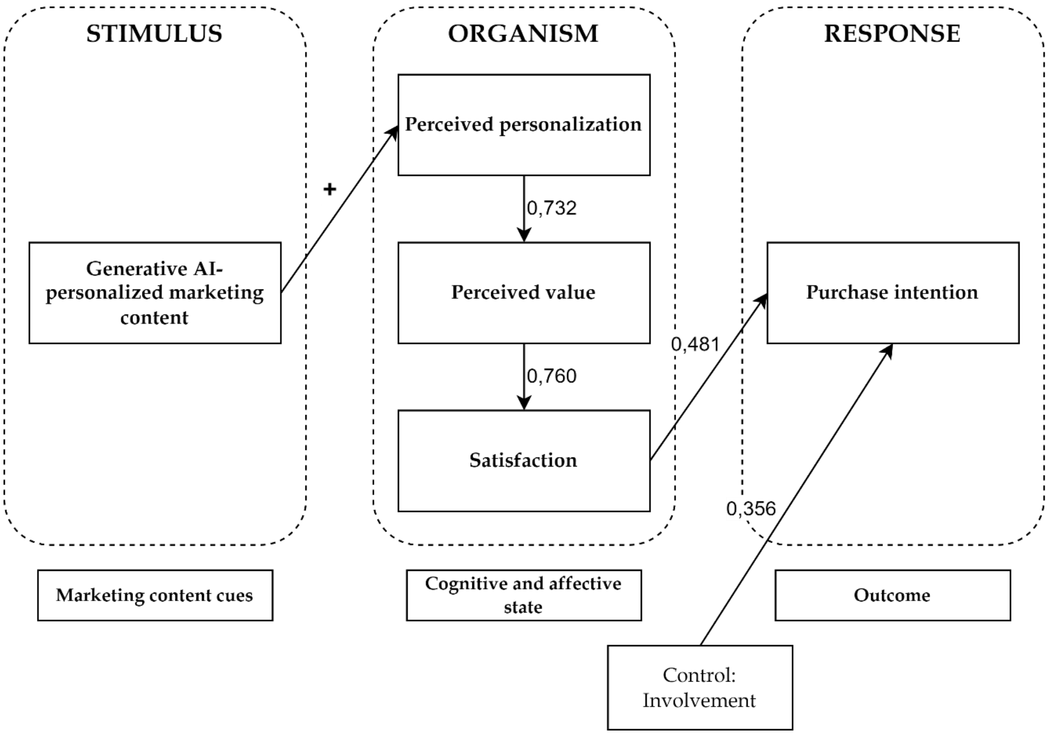

Figure 7. Structural model

6 DISCUSSION

This concluding chapter addresses the research questions established at the beginning of the study and evaluates the empirical results introduced in the previous chapter. Discussions include theoretical contributions and the presentation of managerial implications. Additionally, this chapter examines this research's limitations, and offers recommendations for future research.

6.1 Theoretical contributions

The aim of this research was to study utilization of AI-enabled personalization as a part of CRM. The focus was to examine the relationship between personalization and CRM, how AI can be used to improve personalization tactics, and how generative AI-personalized marketing can be used to initiate relationships. Therefore, three research questions were applied in the beginning of this thesis:

> **RQ1.** *What is the role of personalization in CRM, and can AI be leveraged to improve the personalization process?*
> **RQ2.** *Can generative AI be used to increase customers' perceived personalization?*
> **RQ3.** *Does generative AI-personalized marketing content have an effect on customer acquisition through perceived personalization, perceived value, customer satisfaction and purchase intention?*

First, based on literature review, personalization can be seen as integral part of CRM. CRM strategies can be categorized based on the level of individualization and completeness of customer knowledge (Frow and Payne, 2009). At the core of CRM is the focus on individual customers (Chen and Popovich, 2003; Sin et al., 2005; Nguyen and Mutum, 2012) and treating customers uniquely (Boulding et al., 2005; Chen and Popovich, 2003; Richard and Jones, 2008). Therefore, personalization can be seen as a tactic to achieve those core objects of CRM strategy. Additionally, literature suggests that AI can enhance each phase of the personalization process defined by Vesanen and Raulas (2006), helping to overcome various personalization challenges.

Second, by empirically comparing the impact of generative AI-personalized marketing content to non-personalized on perceived personalization the results indicate that generative AI-personalized content does have a stronger effect on customer's perceived personalization than non-personalized content. This is in line with previous literature, which suggests that personalized marketing content has a positive relationship with perceived personalization (Maslowska et al., 2016) and that it is stronger compared to less personalized content (De Groot, 2022). Additionally, previous literature suggests that generative AI can be used in the personalization of marketing content (Ooi et al., 2023; Fui-Hoon Nah et al., 2023). Thus, using generative AI for personalization in the customization phase appears to be possible, which in turn might improve the efficiency of personalization operations.

Third, based on literature and SOR-framework, it was assumed that customer acquisition subprocess can be improved by generative AI-personalized content through perceived personalization, perceived value satisfaction and purchase intention. The results indicate that perceived personalization does have a positive relationship with perceived value second hypothesis assumes. The reasoning behind could be that the benefits of the content exceeded the sacrifices of consuming the content, which is seen to create perceived value (Eggert and Ulaga (2002). As previous literature suggests, benefits of personalized content are their higher relevancy and meaningfulness to customers (Kumar et al., 2020; Kwon and Kim, 2012), and those benefits can overcome the sacrifices, which in this scenario are minimal.

The relationship between perceived value and satisfaction was examined, and the results indicate that perceived value has a positive relationship with satisfaction. It is consistent with the previous research, which suggests that perceived value has a direct effect on satisfaction (Cronin et al., 2000; Eggert and Ulaga, 2002; Hu et al., 2009; Deng et al., 2010; Uzir et al., 2021). Additionally, the impact of satisfaction on purchase intention was studied. The results indicate that satisfaction has significant effect to purchase intention which was also similar to results of previous studies (Eggert and Ulaga, 2002; Cronin et al., 2000; Bues et al., 2017). In addition, the effect of control variable of involvement to purchase intention was studied. The results support previous literature that involvement affects customer's purchase intentions (Lee et al., 2017).

Overall, the result indicate that AI-enabled personalization can be leveraged in CRM and generative AI-personalized marketing content can be used in the customer acquisition phase of CRM process. As literature suggests that behavioral intentions such as purchase intentions can lead to actual behavior (Morwitz and Schmittlein, 1992; Pena-García et al., 2020), it indicates that utilizing AI to generate personalized marketing content can lead through perceived personalization, perceived value, satisfaction, and purchase intention to customer acquisition.

6.2 Managerial implications

This thesis have several implications for managers aiming to implement more individualized CRM strategies for differentiation and enhancing dual value creation through AI-enabled personalization tactics. First, implementation of CRM strategies that use personalization as tactic requires the company to be organized around customer through consideration of technology, processes and people. Companies need to have a vast amount of tools that they can utilize, including database, data mart, and data warehouse technologies, as well as CRM applications, to collect, analyze, and utilize vast amounts of customer data (Payne and Frow, 2006). When considering processes, organizations must adopt a customer-centric approach, redesigning core business processes from the customer's perspective, while involving customer feedback (Chen and Popovich, 2003) and allocating resources to customers based on the revenue or profits they generate (Ramani and Kumar, 2008). In the people dimension the importance is on organizational commitment, employee performance, and top management support in CRM initiatives (Zeynep Ata and Toker, 2012; Chen and Popovich, 2003).

Second, implementing AI-enabled personalization tactics in the operationalization of individualized CRM strategies, companies need to consider 'what', 'to whom', 'who' and 'how' dimensions of personalization based on their and customers' needs. In 'what' dimension it is essential to determine what is personalized, such as content or functionality, in order to customer to achieve utilitarian or hedonic goals (Fan and Poole, 2006). Therefore, knowledge of customers' objectives when interacting with the company is crucial in order to fulfill the needs of customer. By leveraging AI, collection, storage, management, and retrieval of data can be automated and improved. Additionally, in data processing AI can be used to improve customer insight discovery and predictive capabilities. And also in fulfilling the needs of customer, AI can be used in more accurate timing and location of output delivery, and novel delivery solutions

When considering to whom dimension companies must decide whether to use one-to-N which covers micro personalization and segment marketing, or one-to-one personalization (Kwon and Kim, 2012). In addition, it can be personalized at individual level or individual being part of some social group (Fan and Poole, 2006). Companies need to do careful consideration since sometimes highly individualized personalization does not pay off and using one-to-N level personalization can sometimes be more suitable approach over one-to-one (Malthouse and Elsner, 2006; Kwon and Kim, 2012). The results of this study indicate that one-to-N level personalization was sufficient in creating perceived personalization, perceived value, and satisfaction which can lead to purchase intention.

There might be situations where customers may lack desire for individualized relationships (Frow and Payne, 2009). In these cases companies could tailor the personalization based on expected benefits and customers desire and ability to receive personalized interactions (Miceli et al., 2007). However, AI can also help in more efficient, creative and targeted marketing output creation, which can make micro and one-to-one personalization more cost effective and therefore, more viable.

In the 'who' and 'how' dimensions, companies should examine whether in different situations it is the customer or the system that initiates the personalization and what entity does the learning. In these situation also the AI's customer insight discovery and predictive capabilities can be used. In 'who' dimension it can be used to learn the preferences of the level of system initiation. In how dimension, it can be used in the implicit learning where system can automatically adjust to user's needs without their input.

Thirdly, the dual value creation nature of CRM and personalization enables companies to deliver greater customer value through more tailored content, affecting perceived personalization, value, and satisfaction, which can lead to purchase intentions and customer acquisition. This study supports the use of generative AI in the customization phase of the personalization process, potentially leading to higher levels of customer acquisition. While this research focuses on hypothetical scenarios, in practical settings, companies can leverage actual customer data from existing relationships to initiate and refine future interactions. Therefore, companies should focus on collecting and analyzing data from customer interactions, using it as the foundation for personalized marketing outputs and their delivery.

Generative AI not only facilitates the creation of new outputs but can also enhance older and more generic materials by personalizing them, potentially increasing efficiency. However, optimal outcomes are not achieved only through AI. Instead, the best results are obtained by fostering collaboration between humans and AI (Paschen et al., 2020). Similarly, as noted by Kaplan and Haenlein (2019), while it is unlikely that AI will completely replace entire jobs, there is a growing trend towards outsourcing more tasks to AI.

6.3 Limitations and future research

Although this study produced interesting and meaningful findings, there are some limitations that need to be addressed, along with suggestions for future research. Firstly, one of the goals was to explore how AI can be used in the personalization process. A literature review was conducted to identify as many current and relevant AI use cases in personalization as possible. However, as AI technologies and applications are rapidly evolving, the summary may need updates as new use cases emerge.

Secondly, survey research involves some drawbacks. It is not possible to ensure that respondents have answered carefully and honestly. It is also unclear how successful the response options were from the respondents' perspective. In this study, all questions had to be translated from English to Finnish, and although pilot respondents were used in pre-testing the questionnaire, misunderstandings may have occurred.

This research may also be limited by the use of fictional company content. Using real company content might have yielded different responses. Moreover, the study was focused to B2C content, thus excluding B2B marketing. Future research could explore content differences across real companies in both B2C and B2B sectors. Research was also conducted in a digital context, and it would be interesting to see how, for example, B2B personal selling in an offline setting affects customers.

Additionally, the focus was only on students, as the marketing content was personalized for this segment. Future studies could target different customer groups based on various factors such as demographics to generalize the results. Furthermore, considering the diversity of customer attitudes towards personalization (Micel et al., 2007), future research could profile customers based on their attitudes towards personalized interactions. Taking the cultural context into account and studying the content of domestic companies could also be valuable.

Third, this research compared content personalized by generative AI with non-personalized content. It could be interesting to explore the differences in perceived personalization between content personalized by humans and by generative AI. Investigating these distinctions could provide deeper insights into the effectiveness of personalization techniques, than comparing AI personalized content to non-personalized.

Fourth, this research was limited to the relationship initiation stage. It would be interesting to observe the impact of these findings on customer relationship maintenance, such as retention. Comparing the effects of AI-personalized content on current customers versus prospects could also provide valuable insights.

Fifth, this research focused only on perceived personalization, perceived value, and satisfaction. Future studies could benefit from exploring other organisms influenced by this stimulus. Additionally, examining other factors affected by personalized content through qualitative methods would be valuable. Moreover, responses beyond purchase intentions, such as actual behavioral intentions, should be investigated. This study was conducted at a single point in time and therefore, a longitudinal study could provide more insight for example, into how personalization impacts satisfaction over an extended period since satisfaction may emerge as a response to a prolonged set of multiple experiences (Hu et al., 2009; Santini et al.,2018).

Additionally, the benefits of using AI in the personalization process could be qualitatively studied at company-wide or functional levels. Furthermore, research could examine the resources and capabilities needed to successfully leverage AI-enabled personalization tactics. Both qualitative and quantitative methods could be used to assess the company value created by these AI-driven personalization efforts.

REFERENCES

Aksoy, N. Ç., Kabadayi, E. T., Y&lmaz, C., & Alan, A. K. (2023). Personalization in Marketing: How Do People Perceive Personalization Practices in the Business World? Journal of Electronic Commerce Research, 24(4), 269–297.

Alimamy, S., & Gnoth, J. (2022). I want it my way! The effect of perceptions of personalization through augmented reality and online shopping on customer intentions to co-create value. Computers in Human Behavior, 128, 107105. https://doi.org/10.1016/j.chb.2021.107105

Boulding, W., Staelin, R., Ehret, M., & Johnston, W. J. (2005). A Customer Relationship Management Roadmap: What is Known, Potential Pitfalls, and Where to Go. Journal of Marketing, 69(4), 155–166. https://doi.org/10.1509/jmkg.2005.69.4.155

Bues, M., Steiner, M., Stafflage, M., & Krafft, M. (2017). How Mobile In-Store Advertising Influences Purchase Intention: Value Drivers and Mediating Effects from a Consumer Perspective. Psychology & Marketing, 34(2), 157–174. https://doi.org/10.1002/mar.20981

Bughin, J. (2023). To ChatGPT or not to ChatGPT: A note to marketing executives. 9.

Cavdar Aksoy, N., Tumer Kabadayi, E., Yilmaz, C., & Kocak Alan, A. (2021). A typology of personalisation practices in marketing in the digital age. Journal of Marketing Management, 37(11–12), 1091–1122. https://doi.org/10.1080/0267257X.2020.1866647

Chandra, S., Verma, S., Lim, W. M., Kumar, S., & Donthu, N. (2022). Personalization in personalized marketing: Trends and ways forward. Psychology & Marketing, 39(8), 1529–1562. https://doi.org/10.1002/mar.21670

Chang, H.-J., Eckman, M., & Yan, R.-N. (2011). Application of the Stimulus-Organism-Response model to the retail environment: The role of hedonic motivation in impulse buying behavior. The International Review of Retail, Distribution and Consumer Research, 21(3), 233–249. https://doi.org/10.1080/09593969.2011.578798

Chen, I. J., & Popovich, K. (2003). Understanding customer relationship management (CRM): People, process and technology. Business Process Management Journal, 9(5), 672–688. https://doi.org/10.1108/14637150310496758

Chiou, J.-S., & Droge, C. (2006). Service quality, trust, specific asset investment, and expertise: Direct and indirect effects in a satisfaction-loyalty framework. Journal of the Academy of Marketing Science, 34(4), 613–627. https://doi.org/10.1177/0092070306286934

Cronin, J. J., Brady, M. K., & Hult, G. T. M. (2000). Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments. Journal of Retailing, 76(2), 193–218. https://doi.org/10.1016/S0022-4359(00)00028-2

CX personalization revenue worldwide 2026. (2023a). Statista. Noudettu 27. kesäkuuta 2024, osoitteesta https://www.statista.com/statistics/1333448/cx-personalization-optimization-revenue-worldwide/

Dash, G., Kiefer, K., & Paul, J. (2021). Marketing-to-Millennials: Marketing 4.0, customer satisfaction and purchase intention. Journal of Business Research, 122, 608–620. https://doi.org/10.1016/j.jbusres.2020.10.016

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24–42. https://doi.org/10.1007/s11747-019-00696-0

De Groot, J. I. M. (2022). The Personalization Paradox in Facebook Advertising: The Mediating Effect of Relevance on the Personalization–Brand Attitude Relationship and the Moderating Effect of Intrusiveness. Journal of Interactive Advertising, 22(1), 57–74. https://doi.org/10.1080/15252019.2022.2032492

De Keyzer, F., Dens, N., & De Pelsmacker, P. (2022). How and When Personalized Advertising Leads to Brand Attitude, Click, and WOM Intention. Journal of Advertising, 51(1), 39–56. https://doi.org/10.1080/00913367.2021.1888339

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of Price, Brand, and Store Information on Buyers' Product Evaluations. Journal of Marketing Research (JMR), 28(3), 307–319. https://doi.org/10.2307/3172866

Eggert, A., & Ulaga, W. (2002). Customer perceived value: A substitute for satisfaction in business markets? Journal of Business & Industrial Marketing, 17(2/3), 107–118. https://doi.org/10.1108/08858620210419754

Eroglu, S. A., Machleit, K. A., & Davis, L. M. (2001). Atmospheric qualities of online retailing: A conceptual model and implications. Journal of Business Research, 54(2), 177–184. https://doi.org/10.1016/S0148-2963(99)00087-9

Fan, H., & Poole, M. S. (2006). What Is Personalization? Perspectives on the Design and Implementation of Personalization in Information Systems. Journal of Organizational Computing and Electronic Commerce, 16(3–4), 179–202. https://doi.org/10.1080/10919392.2006.9681199

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. Business & Information Systems Engineering, 66(1), 111–126. https://doi.org/10.1007/s12599-023-00834-7

Fraccastoro, S., Gabrielsson, M., & Pullins, E. B. (2021). The integrated use of social media, digital, and traditional communication tools in the B2B sales process of international SMEs. International Business Review, 30(4), 101776. https://doi.org/10.1016/j.ibusrev.2020.101776

Frow, P., & Payne, A. (2009). Customer Relationship Management: A Strategic Perspective. Journal of Business Market Management, 3(1), 7–27. https://doi.org/10.1007/s12087-008-0035-8

Fui-Hoon Nah, F., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. Journal of Information Technology Case and Application Research, 25(3), 277–304. https://doi.org/10.1080/15228053.2023.2233814

Gong, T., & Yi, Y. (2018). The effect of service quality on customer satisfaction, loyalty, and happiness in five Asian countries. Psychology & Marketing, 35(6), 427–442. https://doi.org/10.1002/mar.21096

Grönroos, C. (2006). Adopting a service logic for marketing. Marketing Theory, 6(3), 317–333. https://doi.org/10.1177/1470593106066794

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). Pls-Sem: Indeed a Silver Bullet. Journal of Marketing Theory and Practice, 19(2), 139–151.

Han, R., Lam, H. K., Zhan, Y., Wang, Y., Dwivedi, Y. K. & Tan, K. H. (2021). Artificial intelligence in business-to-business marketing: A bibliometric analysis of current research status, development and future directions. Industrial Management & Data Systems, 121(12), 2467–2497. https://doi.org/10.1108/IMDS-05-2021-0300

Hirsjärvi, S., Remes, P. & Sajavaara, P. (2007). Tutki ja kirjoita. Tammi.

Homburg, C., Müller, M., & Klarmann, M. (2011). When Should the Customer Really be King? On the Optimum Level of Salesperson Customer Orientation in Sales Encounters.

Hu, H.-H. (Sunny), Kandampully, J., & Juwaheer, T. D. (2009). Relationships and impacts of service quality, perceived value, customer satisfaction, and image: An empirical study. The Service Industries Journal, 29(2), 111–125. https://doi.org/10.1080/02642060802292932

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Key figures on the use of personalization among businesses 2023. (ei pvm.). Statista. Noudettu 27. kesäkuuta 2024, osoitteesta https://www.statista.com/statistics/1415834/personalization-among-businesses-worldwide/

Kim, H.-W., Chan, H. C., & Gupta, S. (2007). Value-based Adoption of Mobile Internet: An empirical investigation. Decision Support Systems, 43(1), 111–126. https://doi.org/10.1016/j.dss.2005.05.009

Kim, J., & Lennon, S. J. (2013). Effects of reputation and website quality on online consumers' emotion, perceived risk and purchase intention. Journal of Research in Interactive Marketing, 7(1), 33–56. https://doi.org/10.1108/17505931311316734

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the Role of Artificial Intelligence in Personalized Engagement Marketing. California Management Review, 61(4), 135–155. https://doi.org/10.1177/0008125619859317

Kumar, V., Ramachandran, D., & Kumar, B. (2021). Influence of new-age technologies on marketing: A research agenda. Journal of Business Research, 125, 864–877. https://doi.org/10.1016/j.jbusres.2020.01.007

Kwon, K., & Kim, C. (2012). How to design personalization in a context of customer retention: Who personalizes what and to what extent? Electronic Commerce Research and Applications, 11(2), 101–116. https://doi.org/10.1016/j.elerap.2011.05.002

Lee, W.-I., Cheng, S.-Y., & Shih, Y.-T. (2017). Effects among product attributes, involvement, word-of-mouth, and purchase intention in online shopping. Asia Pacific Management Review, 22(4), 223–229. https://doi.org/10.1016/j.apmrv.2017.07.007

Li, C. (2016). When does web-based personalization really work? The distinction between actual personalization and perceived personalization. Computers in Human Behavior, 54, 25–33. https://doi.org/10.1016/j.chb.2015.07.049

Libai, B., Bart, Y., Gensler, S., Hofacker, C. F., Kaplan, A., Kötterheinrich, K., & Kroll, E. B. (2020). Brave New World? On AI and the Management of Customer Relationships. Journal of Interactive Marketing, 51, 44–56. https://doi.org/10.1016/j.intmar.2020.04.002

Lin, S.-W., & Lo, L. Y.-S. (2016). Evoking online consumer impulse buying through virtual layout schemes. Behaviour & Information Technology, 35(1), 38–56. https://doi.org/10.1080/0144929X.2015.1056546

Lynch, S. (10.3.2017). Andrew Ng: Why AI Is the New Electricity. Stanford Graduate School of Business. https://www.gsb.stanford.edu/insights/andrew-ng-why-ai-new-electricity

Ma, L., & Sun, B. (2020). Machine learning and AI in marketing – Connecting computing power to human insights. International Journal of Research in Marketing, 37(3), 481–504. https://doi.org/10.1016/j.ijresmar.2020.04.005

Martínez-López, F. J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. Industrial Marketing Management, 42(4), 489–495. https://doi.org/10.1016/j.indmarman.2013.03.001

Maslowska, E., Smit, E. G., & van den Putte, B. (2016). It Is All in the Name: A Study of Consumers' Responses to Personalized Communication. Journal of Interactive Advertising, 16(1), 74–85. https://doi.org/10.1080/15252019.2016.1161568

McKinney, L. N. (2004). Creating a satisfying internet shopping experience via atmospheric variables: International Journal of Consumer Studies. International Journal of Consumer Studies, 28(3), 268–283. https://doi.org/10.1111/j.1470-6431.2004.00368.x

Metsämuuronen, J. (2005). Tutkimuksen tekemisen perusteet ihmistieteissä. International Methelp.

Miceli, G. "Nino", Ricotta, F., & Costabile, M. (2007). Customizing customization: A conceptual framework for interactive personalization. Journal of Interactive Marketing, 21(2), 6–25. https://doi.org/10.1002/dir.20076

Moradi, M., & Dass, M. (2022). Applications of artificial intelligence in B2B marketing: Challenges and future directions. Industrial Marketing Management, 107, 300–314. https://doi.org/10.1016/j.indmarman.2022.10.016

Morwitz, V. G., & Schmittlein, D. (1992). Using Segmentation to Improve Sales Forecasts Based on Purchase Intent: Which "Intenders" Actually Buy? Journal of Marketing Research (JMR), 29(4), 391–405. https://doi.org/10.2307/3172706

Murthi, B. P. S., & Sarkar, S. (2003). The Role of the Management Sciences in Research on Personalization. Management Science, 49(10), 1344–1362. https://doi.org/10.1287/mnsc.49.10.1344.17313

Nguyen, B., & Mutum, D. S. (2012). A review of customer relationship management: Successes, advances, pitfalls and futures. Business Process Management Journal, 18(3), 400–419. https://doi.org/10.1108/14637151211232614

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187–192. https://doi.org/10.1126/science.adh2586

Ooi, K.-B., Tan, G. W.-H., Al-Emran, M., Al-Sharafi, M. A., Capatina, A., Chakraborty, A., Dwivedi, Y. K., Huang, T.-L., Kar, A. K., Lee, V.-H., Loh, X.-M., Micu, A., Mikalef, P., Mogaji, E., Pandey, N., Raman, R., Rana, N. P., Sarker, P., Sharma, A., … Wong, L.-W. (2023). The Potential of Generative Artificial Intelligence Across Disciplines: Perspectives and Future Directions. Journal of Computer Information Systems, 0(0), 1–32. https://doi.org/10.1080/08874417.2023.2261010

Paschen, J. (2020). Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. Business Horizons, 63(3), 403–414. https://doi.org/10.1016/j.bushor.2020.01.003

Payne, A., & Frow, P. (2005). A Strategic Framework for Customer Relationship Management. Journal of Marketing, 69(4), 167–176. https://doi.org/10.1509/jmkg.2005.69.4.167

Payne, A., & Frow, P. (2006). Customer Relationship Management: From Strategy to Implementation. Journal of Marketing Management, 22(1–2), 135–168. https://doi.org/10.1362/026725706776022272

Peltier, J. W., Schibrowsky, J. A., & Schultz, D. E. (2003). Interactive integrated marketing communication: Combining the power of IMC, the new media and database marketing. International Journal of Advertising, 22(1), 93–115. https://doi.org/10.1080/02650487.2003.11072841

Peña-García, N., Gil-Saura, I., Rodríguez-Orejuela, A., & Siqueira-Junior, J. R. (2020). Purchase intention and purchase behavior online: A cross-cultural approach. Heliyon, 6(6), e04284. https://doi.org/10.1016/j.heliyon.2020.e04284

Popularity of generative AI in marketing U.S. 2023. (2023b). Statista. https://www.statista.com/statistics/1388390/generative-ai-usage-marketing/

Prasad Agrawal, K. (2023). Towards Adoption of Generative AI in Organizational Settings. Journal of Computer Information Systems, 0(0), 1–16. https://doi.org/10.1080/08874417.2023.2240744

Ramani, G., & Kumar, V. (2008). Interaction Orientation and Firm Performance. Journal of Marketing, 72(1), 27–45. https://doi.org/10.1509/jmkg.72.1.027

Reimann, M., Schilke, O., & Thomas, J. S. (2010). Customer relationship management and firm performance: The mediating role of business strategy. Journal of the Academy of Marketing Science, 38(3), 326–346. https://doi.org/10.1007/s11747-009-0164-y

Reinartz, W., Krafft, M., & Hoyer, W. D. (2004). The Customer Relationship Management Process: Its Measurement and Impact on Performance. Journal of Marketing Research, 41(3), 293–305. https://doi.org/10.1509/jmkr.41.3.293.35991

Richards, K. A., & Jones, E. (2008). Customer relationship management: Finding value drivers. Industrial Marketing Management, 37(2), 120–130. https://doi.org/10.1016/j.indmarman.2006.08.005

Rodriguez, M., & Honeycutt Jr., E. D. (2011). Customer Relationship Management (CRM)'s Impact on B to B Sales Professionals' Collaboration and Sales Performance. Journal of Business-to-Business Marketing, 18(4), 335–356. https://doi.org/10.1080/1051712X.2011.574252

Rusthollkarhu, S. (2022). Managing B2B customer journeys in digital era: Four management activities with artificial intelligence-empowered tools. Industrial Marketing Management, 104, 241–257. https://doi.org/10.1016/j.indmarman.2022.04.014

Salonen, V., & Karjaluoto, H. (2016). Web personalization: The state of the art and future avenues for research and practice. Telematics and Informatics, 33(4), 1088–1104. https://doi.org/10.1016/j.tele.2016.03.004

Santini, F. de O., Ladeira, W. J., & Sampaio, C. H. (2018). The role of satisfaction in fashion marketing: A meta-analysis. Journal of Global Fashion Marketing, 9(4), 305–321. https://doi.org/10.1080/20932685.2018.1503556

Sin, L. Y. M., Tse, A. C. B., & Yim, F. H. K. (2005). CRM: Conceptualization and scale development. European Journal of Marketing, 39(11/12), 1264-1290,1392. https://doi.org/10.1108/03090560510623253

Soleymanian, M., Weinberg, C.B. and Zhu, T. (2019), "Sensor data and behavioral tracking: does usage-based auto insurance benefit drivers?", Marketing Science, Vol. 38 No. 1, pp. 21-43

Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. Industrial Marketing Management, 69, 135–146. https://doi.org/10.1016/j.indmarman.2017.12.019

Tam, K. Y., & Ho, S. Y. (2006). Understanding the Impact of Web Personalization on User Information Processing and Decision Outcomes. MIS Quarterly, 30(4), 865–890. https://doi.org/10.2307/25148757

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a New Dominant Logic for Marketing. Journal of Marketing, 68(1), 1–17. https://doi.org/10.1509/jmkg.68.1.1.24036

Vesanen, J. (2007). What is personalization? A conceptual framework. European Journal of Marketing, 41(5/6), 409–418. https://doi.org/10.1108/03090560710737534

Vesanen, J., & Raulas, M. (2006). Building bridges for personalization: A process model for marketing. Journal of Interactive Marketing, 20(1), 5–20. https://doi.org/10.1002/dir.20052

Winer, R. S. (2001). A Framework for Customer Relationship Management. California Management Review, 43(4), 89–105. https://doi.org/10.2307/41166102

Yana, A. A. G. A., Rusdhi H.A., & Wibowo, M. A. (2015). Analysis of Factors Affecting Design Changes in Construction Project with Partial Least Square (PLS). Procedia Engineering, 125, 40–45. https://doi.org/10.1016/j.proeng.2015.11.007

Zaichkowsky, J. L. (1985). Measuring the Involvement Construct. Journal of Consumer Research, 12(3), 341–352. https://doi.org/10.1086/208520

Zeynep Ata, U., & Toker, A. (2012). The effect of customer relationship management adoption in business ‐ to ‐ business markets. Journal of Business & Industrial Marketing, 27(6), 497 – 507. https://doi.org/10.1108/08858621211251497

Zhang, J., & Du, M. (2020). Utilization and effectiveness of social media message strategy: How B2B brands differ from B2C brands. The Journal of Business & Industrial Marketing, 35(4), 721–740. https://doi.org/10.1108/JBIM-06-2018-0190

Zhu, B., Kowatthanakul, S., & Satanasavapak, P. (2019). Generation Y consumer online repurchase intention in Bangkok: Based on Stimulus-Organism-Response (SOR) model. International Journal of Retail & Distribution Management, 48(1), 53–69. https://doi.org/10.1108/IJRDM-04-2018-0071

Zhu, L., He, L., Wang, F.-K., Wu, H., & Tian, Z. (2020). How online reviews affect purchase intention: A new model based on the stimulus-organism-response (S-O-R) framework. Aslib Journal of Information Management, 72(4), 463–488. https://doi.org/10.1108/AJIM-11-2019-0308

Malthouse, E. C., and Elsner, R. Customisation with cross-basis sub-segmentation. Database Marketing and Customer Strategy Management, 14, 1, 2006, 40–50.

APPENDIX 1 Survey

JYVÄSKYLÄN YLIOPISTO
UNIVERSITY OF JYVÄSKYLÄ

Tekoälyn hyödyntäminen personoinnissa ja asiakkuuksien hallinnassa

ⓘ Pakolliset kysymykset merkitty tähdellä (*)

Hei ja tervetuloa vastaamaan tähän kyselyyn!

Jos sinulla herää kysyttävää, otathan yhteyttä sähköpostitse:
vili.v.karppanen@student.jyu.fi.

1. Tässä linkki tiedotteeseen, jossa kerrotaan lyhyesti tästä tutkimuksesta.

Linkki tiedotteeseen: Tiedote

2. Mikä seuraavista kuvaa parhaiten sinun tilannettasi? *

Opiskelija

3. Mikä on syntymäkuukautesi?

*

Helmikuu

Seuraava

JYVÄSKYLÄN YLIOPISTO
UNIVERSITY OF JYVÄSKYLÄ

Tekoälyn hyödyntäminen personoinnissa ja asiakkuuksien hallinnassa

Pakolliset kysymykset merkitty tähdellä (*)

Kuvittele, että olet vastaanottanut alla olevan sähköpostin yritykseltä Q koskien heidän uutta tablettia (taulutietokone). Lue viesti tarkasti ja vastaa sen jälkeen seuraavan sivun kysymyksiin.

Tutustu Q-tabletin ainutlaatuisiin ominaisuuksiin!

Q-tabletti on innovatiivinen työkalu muistiinpanojen tekemiseen, joka jäljittelee perinteistä kynän ja paperin käyttökokemusta. Sen käyttö on intuitiivista ja silmiä säästävää, sillä tabletin näyttö on suunniteltu lukemista helpottamaan. Tämä tekee siitä erinomaisen vaihtoehdon pitkäaikaiseen kirjoittamiseen ja lukemiseen verrattuna perinteisiin tietokoneisiin ja tabletteihin, jotka voivat rasittaa silmiä.

Miksi valita Q tavallisen tietokoneen sijaan muistiinpanojen tekoon?

Q-tabletti on suunniteltu erityisesti kirjoittamisen ja luonnostelun tarpeisiin. Sen ainutlaatuinen paperimainen pinta ja erittäin herkkä kynä tarjoavat luonnollisen tunteen kirjoittaessasi, mikä mahdollistaa keskittymisen ilman häiriöitä, joita monien tietokoneohjelmien monimutkaiset toiminnot saattavat aiheuttaa.

Haluatko nopeuttaa työprosessiasi ja tehostaa toimintaasi?

Q-tabletti auttaa sinua järjestämään muistiinpanosi tehokkaasti ja synkronoimaan ne turvallisesti kaikkien laitteidesi kanssa. Voit myös jakaa muistiinpanoja helposti kollegoillesi, mikä tekee yhteistyöstä vaivatonta.

Aloita tehokkaampi ja keskittyneempi työskentely jo tänään Q-tabletin avulla. Tutustu lisää ja koe, kuinka yksinkertainen työkalu voi mullistaa muistiinpanojen tekemisen!

Tutustu Q-tablettiin – opiskelijan unelmatyökaluun!

Q-tabletti tarjoaa ainutlaatuisen ja silmiä säästävän tavan tehdä muistiinpanoja, mikä jäljittelee täydellisesti perinteisen kynän ja paperin käyttökokemusta. Sen erityisesti lukemista helpottava näyttö tekee siitä ihanteellisen vaihtoehdon pitkille opiskelusessioille, ilman perinteisten tietokoneiden ja tablettien aiheuttamaa silmien rasitusta.

Miksi Q on paras valinta yliopisto-opiskelijalle?
Q-tabletin paperimainen pinta ja herkkä kynä takaavat luonnollisen kirjoitustuntuman, joka edistää keskittymistäsi ja ideoidesi virtausta. Tämän ansiosta voit pitää yksityiskohtaiset ja jäsennellyt muistiinpanot luennoista ja seminaareista ilman perinteisen sähköisen laitteen häiriötekijöitä.

Kevyt ja kannettava muotoilu tekee Q:sta täydellisen kumppanin kampuksella liikkuvalle opiskelijalle. Se mahtuu helposti reppuun eikä vaadi jatkuvaa lataamista, joten voit luottaa siihen päivän jokaisessa oppitunnissa ja opiskelusessiossa. Unohda huoli hukkaan menneistä muistikirjoista tai etsimisestä – kaikki tärkeät muistiinpanosi ovat turvallisesti tallessa ja synkronoituna.

Opiskelijaelämää helpottavat ominaisuudet:
• **Synkronointi:** Q synkronoi muistiinpanosi saumattomasti kaikkiin laitteisiisi, joten voit palata niihin milloin tahansa, missä tahansa.
• **Jaa helposti:** Voit jakaa muistiinpanoja ja luonnoksia suoraan opiskelukavereillesi, mikä helpottaa ryhmäprojekteja ja yhteistyötä.
• **Digitaalinen muistikirja:** Säästä tilaa ja rahaa, sillä voit korvata useat fyysiset muistikirjat yhdellä Q-tabletilla.

Koe itse, miten Q-tabletti voi mullistaa tapasi opiskella ja hallita akateemista elämääsi. Hanki oma ja aloita keskittyneempi ja järjestäytyneempi opiskelu tänään!

Edellinen | Seuraava

JYVÄSKYLÄN YLIOPISTO
UNIVERSITY OF JYVÄSKYLÄ

Tekoälyn hyödyntäminen personoinnissa ja asiakkuuksien hallinnassa

Pakolliset kysymykset merkitty tähdellä (*)

4. Vastaa alla esitettyihin väittämiin sähköpostin personointiin liittyen. *

	Täysin eri mieltä.	Eri mieltä.	Jokseenkin eri mieltä.	En samaa enkä eri mieltä.	Jokseenkin samaa mieltä.	Samaa mieltä.	Täysin samaa mieltä.	En osaa sanoa.
Tämä sähköposti on räätälöity tilanteeni mukaan.	○	○	○	○	○	○	○	○
Koen, että tämä sähköposti on muokattu vastaamaan tarpeitani.	○	○	○	○	○	○	○	○
Koen, että tämä sähköposti on muokattu vastaamaan ominaisuuksiani.	○	○	○	○	○	○	○	○
Tämä sähköposti on muokattu profiilini mukaan.	○	○	○	○	○	○	○	○

5. Vastaa alla esitettyihin väittämiin koskien kokemaasi arvoa sähköpostista.

	Täysin eri mieltä.	Eri mieltä.	Jokseenkin eri mieltä.	En samaa enkä eri mieltä.	Jokseenkin samaa mieltä.	Samaa mieltä.	Täysin samaa mieltä.	En osaa sanoa.
Todella hyödyllinen	○	○	○	○	○	○	○	○
Todella tehokas	○	○	○	○	○	○	○	○
Suureksi avuksi minulle	○	○	○	○	○	○	○	○

6. Vastaa alla esitettyyn väittämään koskien tyytyväisyyttäsi sähköpostiin. *

	Täysin eri mieltä.	Eri mieltä.	Jokseenkin eri mieltä.	En samaa enkä eri mieltä.	Jokseenkin samaa mieltä.	Samaa mieltä.	Täysin samaa mieltä.	En osaa sanoa.
Yleisesti ottaen olen tyytyväinen tähän sähköpostiin.	○	○	○	○	○	○	○	○

7. Vastaa alla oleviin väittämiin olettaen, että sähköpostissa esitelty tuote olisi saatavilla. *

	Hyvin epätodennäköistä.	Epätodennäköistä.	Jokseenkin epätodennäköistä.	Ei todennäköistä eikä epätodennäköistä.	Jokseenkin todennäköistä.	Todennäköistä.	Hyvin todennäköistä.	o sa
Olisiko mainostetun tuotteen ostaminen todennäköisempää vai epätodennäköisempää esitetyn sähköpostin perusteella?								
Kuinka todennäköistä on, että harkitsisit mainostetun tuotteen ostamista esitetyn sähköpostin perusteella?								
Kuinka todennäköistä on, että ostaisit mainostetun tuotteen luettuasi sähköpostin?								
Kuinka todennäköistä on, että etsisit mainostetun tuotteen ostaaksesi sen?								

8. Vastaa alla esitettyihin väittämiin koskien asennettasi tabletteja (taulutietokoneita) kohtaan. *

	Täysin eri mieltä.	Eri mieltä.	Jokseenkin eri mieltä.	En samaa enkä eri mieltä.	Jokseenkin samaa mieltä.	Samaa mieltä.	Täysin samaa mieltä.	En osaa sanoa.
Merkitsee minulle paljon								
Hyödyllinen								
Kiinnostava								
Tarpeellinen								
Tärkeä								
Arvokas								
Jännittävä								

Edellinen Seuraava

JYVÄSKYLÄN YLIOPISTO
UNIVERSITY OF JYVÄSKYLÄ

Tekoälyn hyödyntäminen personoinnissa ja asiakkuuksien hallinnassa

Pakolliset kysymykset merkitty tähdellä (*)

9. Ikä *

Valitse

10. Sukupuoli *

Valitse

11. Käytätkö jo tämänkaltaista tuotetta? *

Valitse

Edellinen | Lähetä