THE COMPUTER KNOWS BEST: AI-POWERED PERSONALIZATION IN MARKETING THROUGH THE LENS OF DATA PRIVACY

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ABSTRACT

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Abstract

This master's thesis examines AI integrated marketing personalization and its relationship to consumer privacy. The aim of the research is to enhance understanding on how personalized marketing is made more effective with the use of AI, and how are the possibilities and limitations of the practice reflected on current data regulations and consumer attitudes about privacy. Previous research on personalization has slightly touched on AI integration but has not considered consumer privacy as a significant part of this development. Therefore, it was deemed necessary to examine the three subjects comprehensively.

The study employed a qualitative approach, collecting data through semi-structured individual interviews. Data collection was conducted in April-May of 2024, involving six experts in marketing AI. Data analysis was conducted through an abductive thematical analysis approach.

The research findings highlight many key aspects of AI-driven personalized marketing. AI enhances targeted marketing by leveraging data-driven insights to predict and understand consumer behaviors, creating more tailored and relevant experiences. However, the effectiveness of AI personalization depends on ethical data collection and privacy measures, with a rising importance of unstructured data introducing new challenges for consent and copyright. Additionally, data silos within companies and strict GDPR regulations hinder the development of AI-powered personalization, emphasizing the role of company culture and leadership in ensuring privacy compliance. The study also underscores the significant impact of human error in data categorization on personalization algorithms, expanding the theoretical understanding of biases in AI-driven marketing. Future studies focusing more on these aspects possibly in other contexts could offer new insights for the development and control of personalized marketing in the era of artificial intelligence.

Keywords
Artificial intelligence, personalization, algorithms, privacy, consumer privacy, data, data regulation

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Tiivistelmä

Tämä pro gradu -tutkielma käsittelee tekoälyn avulla tuotettua personoitua markkinointia ja sen suhdetta kuluttajien tietoturvaan ja yksityisyyteen. Tutkimuksen tavoitteena on lisätä ymmärrystä siitä, kuinka tekoälyllä voidaan tehostaa personoitua markkinointia, ja miten tämän käytännön mahdollisuudet ja rajoitukset peilautuvat tietosuoja-asetuksiin sekä kuluttajien yksityisyyttä koskeviin asenteisiin. Aikaisemmassa personalisointia käsittelevissä tutkimuksissa on sivuttu hieman tekoälyn integraation eri aspekteja, mutta kuluttajien yksityisyyttä ei ole tarkasteltu yhtä merkittävänä osana tätä kehitystä. Tämän vuoksi on tarpeen tarkastella näitä kolmea aihetta kattavasti yhdessä.

Tutkimuksessa käytettiin kvalitatiivista lähestymistapaa, ja aineisto kerättiin puolistrukturoiduilla yksilöhaastatteluilla. Aineistonkeruu toteutettiin huhti-toukokuussa 2024, ja osallistujat koostuivat kuudesta markkinointialan tekoälyasiantuntijasta. Aineiston analyysi toteutettiin abduktiivisen lähestymistavan mukaisella temaattisella analyysillä.

Tutkimustulokset korostavat monia keskeisiä näkökohtia tekoälyllä ohjatusta personoidusta markkinoinnista. Tekoäly parantaa kohdennettua markkinointia hyödyntämällä datalähtöisiä johtopäätöksiä ja käsityksiä kuluttajakäyttäytymisen ennustamiseen ja ymmärtämiseen, luoden näin räätälöidympiä ja relevantimpia osto- ja asiakaskokemuksia. Tekoälypersonoinnin tehokkuus kuitenkin riippuu eettisestä datankeruusta ja kuluttajan yksityisyyttä koskevista suojatoimista. Rakenteettoman datan merkityksen kasvaessa nousevat esiin uudenlaiset haasteet datavaihdon suostumuksen ja tekijänoikeuksien osalta. Lisäksi yritysten sisäiset datasiilot ja tiukat GDPR-säädökset vaikeuttavat tekoälypohjaisen personoinnin kehittämistä, mikä osaltaan korostaa yrityskulttuurin ja johdon roolia yksityisyydensuojan varmistamisessa. Tutkimus korostaa myös inhimillisten virheiden merkittävää vaikutusta datan kategorisoinnissa personointialgoritmeihin, laajentaen teoreettista ymmärrystä tekoälyllä ohjatun markkinoinnin harhoista. Tulevat tutkimukset, jotka keskittyvät enemmän näihin näkökohtiin mahdollisesti muissa konteksteissa, voivat tarjota uusia näkemyksiä personoidun markkinoinnin kehittämiseen ja hallitsemiseen tekoälyn aikakaudella.

Avainsanat
Artificial intelligence, personalization, algorithms, privacy, consumer privacy, data, data regulation

Säilytyspaikka: Jyväskylän yliopiston kirjasto

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1 INTRODUCTION

1.1 Research background

Artificial intelligence (AI) powered technology has seen significant advancements particularly in the last few years. A technology that in the past was seen by the general public as mostly just a fascinating part of computational evolution, much reminiscent of science fiction literature and robotics, is now present in the life of nearly all consumers in one way or another. It now seen as a certainty that AI will have an even more wide ranging effect on marketing practice, as it begins to transform different marketing strategies and processes , not to mention its influence on customer behaviors (Davenport et al., 2020). By expediting the decision-making process and providing marketing managers with to data and insights that they could not obtain in any other way, AI is predicted to increase the efficiency of marketing multifold (Overgoor et al., 2019). According to Hildebrand (2019), AI has evolved from a technology to the engine of a new economy that runs on the synergy of data, algorithms, and computational power. AI primarily utilizes "big data", a term for large customer databases that have resulted from an explosion of customer data through advances in communication technology, data storage capability, and computational speed (Rust, 2020). The Big data revolution combined with high performance computing systems has allowed tech and marketing professionals to train and develop different AI methods to suit their needs (Overgoor et al., 2019).

These technological advancements have coincided with shifts in customer expectations, which have in recent decades required increasingly personalized offerings from marketers, thus expanding research on the concept known as personalization. More specifically, personalization aligns with the broader market trend of individualizing consumer-business interactions in contexts with abundant data. (Mehmood et al., 2023.) Personalization is currently at the heart of marketing, though it's research is very multidisciplinary, intersecting with theoretical frameworks of corporate management, computer science, and psychology for example (Chandra et al., 2022) In essence personalization makes use of information sourced from each customer's behavioral and personal data. Proper personalization typically necessitates consumer engagement in order to create a truly personalized experience, which is possible through the collection of social media interactions, purchase data, and customer reviews, among other things. (Cloarec et al., 2022; Lim et al., 2022.) These behaviors and preferences are then used to present (or even produce) advertising content, services and products with the greatest relevance and conversion potential (Shareef & Reddy, 2019).

Unlike customization or other individual marketing efforts, personalization consists of companies determining how to modify a particular touch point for customers, rather than customers taking the initiative (Bleier et al., 2018; Mehmood et al., 2023; Song et al., 2021). In the increasing competition to be the most relevant in the hearts and minds of shoppers', personalization will in the near future likely serve as the basis of robust customer relationships and will become a necessary wager to enter the marketing competition (Pearson, 2019). Loyalty and satisfaction of customers are now deeply intertwined with an organization's capacity to understand, predict, and address individual customer preferences, and not just the quality of an offered product or a service (Rane et al., 2023).

AI can and has been utilized in marketing in many ways, and it is especially helpful in facilitating customer profiling and personalizing content. In personalization efforts the desired benefits are mainly acquired through the use of analytical automation, which Huang & Rust (2021) refer to as analytical AI or thinking AI. Thinking AI is made to analyze data and draw new judgments or conclusions from mostly unorganized data. Text mining and speech recognition are well known examples of thinking AI's proficiency in identifying patterns and regularities in data. Current techniques for thinking AI to handle data mostly include machine learning, neural networks, and deep learning (Huang & Rust, 2021), which all point to clear improvement compared to earlier days of automation and analytics. Many researchers suggest that when used through machine learning to evaluate vast volumes of consumer data to identify client preferences in real time, AI will improve e-commerce by providing more profitable and tailored customer experiences (Davenport, 2023; Nguyen et al., 2022; Peltier et al., 2023). According to Kumar et al. (2019), the significance of AI-powered solutions is in their potential to help companies tackle three major challenges regarding the success of personalization initiatives, which include the volume and quality of customer data, the ability of companies to generate insights from customer data; and the effective implementation of the gathered insights. Personalization and AI are both fundamentally systems that improve their learning and adaptability when they have access to abundant and high-quality user information (Bartneck et al., 2021).

To consumers this purported benefit of a better and more effective customer experience comes with the cost of reduced privacy, and to many consumers the more personalized digital marketing becomes, the more intrusive it is usually viewed (McKee et al., 2023; Smink et al., 2020). Concerns regarding privacy have risen in parallel with the personalization of products and services, as this process inherently demands knowledge about the buyer's sociodemographic characteristics, geolocation, behavior, and in certain situations even biometric data (Scarpi et al., 2022). Data hungry corporations have alerted public policymakers especially in Western societies, and consumers' growing privacy concerns have hindered the acceptance of some digital innovations, especially AI-enabled technologies (Hildebrand, 2019; Peltier et al., 2023). Increasingly apparent risks linked to AI-based data breaches have made consumers value their data even more (Kopalle et al., 2022), even though their online behavior seldom expresses it (Hargittai & Marwick, 2016; Hoffmann et al., 2016).

Personalization efforts in marketing encounter various challenges, including controlling large volumes of data and algorithms, managing data integration and accessibility, addressing privacy concerns, and complying with regulatory frameworks like the GDPR (Aguirre et al., 2015; Mehmood et al., 2023). It is thus essential to see data privacy policy as a crucial part of the equation between AI and personalization, as a steady supply of quality information and data is a crucial prerequisite of effective AI utilization, but too little regulation may make consumers wary of AI-related applications, particularly when they facilitate customer profiling (Davenport et al., 2020). As advancements in data-driven personalization and programmatic advertising persist, worries about the state of consumer privacy have become a major avenue for future research underlined by many scholars (See Boerman & Smit, 2023; T. Davenport et al., 2020; Du & Xie, 2021; Hermann, 2022; Huang & Rust, 2021; Kopalle et al., 2022; Nguyen et al., 2022). Maintaining consumers' willingness to share data is an important objective for marketers who hope to utilize these technologies effectively in the future (Kopalle et al., 2022), thus pointing toward a need for research that explores how AI integrated marketing can potentially compromise consumer privacy (Kronemann et al., 2023). The latest advances in data-driven marketing may be in danger of becoming largely obsolete if consumers primarily see themselves being made increasingly vulnerable. Technological progress should after all be molded by ethical concerns, instead of the two sides annulling each other.

1.2 Purpose of the thesis and research questions

AI in marketing is without a doubt a very trendy research topic, as for example the number of annual publications concerning AI in marketing and psychology nearly quadrupled between 2010 and 2021 (Mariani et al., 2022). But despite having been researched from a plethora of angles in marketing literature, studies concerning AI and other emerging technologies have failed to properly mirror the views of the data privacy landscape, i.e. the effects of strengthening data regulations and consumer attitude trends, to the possibilities in the implementation and development of these technologies. While marketers start to implement AI and other similar technologies, they need to fully grasp the prerequisites of these tools. Never has marketing been so clearly dependent on a steady flow of data, and this dependency will surely be even stronger in the future. Moreover, research on AI's impact on personalization in marketing is limited, lacking a comprehensive understanding of their relationship and ethical challenges. This study focuses specifically on personalization due to its reliance on consumer data collection and analysis, rather than attempting to cover all AI tools and their impacts on consumer privacy within the confines of a single master's thesis.

Therefore, the purpose of this master's thesis is to examine the impact AI currently has, and is expected to have on personalized marketing, and how possible changes in the data privacy landscape will affect the implementation of AI in this context, while outlining the data quality and structure requirements for AI. To fulfil this purpose, this masters' thesis attempts to answer the main research question of *How does AI facilitate greater personalized marketing to consumers, and how is it influenced by consumer privacy regulations and attitudes?* To construct a thorough answer to this question, a comprehensive understanding of the concepts involved will be gathered with the help of the following three sub-research questions:

- RQ1: How does personalized marketing influence the relationship between consumers and companies?

- RQ2: How does the integration of AI technologies contribute to the overall effectiveness of personalized marketing?

- RQ3: What influences the relationship between AI-facilitated personalization and consumer data privacy concerns?

The results of this study provide many theoretical implications about personalization and the critical role of AI in enhancing it and in the development of marketing overall, and how the development of AI capabilities and privacy aspects reflect each other theoretically. Practical implications for companies on how to implement AI-powered technologies in their marketing efforts, and how they should adapt to make the most out of the complex environment of artificial intelligence and data.

1.3 Research structure

This masters' thesis consists of five main chapters. The introductory chapter explains the background and purpose of the study. Additionally, this chapter includes the research questions and structure of the study. The second chapter delves into the world of AI and personalization in marketing and examines the relationship between the two. In the third chapter, the current landscape of data privacy regulations and trends, as well as the different dimensions in data quality and structure are examined. The second and the third chapter combined provide a thorough literature review about the topics at hand and form a theoretical framework to guide the study.

The fourth chapter present the research methodology utilized in the study, including the selection criteria and relevant information about the interviewees as well as the nature of data gathering. This study undertook a qualitative research approach, by collecting data through six semi-structured thematic interviews with marketing professionals that possess expertise regarding artificial intelligence and data. This methodology was selected in order to gather nuanced and information-rich data that was as current and applicable as possible. The key empirical findings of the study are covered in the fifth chapter, in which the interview results are presented through direct quotations and summary paragraphs. Ultimately, the research findings are evaluated and interpreted in the sixth chapter by relating them to the study's theoretical framework. This chapter also seeks to provide comprehensive answers to the study objective and research questions. The study's theoretical contributions are complemented by several management implications, an assessment of the study's strengths and weaknesses, and recommendations for further research in the concluding chapter.

In this thesis, AI-based text applications have been used during the research process. The language model ChatGPT 3.5 has been utilized in editing and formatting of the text. In addition, the language model has been used to help form interview questions and in the translation of interview answers.

2 AI-POWERED PERSONALIZATION

This chapter concentrates on how artificial intelligence has transformed and enhanced marketing procedures and personalization efforts in particular. A specific focus is placed on the features of the technical components under the umbrella of AI, and the different steps in the personalization process. The last subchapter examines ways in which AI benefits personalization specifically.

2.1 AI implementation in marketing

Marketing stands at the forefront of a technological upheaval. As mentioned before, data and intelligence are now the bread and butter of contemporary marketing (Chintalapati & Pandey, 2022). Individual consumers have become boundless fountains of data to customers, and the development of artificial intelligence (AI) technology now allows companies to access and utilize this abundance of customer data remarkably easier, which perhaps more importantly includes enormous amounts of varied forms of data, due to the lack of need for human intervention (Chen et al., 2021). In addition to playing a crucial role in marketing decision-making with contributions to processing and analyzing data, AI has greatly enhanced the development of voice-activated devices, while making intelligent marketing systems an industry standard (Davenport et al., 2020; Wu & Monfort, 2023). A significant catalyst for shifts in job roles due to algorithms especially in marketing and IT, AI is anticipated to be implemented by around 75% of businesses surveyed by the World Economic Forum, a trend predicted to result in both job expansions and job losses (World Economic Forum, 2023).

In general, AI encompasses a range of digital technologies and commercial features that enable the automation of cognitive functions, notably expanding beyond the act of only automating repetitive and routine tasks, to performing processes that require human intelligence (Haleem et al., 2022; Huang & Rust, 2021). Focusing on contemporary marketing, Peltier et al. (2023) define AI as "adaptive learning and decision-making systems that mimic human intelligence through the autonomous processing, analysis, and interpretation of data problem-solving and goal attainment purposes". AI's applicability in marketing spans both B2B and B2C markets, offering insights into customer preferences, perceptions, and actions. By leveraging data analysis, marketers can predict and hyperpersonalize value propositions, potentially mitigating issues like customer churn and shopping cart abandonment, while fostering outcomes like enhanced customer loyalty and positive word-of-mouth. (Latinovic & Chatterjee, 2022; Paschen et al., 2019; van Esch & Stewart Black, 2021.) Definitions of the most salient components under the umbrella of AI are presented in table 1.

While many marketing managers may be easily overwhelmed by all the possibilities of AI, Hanssens (2020) argues that the most impactful marketing actions in the end result from a combination of effective communication, customer value, and distribution. What makes implementing this principle so challenging however are the specialized skills AI initiatives require, resulting in a fragmented mess of decision-making silos in an organization. Thus, integrating the needed technological developments regarding AI with a holistic approach is a key objective for marketing managers. (Hanssens, 2020.) Malthouse & Copulsky (2023) moreover argue that while algorithms are central to AI, they are very much dependent on the surrounding marketing technology environment to be valuable for advertisers and customers, mainly consisting of digital environments that manage important touchpoints and allow for continuous testing and optimizing.

Concept	Definition(s)
Machine learning (ML)	"A subset of artificial intelligence that involves the development of algorithms and models that enable computers to learn from and make predictions or decisions based on data without being explicitly programmed"(Dwyer et al., 2018)
Deep Learning (or Artificial Neural Networks, ANN)	"A subset of machine learning where neurons are organized in multiple successive layers. The increase of layers improves the expression power and performance of these methods and could produce higher level of abstraction. Deep learning currently represents the most advanced machine learning technique for a variety of high-level tasks and applications, especially for problems involving large, structured training". (Chassagnon et al., 2020)
Big Data	"A term used to describe data that due to its volume, rapidity in generation, and its diversity in terms of variety of data types provides marketers with an important area of opportunity to inform decision making" (Erevelles et al., 2016)
Data Mining	"Process of searching and analyzing data to detect implicit, but potentially useful, information" (Linoff & Berry, 2011)
Natural language processing or NLP	"Models that automatically manipulate natural language designed primarily for analysis of text data." (Shankar & Parsana, 2022)

Table 1: Primary concepts concerning Artificial Intelligence.

2.1.1 Main types of AI

Today AI has a role in nearly all marketing processes, ranging from everyday operational tools to important strategic decisions. Huang & Rust (2020) divide this wide array of AI tools in three categories based on their capabilities and functionalities regarding their application in marketing: mechanical AI, thinking AI, and feeling AI. Mechanical AI, much like regular automation, helps marketers streamline processes repetitive routines such as data collection and standardization efficiently, facilitating a base for market research. What separates mechanical AI from automation ability to perform tasks that require a level of intelligence, such as pattern recognition. These systems are also more adaptable and capable in more complex environments An important limitation of mechanical AI is that much of its data is non-contextual, making it akin to lower-level analytics software in interactions containing emotional data. (Huang & Rust, 2021.) A right kind of mechanical AI application excels in dealing efficiently with routine interactions without compromising customer intimacy and data regulations (Treacy & Wiersema, 1993).

Thinking AI on the other hand is able to analyze collected sets of data as to eventually derive insights and make decisions. In processing data thinking AI utilizes primarily machine learning and deep learning methods which are discussed in depth later. Thinking AI concerns the central tools needed for customer personalization due to its capability in identifying trends, correlations with various types of data, and an overall efficiency in transforming data patterns in to informed conclusions. Thinking AI is especially helpful when utilized in product and branding actions, as big data analytics may be used to influence product development to adapt to consumer trends and shifting tastes. Likewise marketing analytics can forecast market trends through thinking AI for product design that more accurately serve the main interest groups. (Huang & Rust, 2021.)

As mechanical AI raises questions about potentially pervasive data collection, so does thinking AI pose ethical challenges. In addition to a likely non-transparent logical function, a major concern with thinking AI involves the possible biases and other unethical consequences that may result from its algorithmic problem-solving. This usually includes amplifying racial biases, or determining a consumer’s willing-to-pay-estimates in order to utilize clearly overblown dynamic pricing. (Haenlein et al., 2022; Shartsis, 2019.)

The third subset of artificial intelligence, feeling AI, is mainly used to show empathy and tailor services immediately, even in real-time. It not only detects human emotions but also replicates and reacts with artificial emotions, such as recognizing a customer's mood as sadness or excitement. Thus, feeling AI can now essentially comprehend and engage with customers on a social, emotional, and relational level. (Huang & Rust, 2021.) These empathetic interactions are particularly helpful in various service fields like healthcare, personal services, and education, but also in retail situations, where AI helps guiding customers throughout their service experience. (Mende et al., 2023; Peltier et al., 2023.) The healthcare sector for instance is introducing emotional assessment methods for mental health work and diagnostics. This however also brings forth significant ethical and privacy dilemmas, particularly surrounding consent and data security, which underlines a pressing need for more responsible and ethical implementation of AI. (Predin, 2024.)

Nevertheless, each of the three AI categories possess great potential in various stages of the strategic marketing lifecycle. Huang & Rust (2021) present that in the continuous lifecycle of marketing, mechanical and thinking AI are essential in analyzing the market and acquiring sufficient amounts of data, after which the findings can be deconstructed into the STP-model. Personalization, the emphasis of this study, applies the research and strategy in action, and feeds the results to help form more market data, thus continuing the cycle, as demonstrated in figure 1. (Huang & Rust, 2021.)

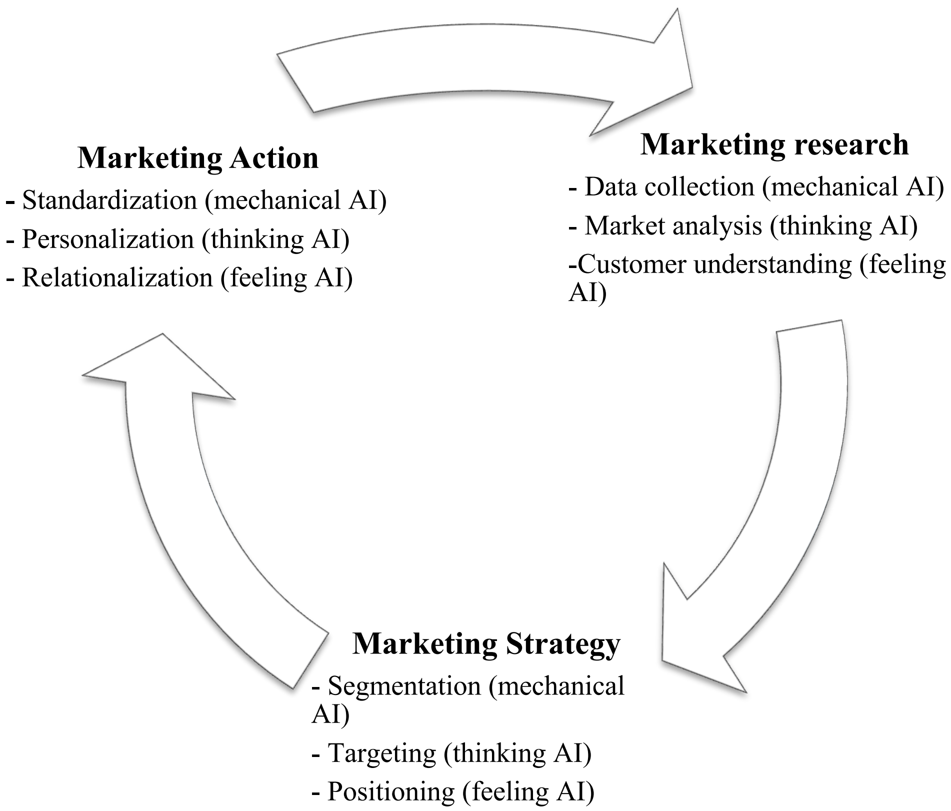

Figure 1: Different AI modes as tools in marketing strategy (adapted from Huang & Rust, 2021)

2.1.2 Technical components of AI

Often in technological discourse, artificial intelligence is used as an umbrella term to mean various types of technological instruments and concepts. AI, ML, and deep learning (DL) are also often used interchangeably despite not being synonymous (De Mauro et al., 2022). AI as a mechanism encompasses a system's capability to interpret external data accurately, learn from it, and apply those learnings to accomplish specific tasks through adjustments (Peltier et al., 2023). An algorithm can consequently be defined as a set of rules that guide an AI program to self-learn (Rodgers & Nguyen, 2022). ML is on the other hand a subset of AI, focused on creating computers that can enhance their performance automatically with experience, mainly through data. It involves methods or algorithms aimed at understanding underlying patterns in data and basing predictions on those patterns. The remarkable efficiency of ML has sparked a relentless hunger for increasingly vast amounts of personal data and the hardware required to gather and analyze it (Das et al., 2023). DL, a branch of ML, involves extracting knowledge from data to form a hierarchy of concepts, allowing computers to grasp complex ideas from simpler ones. These concepts are therefore organized in layers stacked on top of each other. (De Mauro et al., 2022.)

Machine learning is seen by many as the quintessential branch of artificial intelligence and has thus gained more interest in AI research in recent years. AI's potential in marketing, whether broad or limited, hinges largely on machine learning, either in supervised or unsupervised environments (van Esch & Stewart Black, 2021). Recommender systems at e-commerce websites and multimedia platforms like Amazon and Netflix are for example driven by advanced machine learning algorithms (Ma & Sun, 2020), and its impact on optimizing pricing and media strategy is unarguable (De Mauro et al., 2022). All AI models, including the aforementioned machine learning models, utilize computer algorithms to enhance their performance by learning from datasets known as training datasets. After a computer has learned to generate accurate outputs based on these datasets or variables, a separate dataset, known as a testing dataset, is used to assess its performance. This process of training, testing, and refining the algorithm is repeated multiple times until it shows reliability in analyzing large datasets (Moradi & Dass, 2022). Research usually acknowledges three main types of machine learning or learning processes: supervised learning, unsupervised learning, and reinforcement learning (Kaplan & Haenlein, 2018).

Supervised learning techniques link a specified set of inputs to a corresponding set of labeled outputs. These methods are often less intimidating for managers, as they include approaches that may be familiar from basic statistics courses, such as linear regression or classification trees. However, this category also encompasses more advanced methods like neural networks. (Kaplan & Haenlein, 2018.) Similar to a classroom setting where students a guided by a teacher, these models are used to serve a specific task and often contain some amount of manually annotated data, which is part of any of three categories at random: training data, testing data, or validation data (Rani et al., 2023).

Semi-supervised learning on the other hand leverages both labeled and unlabeled data for specific tasks. Initially, the system is trained with manually labeled data, and then it predicts the remaining portion using unlabeled data. Eventually, a complete dataset containing both labeled and semi-labeled data is used for network training. The aim of this is to combine the advantages of supervised and unsupervised learning methods. (Kaplan & Haenlein, 2018.) As the output is autonomously generated by the algorithm, evaluating the accuracy or correctness of the output becomes challenging. Therefore users must rely heavily on the AI system, which may cause worry for marketing managers responsible for its biases. (Rani et al., 2023.) Speech recognition seen for example with Apple’s

Siri is usually conducted through unsupervised learning (Kaplan & Haenlein, 2018).

To many the most efficient learning process, unsupervised learning aims to identify hidden patterns within unlabeled data, eliminating the need for manual annotations. This method typically involves clustering, where the algorithm organizes the data into groups based on similarities, patterns, and differences. It allows the computer to process unlabeled data independently, without the need for human supervision. (Rani et al., 2023.) Beneficial for B2C and B2B companies alike, unsupervised learning facilitates hyper-segmentation, which in turn produces extremely intelligent personalization algorithms (Moradi & Dass, 2022). A distinct concept from the three learning models mentioned is reinforcement learning, in which an agent learns to make decisions by interacting with an environment to maximize rewards or avoid penalties. Essential component of autonomous vehicles, it involves approximating the relationship between actions and long-term outcomes, often utilizing deep neural networks. While applications in marketing are emerging, the main challenges still include balancing exploration and exploitation and handling delayed rewards, meaning that when an agent receives a reward/penalty at the end of a long process it has to track actions leading to it. (De Bruyn et al., 2020.) The reinforcing information is also often qualitative, and thus unhelpful in determining exact measures of error (Bonaccorso, 2018, 21).

Artificial neural networks and Deep Learning are also fundamental components of many AI applications. They are the basis of image recognition algorithms employed by social media platforms, as well as the speech recognition systems of smart speakers (Haenlein & Kaplan, 2019). Deep learning techniques have proven effective across all three previously discussed ML categories. A range of deep neural network structures tailored to different data types have demonstrated notable success, although they require large amount of offline training time and data in the process. (Overgoor et al., 2019.)

All of these mechanics utilized in decision making are made possible through the influx of data inside every business, referred to usually as Big Data (De Mauro et al., 2022). The most important categorization of this heap of data divides it into two main categories: structured and unstructured data. Structured data resides in organized systems presented in rows and columns, like information found in an Excel datasheet, and it adheres to a specific data model. Unstructured data on the other hand lacks a predefined data model. Text files such as customer reviews or their social media posts, images, videos are major sources of unstructured data to companies. (Latinovic & Chatterjee, 2022.) With unstructured data reaching absurd numbers in size, the organizations to first master the extraction and process of it will optimize their AI cycle (Thakur & Kushwaha, 2023).

2.1.3 Ethical concerns of AI marketing

As AI has become more integrated across industries and sectors, it transcends being just a technology, becoming a powerful force reshaping and benefiting societies by reducing costs and increasing consistency in all kinds of processes (Hermann, 2022). While providing innovative and quick solutions to many complex problems, AI-driven marketing and consumption brings forth many ethical controversies and challenges in many different dimensions of business and society, the main culprit being an algorithm built by machine learning and deep learning. Puntoni et al. (2020) importantly point out that algorithms are often characterized as tools produced only out of efficiency and accuracy, an approach popular in computer science that may disregard many complexities on the social and individual level. This outlook indeed provides a breeding ground for algorithmic practices that are outright predatory and discriminatory (André et al., 2018).

Although AI focused research in marketing is booming and many companies are investing in its development, most researchers claim that the knowledge and application of AI-based tools is still often too shallow. Many companies that utilize these systems are faced with the challenge of truly understanding the inner workings of the models and algorithms that yield them great results. According to Rai (2020), no model comes without challenges; Conventional machine learning models, such as decision trees or Bayesian classifiers, provide transparency through direct inspection but may compromise accuracy in the process. Conversely, most deep learning models prioritize accuracy over transparency and are applied in diverse fields like facial recognition. However, due to their complex and nonlinear associations, these models are inherently challenging for humans to interpret. (Rai, 2020.) Haenlein & Kaplan (2019) also point out that while the assessment of the results of a deep learning system is usually straightforward, the actual process of it often remains obscure, whether it being due to certain company policy, technical inexperience, or resulting from a complicated ensemble of different programmers and methods. Cheng (2023) acknowledge this issue as well, pointing out the difficulty of even identifying so called corner cases (a model being unable to interpret a new or rare situation) to explain AI decisions. This provides a chance for various ethical issues to arise as the learning progresses. While powerful AI algorithms can determine causal relationships using large datasets, there's a growing need to understand how this data is generated, and to develop tools to accurately interpret these findings (De Bruyn et al., 2020).

According to Andre et. al. (2018) the use of artificial intelligence in marketing has two major implications for practitioners' understanding of ethics. First of these is autonomy, which in business practices traditionally relies on explicit consumer consent. However, data-driven marketing bolstered by AI can both support and undermine different dimension of autonomy by leveraging consumer data in ways that may not require explicit consent. Second is the concept of nudging, which emphasizes the requirement of intent in ethical marketing and separating it from manipulative practices. AI makes this distinction more difficult with intent being difficult to assign to algorithms. (André et al., 2018.)

In their article promoting "algorithmic realism", Green & Viljoen (2020) list the possible negatives of well-intentioned computational work: algorithms can be biased, discriminatory, dehumanizing, violent, and spread hate speech and other hateful ideas. This viewpoint strives to challenge a dominant way of thinking called "algorithmic formalism", which rests on objectivity/neutrality, internalism (emphasis on mathematical efficiency at the cost of social interactions), and universalism. The authors contend that though reasonable, these ideals have shown to deepen existing social conditions and enforce algorithmic principles at the cost of others. (Green & Viljoen, 2020.) Examples of harmful and discriminatory algorithms include Airbnb's smart pricing tool which exacerbated the gap between white and black hosts (Zhang et al., 2021), search engines that disproportionately targeted men when presenting higher paying stem jobs to men, and software that deemed black hairstyles unprofessional. (Blösser & Weihrauch, 2024; Prahl & Goh, 2021.) Trittin-Ulbrich and Martin (2022) agree that indeed the major fallacy of technologies like AI lies in their misleading promise of efficiency and flawless automated decision-making, which supposedly overlooks the imperfections of human decision-making. This belief according to them is based especially on two flawed assumptions: that technology development is neutral and objective akin to algorithmic formalism, and the limited economic lens of managers that overemphasizes the goal of enlargement of shareholder value through continuous advancements in firm efficiency.

The increasing use of AI in marketing and business overall has simultaneously called more attention on AI-related CSR (Corporate social responsibility) (Du & Xie, 2021). As AI essentially changes the perception of technology by accelerating its integration, using data to generate more data and giving marketers more power over consumers (Walker & Milne, 2024), corporate responsibility must expand adjustingly. However, Clarke (2019) argues that while CSR and business ethics have potential in promoting responsible AI, their effectiveness is limited by directors and their legal obligations to prioritize company interests. This focus on company success often conflicts with broader ethical considerations, as evidenced by standard texts and regulatory guidance which largely overlook ethics and social responsibility. (Clarke, 2019) Therefore ethically coherent AI utilization largely remains an ideal for the future.

2.2 Personalization

In today's digital marketplaces the variety of goods and services available is in many instances unfathomably large, which in turn produces an abundant amount of advertising and marketing communication. In terms of advertising, the difference between the internet and other mediums is stark, as people for example often find the thematic connection between a tv-program and the ads shown with it quite crude and amusing. Through a constant confrontation with personalized ads, we seem to be aided in our consumer identity performances in addition to their logical value in presenting us offers that, more likely or not, would interest us.

As mentioned in the introduction, personalization is a broad concept that has been the subject of study in several academic fields. In marketing literature it has been further examined from several perspectives, including game-theoretic models and consumer behavior studies. (Rafieian & Yoganarasimhan, 2022). Although personalization has always been a major concern in marketing applications—since the very beginning, when modern marketing philosophy was applied—recent advancements in artificial intelligence and information technology have elevated the phenomenon to a much more crucial level for all kinds of marketing initiatives (Salonen & Karjaluoto, 2016). Until recently, few firms possessed the necessary data and modeling capabilities to tailor unique offers to each consumer. As a result, full personalization remained more of a concept than a reality for the first decades of its existence, often indistinguishable from segmentation in practice (Davenport, 2023). Perhaps the most successful company to monetize the fountains of consumer data was Google, which capitalized on data collected from across the web with Google AdWords to deliver targeted advertising alongside search results. This made Google focus on leveraging user data to benefit advertisers rather than its search technologies. (West, 2019.)

Personalization, defined by Chellappa & Sin (2005) as the ability to utilize personal and preference information to dynamically and proactively tailor goods to each customer's preferences, has proven to be a strategy worth perfecting. McKinsley reports that when worked on diligently, personalization measures have the possibilities to nearly halve customer acquisition costs, as well as raise marketing ROI by 10 to 30 percent, and improve sales by 5 to 15 percent (McKinsey, 2023). The benefits for business are unarguable, particularly in large online marketplaces such as Ebay or Amazon. According to Zhou & Zhou (2021), personalized recommendation systems are now the primary drivers of revenue for most online marketplaces, contributing upwards to 35% of transactions on Amazon and 40% of app installs on Google Play, for example. However, prices are a significant factor determining personalization in these contexts in addition to consumer data, since most marketplace commissions are based on a percentage of product prices, such as 15% on Amazon. These kinds of profit-based recommendation systems thus might suggest more expensive and unsuitable products to consumers even if they prefer less expensive options. (Zhou & Zou, 2023.) This is one example in which personalization does not fully work in the consumers' favor, even as its primary purpose is to help the customer make optimal purchase decisions.

The personalization capacity of businesses is all about their ability to differentiate between individual consumers (Rafieian & Yoganarasimhan, 2022). In its core, gaining a competitive edge through personalization involves matching, educating, and providing said individuals with goods and services. Through personalization, companies seek to help customers by reducing disorientation and directing them toward solutions that, at least from the companies view, best suit their needs. (Chandra et al., 2022; Murthi & Sarkar, 2002.) Kumar et al. (2019) add that the process of personalization strengthens and solidifies the relationship between marketers and consumers, and thus relationships which involve emotional bonding may eventually evolve to a state of genuinely beneficial engagement. This viewpoint is nicely summarized by Vesanen (2007), who states that "the urge to personalize is largely driven by the expected benefits of one-to-one marketing and customer relationship management". Especially the capacity of big data to gather and assess dynamic market information empowers organizations to effectively cater to individualized requirements and build more coherent CRM strategies (Kamel, 2023). The claim of increased emotional bonding is nowadays on shaky ground however, as the consumer behaviors of young generations differ in many ways from previous consumer segments in terms of their attitude toward personalized marketing (McKee et al., 2023).

Every step of the purchase journey can be impacted by personalization, including advertising to customers prior to a purchase, the selection of goods and services that customers are showcased, the actual shopping and purchasing experience, and the follow-up communication with customers (Gao & Liu, 2022). This view of a continual personalized process is visualized in figure 2. Essentially, an optimal personalization system, to the seller at least, provides an experience that incorporates as many recognizable and unique interests and preferences of an customer throughout their purchase journey (Liaukonyte, 2021). Some researchers have even replaced the traditional 4 Ps of marketing with the five I's: identification, individualization, interaction, integration, and integrity. This framework emphasizes the importance of marketing strategies that focus on understanding individual customers, engaging with them effectively, personalizing offerings to meet specific needs, integrating all customer-related activities within the company, and maintaining integrity and trust in all interactions. (Dawn, 2014.) Kaptein & Parvinen (2015) simplify the guideline of a working personalization process and argue that for any successful personalization attempt to succeed, the company requires an understanding of both customer behavior and technological methods. The latter becomes particularly essential as AI and machine learning become more widely utilized tools in the field.

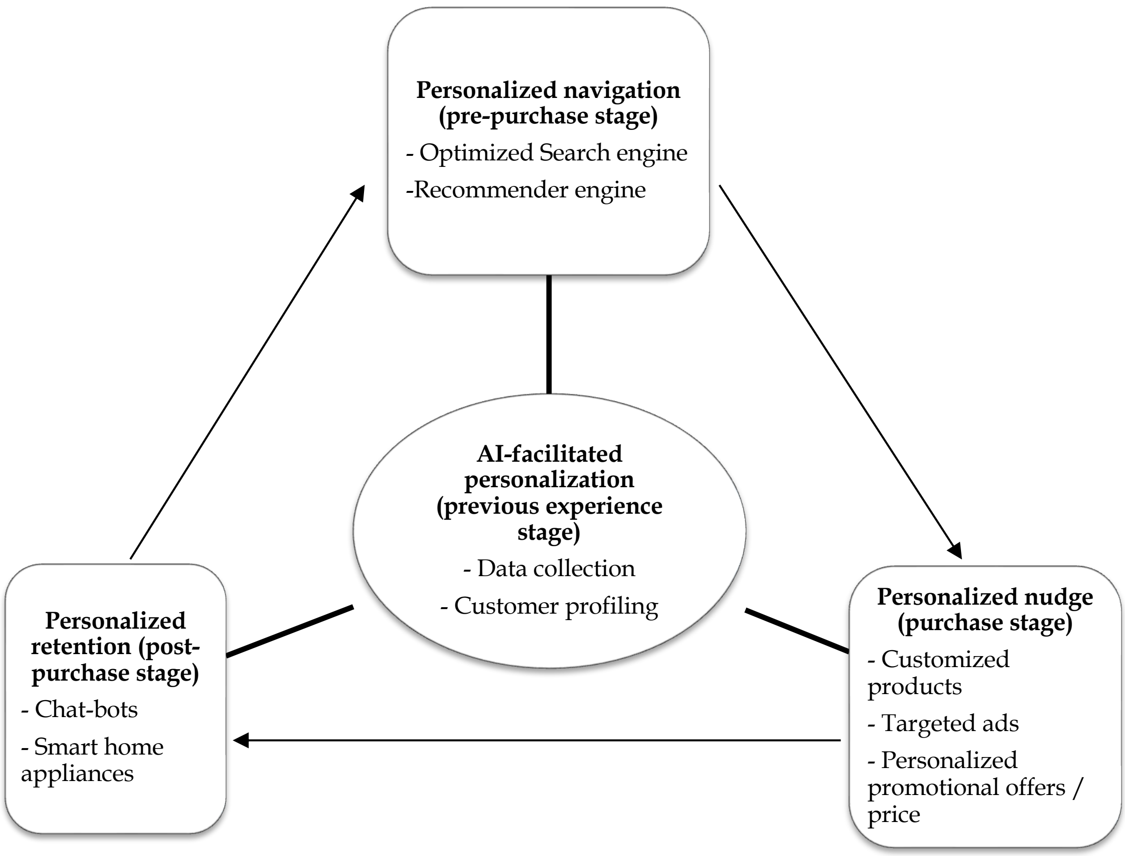

Figure 2: Personalization in the purchase lifecycle (Adapted from Gao & Liu, 2022)

While personalization may on the surface seem only beneficial to a customer's purchase journey, researchers are not entirely unanimous when it comes to the positive impact of personalization. Many studies have indeed underlined the significance of personalization in influencing customer attitude, intention, and brand use, but others have argued that target customers become accustomed to personalized marketing, and are thus not responsive to personalized offerings trough time (Chandra et al., 2022; Pfiffelmann et al., 2019). Some studies suggest that exposing consumers to numerous tailored adverts can more critically lead to various negative phenomena such as "ad wear-out" or "ad annoyance" (W. J. Choi et al., 2023; Cloarec et al., 2022). While increased personalization logically should ease a customer's journey and enhance their relationship towards a company, highly personalized marketing tactics can easily be perceived as intrusive or manipulative, which risks weakening brand perceptions and, almost paradoxically, customer loyalty (Kopalle et al., 2022). Critics have additionally pointed out the one-sided emphasis on the business implications of personalization algorithms, rather than a more nuanced investigation of how customers and algorithms negotiate and interact (Kant, 2020; Obiegbu & Larsen, 2024).

Personalization research has grown increasingly crucial as Generation Z, which encompasses those born between 1997 and 2012, increases influence in the global marketplace. Being the first generational cohort whose members were all raised in a time when digital technologies were widely accessible and used in daily life, Gen Z has made the study of digital personalization even more important for effective marketing research. (Childers & Boatwright, 2020; McKee et al., 2023.) However, Gen Z's tech-savviness also means that the flow of data may decrease significantly, as young consumers increasingly opt for non-tracking options, digital blocking software, and private browsers among other avoidance tactics. This is especially the case when they believe that a brand's attempts at personalization don't fully line with their preferences. (McKee et al., 2023.) They furthermore lack the usual brand loyalty of previous generations. A study on consumer decision-making found that Gen Z consumers tend to compare and contrast products to a greater extent before making purchases, a style that should affect which features e-retailers choose to prioritize in their marketplaces (Thangavel et al., 2022).

2.2.1 Personalization process

In the conceptual base for a large amount of personalization literature, Murthi and Sarkar (2003) divide the process in to three main steps: learning, matching, and evaluation. The first step consists of data collection concerning a company's customers and their preferences, either explicitly or implicitly. In other words, customers can provide data directly using online surveys and registration forms, or it can be gathered through tracking user behavior and interactions on a website or marketplace. (Murthi & Sarkar, 2003.) Both have clear advantages, as for example more implicit or covert data collection is usually more abundant and unbiased, leading to a richer understanding of a customer base (Aguirre et al., 2015). The downside of this is the possible lack of transparency about data collection to the customer (McKee et al., 2023).

Explicit data collection on the other hand stresses the importance of transparency and consent, and survey/registration-based consumer input is especially crucial for new companies in kickstarting their personalization processes. These questionnaires help acquire information about a person's profile and even some highly personal information, such credit card numbers or residence address. (Aguirre et al., 2015; Mehmood et al., 2023; Zeng et al., 2021.) Explicit data collection has in recent years become commonplace due to industry regulation such as GDPR in the EU, which has forced websites and marketers to clearly communicate to customers the amount and type of data they intend to collect (W. J. Choi et al., 2023). Requesting consents to collect cookies on a website etc. differs of course from survey-based data collection, even as they both represent explicit data collection. Grigorios et al. (2021) found that openly informing users about data collection for personalized advertising received positive responses, while covert practices elicited negative reactions due to perceived advert intrusiveness. Mehmood et al. (2023) add that in addition to privacy concerns and transparency requirements, whether consumers prefer explicit or implicit collections is largely dependent on the broader purchase environment. Different data types, relationship qualities, and consumer characteristics have been identified as key factors in this question. (Mehmood et al., 2023.)

Matching data involves utilizing collected information in building a personalized customer experience, i.e. presenting customers with personalized ads and product recommendations. In addition to certain products, customers are targeted to personalized communications and prices based on their preferences. Behind this process is usually a recommendation system that utilizes advanced rule based product/content-filtering techniques. (Murthi & Sarkar, 2003.) Adomavicius & Tuzhilin (2005) divide this part of the process in to two steps, matchmaking and delivery or presentation of personalized information. During this step the company must detect the types of data that are most relevant in creating a personalized experience, and utilize it through recommender systems, predictive approaches, or rule-based systems. The evaluation step refers to companies measuring the effect of personalization on customer experience and behavior (Lambillotte & Poncin, 2023), a process that requires examining both the learning and matching phases. In the online context, this step usually involves assessing the performance of the personalized strategy using quantifiable metrics, such as click-through rates or average view duration (Aguirre et al., 2015).

Although personalization may seem a simple concept, it involves numerous methods and contextual factors, leading to a wide range of possible personalization dimensions. Aksoy et al. (2021) offer a typology of personalization practices (visualized in figure 3) which according to them can be categorized and explained utilizing six types of criteria, the first of which concerning that of what is personalized, i.e., what aspects of the individual are used for personalization? Arguably the most crucial criterion, it is the only one that will remain structurally unchanged and will only be affected by the scope of its content. Naturally as technology advances, this category will have access to even more information that is used today to customize all different types of content. (Aksoy et al., 2021.)

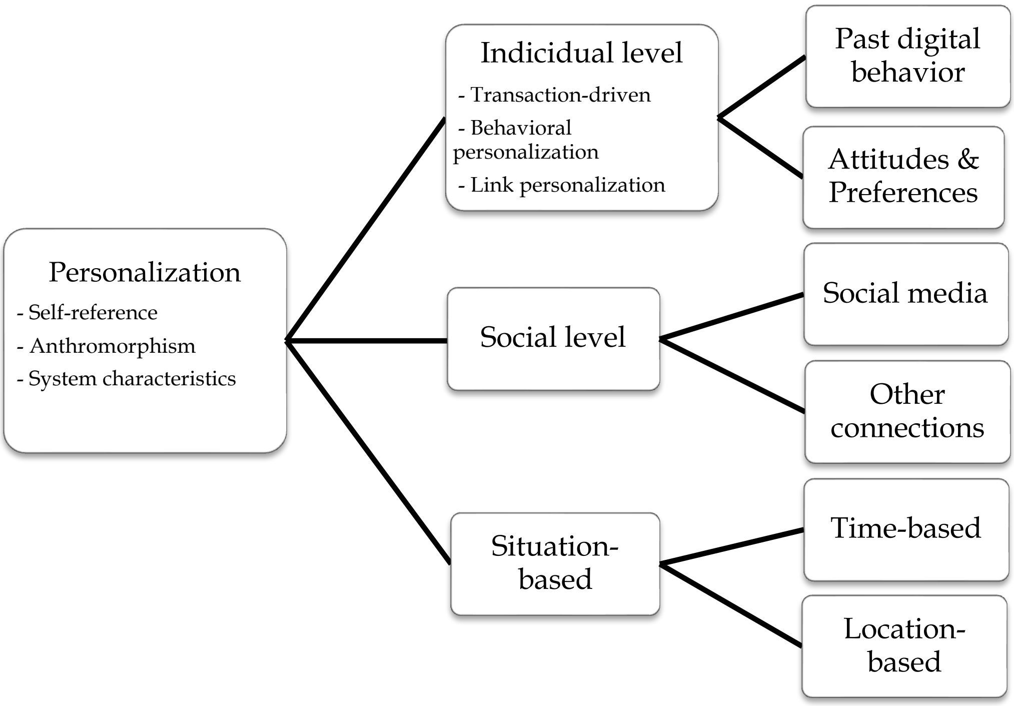

Figure 3: Classification framework for personalization (adapted from Aksoy et al., 2021)

Studying personalization techniques may be accomplished in part through a technological approach and concentrating on the channels and means by which clients are informed about personalized designs. Therefore, personalization techniques may be divided into three main categories: the self-reference method, anthropomorphism, and the system characteristics method. The self-reference method refers to the process of providing individuals personalized experiences by highlighting how well the system understands them, i.e. acknowledging the personal information collected. (Aksoy et al., 2021.) The method thus promotes increased transparency in personalization, which requires the sender to disclose any data collection, processing, or sharing, and give detailed explanations of how personal data is handled, along with disclosures of covert data collection methods like cookies and their purpose. “Why am I seeing this ad?” -type messaging is a prominent example of personalized communication striving for transparency. (Dogruel, 2019; Segijn et al., 2021.) Another method to put the self-reference approach to use is to have an interactive conversation. For example, agents might welcome customers by name and show them interactive information that has actual personalization aspects. (Aksoy et al., 2021; Vinodh et al., 2015).

Anthropomorphism is defined as the act of attributing human traits, intents, motives, or feelings to nonhuman entities, with the intention of both reducing customer wariness concerning intelligent personalization tools and agents, while increasing consumer favorability toward certain products or services (Fronczek et al., 2023). Studies concerning consumer attitudes towards conversational agents e.g. chatbots have greatly emphasized the role of anthropomorphism, and its purported effect of encouraging customers to provide more personal information to the company on their purchase journey. It is also seen as a critical construct from which to gain a deeper understanding of human interactions with technology. (Kronemann et al., 2023.) There is still, however, no clear consensus in research about a linear relationship between anthropomorphizing and business outcomes. While reaching consumer by humanoid tools can generate positive marketing results, the risk of various negative effects persists. Excessive anthropomorphism can cause discomfort for consumers (the "uncanny valley") and decrease their favorability toward conversational agents that drive personalization, and overly humanized agents run the risk of setting unrealistic consumer expectations that ultimately result in dissatisfaction and even abuse. (Thomaz et al., 2020.)

System characteristics refer to a communication strategy in which the system does all the personalization work by itself. Since a system may be already familiar with the user, it can make decisions on their behalf. In essence, system-based personalization is provided to individuals' with tailored information (recommendation system) by intelligent systems and algorithms (Chandra et al., 2022). Although each of the methods may be used alone or together depending on the firm's strategy and tools, the exact benefits and interplay of them are largely unstudied (Aksoy et al., 2021). Focusing on the kinds of information that are being emphasized through a business-oriented approach, Aksoy et al. (2021) group the types and levels of information used to broadly classify three different personalization practices: practices that prioritize individual-level personal information; practices that prioritize social-level personal information; and practices that prioritize situation-based personal information. These focuses can be used independently or in combination, depending on the product/service and the intended outcomes for the company.

The foundation of individual-level personalization is built on consumer insights and individual digital activity (previous purchases, reviews, ratings, comments, etc.). Personalization at the individual level can be characterized as transaction-driven-, behavioral-, or link personalization, which all point to a similar procedure (Aksoy et al., 2021). Behavioral personalization consists of data from a consumers' online behavior, such as websites visited, media consumed, and pretty much any behavior that includes using a search engine. App purchases and use, clicks on ads, and communication content e.g. social media texts also critically contribute to the overall body of behavioral data companies may utilize. (Boerman et al., 2017.) Transactional personalization naturally refers to the use of transaction-driven customization algorithms, through which online retailers can tailor content to each customer by using the information gathered from their previous purchases (Ho et al., 2007). Purchase of a laptop, for example, will most likely produce ads of computer related products or software services. Link-based personalization can be characterized as a key feature in the other two methods (Aksoy et al., 2021).

As basically all consumers exist in a social environment, the significance of social networks and data produced out of them in the creation of personalization algorithms is massive. The exchange of data between social media companies and large e-commerce entities is well visible in recommendation systems that work collaboratively by identifying similar users, and suggesting current items based on those users' preferences utilize social interactions. Showcasing other users, such as close friends and others with similar preferences and purchase history, has been proven to increase ad efficiency. (Aksoy et al., 2021; Choi et al., 2011; Ochi et al., 2010.)

Situation-based personalization refers to customizing an individual customer journey based on their immediate environmental factors (e.g., time and place) (Chandra et al., 2022). Current location data is used by programmatic advertisers, brands, and retailers for inventory pricing, bolstering offline-to-online attributions, and creating more successful advertising campaigns because it is a likely indicator of purchase intent. Additionally companies use geolocation data for forms of personalization that amass better engagement by evoking relevance, self-reference, and goal specificity. (Banerjee, 2019.)

2.2.2 Personalization paradoxes

Personalization promises consumers both a plethora of benefits on their purchase journeys in exchange for almost free access to personal information and online behavior. In addition to this proposed exchange, consumers often experience ambivalent perceptions of increasingly powerful and pervasive technological processes. With many complex contemporary technologies, customers experience an inner battle between privacy concerns and use enjoyment (Lambillotte & Poncin, 2023). While the benefits of personalized algorithms have increased, so has also the awareness of the importance of data security and the often-pervasive nature of large organizations collecting and selling consumer data.

However, in many cases far from a rational thought-out procedure, consumers act paradoxically when weighing in their data privacy needs with all the benefits that personalized brand and services may bring. This discrepancy between privacy attitudes and concerns compared to actual privacy behaviors is commonly referred to as the privacy/personalization paradox, and has been under great amount of research in the last few years (van Ooijen et al., 2024). Research often delves into the matter through the lens of privacy calculus theory, which posits that consumers engage in a rational cognitive assessment when weighing the pros and cons of personalization. Scholars have applied this theory to explore consumer behavior in diverse digital settings, such as mobile apps and social media. (Chandra et al., 2022; McKee et al., 2023.) Cloarec et al. (2022) on the other hand examine the process through the lens of social exchange theory, which similarly looks at the trade between data and personalization benefits as a social exchange with certain assumptions and rules. A notable implication of the study is that happiness with the internet is potentially a stronger mediator of privacy-related decision making than trust and risk beliefs towards an organization.

In addition to the privacy-benefits paradox, McKee et al. (2023) conceptualize a second tension within consumers called the avoidance-annoyance paradox, which concerns the relationship between marketing avoidance i.e. use of AdBlock and deleting cookies etc., and the possible resulting frustration toward non-personalized marketing. Brand avoidance refers to the acts or instances where consumers intentionally reject a brand, which can be manifested either through negative brand attitudes or active efforts to distance oneself from the brand and its marketing activities. The trade-off between limiting tracking and receiving less personalized brand content is particularly eminent among Gen Z consumers, who are more proactive in terms of advertising avoidance. (McKee et al., 2023.) This paradox, where avoiding personalization efforts can become annoying for consumers, may end up hurting brands due to consumers perceiving it less effective as marketers possess inadequate data for personalization (Aksoy et al., 2021). Implementing Cho & Cheon's (2004) three consumer ad avoidance responses in the context of personalized marketing, consumers may engage in avoidance in three main ways: ignoring personalized ads consciously (cognitive avoidance), avoiding personalized ads if they dislike them (affective avoidance), or immediately discarding personalized content such as emails without consuming them (behavioral avoidance).

Through their research Lambillotte & Poncin (2023) shine light on two additional paradoxes. The first one of these is called the personalization-stereotype paradox, which highlights the conflicting emotions experienced by customers torn between the excitement sparked by personalization and the sense of being categorized. Although feeding customers personalized ads and content may awaken needs and desires linked to a company's products and services, after a certain period of time said content can feel limiting or dull to the customer. (Lambillotte & Poncin, 2023.) This paradox can in some ways be linked to the avoidance-annoyance paradox, as negative user stereotypes are considered a cause of brand avoidance as well (Hogg et al., 2009). The core tension of the paradox revolves around the similarity between segmentation and stereotyping. While long a key marketing tool, it has been argued that segmentation often reinforces biased practices and cultural stereotypes. (Jeffrey, 2021.) This concern notably extends to the possibility of bias in algorithms, either through bias in the program, or inherent biases acquired from the analyzed data that includes discriminatory patterns that exist offline (French, 2018). To combat the stereotype paradox, Lambillotte & Poncin (2023) state that companies should strive to provide valuable personalized content with the focus of unexpected dimensions and visual signaling cues to personalize content based on individual preferences rather than generic stereotypes.

The second paradox discussed by Lambillotte & Poncin (2023), called the personalization-influence paradox, concerns the tension between the benefits of personalization and the consumers' feelings of being explicitly influenced. Some consumers may feel their free will or ability to act undermined by personalized advertising (Lambillotte & Poncin, 2023), with the feeling of crumbling autonomy in online environments particularly tied to advancements in computational power and AI (Das et al., 2023). Thus, companies aiming for hyper-personalized marketing and sales funnels may impose a detrimental sense of restriction upon them, even though their primary motivation is to aid customers in their purchases and decision making. All of these aforementioned paradoxes (defined briefly in table 2) may impact the consumer's decision-making process in ways marketing managers need to be fully aware of.

Privacy-benefit paradox	• Tension between privacy concerns and perceived benefits of personalized marketing
Avoidance-annoyance paradox	• Paradox between the avoidance of personalized marketing efforts and simultaneous negative attitudes towards non-personalized marketing
Personalization-stereotype paradox	• Conflict between perceived personalization benefits and the sense of being stereotyped/labeled
Personalization-influence paradox	• Paradox between the perceived benefit of personalization and the feeling of being heavily controlled and influenced

Table 2: Four major paradoxes concerning personalization, privacy, and brand relationship (Chandra et al., 2022; Cloarec et al., 2022; Lambillotte & Poncin, 2023; McKee et al., 2023)

2.2.3 Personalization powered by AI

Personalization is currently a very automated procedure, which benefits greatly from artificial intelligence and related technologies. AI has allowed a major paradigm shift in marketing in moving from a rules-based, expert systems approach to a strategy governed by data-driven, deep learning methods (Kumar et al., 2019). According to Aksoy et al. (2021), the principal of personalizing experiences based on system characteristics underscores the role of big data and artificial intelligence technologies in transforming personalization processes, allowing companies utilizing this approach to capitalize on financial and time-saving benefits. AI and big data more importantly establish the next stage of personalized marketing and CRM often referred to in marketing research as hyper-personalization (Jain et al., 2021), which among many other things can be able to combine online and offline shopping experiences sufficiently (Shareef & Reddy, 2019).

To deliver an effective, fine-grained personalized policy, a company needs a huge amount of data out of individuals, which is why almost all platforms that employ personalization acquire data on a vast scale (Rafieian & Yoganarasimhan, 2022). In addition to AI helping to find customers easier and retain them better, Libai et al. (2020) posit that firms can also themselves "decide who NOT to invest in". Specifically in interactive marketing, the integration of AI-driven CRM personalization is seen to facilitate a shift towards selective customer development and retention, i.e. emphasizing a certain subset of customers. This focus on expected lifetime value has prompted firms to enhance their cross-selling campaigns on higher-value customers (Libai et al., 2020; Senior et al., 2016).

Firms have for some time utilized AI for personalization through rule-based systems, albeit with limited precision. However, the emergence of machine learning has revolutionized personalization, enabling more sophisticated and precise targeting. Unlike rule-based methods, machine learning can handle multiple attributes seamlessly, resulting in millions of unique offers tailored to individual customers or contexts, approaching 1:1 segmentation, a long-standing aspiration in marketing. (Davenport, 2023.) However, research highlights another aspect, which is that when personalization infringes on a consumer's freedom of choice and triggers privacy concerns, it can lead to psychological reactance and subsequent oppositional actions, which underscores the complexity of implementing AI for crafting personalized marketing experiences. (Gao & Liu, 2022; Pizzi et al., 2020.) While for example the curation process of recommendation engines hopes to alleviate the cognitive load on consumers and transfer the responsibility of identifying optimal choices to the search platform or brand (Kumar et al., 2019), giving up decision making power and data to an recommendation system or algorithm may strain the purchase attitude significantly for many consumers.

AI introduces new capabilities into personalization in many ways, as visualized in figure 5. Kopalle et al. (2022) outline the most important capabilities of AI through five core principles. Firstly, AI enables advanced data processing, allowing for the analysis of large volumes of data, including unstructured data like speech and images. This points to the power of mechanical and feeling AI, through which Big Data and AI empower marketers in customer profiling by leveraging the vast pool of data individuals generate through their online activities, both willingly and inadvertently (D'Arco et al., 2019). Secondly AI excels in complex pattern recognition, identifying subtle correlations for more nuanced personalization. Machine Learning algorithms are crucial tools in identifying lookalike consumer groupings and anticipating customer demands, which enables businesses to adapt to specific, tailored offers (De Mauro et al., 2022).

Thirdly, AI enables real-time personalization, swiftly generating tailored recommendations based on incoming data. Haleem et al. (2022) state that when integrated with AI-driven smart notifications, sophisticated AI tools such as facial recognition software can deliver real-time discount offers and personalized greetings to individual visitors, elevating the level of tailored user experience even further. This can be done by tracking customers' visits to physical stores and associating their images with their social media profiles. (Haleem et al., 2022.) Fourthly, it supports continuous learning, adapting to new information for dynamic updates to user profiles. As mentioned before, artificial intelligence not only uncovers concealed data but also guides and incorporates it into new marketing strategies, while refining messages for maximum relevance to users. Hence with time, AI solutions will evolve to be more intelligent and efficient, facilitating even more effective real-time decision-making processes. (Kopalle et al., 2022.)

Fifthly, AI ensures scalability, facilitating personalization across various touchpoints and channels simultaneously (Kopalle et al., 2022.) AI-driven marketing tools for instance enhance the effectiveness of email marketing campaigns for many companies by aiding in the strategic timing of personalized email dispatches and tailoring content or product recommendations to diverse audience segments. AI is used to ensure the delivery of the most relevant content precisely when it is most impactful. (Haleem et al., 2022.) These capabilities of AI are especially visible through behavioral analysis, predictive analytics, natural language processing, recommendation systems, dynamic content generation, and segmentation/targeting. By leveraging these capabilities businesses hope to deliver hyper-personalized experiences that drive engagement, conversion, and customer loyalty. (Kopalle et al., 2022.) The use of AI also helps to achieve an optimized version of the familiar Marketing Mix by identifying the most effective channels, messages, and offers for each customer segment. Differing from the existing marketing practices that largely focus on firm-level objects such as competitive edge, in an AI-powered setting, personalization is achieved by tailoring marketing content and strategies, i.e. the 4Ps. This targeted approach strives to maximize the impact of marketing campaigns and improve ROI (Kumar et al., 2019.)

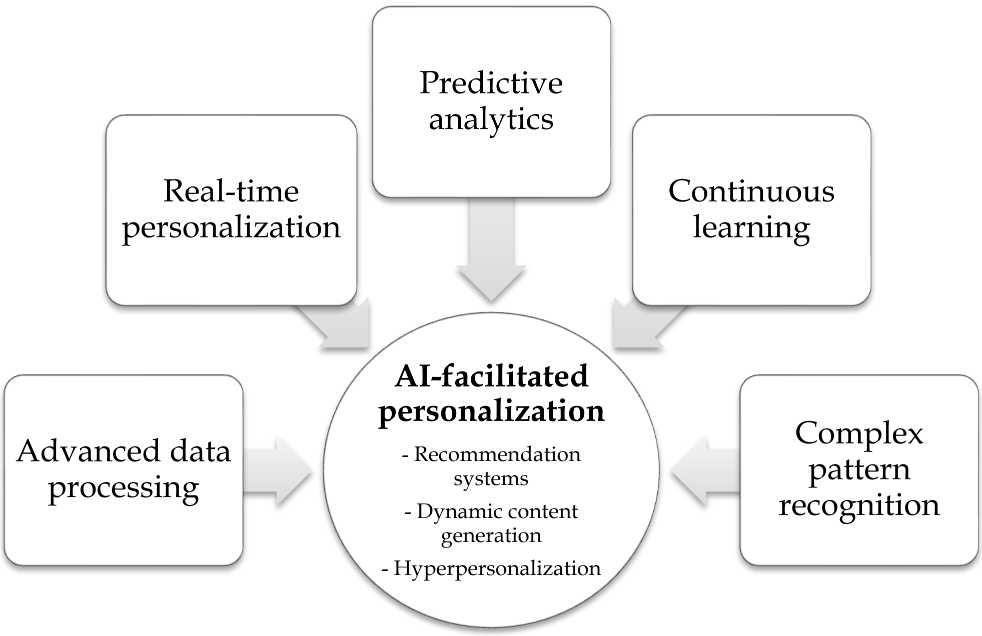

Figure 4: Components and capabilities of AI-facilitated personalization (T. Davenport et al., 2020; Haleem et al., 2022; Kopalle et al., 2022; Kumar et al., 2019)

The possibilities and limits of AI-powered hyper-personalization are still largely unknown. According to Davenport (2023), the low quality and/or amount of data, combined with tenuous customer profiles and lack of methodological expertise is keeping many companies in the early stages of personalized marketing procedures. While it is clear that hyper-personalization reflects every element of the marketing mix through optimizing content, timing, pricing, and marketing channels to position brands favorably with consumers (Shareef & Reddy, 2019), value and user experiences must be maximized with a balanced outlook. Perhaps the greatest pressure concerns respecting customer privacy, which forces companies to ethically navigate privacy concerns requiring transparent communication, explicit consent, and strong data security measures. This is an essential counterforce critical for successful hyper-personalization efforts across all markets. (Jain et al., 2021; Rane et al., 2023.)

3 AI AND DATA PRIVACY

The next chapter is the second theory chapter of the study, in which the relationship between AI-facilitated personalization and data privacy is examined further, with a particular focus on how privacy regulation and consumer behaviors affect data availability for companies. The conceptual framework, drawn from the theoretical chapters and applied in the empirical segment of the study, is presented in the final subsection.

3.1 Understanding consumer privacy in AI contexts

Privacy concerns about personal data has for long been a major theme in marketing literature in both offline and online environments, the latter in particular increasing significantly in recent years (Fortes & Rita, 2016) After the start of the 2010's, increased computational power has pushed customer analytics to become a central part of personalization procedures (Chandra et al., 2022), often leading to companies taking advantage of consumers that lack adequate knowledge and control of their personal data (Cloarec, 2022). The scope of data collection has significantly increased as people have become accustomed to sharing large amounts of personal information, while extensive A/B testing to optimize user engagement and gather a wide range of information has become an industry standard (Aho & Duffield, 2020). As large amounts of high-quality data are essential for AI to operate, it is heavily linked to ethical issues pertaining to data governance, such as permission, ownership, and privacy. AI is naturally not the sole reason certain data-related problems worsen, but as an unique kind of autonomous and self-learning agency it faces new specific ethical challenges. (Taddeo & Floridi, 2018.)

Du & Xie (2021) consider the challenges and opportunities of AI-enabled products and services to either product-based, consumer-based, or society-based, all of which more or less concern consumer privacy and autonomy in some way. On the product level, biases and unethical designs of algorithms and recommendation engines must be controlled and made understandable to the consumers (Querci et al., 2022). On the consumer level lie the essential challenges companies need to address, involving for instance transparent and fair privacy policies, ensuring consumers of proper control over data, and integrating various security measures in AI-tools. The society level not only looks at the larger picture trough unemployment, but also presses the need for individual autonomy and wellbeing as central drivers of AI development. (Du & Xie, 2021.) Privacy and autonomy are thus central issues of the AI-related CSR framework.

As consumers use various online services, they're realizing an explicit need to share personal data. This creates tension between personalization and privacy, which is important for marketers and retailers to handle, as concerns about internet privacy raise risks perceptions while conversely lowering trust in online platforms (Cloarec et al., 2022). Growing worries about data governance have also been expressed in a desire for privacy-protection measures. Apple's iOS 14.5 update for instance introduced a new privacy feature limiting user tracking methods, which intensifies the pressure on companies to encourage customers to share information willingly while reducing efforts to safeguard it. (Wanjugu et al., 2022.) However, many consumers already see conventional personalization methods, such as tracking and analyzing customer online activities and transactions as a form of surveillance capitalism. Therefore AI-infused hyper-personalization may well be deemed too pervasive of an concept among consumers in many shopping environments. (Davenport, 2023.)

In contemporary data-driven markets, three pivotal privacy rights emerge as essential protection for consumers. Firstly, individuals should possess the right to provide explicit consent before agreeing into data collection practices (Ke & Sudhir, 2023). Secondly, the right to be forgotten, which essentially means the necessity for data to be promptly erased upon a consumer's request, thus ensuring their control over personal information. The third crucial right points to data portability requirements, meaning that any data about the individual that is not purchase related (e.g., sales, revenues from customer) should be transferred upon the customer's request to another business. (Calder, 2016; Ke & Sudhir, 2023.) These rights serve as foundational pillars for ensuring transparency, autonomy, and privacy in the increasingly digitized landscape of modern markets. Thanks to the era of Big Data however, individuals who wish to safeguard their privacy in online environments have become extremely vulnerable to a handful of technology companies (van Ooijen et al., 2024). West (2019) sees these asymmetrical power dynamics as the primary symptom of today's data capitalism, a system in which the "commoditization of data enables a redistribution of power in the information age." It is important to also note that various vulnerable populations and consumer segments, such as elders or children, often suffer disproportionately from privacy violations and limitations (Bartneck et al., 2021). Thus, consumers should not be considered as one homogenous block in terms of data privacy.

In addition to highly reserved attitudes toward AI-powered data collection, research has highlighted significant skepticism among consumers regarding AI-powered recommendations regarding products and services (Kim et al., 2021). Consumers often lack understanding of how recommendation agents operate and influence their decisions, and this lack of awareness undermines trust in the algorithm and may hinder data sharing with companies using it (Rohden & Zeferino, 2023). Shin (2021) emphasizes the importance of users' perceptions of fairness, accountability, transparency, and explainability (FATE) in accepting algorithmic recommendations, even though algorithmic fairness especially lacks a widely accepted definition. These subjective judgments are however integral to understanding users' perceptions of algorithmic performance and decision-making processes. Querci et. al. (2022) remind that while younger generations may be more internet-literate, many consumers and professionals still lack expertise in computing to view AI algorithms as something more than just complex and ambiguous black boxes. Consequently, processes by which these algorithms collect and utilize personal data remain unclear, raising concerns about sharing personal information. (Querci et al., 2022; Thomaz et al., 2020.) Cloarec (2022) notes that AI-powered real-time personalization exacerbates these concerns, leading to weakened data streams to companies.

Drawing from Solove's (2006) taxonomy of privacy violations, Das et. al. (2023) analyzed over 300 documented AI privacy incidents from the AI, Algorithmic, and Automation Incident and Controversy Repository (AIAAIC). The findings indicated that AI's unique abilities and data needs can introduce new privacy intrusions and exacerbate existing ones across 11 categories (Figure 5). For instance, AI's capacity to generate human-like media introduces new exposure intrusions such as deep fakes, while AI's demand for vast amounts of personal data can lead to secondary use intrusions, as seen in the collection of personal data streams for training AI models like GPT-4. Moreover, AI in many ways establishes a more pervasive environment for intrusive identification of consumers. (Das et al., 2023.) Overall, AI both creates new privacy threats and amplifies existing ones due to its unique capabilities and data requirements. Effectively addressing these threats and challenges demands a comprehensive strategy encompassing ethical guidelines, regulatory frameworks, responsible development protocols, transparency standards and user empowerment initiatives among other acts (Kunz & Wirtz, 2023).

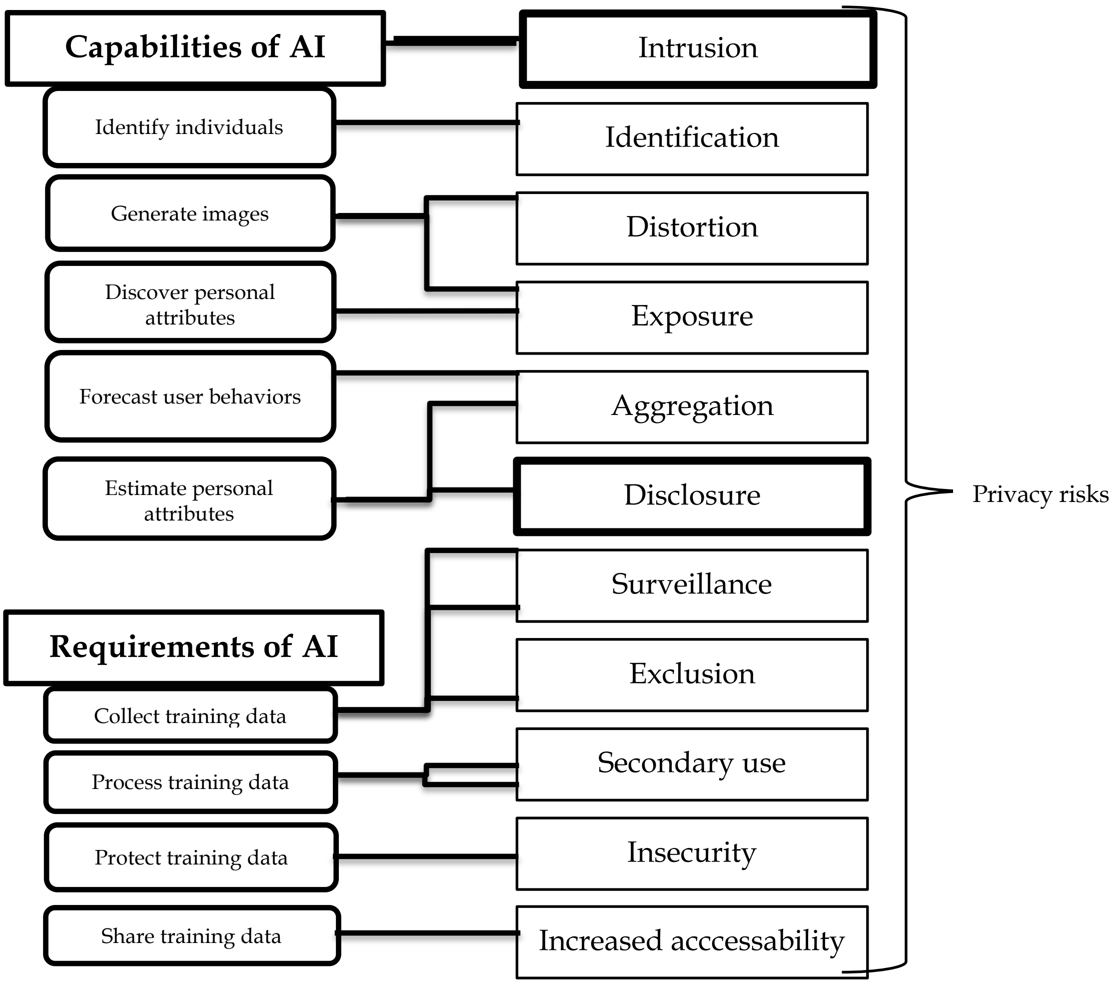

Figure 5: Relationship between AI and privacy risks (adapted from Das et al., 2023)

An important barrier regarding especially consumers and thinking AI like analytics, Mülhoff (2023) promotes an approach called predictive privacy, which involves a pivotal shift from emphasizing individual rights to safeguarding collective data interests. According to the author, by acknowledging predictive privacy as a safeguarded asset and prioritizing ethical principles concerning collective welfare over individual concerns, potential risks associated with predictive analytics can be more effectively mitigated. While several privacy preserving mechanisms have been developed in the realm of machine learning, such as differential privacy and secure multiparty computation, different security aspects such as confidentiality, integrity, and access control need to be addressed to ensure comprehensive data protection (Herhausen et al., 2024).

The combination of AI and big data within marketing certainly brings forth both possibilities and obstacles. Aldboush & Ferdous (2023) highlight that AI can facilitate better interactive marketing and offer more personalized and effective services for customers, yet it's crucial to tackle all ethical issues that stem from its use, such as bias, intrusion, and distortion. By emphasizing responsible data usage, adhering to regulatory standards, and implementing secure technology, firms can safeguard customer privacy and support sustainable marketing. Collaboration among stakeholders is particularly essential for keeping AI environments privacy-focused. (Aldboush & Ferdous, 2023.)

3.2 Consumer perceptions of the data exchange

Consumers and their attitudes are a central area of research when it comes to data, online privacy, and consequently AI. Worries regarding data collection, coupled with the vast capabilities of AI in analyzing personal data, significantly influence consumers' decisions to postpone or avoid adopting these technologies in both online and offline contexts (Querci et al., 2022). Thus, a complex mixture of changing privacy policies, company guidelines, novel technologies, and consumer behaviors and paradoxes bring new characteristics to the consumer perceptions of exchanging private data and information. Jin (2018) summarizes the demand side of the privacy field, i.e. consumer attitudes toward risks in privacy and data security, as "heterogenous, evolving, and sometimes self-conflicting." While regulative forces work to bolster individual rights by requiring informed consent for data disclosure (Mazurek & Malagocka 2019), Kroneman (2022) argues that it's uncertain how aware consumers are of certain legislature or if it impacts their privacy behavior in any significant way.

Privacy is the price consumer pay for personalized and relevant marketing, and the perception of this price varies based on the level of privacy concerns that influence consumers' response to firms' data requests. Plangger & Montecchi (2020) note that highly concerned individuals quickly reject such requests, while consumers with lower privacy concerns may lack such heuristics, potentially spending more time evaluating them. Those with moderate privacy concerns typically weigh privacy alongside other contextual factors, akin to the privacy calculus concept, in making disclosure decisions. (Plangger & Montecchi, 2020.) According to Maseeh et al. (2021), the main factors moderating privacy concerns of consumers (defined in table 3) are risk perceptions, benefit perceptions, familiarity, reputation, privacy policy, and trust concerning the organization or brand, which in turn affect customers' attitudes and usage regarding e-commerce platforms and retail sites. AI's significant impact is a certainty across all these factors, be it negative or positive.

Consumer risk perceptions are typically categorized into two types: information risks, which refer to individuals' concerns about privacy violations when engaging with e-commerce platforms, and financial risks, which pertain to the likelihood of monetary losses resulting from sharing personal information on such platforms. (Maseeh et al., 2021.) Fortes & Rita (2016) consider these risk perceptions to be the primary obstacle in the way of growth of e-commerce and the utilization of data in gaining a competitive advantage. The fear of these risks is balanced by the perceived benefits a consumer sees themselves gaining in the interaction, i.e. what marketers provide them in exchange for accessing their personal data (Cloarec et al., 2022). The interplay of these essential factors is heavily affected by a set of the consumers subjective and objective views regarding each brand or organization asking for personal data. These remaining four factors can be seen as dependable pairs of each other (familiarity/trust & reputation /privacy policy)

Familiarity toward a company or brand, ironically often the main prerequisite of effective personalization efforts, reflects all past experiences with a company to perceive possible dangers regarding private data. Positive familiarity strengthens trust that the customers data is at safe hands, and that the marketer turns that possession of data into something truly beneficial to the customer (Haleem et al., 2022; Järvenpää et al., 2000) Trust is essential for influencing consumers' responses to advertisements, but merely being trusted does not guarantee retailers' success in personalization; Bleier & Eisenbeiss (2015) point out that even trusted retailers can evoke privacy concerns with highly personalized advertisements. Therefore, beyond optimizing personalization processes, trusted retailers must take extra measures to address privacy concerns in marketing encounters. (Bleier & Eisenbeiss, 2015.) Familiarity and trust are especially tested when consumers interact with AI-based assistants and chatbots which ask for information (Acikgoz et al., 2023; Peltier et al., 2023).

Factor	Definition
Risk perception	The possibility of negative outcomes, either as violations on private information, or the risk of financial losses caused by disclosing personal information (Haleem et al., 2022).
Benefit perception	The weighing of possible benefits received in exchange of providing personal information with marketers and other organizations (Cloarec et al., 2022).

Familiarity	Individuals' prior experience or knowledge about a brand or commerce platform, which often affects their trust in a brand/seller accordingly (Haleem et al., 2022; Tanantaputra et al., 2017).
Trust	The expectation that, considering their own characteristics and the transaction environment, consumers can rely on the word or promises made by retailers, and trust that that retailers will not exploit their vulnerability in terms of data (Järvenpää et al., 2000; Ratnasingam et al., 2005).
Reputation	General assessment of the company's product and service proficiency, social attributes, customer interactions and messaging regarding its capacity to meet customer needs, indicating how the company manages customer matters including privacy (Li, 2014).
Privacy policy	The regulations and duties of organizations' regarding managing customers' personal information. Commonly refers to documented or published statements outlining an organization's policy on handling personally identifiable information collected from consumers and utilized in routine business operations (Haleem et al., 2022.)

Table 3: Primary factors moderating consumer privacy concerns in an online setting

A robust consumer-company relationship built on trust may be paradoxical however, as it can lead to heightened negative reactions if the company misuses or mishandles consumer data. This breach of privacy may evoke feelings of betrayal particularly among closely connected customers, despite the initial trust fostered by the relationship. (Wanjugu et al., 2022.) Becoming a respected entity in terms of privacy and safety is still a crucial objective for all organizations. According to Fortes & Rita (2016), building a good privacy reputation in the digital marketplace requires developing a clear and understandable privacy policy, presenting and communicating it to users prominently, as well as obtaining certification from external entities such as TrustGuard etc. Highlighting the ethical responsibility of organizations, Thompson & Siamagka (2021) find that going beyond regulations in the way of behavior coined as 'organizational privacy ethical care', which represents a more empathetic and holistic approach to privacy concerns, is critical in mitigating consumer fears and privacy subversion behavior.

Certain viewpoints explored in data privacy literature underline behaviors among consumers that may be more common, or at least more understandable in every day online transactions. One of these is Hoffmann et al.'s (2016) concept of privacy cynicism, defined as "an attitude of uncertainty, powerlessness, and mistrust toward the handling of personal data by digital platforms, rendering privacy protection subjectively futile." The authors see this type of cynicism built on an individual's assumption that the company or organization is primarily motivated by self-interests that diverge from their own, and thus may likely exploit or deceive the individual. This perception can be seen serving as a kind of cognitive coping strategy, allowing consumers to justify their liberal data management behavior despite significant breaches in online privacy (Hoffmann et al., 2016; Khan et al., 2023). Therefore, even with significant perceived risks and the company considered untrustworthy, consumers may still choose to disclose their private information to the organization. Hoffman et al. (2016) emphasize the role of internet-related skill/literacy in regard to privacy cynicism, arguing that the two combined might encourage risky behavior by leading individuals to pass up opportunities for various protective measures. Draper & Turow (2019) address the incapability of consumers to control their data through the concept of digital resignation, a feeling which arises from a sense of futility regarding the way companies treat consumer privacy.

The practically identical concept of privacy apathy was coined by Hargittai and Marwick (2016), after their focus group data sourced from university students showed a severe lack of privacy protection behaviors, characterized primarily by a sense of resignation toward privacy violations. Even when expressing a certain level of cynicism, participants were inclined to safeguard their privacy with an attitude labeled as "resigned pragmatism", which reflects a recognition of surveillance realities coupled with a pragmatic acceptance of limited alternatives. Other mechanisms described in the literature include surveillance realism, described by Dencik & Cable (2017) as the pervasive presence of surveillance technologies, coupled with a lack of transparency and understanding, resulting in their normalization despite widespread concerns. Rather than implying acceptance or consent, this construct primarily reflects a pragmatism observed in studies of public attitudes after Edward Snowden actions as a whistleblower sparked discussion about both individual privacy and national security.

Not all consumers react to the pervasive data collection with apathy, however. To counter feelings of helplessness and a lack of control in online environments, certain consumers intentionally provide false information, aiming to regain a sense of power, a practice that poses a significant challenge to digital marketing professionals (Cloarec, 2022). Bandara et al. (2020) see the impact of privacy empowerment as a double-edged sword, claiming that privacy empowerment may have a negative impact on privacy concerns and defensive behaviors; however, consumers with higher levels of privacy empowerment might engage in more online transactions. Conversely, a lack of privacy empowerment can lead to increased privacy concerns and defensive behaviors, posing challenges for companies in managing consumer backlash in the form of data poisoning. This complex relationship points out a largely unconscious “control paradox” in consumers, one where users who perceive greater control over their privacy they tend to disclose more information, which then may increase their vulnerability (Cloarec, 2022). Privacy concerns contribute to inaccuracies in data gathered from social media platforms especially (Kolotylo-Kulkarni et al., 2021), with Bright et al. (2022) finding that privacy concern negatively affects social media engagement, thus making the management of users' privacy concerns crucial for sustaining their engagement on social media platforms.

Cukier (2021) argues that the impact of AI on customer experience has been examined too one-sidedly in literature, while being particularly critical of a paper by Puntoni et. al. (2021) concerning how consumer navigate different AI consumption contexts. According to Cukier (2021), users are not only helpless victims of constant data privacy breaches, but instead actively choose to participate in the exchange based on perceived benefits. Moreover, the concepts of value exchange and user agency in AI experiences are missing from concerns raised by Puntoni and others, while simultaneously disregarding AI's possibilities in mitigating potential harms faced by consumers. Whether it pertains to data of limited value or data of higher value, the collection of data should be seen through the value exchange instead of taking or stealing. (Cukier, 2021.)

Social exchange theory may be the most popular theoretical perspective on privacy, but other frameworks such as the reactance theory (eg. Bleier & Eisenbeiss, 2015; Huo et al., 2020), and the behavioral decision theory (eg. Acquisti et al., 2013) also encapsulate consumer perceptions and behaviors in response to privacy and data enclosure. Reactance theory, which is particularly relevant to personalization, explains how individuals respond to situations where their freedom of choice is restricted, making the restricted choice more attractive. Disclosures and click-troughs increase when consumers perceive they have freedom and control. Conversely, limiting these attributes negatively impacts marketing outcomes. (Bleier & Eisenbeiss, 2015; Martin & Murphy, 2017.) Behavioral decision theory on the other hand, as applied to consumer privacy research, examines how contextual cues and perceptions influence decisions involving privacy risks, uncertainties, and informational asymmetries. Perceptions about privacy are based on a rational assessment of various factors, most importantly perceived vulnerability and control, in disclosing personal information to marketers. Said contextual cues also influence consumer willingness to pay for privacy safeguards. (Acquisti et al., 2013; Martin & Murphy, 2017.)

Consumers' willingness to share data during transactions is clearly multifaceted regardless of the presence of AI. Jin (2018) highlights that behavioral influences like small incentives, minimal navigation efforts, and even irrelevant but privacy-reassuring information can sway consumers toward disclosing personal data. Also prominent among consumers is the tendency to prioritize immediate benefits versus future concerns. Consumers additionally perceive the extra risk of sharing data with another organization as often minimal, highlighting the trend of privacy cynicism/apathy (Khan et al., 2023; van Ooijen et al., 2024). When contemplating the relationship between AI and consumer perceptions of private data exchanges, one can see a clear conflict arising from consumers underestimating the value of their data, either though resignation or apathy, and the development of artificial intelligence and effective data collection. But even as consumer privacy concerns may be unclear or paradoxical at times, the changing landscape of data control and aggregation driven by AI points toward more comprehensive measures in consumer privacy protection. Not only does the application of AI in marketing mean an increased amount of perceived risks among consumers, but it also requires a heightened knowledge of algorithms, learning models, and AI capabilities among companies, and adoption of broader privacy policies (Querci et al., 2022).

3.3 Regulatory influences in AI and data

As with any area of business, proper regulation is essential to the welfare of all stakeholders. The fast and constant development of the internet and other information technology has forced regulators to play catch-up for many years, often resulting in data breach scandals such as the one Facebook faced in 2018. At the same time the widespread use of AI tools across various sectors, both private and public, has garnered attention from governments worldwide regarding the tensions between data privacy, protection, and the integration of AI technology. Mazurek & Małagocka (2019) see many sides and motivations around the issue: policymakers and human rights advocates stress the importance of understanding opportunities and challenges posed by AI, emphasizing the need for nuanced approaches to address legal compliance and ethical considerations. Scholars and market analysts similarly emphasize the necessity of developing specific principles, best practices and accountability tools to promote responsible data management, and the need to uphold data protection standards in the ongoing evolution of AI technologies. (Mazurek & Małagocka, 2019.)

Ke & Sudhir (2023) highlight that in protecting consumer data with regulation lies a crucial dilemma of finding the balance between safeguarding consumers from possible risks, while also ensuring that they and society can access the maximum benefits from sharing data with others. This yearned balance is the middle ground between outright banning data collection and usage by firms, and a wild west -like environment that largely disregards individual data privacy. Mazurek & Małagocka (2019) likewise see balancing technological advancement with consumer welfare as crucial; Data for AI often comes from diverse sources necessitating seamless cross-border movement, which when overly regulated can result in inflated data acquisition costs and increase in technology expenses. Data regulation naturally has many other important purposes not just in the realm of consumer privacy. Some significant implications include the encouragement of firm entry, thus improving market competition, and the overall battle against detrimental societal effects proposed by unregulated AI (Canayaz et al., 2022). Peukert et. al. (2022) indicate that certain key outcomes of the General Data Protection Regulation (GDPR) for instance extend beyond privacy concerns to encompass antitrust policy and regulatory competition. Such spillovers have broader implications for discussions surrounding data and AI governance.

AI-powered data collection has caught the eye of regulators especially as other data exchange methods have become less effective. For instance, utilizing third-party cookies has been the primary way for of identifying and tracking consumers for many years. When placing digital advertisements, businesses have conventionally relied on cookies as a valuable data source, providing insights into the websites visited by customers and aiding in predicting their ad preferences (Davenport, 2023). However substantial changes are now underway regarding the use of cookies in data collection. Google's Chrome browser is anticipated to soon prohibit third-party cookies, even those that sometimes pass for first-party (Latvala et al., 2022), a measure already in place with Safari and Firefox.

Given Chrome's dominant position as the primary browser, especially in Europe with over a 60 percent market share, Google's impending cookie policy is thought to essentially terminate cookie-driven advertising. (Ahuja et al. 2022.)

The GDPR in Europe is often viewed as the gold standard for regulations concerning personal data protection (Ke & Sudhir, 2023), which mandates that the strictest privacy settings are set as the default, therefore limiting both the quantity and the quality of data that AI applications crave (Campbell et al., 2020). But even as the primary benchmark for regulation, GDPR sometimes suffers from unspecific guidelines, such as in the case of asking for data collection consent. Due to undetailed design regulations, marketers and website designers often resort to using what are known as "dark patterns”, which refer to design features intentionally crafted to steer users towards selecting options that involve sharing information (Berens et al., 2024). Tricks like dark patterns highlight the way in which collection and distribution of data among organizations is becoming increasingly complicated under the new legislative landscape, which also contributes to the formation of “data silos” i.e. isolated pockets of sensitive data within an organization. These silos are seen in combination with increasing privacy concerns as a major challenge of AI progress inside companies. (Cheng et al., 2020.) One of the challenges hindering the enactment of more comprehensive privacy regulation lies in psychology, as in privacy related problems appearing abstract, nontangible, or rare. Aqcuisti et al. (2020) for instance show that despite concerns reported in closed-ended surveys, privacy issues rarely emerge as top-of-mind problems in open-ended questions presented to consumers, hence appearing as a clear parallel to the debate on climate change. The authors claim that one reason for this disparity is a lack of immediate or tangible consequences of privacy breaches.

According to Panagopoulou (2024), sufficient regulation of artificial intelligence requires a comprehensive strategy that balances data protection, the free flow of information, and the promotion of technological and research advancements. And in order to be truly effective, privacy regulation must give clear guidelines to professionals working in both marketing and AI. In an effort to examine the competencies of AI professionals, Das et al. (2023) found that despite regulatory compliance serving as a key motivator for privacy work, practitioners often prioritize meeting minimum standards rather than addressing AI-specific risks. The study thus underlines the reliance of practitioners on general design references and automated audits, resulting in a lack of real knowledge on the privacy issues exacerbated by AI. Claiming regulations as insufficient thus far, the author call for a design methodology called “privacy through design”, which should address the imbalance of utility and intrusion in AI products. (Das et al., 2023.)

AI is expanding the utilization of data and may provide predictive insights into the nature of collected information (Bartneck et al., 2021) According to Pentland (2022), achieving a balanced global marketplace requires involvement from diverse stakeholders in managing data, goods, and intellectual property. More importantly an overall shift towards a sustainable digital economy that benefits many instead of few requires cooperative organizations. This potential force to counterbalance dominant data platforms exists worldwide. (Bartneck et al., 2021) The main challenge lies, similar to the views of Ke & Sudhir (2023) and Panagopoulou (2024), in ensuring safety and ownership rights while maintaining global connectivity (Pentland, 2022). Without intervention or changes however, the restoration of privacy seems unlikely. Individuals lack the ability to negotiate their privacy directly with institutions, and regulators often become influenced or aligned with the industries they are supposed to regulate (Acquisti et al., 2020; Oyserman & Schwarz, 2020), a scenario all too familiar in many industries globally. And while the importance of privacy among consumers varies significantly based on cultural and historical contexts, a universal need for more adaptable privacy regulation is needed due to AI.

3.4 Conceptual framework

The conceptual framework of the study (Figure 6) was built on the theories discussed in the literature review and focuses on the prerequisites and limitations which moderate the effectiveness of AI-powered personalization. The framework is divided into interconnected segments: AI's advanced learning models are made possible through the plentiful stream of big data, and the interplay of both is moderated by AI and data regulation. With or without big data personalized marketing is developed, but only with the integration of AI is it possible to serve consumers through hyper-personalized measures. The effectiveness of hyper-personalization and the overall data flow of marketing is influenced by consumers' behaviors and attitudes in the data exchanges.

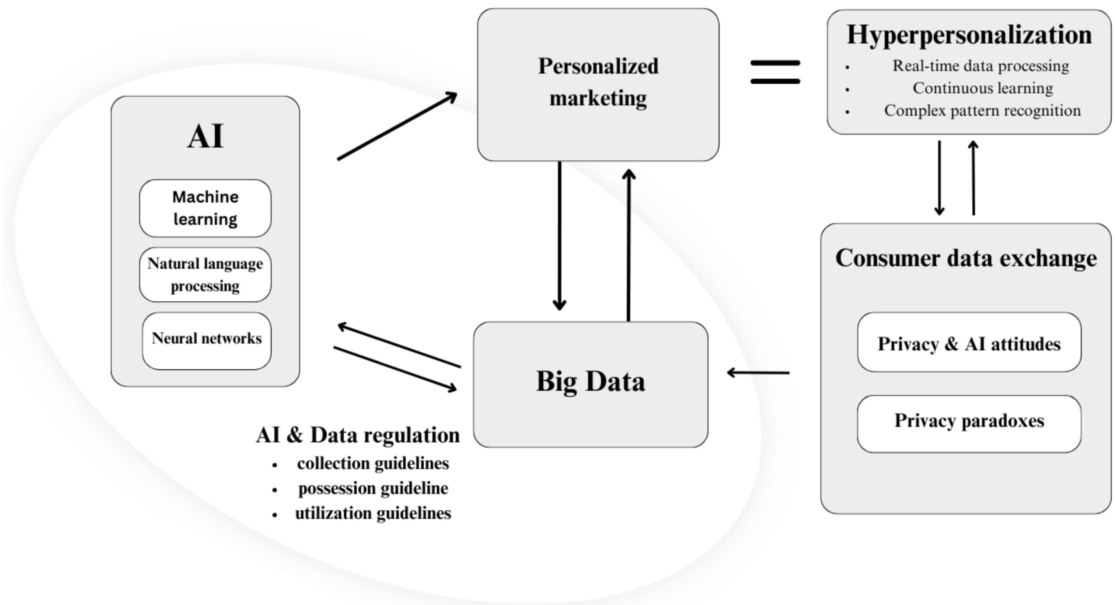

Figure 6: Preliminary conceptual framework

4 DATA AND RESEARCH METHOD

This chapter presents the methodology of this study while examining its validity and reliability in terms of the subject matter at hand. The chapter presents the research method, data collection, research subjects, and analysis of the empirical material. The choices regarding these methodological dimensions are to be derived from and justified based on the research questions presented in the introduction chapter. The aim of this study is to increase the understanding of the use of AI in marketing and personalization in particular, and the impact this progress has on the consumer privacy and personal data autonomy. The study aims to identify the benefits as well as ethical challenges arising from AI-powered personalization and examine this area of marketing through an environmental lens of regulation and consumer behaviors and attitudes.

4.1 Research method

A qualitative method was chosen for this study. The purpose of this was primarily to highlight all the various perspectives marketing and AI experts possess on the topics in maximum detail and variety. Since the research questions of this study have been scarcely examined in previous literature, they require rich and nuanced answers through in-depth interviews. Hirsjärvi & Hurme (2022) argue that qualitative methods bring the researchers closer to those meanings that subjects give to various phenomena and events. In other words they effectively reveal the perspectives, ideas and feelings of the people interviewed. (Hirsjärvi & Hurme, 2022) This also means that processes of interpretation and understanding must be examined in qualitative research. To withstand the general requirements of valid research set by the scientific community, a researcher must be familiar with the characteristics and the process of qualitative research, and its distinctions from quantitative studies (Puusa et al., 2020). All these demands were considered to conduct scientifically sound and comprehensive research.

The semi-structured individual interview was chosen from all possible qualitative methods, as it provides a natural and a conversational setting for both the interviewee and the interviewer. This research set-up allows for supplementary question to be asked if needed, which in a topic as complex as AI and data is often required to clarify and expand on certain questions. Instead of resulting in informal interviews with excessive variation, the semi-structured interview approach ensures that questions can be formatted effectively for respondents to describe each topic in their own words. The motive behind conducting interviews is usually the desire to place the interviewee's answers into a broader context (Hirsjärvi & Hurme, 2022), which is an especially beneficial approach for a study examining trendy and complex topics, such as AI and algorithms. Conversational interviews also provide subjects a chance to freely reinforce their answers with anecdotes and events from their professional career. Compared to surveys or questionnaires, interviews allow the interviewer to correct misunderstandings, clarify questions and make conversation with the interviewee. It should be noted however, that conversational in the case of this study is distinct from dialogue-type interviews, where the researcher actively engages in the conversation. (Tuomi & Sarajärvi, 2018) 1-to-1 interviews were naturally preferred to group interviews, as they allow interviewees to give detailed answers without interruptions. In group interviews subjects can also be easily influenced by the presence and opinions of others, therefore negatively affecting the overall research process and the quality of data. The questions in a semi-structured interview are predefined and uniform for all subjects, but the order or wording of the questions can be adapted for different interviews. (Hirsjärvi & Hurme, 2022). This is especially helpful when the interviewees' expertise and professional backgrounds differ.

The base structure of the interviews (attached as appendix) was built in a way to gain as comprehensive and nuanced information related to the topics as possible. The interviews were built around three themes integral to this studies theoretical framework: 1) personalization and its processes in contemporary marketing, 2) the utilization of AI in marketing and specifically in personalization, and 3) the relationship between AI-powered marketing and consumer data privacy. Interviewees were at first asked to describe their professional background, areas of expertise and current role within their respective companies or organizations, as well as their experience and knowledge regarding AI tools and principles. After these initial questions we proceeded to examine personalization in marketing, in which the subjects were inquired about the definition, best practices, current trends, and limitations of personalized marketing. The first question for all interviewees was to define personalization, an inquiry that served as a clear and uniform starting point in all interviews and made it easy to guide each interview forward.

The final question within the theme of personalization considered the future and prerequisites of hyper-personalization, which provided a good segway into the theme of AI in marketing and personalization. Interviewees were asked to identify the benefits and challenges of AI utilization in personalization and marketing in general, with follow-up questions focusing on the strategical and ethical dimension of AI implementation. Inquiry about AI-related challenges guided the interview to the last theme, in which questions focused on the tension between personalized marketing and consumer privacy particularly due to increased AI powered data collection by companies. Final questions of each interview concerned the current data landscape, data requirements of AI and the role of regulation in customer targeting in the near future. This theme used a large number of different questions and follow-up questions to gain a deeper understanding of which factors inside companies and with consumers moderate the effectiveness and use of AI. Follow-up questions were utilized with every theme when required, as Tuomi and Sarajärvi (2018) state that the use of additional clarifying questions based on the interviewees' answers is a good way to achieve rich and meaningful interviews.

4.2 Data collection

The interviews for this thesis started at the end of April 2024, with the last interview completed in mid-May. Available interviewees were inquired through several companies and organization which employed experts on AI-marketing and data privacy, with usually some emphasis on either topic. The selection of interviewees was thus based on their already existing knowledge about the researched topic, which is also known as a purposeful and discretionary sample (Puusa et al., 2020). This approach to data collection is especially integral when the topic is complex or the number if interviewees is smaller (Eskola & Suoranta, 1998). Interview requests were sent to organizations or to individual directly by email, which communicated clearly the type of expertise preferred to avoid any misalignments between the research topic and interviewees. Demographic criteria such as age or gender or any other factor not tied to the expertise of AI, marketing, or data privacy was not considered relevant in the selection of the interviewees.

All interviews were conducted remotely through Zoom, mainly because it would be easy to collect data regardless of where the interviewee lived or worked. Such remote interviews also allow effortless recording and handling of the interviews afterwards. As many white-collar occupations have transitioned toward remote work, the Zoom-environment was familiar to every interviewee and did not impede any discussion. Privacy notices and information related to the anonymous nature of the interviews was presented together with each interview request. Specific questions and the detailed structure of the interview was instead not disclosed, as prior information such as that may guide, limit or even restrain answers, therefore negatively affecting the content of the interviews (Puusa et al., 2020). Before recording started in each interview, the privacy notice, assurance of anonymity, and the willingness of the interviewees to participate in the study was recited. The title of the study was shared at the beginning, after which every theme was discussed in detail. The interviews were conducted in Finnish as every interviewee was a native Finnish speaker, which meant that no answer could be negatively affected by a language barrier or lack of knowledge in English business terminology. Interview transcriptions were destroyed after the they were translated from Finnish to English.

The questions were formulated as what, why and how questions, so that each interviewee could answer them as broadly or as in detail as possible while reflecting their own background and experience. Some questions explicitly inquired the interviewees previous experience and knowledge with AI tools for instance, which simultaneously provided a great starting point for questions about characteristics and possibilities of these technologies, while also forming a comprehensive overview of the kinds of AI procedures utilized in business currently. Puusa et. al. (2020) point out that a common beginner researcher's mistake is to make it the interviewees task in a sense to answer the interview questions, which often leads to the interviewer forming abstract questions with difficult terms, resulting in interpretative mistakes in the final analysis. This challenge was considered before the interviews of this study, and so the questions presented were formed to be as clear and jargon-free as possible.

4.3 Overview of data

Six interviews were collected in total, with durations ranging 43 between 59 minutes. This was mainly due to some interviewees giving shorter answers than others, which is ultimately a very common aspect of conducting interviews as a method of research (Tuomi & Sarajärvi, 2018). Some interviewees on the other hand presented detailed anecdotes and examples related to the topics at hand, and some were asked more follow-up questions than others depending on their answers. This was largely due to participants having varied backgrounds and specialities, which made every interview at least on some topics unique.

All experts involved in the study possessed a professional career of over 10 years, many much more, with some specializing more intensely on topics such as AI-strategy or data security. Each participant had at least a decent amount of experience with AI-marketing in the B2C markets, and with some more in charge of day-to-day business operations and some more focused on strategy and big-picture consulting. Each participant had distinct and passionate perspectives and viewpoints regarding the possibilities and ethics of AI, current trends and best practices of personalized marketing, as well as the current consumer privacy and individual data landscape. All participants were occupied in Southern-Finland and conducting business nationwide or in other Nordic countries as well. Information about the interviews and interviewees can be seen in Table 4.

Participant	**Current organization**	**Interview duration (min)**
P1	Marketing agency	59
P2	Digital consulting firm	48
P3	Marketing agency	50
P4	Business consulting firm	52
P5	Digital consulting firm	56
P6	Marketing agency	54

Table 4: Interview summary

4.4 Analysis of findings

The data was analysed using the revised version of the popular framework of thematic analysis by Braun & Clarke (2006), one which is often credited as the main reason for increased interest in the method that was before in many ways poorly demarcated and understood (Byrne, 2022). The data analysis of this master's thesis follows the steps laid out in the 2006 paper, while considering the key conceptualisations and corrections stated by the authors in their reflexive commentary published in 2019, in which the method adopts a name of reflexive thematic analysis (Braun & Clarke, 2019). In essence, thematic analysis is the search for repeated patterns of meaning across a data set through the act of coding, which then form various themes. Thematic analysis is distinct from other analytical methods used to dissect and identify patterns within qualitative data, such as thematic discourse analysis, thematic decomposition analysis, or grounded theory. Unlike grounded theory for example, thematic analysis is more approachable requiring less specific theoretical and technical knowledge, and compatible with various theoretical frameworks. It is therefore highly flexible, versatile, and capable of gathering data that is rich and nuanced. (Braun & Clarke, 2006.)

The methods flexibility is specified in the revised paper however, with the authors stating its limitation by the underlying paradigmatic and epistemological assumptions about how meaningful knowledge is produced. With reflexive thematic analysis the emphasis is on the qualitative paradigm, focusing especially on deep engagement with the data and iterative coding. Codes in reflexive thematic analysis above all reflect the researcher's interpretation of patterns in the data, shaped by the dataset, theoretical assumptions, and the researcher's analytical skills. Themes do not magically appear from data, they are found. (Braun & Clarke, 2019.) With these important distinctions in mind the analytical process was conducted by following the initial framework by Braun & Clarke (2006).

The first phase of the framework entailed an initial examination of the data, i.e. transcribing, reading, and taking preliminary notes about the text. Following instructions by Puusa et. al. (2020), the quality and content of the interview answers were observed through multiple readings, contemplating for instance the comparability of each perspective and interpretation. Initial codes were then generated, meaning features of the data important to the researcher, either semantic or latent in nature. This process is largely dependent on whether the themes are more data driven (inductive), or theory driven (deductive). (Braun & Clarke, 2006). These two approaches are differentiated between "tight and pre-structured" deductive frameworks and "loose and emergent" inductive frameworks. This study utilized an abductive approach, which builds upon systematic combining that suggests using "tight and evolving" frameworks, meaning they should be precise but allow for evolution based on empirical findings. As recommended by Dubois & Gadde (2002), concepts were thoughtfully to act as a reference point and guide when engaging with empirical data, which then evolves throughout the study by being gradually adjusted due to empirical findings and theoretical insights gained during the process. (Dubois & Gadde, 2017.)

The third phase consists of grouping the codes into overarching themes, considering main themes and sub-themes, and ultimately leaving some codes discarded completely, although a theme around miscellaneous codes was created. (Braun & Clarke, 2006) While preferably unique and even contradicting, themes were shaped to collectively form a clear and coherent understanding about the set of data (Byrne, 2022). The fourth phase involved the review of the themes gathered: examining each theme through the collected data extracts and seeing whether they form coherent units, and considering the bigger picture by looking at the thematic map (Braun & Clarke, 2006). Topics and basic summaries of data domains were separated from fully realized themes, or "patterns of shared meaning underpinned by a central organising concept"(Braun & Clarke, 2019). The fifth phase involved identifying sub-themes if necessary, and minimizing overlap between themes to create a clear and structured analysis (Braun & Clarke, 2006). Overall, three main themes were identified in the data. First of these was personalization and its effectiveness in contemporary marketing, of which one subtheme enriched the concept of the cycle of personalized marketing, while the other emphasized the importance of personalized messaging. The second theme formed out of the characteristics of AI driven personalization, in which two subthemes supplemented the conceptual framework by emphasizing limitations in the use of NLPs and algorithms in AI personalization, and the inherent risk in AI investment. The third theme focused on the side of consumer privacy and the restrictions of data movement. Through this theme the framework was complemented by the emphasis of the role of unstructured data and the causes and consequences of data silos.

During the sixth and final phase of the analysis, a written report was produced based on the set of fully realized themes. Vivid and illustrative data extracts were meant to demonstrate the prevalence of each theme while ensuring they are seamlessly integrated into a coherent and transparent narrative. As analysing interviews alone will not suffice to present meaningful results for the research, synthesizing the data to highlight the key points relevant to the research questions was seen as essential (Puusa et al., 2020). The order in which the themes were reported was made so that they build a narrative on top of each other while also standing out as individual narratives if isolated. (Byrne, 2022.) The written report of this thesis following these guidelines is presented in the next chapter.

5 RESEARCH FINDINGS

This chapter examines the results of the empirical research. The findings are divided into themes based on the thematic analysis explained in the previous chapter. The report of the results will first go through the findings considering each sub-research question and themes in a manner that conducts a coherent narrative, and finally examine the main research questions as a whole.

5.1 Personalization in contemporary marketing

The first theme of the analysis focused on how personalized marketing is treated as a process, and how it is used and developed regarding the current marketing landscape. Each participant was initially asked to define personalization according to their best understanding, after which the various characteristics and practical trends they perceived were outlined in the following questions. The definitions themselves were all quite similar in nature, with nearly all participants echoing the positive ideal of personalized marketing as a necessity of succeeding in both the B2C and B2B markets, as seen in many research articles. Some participants saw the process more as a mode of continuous symmetrical communication in consumer markets, while some emphasized the synergy of the right kinds of mediums, messages, receivers:

> *"It is marketing that is as personal as possible, and it reaches that one person as well as possible, that's what you're trying to do. Essentially trying to turn a mass product personal, like a face-to-face sales event is at its best."* -P1

> *"It is essentially communication that is completely targeted to the individual, so that it doesn't even feel like marketing anymore, but it's more like communication with the end customer or consumer and they can feel that it's genuinely useful to them, instead of trying to serve everything to everyone.* -P4

> *"It can all be boiled down to the basic objective, which is that I deliver the right message to the right customer in the right channel at the right time and to the right need."* -P2

Some participants built their answers around terms such as one-to-one marketing and microsegmentation, which are terms often used interchangeably with personalization (Chandra et al., 2022). Responses were especially reminiscent of Vesanen's (2007) idea of personalization being based around the expected benefits of 1-to-1 marketing and effective customer relationship management. Mirroring this mix of older and newer terms and labels, participants realized that personalization in marketing is far from a novel idea, with one participant characterizing it as just commercial, often exploitative pandering that evolves every time there is more to know about both consumer and products. They however also agreed that on many occasions a personalized offering is more fruitful than the generic one. One participant even highlighted that the more effective personalized digital marketing becomes, the more sustainable the field is ecologically through lessening a large carbon footprint.

While most participants saw the increased focus on personalized marketing as logical progression in practically any field of business, there were many limit and paradoxes evident on answers regarding the practice, especially in today's climate of big data and fast-moving digital content. P2 argued that where personalization often errs in the customers point of view is product recommendation, pointing to the scenario where a product recently purchased by a consumer is then marketed to them across many platforms, thus missing its mark and likely doing more harm than good toward the marketer's goals. This sentiment was echoed by P3, who emphasized the aim of predicting future acts instead of feeding past behavior of a customer, which is the more possible the further the customer is in their purchase journey, establishing more touch points and consequently creating more data. P1 likewise noted that like in any process involving selling, the more familiar you are with the customer, the better you can serve and personalize for them. Conversely, effective personalization is less a possibility for a fresh customer, at least without a sufficient amount of past behavior or demographical data.

Examining these views through Gao & Liu's (2022) framework of personalization in the lifecycle of a purchase, it can be argued that the areas where the practice needs the most development on are the pre-purchase and previous experience stages. This in some way seems to be a paradox built into the heart of personalization itself: consumers at the top of the purchase funnel or approaching it are more likely to be repelled by pervasive or delayed personalization, thus interrupting their progress toward vital touchpoints from the company's point of view. A repeated sentiment between participants was that an excessive focus on personalizing a certain part of a customer's purchase cycle is ultimately not fruitful enough, and marketers must instead think how the personalization they enforce affects the entire customer experience. P2 argued that only when firms move away from the traditional way of only reflecting clicks and conversions to KPI's will they discover the steps that are the most beneficial in term of customer experience. This is an interesting holistic perspective, and the focus of which certainly varies culturally as well as according to each field of business.

In addition to contact with the consumer established often too late to be effective, the actual content of the personalized marketing message being too general was also deemed a usual pitfall. In addition to creating messages that serve each customer personally, nearly all participants saw it important to serve them with different messages at different stages of the purchase journey, depending on their level of awareness which could be identified though correct measurements. P1 argued that while many companies strive for comprehensive personalized customer experiences, the importance of a truly personalized message is often forgotten, leading to a sort of faux personalization:

> *"If we offer consumers the same messages, then it's just similar groups and individuals on different brackets in the advertising management platform. Thus, it's*

> *really not much of any value. Someone will observe that yes, we created so many great target groups and segments, but ultimately its redundant."* -P1

This focus on message within all participants was often tied together with a concern for strategic thinking and action. Similar to responses concerning technological investments and projects, personalization initiatives were also seen to require a thoroughly planned approach, despite its fairly straightforward logic and perceived benefit. These insight focused particularly on the channels and mediums utilized, the ability to identify relevant consumer behavior regarding the products and services offered, and the potential pay-off of constructing personal messages toward various segments. One participant argued that often there is not enough data to fulfill these requirements, either due to privacy regulation or the type of product in question, so it may be wise to concentrate on one subset of personalization, which could for instance concern price if the product is more sales driven. The overall sentiment is therefore to do personalization holistically or in a more concreted manner.

Answers additionally considered the effect of platformization on personalized initiatives, with many participants highlighting the restrictions social media platforms introduce, mainly through the weakening of data currents. P3 maintained that while the whole ecosystem of personalized marketing is quite heavily based on creating audiences and measuring them, it ultimately has to be built upon a sound competitive strategy like any other type of marketing initiative, as practically all companies want their share in the consumer everyday digital diet:

> *"It is clear that personalized marketing starts from the company's strategy, thinking about the personalities and differentiation factors and competitive advantages. From these the message is then formed. The art of measuring of course also essential, in that are we reaching the right people and getting them to behave in a certain way." –P3*

Ironically, the message that is carefully personalized for the customer suffers from the enduring tension between personalized marketing and customer attitude and identity. All participants acknowledged that a marketer should be wary of expressing all the information they have of a customer, or in other words avoid appearing creepy, as P1 expressed it, drawing a parallel to the uncanny valley -problem burdening robotics development. In addition to possibility of making communication too personal with customers, the negative implications of labeling and segmenting consumers by either demographical of behavioral information was deemed a fundamental limitation, although the significance of which was judged to vary greatly between cultures and product types. The answers seem to imply however, that more accurately targeted marketing should alleviate the issue of stereotyping, as the process emphasizes behavior data. Through collection of behavioral data can the targeting be developed into something less stereotyping. One interviewee called upon the personalization-stereotype paradox in heart of personalized marketing and the danger of turning customer away by profiling them. The participant criticized the overemphasis on buyer personas and profiling by firms, suggesting that these strategies often rely on broad generalizations, which can lead to ineffective marketing. Moreover, when consumers perceive that they are being categorized in such a manner, they are more likely to react negatively, potentially harming the company's reputation and marketing efforts. This outlook is nearly identical to the arguments made by Lambillotte & Poncin (2023).

Questions about the current trends and methods of personalization received similarly pessimistic views regarding the relationship between personalization and consumer privacy. P1 admitted to shifting away from so-called heavy personalization at least, because privacy concerns have greatly limited the number of individuals who can be effectively targeted. According to them, responsibly constructed cookie-walls see usually about 50 % of customers declining companies' access into their information and behaviour, essentially disincentivising many marketers from creating personalized marketing to half of their audience, although they didn't dismiss the argument that this type of consent transparency generally aids overall personalization strategy. Nevertheless, in already tight markets and relatively small audiences this is naturally extremely detrimental to the aim of maximizing the amount of effective 1-to-1 customer relationships.

5.2 Possibilities and limiting factors of AI-powered personalization

Following the best practices and limitations of personalization in marketing, the interviewees were inquired about how AI is integrated into the practice and where the clearest benefits can be seen. A few participants saw many tools acquired in recent years as being only ostensibly AI, or AI in name only. P1 mentioned the bidding system on Meta's platform as an example, which is according to him presented as a kind of a black box that looks for the consumers most likely to convert. This is thought of as AI-based, although the AI part of the process is concentrated mostly in data clustering algorithm, which is often aided by human intelligence. Nonetheless more supervised or not, many saw the analytical algorithms as game changers, with one participant noting their capabilities in optimizing a large digital out-of-home advertising campaign.

When asked about the most common practical uses of AI in marketing tasks, the most prominent type in many participants answers was generative AI. Especially ChatGPT, unarguably the most popular and widely known natural language processing model, was considered by many participants as the quintessential way of utilizing AI in content creation. P3 however emphasized the need for human expertise in actual content production and personalization, as they at least should understand the business and buyer personas thoroughly. In other words, content is key, but AI can't be relied on entirely. P1 possessed a more critical outlook on the current consumer impact of generative AI, stating that although AI generated visual and textual can be well-targeted, it is very unlikely to be more effective than for example a slightly more generic marketing message created with care and stemming from a sound strategy. While P1 acknowledged

GPT being much more accessible than other more complex AI tools and systems on the market, they argued that the challenge with each of them lies in the sufficiency of data:

> *"I certainly see generative AI as the first one that has been really visible. Of course, we have had these trail blazer types that have long ago produced some kind of AI-based data in the Finnish market. Either way, it has certainly been a primary problem that we need large masses of data that have been difficult to obtain in order to produce enough learning material."* -P1

One participant noted that even a more straightforward tool like ChatGPT suffered from largely unfiltered algorithms, thus over 30% of responses were inappropriate. Only when this was reduced to under 10%, commercial use of the tool became a possibility, although poor responses still need to be filtered out both from the training data and the output. In any case, cleaning and refining of data is constant task. P3 characterized the process as build tailored solutions by teaching the GPT-like AI specific tasks, for instance using it in advertisement copywriting and letting it generate headlines and descriptions through each products' landing page URL. This combination of AI with buyer personas generates targeted ad copy, which the participant saw speeding up the overall process and saving time significantly, even though all of the content was checked and modified. This simple enough process demonstrates AI's functionality in direct digital consumer traffic and making it effective.

Nearly all participants saw AI as the next step in personalized marketing, and essentially as the prerequisite to hyper-personalized marketing. A frequent sentiment from the interviewees was that with AI, the targeting doesn't run behind the consumer, and is constantly looking for more consumers and look-a-likes, thus constantly becoming richer in data. One participant characterized the primary benefit of AI integration in targeting as its ability to perceive entire consumer lifecycles and understand the consumers thoroughly eg. through job or personal interests. The database through time and identification of similar behavior patterns gets enriched, and the AI continually finds more similar profiles, creating a beneficial loop. Other participants highlighted AI's value of finding and refining segments and making it simple to find the right audience, trusting it to identify trends, flops, and hot topics for each demographic. Additionally, by integrating AI with customer databases, external information from a multitude of sources can be used to enrich the company's communication effectively. This was especially crucial for one participant, who maintained that if someone strives toward hyper-personalized marketing, the message must be personalized as well. But although the system may be effective and comprehensive in its calculations and predictions, P2 emphasized the importance of genuinely valuable customer knowledge as a base for all initiatives:

> *"Nowadays, with the help of AI, you can make those personalities with less effort. In the past, they thought about personalization and the purchase journey through the lens of you have this and that, now the focus is on the big picture, because AI*

is more advanced in its predictions and conclusions. Ultimately the process depends on the type of customer you are dealing with." -P2

While many participant shared the vision of AI slowly revolutionizing the process of consumer profiling and the establishment of look-a-likes by continuously finding the right people and improving its work overtime, one participant maintained the skeptical outlook toward buyer profiling mentioned in the previous subchapter, and thus doubted AI's capability of making the process any more fruitful, especially in smaller markets such as Finland. One other participant also deemed effective customer profiling as a rare occurrence even in larger companies with larger databases.

During discussions about AI utilization in marketing and specifically personalized marketing, insights from the participants revealed many common challenges and principles regarding AI integration and its success commercially. Nearly all participants held that investment in AI are generally too costly, and that the potential payoff particularly in the Finnish/Nordic market is still often insufficient through currently available tools and systems. Although agreeing with the sentiment that projects are incredibly risky P5 contended that the initial investments are not that costly as many firms often purchase it as a service. P1 points out that even with detailed AI-powered personalization, practical constraints imposed by major advertising platforms such as Google and Facebook must be realized, as they prevent effective targeting of very small groups, usually meaning under a 100 consumers. This naturally again raises questions about the cost-effectiveness of investing in advanced technology for potentially minimal returns. P5 argued that in addition to the smaller market the language barrier also plays a significant role, stating that more advanced AI tools often work only in languages like English, German, or Spanish, which don't meet the needs of the average Finnish customer. This means that the marketing initiatives are usually kept focused on largely organic mediums and forms of content:

"State-of-the-art marketing tools are usually designed for larger organizations, and there are few companies in Finland that can leverage them effectively. Which is why as a result many are often reverting back to using social media channels, posting blog updates, and sending newsletters because these methods require less investment." -P5

A participant who had worked extensively with GPTs deemed capacity the most significant challenge together with privacy limitations. The former points to the model's tendency to start hallucinating i.e. creating false and misleading content quite quickly, meaning they can't be used for too extensive work. The task also needs to be quite limited, as according to the participant the model's capacity will simply run and begin to hallucinate if they were to try to combine the creation of for example Google ad texts and other form of content. Nonetheless the goal is in creating a customer-specific, comprehensive solution that might consist of different individual GPTs.

In the case of many Finnish companies, AI powered tools and platforms are largely derived from big tech companies, outlining use and possibilities from the beginning, thus often restricting the chance for a correct system solution. Some insights also expressed a certain lack of AI-expertise in in-house teams, often due to the preference on generalist abilities or the inability to truly keep up with AI's extremely fast-moving development. One participant especially highlighted the discrepancy between the companies presently acquiring AI tools and those supplying them, leading to a solution purchased that does not really serve the right needs of the customer company:

> *"A big buffer is the fact that the AI vendors are a different company, and the AI buyer is a different company. So, the conversation is kind of insufficient, in that the buyer says what they want, and the seller says what they have to offer, but that's it. -- The people who decide to buy such and such expensive project usually don't have a clue about the technology. In big companies, it is often thought that the more money you put in, the better, which doesn't necessarily guarantee a good result."* -P6

Similar to personalized marketing, many insights shared a significant concern for strategy regarding AI utilization in various marketing efforts. All participants had a similar twofold view on the relationship of AI and business strategy, in that AI, although useful in many tasks and projects, will in very few cases significantly change a business's overall strategy, but the implementation of it must always be heavily guided by it. P5 specified that while AI does not change strategy per se, it should always increase the firm's ability to adapt and keep up with market trends and global changes. P4 argued the AI's relatively low impact on marketing strategy is most likely reflected in the fact that it is often outsourced, thus delegating the technical solutions as well as the potential problems possessed by the various systems and tools suppliers offer. P6 particularly yearned for companies to connect their need with the best solutions to available:

> *"You have to have some kind of discussion and some kind of reasoning about what you need to know and what you want to know. Then you need to see if any data contains the answer to that question. Often, it's just the black box situation where the data is there, and the machine maybe knows the answer to some mysterious question that no one is interested in."* -P6

> *"Does it help us to better form those micro-segments or does it help us to better select, at which customer in this moment in time is worth putting this message through this and this channel? The clear benefit must be identified." -P5*

One participant maintained a similar attitude that ultimately the integration has to start in the analysis of the firm's current situation and its short- and long-term goals. Attentiveness toward the competitive field was also seen a crucial key to making things strategic. Paradoxically some participants emphasized the unrealistic and even quite detrimental task of creating a multiyear plan of action and strategy in such a dynamic and volatile field of business. P5 particularly implored professionals away from planning any type of strategic roadmap longer than two or three years. P1 described the correct role of AI in firms as never being the main course. They argued that firms should always strive to perfect things like brand customer satisfaction or product packaging and others that have been found essential within effective marketing. Good AI work is to them one small condiment in the whole, which is not able to save anyone's bad marketing. P5 reminded that with or without AI the quality of the firms database is crucial, in that if the data is wrong or corrupted it hurts any kind of potential results very significantly. P6 additionally emphasized this by saying that about 80 percent of the work time goes into trying to clean up the data in nearly any data-driven apparatus.

What many considered fundamental regarding AI infused personalization were the potential benefits and problems of the way consumer data is collected to fuel the practice. Participants P1, P2, and P3 said they had observed a remarkable shift in the motives and strategies of data collection particularly in the last decade, as previously the trend was to collect all the data without a real plan of knowing what to do with it or when to use it, resulting in wasted data and inactivity. P1 argued that now AI solves this in certain cases, either through more intelligent data collection or with its analytical capabilities. A clear sentiment was still shared between interviewees that AI needs enormous amounts of varied data to constantly improve its decision making and to contextualize consumer behavior. This naturally made all participants consider the AI integration from a privacy perspective, specifically on how data is collected and how the algorithms inside the AI process it to avoid creating significant bias and disruptive learning. Participant 4 emphasized how the overall landscape of data collection changes with AI, primarily through its capability of using a wider array of information, consequently raising the potential of the use of unauthorized or inappropriate data. This calls for the ethical responsibility of those utilizing the data, as well as better employee coaching in AI algorithm training:

> *"It's in the case of marketing that personalization becomes a different matter, because when the AI is told to look for information it may start unwittingly, unknowingly, or deliberately looking for information that is not necessarily intended for the free market. So that is quite different from a human being wading through the same information. From the AI's point of view, everything it has the right to read, it will use."* -P4

Overall, AI was noted as being a component that develops continuously, and the next paradigm shift may be behind the corner. Many participants shared the view that instead replacing the marketing workforce, the tasks that now create effectively personalized marketing will move away from consisting just data analysis to the management and development of AI tools and systems. P1 saw this transformation period stemming from a familiar place for most business and technological innovation:

> *"AI innovation to marketing will likely be sourced from the public and defence sectors, through which we will then have one AI whose specialty is structuring data and schematizing it for use by another AI, and then we have different kinds of AI operators talking as agents. There have been talks about this kind of*

development, and of course the integration to our operations must happen if it really adds the best value." -P1

5.3 Data movements and privacy regulation

The third major theme of the analysis concerned the current environment of consumer data, how it is moderated by mainstream consumer attitudes and regulation, and how this environment consequently allows AI marketing to be developed. All participants deemed the current trends being largely unfavourable to progress in AI and personalization, specifically through the restriction of data movement in the EU market. P1 highlighted the legal and privacy implications of consumer data collection, emphasizing that only data that is considered necessary for commercial use can be possessed, and even it must be deleted if unused after a certain period. Moreover, they highlighted the additional risk of using often non-transparent outsourced AI models, of which the added layers of complexity and risk may go unnoticed, but also argued that the line between necessary and unnecessary information was very much blurred. Other participants also held strong reservations about collecting and storing maximal data about customers due to the substantial risks involved.

Regarding this P3 emphasized the increasing importance of first party data, a trend which is already visible with many online platforms requiring users to log in and set up accounts, even if there is no paid subscription involved. This behavior is heavily implored, and once the customer is engaged the firms can then look at how they behave on the website and other services. In addition to the data being more easily analysed and stored, many participants saw that emphasis on first party data decreases the dependency on larger platforms such as Meta or Google, from which the data is not easily combined to the firm's first party data. P1 argued that before first party data can become the primary driver of personalization, or AI manages to collect and combine all the relevant data, the environment is far from straightforward:

> *"The data landscape is very fragmented. The big picture is basically this: we have data from the big players on the customers on one side, and then the smaller companies have a little bit of their data on customers on the other side. Combining these is difficult, if not impossible in many cases. Firms need to, and some already thankfully are, cultivating a sound database for themselves."* -P1

Data silos were brought up frequently by participants when inquired about the requirements of effective data utilization within companies. P3 argued that this is not a new problem brought up with AI, but a significant issue of data siloing in advertising. They explained that when advertising is conducted for a client company, data is collected and segmented by different platforms such as Google and Meta, with each platform retaining its own data. This fragmentation limits the integrated use of data across platforms. P2 emphasized that the problem also resides between different departments in firms, giving the example of customer service data residing somewhere where neither IT, marketing, nor sales can use it to full effect. Although AI might be assumed to change this scenario, it does not inherently solve the issue of data being siloed. Instead, AI may further restrict the use and combined benefits of data within companies by reinforcing these silos, thus limiting the overall effectiveness of data utilization.

Highlighted in the participants answers was also the agreement on the human role of AI and algorithm control, and the ethical dangers included in trusting these systems to make conclusions based on the data they consume. P4 emphasized that in data categorization and database building the data gets biased when moved and categorized due to human impact. They therefore see a certain degree of risk that the data may not necessarily be what it was initially thought to be, which is why the structure of the data must be always considered:

> *"Because it's not done in software per se. Of course, the data is probably categorized and classified, but again, there's a human being in the background who's built the algorithm. When I compartmentalize this data, any slight skew will, over time, resemble the leaning tower of Pisa. The higher it gets, the more it starts to lean in one direction or another."* -P4

Based on the perspectives of all participants, the average outlook on the GDPR could be characterized as both appreciative and ambivalent at the same time. Some participants naturally didn't appreciate its often-harsh restrictions on firms striving to build a sufficient database, but still saw the regulatory framework as very much needed to avoid large scale misuses. P4 acknowledged that one must always remain realistic and question of how strictly the guidelines are followed and enforced in practice, by noting that there have already been numerous GDPR violations and even crimes related to data protection. P1 possessed very much the same perspective regarding regulation compliance within firms and emphasized that the way of action is largely dependent on the individuals leading the projects as well as the culture of the company. They also argued that quarterly culture almost always drives past ethical considerations, and from a game theory perspective, taking risks with consumer data for the potential benefits outweigh the fines more often than not. While focusing on the regulative environment and its influences on the data requirement of AI marketing, P3 also highlighted the challenge of training AI models without leaking excessive information outside of the area of European regulation, to which they plan to toward a cloud system, which keeps the data in Europe.

In terms of consumers themselves and their attitudes many participants saw a sharp divide in the privacy awareness between different segments of consumers, as well as paradoxical behavior within many consumers themselves. P1 saw especially young adults and people in their peak working years are the most privacy-conscious, as they grew up when digital technology was emerging, thus gaining a deeper understanding of technology. According to them, this leads to the younger generation "valuing and often preferring to protect the privacy they once had". Other participants 2 and 3 also saw Gen-Z as more knowledgeful about their privacy matters, although that aspect may be canceled out in some sense by AI’s ability to derive consumer data from many kinds of user generated content. Participant 4 additionally highlighted the ultimately irrational behavior concerning data privacy that many consumers unfortunately possess:

> *“We’ve probably noticed it in many cases that there are certain situations where people are suddenly very aware that 'this is my data, and it shouldn't be used or leaked anywhere.' Then, five minutes later, they are on X YouTube, or Facebook, sharing their life stories and medical histories, fully aware that all this information can be sold forward.” -P4*

P2 in discussing the rapid development of data enrichment and the varied channels used noted that the general lack of awareness about data collection among ordinary consumers is especially prevalent when it comes to familiar devices. They also suggested that as services improve in providing relevant information, less concerns will be noticeable about data privacy. Ordinary consumers lack the knowledge to be truly worried contrary to IT professionals for example. One participant illustrated the dangers of AI assistance through a scenario where a major brand asks users to accept the use of AI across all their devices, essentially making users' data "fair game".

What ultimately makes AI’s impact on consumer data privacy and autonomy significant is its ability to accumulate unstructured data such as sound, photos, and videos, blurring the line between consensual and non-consensual data collection. Many participants indeed saw the ethical dimensions of this recent phenomenon difficult to characterize, as the usual privacy guideline requiring cookie walls and other banners may in the near future become less relevant. P2 pointed out that many people might not fully grasp how many things actually constitute as data, especially when interactions are transcribed and vectorized. P3 and P4 were interested in the recent stories informing people about how Meta and TikTok on default utilize user content on training their AI and marketing. The public discussion about the subject signalled to P4 a clear contrast between EU data privacy standards and global practices, where for example in the US regulation and consumer attitude may be more lenient toward businesses. However, ultimately even the European privacy regulation and standards were seen more or less as guiding post for marketing innovation:

> *“I don’t think regulations create much in the way of much about adaptation. Of course, it's about setting boundaries to operate according to privacy regulations. And then, of course, marketers try to stretch those boundaries as much as possible, to do a bit more than they might actually be allowed. If including ethical considerations takes too much effort, then it's not worth doing. Instead, you should take the risk, and if it succeeds, you'll be a hero. If it fails, you can just move on and look for the next leadership position somewhere else.” -P1*

6 CONCLUSIONS

In this chapter the theoretical contributions and managerial implications of the study are presented based on the research questions, and at the end a revised theoretical framework is presented. Additionally, this chapter evaluates the reliability of the study and describes its limitations. Finally, proposed topics for future research are suggested.

6.1 Theoretical contributions

This research examined the implications of AI utilization to the effectiveness of personalized marketing and its impact on consumer data privacy. Previous research literature can be found on each of these three topics, but none of them contained deeper exploration into the developing relationship between them. Esteemed articles have been focused on especially the current trends and tensions within personalized marketing ((Chandra et al., 2022; Cloarec et al., 2022; McKee et al., 2023; Mehmood et al., 2023), AI implementation in marketing (Haleem et al., 2022; Huang & Rust, 2021; Kopalle et al., 2022), and consumer data privacy attitudes and restrictions (W. J. Choi et al., 2023; Ke & Sudhir, 2023; Kronemann et al., 2023). This study was conducted using qualitative methods through semi-structured individual interviews. The research aimed to gain insight about the possibilities and limitations of AI-powered personalization in marketing through the lens of consumer privacy and data regulation. This study provides new insights into the topic, and the results indicate that the many ways in which AI technologies aid personalized marketing consequently increases risk in the realm of consumer privacy.

The theoretical contributions of the study will now be presented based on the research questions of the study.

Main research question:

How does AI facilitate greater personalized marketing to consumers, and how is it influenced by consumer privacy regulations and attitudes?

Sub-questions:

- Q1: How does personalized marketing influence the relationship between consumers and companies?
- Q2: How does the integration of AI technologies contribute to the overall effectiveness of personalized marketing?
- Q3: What influences the relationship between AI-facilitated personalization and consumer data privacy concerns?

The findings of the research indicate that personalization as a part of marketing is understood to be transforming targeted marketing procedures increasingly toward an ideal of 1-on-1 customer communication. As mentioned in the literature review, Rafieian & Yoganarasimhan (2022) argued the core of personalization being the business's ability to identify and understand individual consumer preferences and behaviors. While similar to the sentiments expressed in the findings section, this study emphasizes the moment of customer contact and the level of consumer awareness at the moment of contact. This differentiation between awareness levels and consumer categorizations is crucial for personalized marketing strategies to meet the unique needs of each consumer effectively and with the correct messages. The focus on truly personalized messaging was additionally emphasized in this study as a prerequisite for efforts striving toward hyper-personalization. While some research such Dwivedi (2023) praise ChatGPT's competency to provide content that ensures beneficial customer relationships, the findings emphasize that it is still just a low-level AI tool that must be guided by an employee with significant knowledge about consumers, their behaviors and the products marketed. This of course among other things can change in no time.

The effectiveness of personalized marketing strategies is further complicated by paradoxes and other consumer attitudes inherent in its implementation, which is a topic much discussed in current literature. Notably, the most commonly mentioned phenomenon among these was the stereotype/labeling paradox., in which the benefits consumers receive from personalization might easily be overshadowed by the feeling of being put in certain box. The findings build on previous research of Lambillotte & Poncin (2020) by arguing that this is a prominent effect of inadequate levels of personalized messaging and personalization running behind the customer. As argued by Davenport (2023), many companies indeed remain stuck in the initial stages of personalized marketing due to poor data quality or insufficient data, weak customer profiles, and a significant lack of methodological expertise. However, the findings of the indicate that the lack high quality data is largely dependent on the regulatory environment as well as the cultural attitude toward privacy. Due to these findings the first main and sub-proposition was then formed:

1) Personalization shapes the relationship towards a 1-on-1 communication process by prioritizing the effectiveness of identifying and understanding individual consumer preferences and behaviors and delivering more targeted and relevant messages toward that relationship.

1b) In addition to a possible lack of clear personalization benefits acknowledged by the consumer, the company-consumer relationship often suffers from pervasive personalized marketing that undermines consumers' individuality and autonomy.

AI's benefits to personalized marketing were experienced the same by the interviewees as characterized in literature. Like Kopalle et. al. (2020) & Haleem et. al. (2019), participants agreed that AI significantly enhances personalization in marketing by leveraging data-driven insights to create more tailored and relevant consumer experiences. It effectively streamlines targeted marketing by using advanced algorithms to understand and predict individual consumer behaviors and preferences. The emphasis was on the word predict, as one of the main benefits that AI supplied was the chance to really keep up with the customer, and not be left behind to recommend something that was already bought. AI tools can moreover optimize advertising campaigns and improve customer engagement by continuously refining consumer profiles and finding look-alikes. In an analytical sense despite the need for human oversight and high-quality data, AI aids in efficient data analysis, reducing the time and effort required for creating personalized content. This is the step however when its effectiveness hinges on the ethics of data collection and sound privacy measures.

Regarding ethical data collection and possession, this study highlights the increasing relevance of unstructured data in marketing, which has been left largely under the radar in literature. As AI is trained and developed through more unstructured multimedia content, the usual scenarios of cookie walls and other straightforward moments when a consumer has to consciously consent to data collection may become obsolete. At the time of interviewing many news stories commented on the pervasive interest of social media companies as well as language processing tools to get full access to user generated data. Due to the findings made during the research it can be argued that autonomy and privacy will shortly be examined together with copyright dimensions of social media users and consumers in general. A second main and sub-proposition was formed based on the aforementioned findings:

> *2) AI significantly enhances personalized marketing thorough advanced algorithms and predictive learning to create tailored real-time consumer experiences and optimized advertising.*
>
> *2a) AI's significant role in personalization development is especially evident in the increasing importance of unstructured data, which allows for a greater stream of data concerning consumer preferences and behaviors, which is consequently able to be analyzed in larger quantities thanks to AI-based tools.*

The negative effect of data silos was remarked in previous research most notably by Cheng et. al. (2020), but only as a problem brought upon by regulative forces. As the findings showed, data siloing exist heavily also between different departments inside companies, which is a major problem as gathering data inside the company is already a risky procedure. What the findings also contribute theoretically is that the human role in data biases and erroneous categorization is more usual than previously apparent in research. While before the speculation regarding algorithms focused on the discriminatory biases, non-transparency and blurred lines about the ones responsible for them. This study's findings build upon this literature by bringing forth the problem of non-discussed human error and its consequences on personalization algorithms.

The findings moreover bring forth several key aspects regarding consumer data and privacy regulation within in the context of AI-driven personalized marketing. One of these is that GDPR regulations on data movement present requirements that necessitate careful handling and timely deletion of consumer data and prohibit unnecessary data to be collected. Consequently, firms are increasingly focusing on collecting and analyzing first-party data. The combination of these factors has been dealt lightly in previous research, but this thesis notes them as two key factors restricting the development of AI powered personalization. What is also interesting form both a theoretical and a managerial point of view is the finding that privacy compliance often hinges on company culture and leadership, while at the same time consumer privacy awareness varies.

Consumer's trust in the ethical use of their personal data is nevertheless hardly benefiting from the integrations of AI, and as argued by the interviewees, may likely be a driver for the normalization of privacy apathy. Greater personalization effectiveness for companies often takes more control away from consumers, in addition to the lack of transparency fostered by complex tools and algorithms as well as unethical company principles. Along with unstructured data complicating consentual exchange of data, regulation continues chasing companies that rather take a risk of privacy mismanagement than missing achieving the competitive edge. A third main and sub-proposition was presented based on the aforementioned findings:

> *3) AI-driven personalization complicates the traditional framework of privacy regulation compliance and familiar consent principles with consumers, thus increasing the sentiment of privacy apathy between consumers.*

> *3a) The pervasiveness of AI personalization is restricted by regulations and resulting data silos, although the compliance of them are ultimately determined by the culture and leadership in each company.*

Due to these findings, the research reinforces the understanding of many previously identified dimensions in the relationship between AI marketing and privacy and also founded a solid theoretical base from which to examine the development of personalization practice in the time of rapid paradigm shifts in the realm of consumer data. Based on these findings and conclusions, the conceptual framework of the study has been refined. In the revised version (figure 8), unstructured data is now recognized as a vital although largely obscure part of the consumer data exchange, supplying data to companies largely unaffected by consumer privacy attitudes. The findings also highlight that the cycle of consumer data, AI, personalized marketing is as a process greatly restricted by the formation of data silos both between different platforms and company departments. The framework additionally acknowledges the challenges associated with machine learning biases and NLP hallucinations, which currently constrain personalized marketing efforts and many other commercial uses. However, as technology advances, these issues can be expected to become less significant.

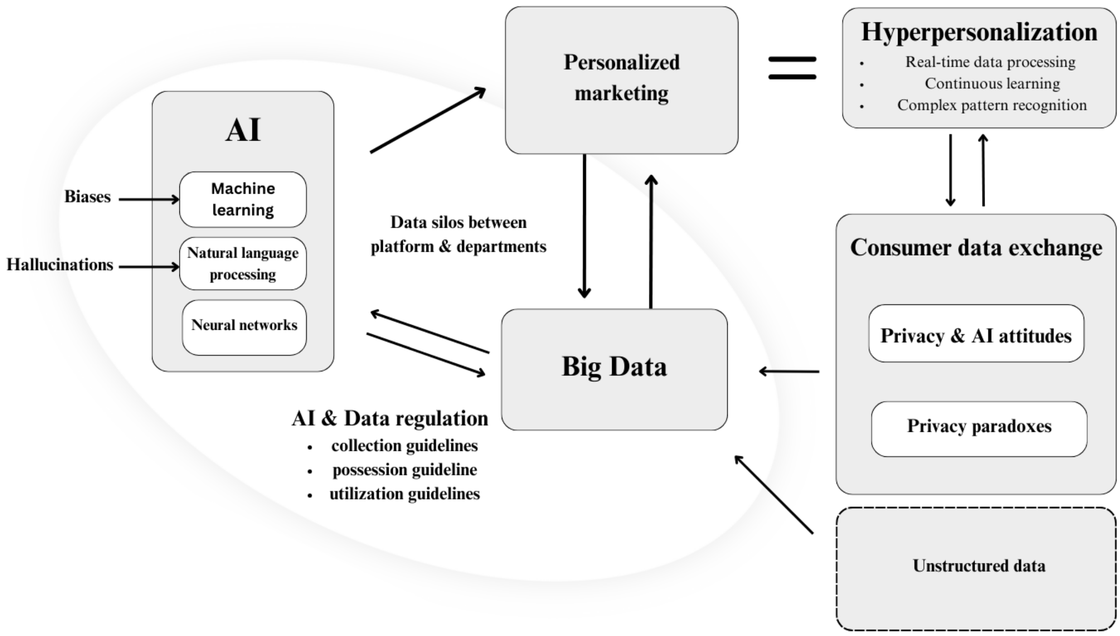

Figure 4 Revised conceptual framework

6.2 Managerial implications

Personalization with or without AI should always be strategical. In choosing the medium, message and most importantly customer, firms must guide these processes in relation to the market trends, competitor capabilities, and clearly defined KPI's. Personalization should be aimed to predict future customer behavior rather than just reflecting on past actions and data. More importantly to avoid faux personalization, managers should ensure that they have sufficient and accurate data to create truly personalized experiences especially considering the message the consumer receives. While this includes leveraging both demographic and behavioral data, the latter should be more heavily emphasized and utilized effectively. In order to achieve a robust database, first party data must be emphasized, as many other companies adapting to the fragmented data flows are collecting and leveraging first-party data to reduce dependency on external platforms like the major social media sites. Because first party data is easier to utilize and categorize, managers should focus on creating engaging environment within their own platforms and channels to ultimately construct robust databases that enable better personalization and more adaptable marketing strategies.

When investing in AI the true benefits and motivations around the purchase must be identified. Not only to bridge the gap between AI based systems and tool that promise to provide easy success and the companies enamored by the sheer though of using intelligent tools, but to also find the option that genuinely serves the firm and their targeted consumer base, which with the right choices can been expanding as well. AI should also never dictate the course of marketing strategy. If and when AI models are outsourced, managers must look to ensure transparency and manage the added complexity and risks, especially by focusing on developing employee training and expertise. Self-regulation is also key, as regular audits and assessments as well as clear codes of conduct regarding these models can help mitigate potential issues.

To combat the development of data silos inside their company, managers must focus on improving communication and data sharing practices between departments, and not only between IT and marketing but also across sales, customer service and other departments. Additionally, platforms and data utilized in day-to-day operations must be unified to achieve effortless audits. This level of comprehensive integration of data across different platforms and departments is crucial for maximizing the benefits of AI-powered personalization.

AI and marketing experts must also recognize and respond to the wide range of consumer privacy awareness, taking into account the medium and message presented. To build trust and decrease customer worries about privacy, autonomy, or surveillance, marketing messaging should be open and honest about how they use data and provide consumers distinct value propositions when they approach them digitally. The previous literature and findings of this research argue that marketing techniques can be more effectively tailored if one is aware of the privacy concerns of various consumer categories, particularly of the more tech-savvy Gen-Zers. Going beyond regulations and embracing a more empathetic and holistic approach suggested by Thompson & Siamagka (2021) will likely improve acceptability and ensure consumers that the company is not just preying on those that have given up their fight for privacy and turned to apathy or cynicism.

Finally, as AI tools can be expensive particularly for smaller markets, managers must determine if the investment will yield concrete results. Language limitations and market size naturally have to be taken into account, but many generative AI solutions are applicable with minimal risks. Ultimately in this and other tactics of personalization however, human creativity and strategic involvement are still crucial. AI can be a very good servant but an awful master.

6.3 Reliability of the research

Due to its multifaceted nature, qualitative studies have required a heap of literature to determine the correct way of assessing qualitative research. According to Puusa et. al. (2020), qualitative research is reviewed based on its reliability, which can encompass various criteria depending on the author and article. In reviewing the reliability of this research, the four-dimensions criteria by Lincoln and Guba (1986) was used. This criteria includes credibility, transferability, dependability, and conformability (Lincoln & Guba, 1986).

Credibility concentrates on the trustworthiness of the research findings and the level to which they offer thorough and reasonable interpretations of the data. Its aim is to build assurance that the outcomes from viewpoints of the participants are accurate, reliable, and convincing. This may involve strategies such as extended interaction, peer review, and participant validation among other (Enworo, 2023; Lincoln & Guba, 1986)

Dependability on the other hand refers to the consistency of research results, meaning that the same findings should be achievable if the study were repeated under similar conditions. Thus the research process must be logical and transparent, allowing the different parts of the research process to be traceable and auditable, and ensuring the coherence between methods and findings. (Enworo, 2023). According to Tynjälä (1991), the researchers should consider not only the external factors causing variations but also factors caused by study and the topic itself (Tuomi & Sarajärvi, 2018). These factors were considered in regard to the topic, and the structure of the thesis was planned and executed in a way that allows readers and peer reviewers to easily connect the methods and findings to each other. Data collection techniques and analytical choices were aimed to be as well documented as possible.

The criterion of confirmability in qualitative research is essentially reflecting the concern for objectivity. According to Shenton (2004), measures must be taken to ensure that the findings accurately reflect the participants' experiences and ideas rather than being influenced by the researcher's biases or preferences. This can mainly be done by a peer reviewing the findings, conclusions and suggestions (Niiranen, 1990; Tuomi & Sarajärvi, 2018). To achieve confirmability, data were checked and rechecked to ensure that at least no significantly different conclusions or perceptions could be made by other researchers or readers.

The main aim of the fourth criterion, transferability, is to determine the extent to which the outcomes of the study can be generalized or applied to different contexts or environments According to Guba and Lincoln's (1986) guidelines, this can be achieved through detailed descriptions, intentional sampling, and reflective practices (Enworo, 2023; Lincoln & Guba, 1986). Niiranen (1990) notes that the transferability of results to another context depends on how much similarity there is between the researched environment and the applied environment, while Eskola & Suoranta (1996) argue that generalizations are not possible due to the diversity of social reality (Tuomi & Sarajärvi, 2018). While the findings are connected to the business and marketing environment of Finland and Europe, the most relevant findings were assessed to be applicable to many other contexts and situations through reflection and aim for detailed descriptions of the participants’ answers.

6.4 Limitations and suggestions for future research

This research contains some limitations and considerations for future researchers. First of all, even though interviews were considered in-depth and insightful, they could have been more plentiful in quantity to help form a more comprehensive analysis. Because the expertise between marketing professional is usually very varied, more interviews would have probably been beneficial. On the other hand, the selection of interviewees could have been even more precise, emphasizing certain skills even more. Ultimately the broad topics that this research examined are difficult to tackle sufficiently even with penetrating interviews and refined questions.

One of the main issues of this research, as one of the participants pointed out by sharing a story of another new master's thesis concerning marketing AI, is ultimately that AI and data privacy are two fields that develop extremely quickly. Even though this research aimed to seek and present the most up to date implications and trends, conclusions and implications derived from the existing state of technology and regulations may unfortunately become swiftly out of date.

As the study concentrates exclusively on AI's and adjacent technologies' function in personalized marketing, it is not able to address other important uses of AI in marketing, which are plenty. Therefore, similar studies focusing on chatbots or pricing strategies for instance could be interesting and fruitful topics for future research. As the interviewees were all working for Finnish companies, the literature could benefit from a similar study conducted in some other region. A similar study done on the North American or Asian markets would be extremely interesting, as their culture of privacy possesses different dimensions. Also, many cutting edge AI and marketing technologies could be examined more thoroughly through interviews in the United States. A case study of one of these companies and their privacy processes would additionally be a great topic of research.

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APPENDIX - INTERVIEW FRAMEWORK

Initial questions	• Can you briefly describe your current role and responsibilities within your organization? • How long have you been working in the field of marketing? • What are your primary areas of expertise or specializations within marketing? • In your role, how frequently do you interact with AI technologies or tools for marketing purposes?	
Research question	Theme/keyword	Interview question
How does personalized marketing influence the relationship between consumers and companies?	Personalization	1. How would you define "personalization" in the context of marketing? 2. What are the key benefits of personalized marketing? 3. How are successful personalized marketing campaigns done? 4. What is the current relationship between personalized marketing and the customer purchase journey? 5. Are there some types of personalization more prevalent than others? What specific trend do you see in the business today?
	Hyper-personalization	6. How would you differentiate between personalized marketing of today and hyper-personalization? 7. Is interest and development toward hyper-personalization ultimately beneficial in the long run? 8. Are AI's abilities they key to hyper-personalization?
How does the integration of AI technologies contribute to the overall	Artificial intelligence in marketing	9. How have AI technologies, such as machine learning and predictive analytics, influenced marketing strategies?

effectiveness or process of personalized marketing?		10. What ethical challenges or barriers have you encountered when integrating AI into marketing processes?
	AI-facilitated personalization	12. In what ways has AI-driven personalization improved marketing effectiveness? 13. Do companies with AI consider consumer privacy, in which ways? 14. What are some of the key challenges you face when implementing AI-driven personalization strategies in marketing?
What influences the relationship between AI-facilitated personalization and consumer data privacy concerns?	Consumer privacy	15. How do you perceive the relationship between personalization and consumer privacy? 16. How does AI affect this relationship? 17. What strategies or approaches do you employ or should be employed to address consumer privacy concerns related to personalized marketing? 18. Do you see privacy cynicism or privacy apathy rising among consumers? Does this coincide with AI use in marketing? 19. How do you foresee AI-facilitated personalization affecting future privacy regulations and data security?
	Data availability and regulative landscape	20. What is the current data landscape? 21. Is the general form and availability of data changing 22. How important are data quality and structure in enabling effective AI-powered marketing? 23. What are the key requirements for leveraging analytical AI successfully in marketing operations? 24. How should marketers adapt their strategies to evolving data

		privacy regulations and consumer expectations?