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Using AI technologies in e-commerce advertising

Personalization from the perspectives of privacy protection and transparency

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ABSTRACT:

Tekoälyteknologioita hyödynnetään laajasti verkkokauppojen markkinoinnissa, erityisesti personoinnissa. Tutkimuksen tavoitteena on saada selville, miten tekoäly mahdollistaa personoidun markkinoinnin, millaisia hyötyjä sekä mahdollisia haittoja ja riskejä se aiheuttaa. Lisäksi siinä tutkitaan tekoälyn käyttöön liittyviä eettisiä haasteita, sekä miten sen käytön avoimuutta voidaan parantaa, jotta kuluttajien luottamus vahvistuisi.

Tutkielman tulokset osoittavat, että tekoälyn avulla voidaan tehostaa markkinoinnin personointia ja kohdentamista muun muassa suosittelujärjestelmien ja kuluttajien datan avulla. Personointi kuitenkin altistaa yritykset riskeille, sillä se edellyttää laajamittaista datankeruuta ja sen analysointia. Nämä altistavat kuluttajia yksityisyydensuojaan liittyviin riskeihin, algoritmien vinoumille sekä päätöksenteon läpinäkymättömyydelle.

Tutkimuksen perusteella kuluttajien luottamus ei rakennu pelkästään lainsäädännölle, vaan yrityksillä on suuri vastuu sen rakentamisessa. Läpinäkyvyyden lisääminen sekä tekoälyn toiminnan avaaminen selkeästi ja ymmärrettävästi vähentävät eettisiä riskejä ja nostavat kuluttajien luottamusta. Vastuullisten tekoälypohjaisten markkinointikäytäntöjen kehittäminen sekä avoimuus tukevat yritystä ja luovat kilpailuetua. Tutkielma korostaa, että teknologisen tehokkuuden lisäksi yrityksen pitää ottaa huomioon eettinen vastuu.

KEYWORDS: AI ethics, Algorithmic bias, Artificial Intelligence, Consumer trust, Data privacy, E-commerce, Personalization, Transparency

Contents

1 Introduction 4

2 RQ1: How does AI enable personalization in e-commerce marketing? 7

2.1 The role of AI in modern marketing personalization 7

2.1.1 Recommender systems 8

2.1.2 Personalized pricing 9

2.1.3 Personalized marketing campaigns 9

2.2 Positive impacts of AI-driven personalization 9

2.2.1 Positive impacts for businesses 10

2.2.2 Positive impacts for consumers 11

2.3 Negative impacts and potential risks for businesses 12

3 RQ2: What are the ethical challenges of AI-driven personalization? 14

3.1 The challenges of privacy and data protection 14

3.2 Bias and discrimination in algorithms 16

3.3 Examples from marketing 18

3.4 Consumer trust and ethical responsibility 20

4 RQ3: How can the transparency of data processing be increased to secure consumer trust in e-commerce? 22

4.1 Transparency in data processing 22

4.2 Challenges in communicating transparency to consumers 24

4.3 How to improve transparency practices to gain consumer trust 25

5 Discussion 27

5.1 Limitations 28

5.2 Conclusions 28

References 30

1 Introduction

Over the last decades, technological development has changed many industries. Nowadays, traditional companies utilize electronic commerce (e-commerce) to enhance access to various markets and increase visibility (Rosario & Raimundo, 2021). This has led to the growth and expansion of e-commerce and increased the need for companies to understand their customers' behavior and needs even better. Consumers are making more purchase decisions online, and the competition is tough. Meeting the needs of consumers and knowing how to attract them to purchase is a big problem and concern for companies (Li, 2021). We can attract people to make purchasing decisions via personalized marketing. Hurme (2022) says that Artificial Intelligence (AI) is the best targeted marketing tool. According to Hurme (2022), with the help of AI and customer data, we can better understand our customers' behavior and create more personalized marketing for them. E-commerce companies provide rich AI-driven personalization for their customers due to the large amounts of customer data gathered online. AI is a central driver behind personalization in digital marketing, making it influential in the context of e-commerce.

Marketing practices are changing, and AI's value in marketing is growing (Gao & Liu, 2023). Unlike other marketing contexts, personalization in e-commerce also influences consumers at the point of purchasing. This highlights the importance of focusing on the ethical, transparency, and privacy-related issues of AI-driven personalization. Various AI technologies are used in different stages of personalization. Recommendation systems are one of the technologies that are used when making personalized marketing. These systems use AI-based algorithms to analyze customers' data to give them personalized suggestions based on their interests. With the help of these technologies, companies can analyze large amounts of data more efficiently, which provides them with a better understanding of their customers and how they can target and connect with their audience (Arora & Thota, 2024). According to Vähä-Ruka (2024), AI has great power, but with power comes a great responsibility. The use of these technologies raises a few ethical questions. Is our privacy and data protected and respected? Are the companies transparent about how they use our data, and do they use AI? Vähä-Ruka (2024) says that GDPR made companies pay more attention to collecting and using our data, but questions about privacy protection still increase when talking about this topic. As e-commerce grows to be the dominant channel for retail, understanding the balance between effective personalization, consumer privacy protection, and transparency has become more important. By being transparent and active, companies can ensure and maintain trust with consumers.

This thesis addresses the research gap regarding the privacy implications of personalized marketing made by AI technologies and their ethical considerations. It explores how AI enables personalization in e-commerce marketing and examines its benefits, possible negative impacts, and risks. In addition, it examines the ethical challenges and transparency when using AI technologies to create personalized marketing campaigns. It focuses on the possible challenges and ethical aspects of using data and ensuring privacy protection while being transparent. In addition, it discusses the transparency practices, possible challenges in there as well as evaluates the regulatory frameworks. This study aims to highlight how companies can improve their transparency practices and the potential negative impact and risks for companies.

The study aims to address the following three research questions (RQ):

RQ1: How does AI enable personalization in e-commerce marketing?
RQ2: What are the ethical challenges of AI-driven personalization?
RQ3: How can the transparency of data processing be increased to secure consumer trust in e-commerce?

RQ1 creates a background to the topic and concentrates on the role of AI in modern e-commerce marketing, its benefits and disadvantages, as well as the potential risks it has for businesses. RQ2 deepens the topic into an analysis of the ethical implications of AI-driven personalization. It discusses the main ethical challenges between personalization, data protection, and privacy, and highlights biases and discrimination in algorithms. In addition, it discusses the issues related to ethical responsibility and consumer trust. RQ3 shifts the perspective to solutions and challenges of transparency and accountability. It aims to answer the question of how data processing transparency can be increased to secure consumer trust. It explains the importance and challenges of achieving transparency. This is done by studying the current processes and drawing conclusions from them.

This study is based on a literature review based on previous research and academic articles. These articles will be compared and combined. AI-driven personalization is an extensive field, and the thesis is limited based on the literature review. These limits still enable an in-depth analysis of the much broader phenomenon. The outcome of this study is to create an overall picture of how businesses can act ethically and transparently while offering personalized marketing using AI technologies. In addition, it aims to highlight the importance of transparency and consumer trust for the companies.

This study consists of six main chapters. The first chapter introduces and analyzes this topic. It focuses on its importance and presents some key topics. The second, third, and fourth chapters answer the research questions. The fifth chapter summarizes my findings, limitations, and views on the future. The sixth and final chapter concludes the study. The grammar and spelling of the thesis have been supported and reviewed with a language-editing tool (Grammarly), but the interpretations and arguments of the work are the author’s own.

2 RQ1: How does AI enable personalization in e-commerce marketing?

The development of digitalization and artificial intelligence (AI) has changed the online marketing practices significantly. Digitalization has enabled companies to build their marketing around customers' data (Bleier et al., 2020). Consumers give up their privacy if they benefit from it (Chellappa & Sin, 2005). They say that, for example, non-monetary benefits, such as the convenience of personalization, can incentivize consumers to share their preferences and personal information. Through data analytics, recommendation system algorithms and machine learning, e-commerce companies can predict their customers' preferences and optimize their advertising content and product exposure in real time. Personalization's convenience usually means recommendations, discounts, or personalized product pages made for you. Personalization has emerged as one of the key competitive advantages for companies. However, the privacy of the data we give threatens both consumers and companies. If the data is misused, it can lead to security risks, a lack of trust and even regulatory violations. In addition, these technologies can create challenges for consumers, which will be examined in the following paragraph.

This chapter examines how e-commerce businesses enable AI-based personalization in marketing and what are the positive impacts for businesses and consumers. It also explores the possible negative impacts on businesses.

2.1 The role of AI in modern marketing personalization

Artificial Intelligence (AI) has enabled a transforming force in marketing, which has exceptional levels of personalization. AI-driven personalization can be applied in every stage of the customer journey (Gao & Liu, 2023). For example, in the pre-purchase stage, the search engine might be optimized, or products might be recommended by recommender systems. In the purchase stage, the ads can be targeted or the price personalized. In the post-purchase stage, chatbots can track your deliveries, handle returns, and issue refunds. AI systems process extensive amounts of data, where they can recognize patterns and adapt content, which allows the company to tailor its marketing strategies based on the customers' preferences and behaviours.

Huang and Rust (2020) have developed a three-stage framework for strategic marketing planning with AI benefits. It includes mechanical AI, thinking AI and feeling AI. Marketers can leverage all three of these AI intelligences in every marketing stage. The marketing stages they refer to in their article are research, strategy and action. According to Huang and Rust (2020), mechanical AI can be used in standardization, data collection, and segmentation. Thinking AI can be used in personalization, market analysis, and targeting, while feeling AI can be used in relationalization, customer understanding, and positioning. The personalization can be, for example, recommending products based on preferences, personalizing prices, marketing campaigns, or interactions.

2.1.1 Recommender systems

Recommender systems are used by businesses to help consumers find the right products (Schafer et al. 2001). Recommender systems are algorithms that give predictions (Konstan & Riedl, 2012). They say that an algorithm can predict if a specific consumer likes a specific product, based on the group of similar users that the algorithm has chosen for you. This selection can be referred to as neighbourhood selection, and it is performed by computing measures that explain your similarity to others. Schafer et al. (2001) also say that the products recommended can also be either top sellers or recommended for you based on your data, like demographics or purchasing history. These systems are used to help the business adapt to each customer. In addition, these systems improve the cross-sell, which means they suggest additional products that the customer could purchase or be interested in.

2.1.2 Personalized pricing

Personalized pricing is one of the central data-driven strategies in marketing. It is a strategy where the retailer can adjust the price based on the customer's data. Misra et al. (2019) argue that large e-commerce retailers have a large number of products in their selection and possibly introduce thousands of new ones a day. When pricing new products, the managers might not have information about the product's demand. According to Misra et al. (as cited in Baker et al., 2014), in these moments, managers should consider setting automated pricing policies, for example, real-time retail prices. As they state, this type of dynamic and adjusted pricing with incomplete information can be approached with multiarmed bandit (MAB) algorithms combined with statistical machine learning methods and insights from microeconomic choice theory. This model tests multiple prices and quickly shifts to the most effective. It also considers the context of the buyer, for example, time, location or device.

2.1.3 Personalized marketing campaigns

Another central AI-driven strategy for businesses is personalized marketing campaigns. There are various ways to personalize marketing for a specific individual. Typically personalization affects who sees the message, what they will see, where they see it and when they see it. With the help of AI technologies such as different machine learning models, marketers can tailor their promotions, suggestions, messages and content based on the customers' data. Ma and Sun (2020) say that, usually a machine learning algorithm is given an objective and a dataset where the algorithm does not perform data acquisition, only the analysis. They say that machine learning models take personalization to higher levels.

2.2 Positive impacts of AI-driven personalization

AI-driven personalization gives the company various positive impacts for both the business and consumers. Martin and Murphy (2017) say that sophisticated use of consumer data gives the companies possibilities to offer discounts, free services, tailored product offerings and recommendations and more relevant content as well as marketing communications. They argue that marketers do this because they can operate more efficiently with all the information.

2.2.1 Positive impacts for businesses

Consumers often look at websites without the purpose of buying anything (Schafer et al., 2001). This is a situation where recommender systems can help businesses to gain more sales as they can recommend consumers' products they wish to purchase. Schafer et al. (2001) argue that recommender systems increase the order size if the recommendations are good. This means, for example, recommending complementary or additional products in the checkout based on the cart. Misra et al. (2019) proposed an algorithm for dynamic pricing in their study, and it was predicted to lead to higher profits. Bleier and Eisenbeiss (2015) state that, especially at the early phase of the purchasing decision process, personalization increases the click-through rates, increasing the revenue.

Another positive impact is the better knowledge of customers and improved customer loyalty. Schafer et al. (2001) state that recommender systems create value for the business and customers. Businesses are investing to learn about their customers to develop their interfaces for the customers' needs. Schafer et al. (2001) argue that this improves loyalty, as the customers will return where they get their needs matched. In addition, better customer knowledge and recommendations can lead to more loyal customers.

The use of AI in marketing can improve the company's effectiveness in marketing operations, as well as make it less labor-intensive and possibly save costs. Kumar et al. (2024) argue that AI helps businesses to get more accurate targeting, which optimizes their marketing expenses, generates higher-quality leads, and allows them to focus on their strategy better. Huang and Rust (2018) state that it can automate both routine and more complex tasks by analyzing complicated data and simulating human thinking and behavior, and learning from these experiences. One example of this kind of automation is chatbots that can act as agents, for example, in customer service. Kumar et al. (2024) argue that chatbots are a cost-effective way to manage customer communication, generating leads and increasing sales. Chatbots can offer personalized service with speed, convenience, and seamlessness, as they can be open 24/7. This can make the customer–company relationship better and increase loyalty.

Using AI for data collection and the data flow process can make your marketing budget more effective, as Accenture has reduced its data flow process time by 80% (Mishra et al., 2022, as cited in Kumar et al., 2024). This enabled the company to reduce insight generation time from 5 months to 5 weeks, which enabled Accenture to achieve an additional $300 million in sales without increasing marketing spend (Accenture, 2024, as cited in Kumar et al., 2024). All of these combined explain why AI-driven personalization can be a differentiator and create competitive advantages for businesses.

2.2.2 Positive impacts for consumers

As mentioned, consumers also benefit from personalization as the shopping experience becomes more efficient, relevant, and satisfying. With the help of AI, consumers receive discounts, better recommendations, and more relevant content. E-commerce businesses can utilize virtual assistants to provide online customer support. This reduces the information overload and the fatigue in decision-making (Puntoni et al., 2021). This makes the shopping experience more enjoyable for the consumer, and makes them return. By providing consumers with more relevant products, reviews and comparisons, they can make better decisions. Overall, when the experience gets more relevant and seamless, consumers gain trust in the business. When consumers trust a business and have positive customer experiences, they return to make more purchases later.

2.3 Negative impacts and potential risks for businesses

Despite the benefits personalization has, it also includes risks and negative impacts. When we are using complex systems, automation, and we are heavily dependent on customer data, we can have unpredictable risks, or the expectations and regulations might misalign. The first negative impact is the privacy concerns that arise from the use of data and these complex systems. These privacy concerns can make consumers sceptical, which motivates them to avoid the advertising (Shamsuzzoha & Raappana, 2021). They argue that some marketers say younger generations would not value privacy as much as older generations, but it is actually a critical issue for all ages. Often, organizations make data protection decisions by weighing profitability and privacy (Shamsuzzoha & Raappana, 2021). According to them, it is especially relevant when the data is shared or sold with third parties. This is made for generating additional revenue, product development, and market research, but the results might be negative as it threatens privacy. In the end, it can result in decreased brand value, trust, and possibly lead to legal penalties.

When companies become too dependent on recommender systems and algorithmic decision-making, it creates vulnerabilities and introduces biases. Selection bias happens when consumers interact with skewed recommendations or non-representative data (Chen et al., 2023). According to them, exposure bias means that some items are shown more frequently and in higher positions, and they are more likely to be bought. This reduces the diversity and limits the visibility for newer or more niche products. They also introduce popularity bias, which means some products might be over-recommended. This reduces the personalization, hurts user experience, and reduces the exposure of other products. These biases will lead to missed opportunities and not the most optimal results.

The intrusive use of data personalization raises concerns about privacy violations and biases. Highly targeted advertising depends on the collection and analysis of a vast amount of personal data (Gao et al., 2023). This raises privacy concerns for both consumers and regulators. This growing concern about privacy raises regulatory and compliance risks for businesses. While the ethical standards are still being developed and each region has its own policies and standards, it is complex for companies to be compliant (Dhirani et al., 2023). They address the issue of having vague and inconsistent guidelines that leave a grey area, which can lead to privacy and ethical issues and data breaches. Businesses must navigate through multiple regional regulations, like GDPR, and wait for regulations that are still under development and evolving, with no proof of their effectiveness. In addition, failing to meet the regulatory requirements can lead to penalties and loss of brand reputation. Bleier et al. (2020) raise a question about the trade-off between privacy and accuracy. If regulation forces companies to use less accurate systems, will it lead to more biased results? They give an example of how privacy regulations can have negative effects on both users and firms. For example, consumers must accept cookies when entering a website, which can create friction during browsing. Therefore, consumers might have fewer options to choose from before purchasing, which reduces cross-checking.

3 RQ2: What are the ethical challenges of AI-driven personalization?

Rising advancements in AI technology have created many advertising opportunities and increased the efficiency of processing information and making decisions. In addition, consumers are demanding more personalized advertising content, which requires companies to use their individual data (Shamsuzzoha & Raappana, 2021). Shamsuzzoha and Raappana (2021) argue that marketers face a critical issue when balancing privacy and personalization. This creates the dilemma of balancing risks and benefits of online privacy, also known as the privacy paradox (Liyanaarachchi, 2021). In addition, we need to understand some ethical considerations and challenges to keep customer data safe. As the current privacy legislation only provides limited protection for consumers and their data (Zuboff, 2015), it is important for companies to act more sustainably. Currently this is regulated through regulations like GDPR, however, it is not enough for businesses because the law cannot keep up with rapidly developing technologies (Shamsuzzoha & Raappana, 2021). This is why organizations need to consider ethical practices. This chapter focuses on the key ethical challenges of using AI when balancing personalization and privacy. It also examines the biases and discriminations of algorithms, and how the ethical responsibility is linked to consumer trust.

3.1 The challenges of privacy and data protection

The increasing volume of data collection creates ethical issues related to data protection and privacy. Our data can be collected either from direct or indirect sources, such as payment records or browsing history (Liyanaarachchi, 2021). This makes the boundary of explicit consent uncertain for consumers. Companies also use so-called dark patterns to subtly manipulate consumers to give more data. Dark patterns take advantage of cognitive biases and they can be categorized into several categories (Mathur et al., 2019). They argue that sneaking dark patterns hide or delay information, such as pre-selecting check boxes and misdirection dark patterns use visual tricks or confusing language.

Forced action dark patterns make it easy to sign up, but hard to delete information and scarcity dark patterns display fake notifications to create pressure for quick decisions rather than careful review of privacy terms. Typically, consumers stick with pre-selected options, which is called the default effect (Mathur et al., 2019). Garcia-Rivadulla (2016) highlights the issue that our data is not only for sale, but it can also be hacked or accidentally disclosed. In addition, she states that governments and companies can gather far more information and insights than we are aware of, and this vast amount of data available without consent or knowledge raises significant privacy risks. Garcia-Rivadulla also introduces a situation called “privacy-paradox” which refers to consumers being concerned about their privacy, but not acting accordingly. In this situation, consumers prefer the convenience more than their privacy. Liyanaarachchi (2021) introduces privacy as a key factor in data protection, as in 2014, eBay was hacked and 145 million users’ data was exposed, including their passwords. This is why consumers should be aware of the risks of data collection and analysis as well as companies should focus on security.

The challenges of data protection and privacy arise from the inconsistent and complex regulations, and organizations lack awareness or resources for security and policies. Campbell et al. (2015) mention that when the privacy regulations are not clear, consumers are vulnerable to harm when they consume digital products, as the data exploitation rules are poorly defined. This enables companies to extract, analyse and use personal information in ways that increase the risk of manipulation, privacy losses and discrimination. Regulations like GDPR in Europe aim to reduce these challenges by forcing companies to adopt principles. Liyanaarachi (2021) states that GDPR is considered a global standard of data privacy. GDPR is designed to protect against privacy violations and data breaches, covering all companies processing or holding data of EU citizens regardless of the location of the company (Shamsuzzoha and Raappana, 2021). Organizations that fail to apply the requirements can get heavily fined. Shamsuzzoha and Raappana (2021) state that under GDPR, individuals should be notified how their data is collected, used and stored, as well as they need to give consent for the use of their information. Campbell et al. (2015) mention that most regulations require companies to secure one-time explicit consent from consumers for their personal information. However, this is insufficient as the data practices evolve over time. Bleier et al. (2020) state that GDPR is strengthening individuals' rights as companies must obtain consent and provide information on how their data is used when consumers ask for that. In addition, it includes the possibility to access or delete customers' data, and makes corporations incorporate privacy by design principles for their systems. The GDPR has set new standards also in fines, as they can go up to 20 million euros or 4% of the global revenue (Bleier et al., 2020).

3.2 Bias and discrimination in algorithms

Algorithms used in personalization can lead to biased and unfair results, which create ethical challenges and problems. These challenges can arise from biases in data, machine learning models or results (Chen et al., 2023). Akter et al. (2022) state that machine learning algorithms can be manipulated using nonrepresentative training data which causes harm for individuals, possibly for the company too. The models are created by humans, which means they can have errors. Akter et al. (2022) consider this as personal bias, which is embedded through gender, race or sexual orientation. Even though we try not to present these values in the models, the training data tends to be biased and underrepresent minorities, which leads to biases towards specific groups. They also state that demographics and socio-cultural factors play a central role in modern marketing. The challenge here is that algorithms can be trained with datasets that are embedded with historical and social biases against disadvantaged or marginalized groups. These types of manipulation increase inequality and social injustice. Their study also states how the machine learning system can be designed to create biases through the non-representative datasets, inappropriate methodological choices, and insufficient specification of the machine learning model.

To tackle the model bias, the model should use clearly defined causal variables that are transparent and understandable (Aktar et al., 2022). In addition, they should take into account the confounding variables to meaningfully connect the predictors and outcomes to get reliable and valid results. One of the other biases arising from the machine learning models is popularity bias, which means that some products might get recommended more than they should (Chen et al., 2023). This creates an unfair situation where over-recommended products receive more attention, while unpopular, newer, or more niche products are discriminated against with limited visibility. Chen et al. (2023) explain that this can happen because long-tailed data in the training models often overvalues popular items and treats less popular ones as irrelevant. As a result, recommendations can get skewed.

Garcia-Rivadulla (2016) points out this issue, as it narrows our options down without us noticing. We are only seeing what the algorithm wants us to see and supports its view of the world. Data bias can arise from the training data that is not ideal (Chen et al., 2023). Akter et al. (2022) add that using representative training data is crucial, as the datasets are one of the primary reasons for algorithmic bias. They say that it is critical to notice the sampling errors, bias blind spots, errors in data selection and reporting, as well as stereotypes and associations, since the machine learning learns from data. Because machine learning model developers often lack the expertise in developing machine learning applications, these systems can suffer from poor problem definitions, which leads to discriminatory outcomes (Akter et al., 2022). These outcomes fail to account for the contextual nuances and risk of overgeneralized findings. Weakly designed algorithms can result in unfair outcomes for customers in value creation, delivery and management.

A real-life example of this could be Apple's machine learning system that they had developed for credit card applications (Akter et al., 2022). Females gained lower credit limits, as well as credit and loan values were made based on the geographical indicators like zip code, which can be discriminatory towards different socio-economic groups or races. Socioeconomic issues and biases in machine learning need to be taken seriously as they concern diversity and inclusion. This is important because if consumers perceive recommendations as unfair or biased, their trust and satisfaction will decline, leading to increased retention and decreased revenue. The GDPR will affect the algorithmic decisions to become more transparent, as Article 12 requires companies to provide information on how the decision was made or how the algorithm arrived at a specific decision (Bleier et al., 2020).

3.3 Examples from marketing

According to Akter et al. (2022), marketers target different cultures to offer them tailored products and services. Delivering this through algorithms has led to discrimination emerging from cultural biases, for example, Akter et al. (2022) mention an example where African Americans and Jews were prevented from showing advertising on housing, credit opportunities and employment on Facebook. Their research shows that biased machine learning outcomes can impact all four pillars of marketing, also known as 4 Ps (product, price, place and promotion).

Marketers tend to use user engagement signals such as Facebook likes as predictions for the demand of the new products (Akter et al., 2022). However, when this data is added to machine learning, the model predicted sensitive personal traits such as sexual orientation, political and religious views, and attitudes towards minority groups. This raises ethical concerns, as this information can be used to design products to disadvantage a specific group. Akter et al. (2022) mention a real-life case about digital cameras that were biased towards Asians. When capturing a photo of a face, it was displaying a “did someone blink” warning message. This shows that when the product development is based on behavioral data, minorities may be overlooked and the results can be disadvantageous for some groups. The companies should put more effort into ensuring that personalization and product development do not privilege others at the expense of others.

For maximizing profits and remaining competitive in the markets, marketers have leveraged price-discrimination strategies like discounts, coupons and loyalty points

(Akter et al., 2022). While it is designed for companies to maximize profits, it raises ethical questions if the systems favor certain consumer groups. Akter et al. (2022) mention that the pricing can be tailored based on the loyalty score, which usually targets individuals who buy more frequently and spend more money. This approach often favors customers with higher buying power and gives fewer offerings for lower socio-economic groups. They also mention that many companies have attempted to manipulate machine learning systems using non-representative and biased data to increase revenue and gain unfair advantages. This is a discriminatory practice where equal marketing offerings are restricted from certain groups of customers. Despite it being restricted in regulations, many companies with a reputation have used it to gain market share and a competitive advantage.

In algorithm-based marketing, place includes location, device and channels. While the location might improve efficiency and relevancy of marketing practices, it raises ethical issues of socioeconomic status, race and income levels. Akter et al. (2022) raise an example of ride-sharing applications having higher prices for poor suburbs with higher crime rates. They also introduced that machine learning models have given higher insurance prices for high-crime areas, which is based on geographical characteristics rather than a person's own behavior. These cases demonstrate that algorithmic decision-making driven by profits can discriminate based on geographic location.

Algorithm-based promotion is used to personalize advertisements, offers and content based on the consumer data. While improving relevancy and efficiency, it raises ethical questions if the visibility of promotions is distributed evenly between different groups. Akter et al. (2022), show an example of African Americans and Jews being prevented from showing advertising on housing, credit opportunities, and employment on Facebook. Practices like this prevent consumer awareness of their opportunities and strengthen inequality. Akter et al. (2022) state that when designing advertisements, marketers choose keywords to target a specific group. This does not serve a mass, but it skews the promotion towards specific groups. Big technology companies such as

Facebook have faced criticism, as they prioritize financial and advertising optimization metrics, for example, return on investment and revenue per click, rather than their ethical and legal responsibilities (Akter et al., 2022).

3.4 Consumer trust and ethical responsibility

Consumer trust is crucial when you want to succeed in AI-driven personalization, as it relies on data and algorithms. When consumers trust the company, they are more willing to share their information. Martin and Murphy (2017) add that consumers are also more accepting of advertising and purchasing, when they have trust. In addition, Bleier et al. (2020) mention that consumers might pay a premium to purchase from a website that openly discloses their privacy policies. A study made by Ameen et al. (2021) recognized trust as a key factor in developing and maintaining strong relationships between buyers and sellers, especially when technology is involved in the interactions. They also noticed that the customer experience can be improved when the customer trusts the technology, brand, and AI service process. This same thing happens when an AI service is seen as reliable and secure, and the company offers support if needed. In AI-enabled customer service, trust is not only seen as brand and technology but also its purpose and process (Ameen et al., 2021).

The use of AI systems carries ethical responsibilities for the companies. They must ensure that the profits do not come at the cost of privacy or fairness. Jobin et al. (2019) have found five ethical principles which are privacy, transparency, responsibility, justice and fairness and non-maleficence. One of the central principles was privacy, which refers to protecting users' personal data and the data security. Ethically responsible systems should limit the data collection to only essential data, secure it, obtain consent and be transparent about how it is used. In their study, transparency was seen as essential for gaining trust, minimizing harm and meeting the legal standards. Ethical responsibilities in transparency highlight the importance of interpretability, explainability and transparent communications of the decisions and AI systems. Justice and fairness mean that the AI systems should be prevented from biases. Ethical ways to ensure fairness could be to use diverse training data, audit regularly, and actively mitigate bias. Non-maleficence means that the AI systems should avoid causing any kind of harm and prevent the misuse or any unintended harmful impacts of AI. Lastly, responsibility and accountability mean that the company is responsible for the decisions made by AI. This is why ethical organizations maintain that AI systems do not operate without humans reviewing the results and mechanisms. If errors are found, they should be addressed.

Shamsuzzoha and Raappana (2021) argue that when a company is emphasizing long-term objectives, it can operate ethically while maintaining profitability, and customers reward this with loyalty and trust. These are the kind of customers companies need because they provide stability, lower the marketing costs, and possibly share experiences that might lead to new customers.

4 RQ3: How can the transparency of data processing be increased to secure consumer trust in e-commerce?

Transparency in data processing means the clear communication of how the data is collected, used, and stored. This is especially important for e-commerce businesses, as personal data is collected through consumers' behavior online. When consumers feel that they can control their data and trust the company, they are more likely to engage with it. Lack of transparency can lead to reduced loyalty, skepticism, and possibly legal consequences. Bleier et al. (2020) argue that when consumers are concerned about privacy, companies incur a loss in revenue. That is why it is important to focus on transparency, so consumers are not concerned about the practices. In addition, Bleier et al. (2020) mention that companies can create opportunities created through privacy concerns, which may lead to competitive advantages.

This chapter focuses on examining what transparency is, what the practices are, and the possible challenges today. It evaluates the practical strategies and regulatory frameworks and aims to give examples of practical ways to improve transparency.

4.1 Transparency in data processing

Transparency in data processing means the clear and accessible communication of how the data is processed and how the decisions are made. It not only asks how they are made, but it also raises a question of why it is so, and what the possible consequences are. Felzmann et al. (2019) note that transparency includes elements from a prospective and retrospective perspective. Prospective transparency means that users are informed before the data processing takes place. Retrospective transparency refers to the ability to explain how the decisions are made and why. Transparency is important for various reasons. Transparency signals trustworthiness and willingness to be accountable, which is important for individuals (Felzmann et al., 2019). They also state that being transparent makes individuals make more informed choices, which supports their trust and reduces suspicions. In addition, transparency allows inspecting explanations of certain decisions, which is essential when identifying errors, auditing the systems and ensuring the fairness. Lastly, if transparency is not necessary, organizations can have too much power over individuals, which may enable manipulation or exploitation.

Typically, data processing consists of three stages: pre-processing, processing and post-processing (Yukselen et al., 2020). In the pre-processing stage, low-quality data is filtered out, which is critical for the next steps and results, as it avoids biased or unrepresentative datasets. For of e-commerce businesses, it is crucial to focus on this stage, as biased and unrepresentative datasets will lead to bad performance. In the pre-processing stage, companies should also label and categorize the data, make it anonymous and determine the purposes for the processing. The processing stage involves assembling the data and analysing it. It can also include the training of machine learning models. The post-processing involves evaluation of the results, storing the data, and auditing the performance.

Main challenges in transparency in the data processing process come from the quality of the data or the collection process. Whang et al. (2023) state that data sets can contain errors, be small and biased, which limits the model's effectiveness. Data collection is also expensive and time-consuming, especially when labelling the data. Labelling the data, either manually or automatically, introduces errors, especially when the criteria for labelling are not transparent, and the supervision is weak. Being transparent and documenting clearly, step-by-step, the process when cleaning and labelling the data will help understand possible errors later. Transparency is especially important for e-commerce businesses, as consumers' personal data is collected continuously through their online behaviour. In addition, e-commerce platforms do not use the data only for content personalization, but also for transactional reasons, for example, pricing and payments. Whang et al. (2023) raise concerns about the issue of data poisoning, which is caused by attackers generating data to reduce the accuracy of AI applications. Another issue is the unclear traceability of where the data originated from and how it was collected. This may lead to the use of biased or low-quality data.

Companies have legal obligations of data processing transparency. For example, the GDPR has established transparency as one of the core principles (Felzmann et al., 2019). They refer to consumers' right to be informed, as consumers should know the purpose of data collecting, what is collected, how long it will be stored, who it is shared with, the right to access and delete the information, and the existence of automated decision-making. The GDPR right to be informed has developed consumer rights and knowledge, but it still has challenges. Felzmann et al. (2019) mention that the stakeholders can have different expectations for the same concepts. In addition, the GDPR states that the information must be provided in clear language, but consumers have different abilities to understand and act on the information given, as overly technical explanations can overwhelm users. In addition, it can be unclear what is sufficient and useful for the individuals. The complex and rapidly evolving AI systems create more challenges for the right to be informed, as when the models are trained and optimized, their logic and objectives might get repurposed.

4.2 Challenges in communicating transparency to consumers

The challenges of privacy communication for consumers arise from the complexity of the information (Christensen & Cheney, 2015). In e-commerce, communication introduces specific challenges as businesses must balance clear communication with an efficient shopping experience. At the purchasing point, consumers are focused on completing the purchase, so they often overlook the transparency mechanisms embedded in cookie banners or privacy policies. This comes from the motivation to do the purchase, or due to time pressures for the purchase made by dark patterns that e-commerce businesses use. The complexity of the information reduces the effectiveness and limits access. Christensen and Cheney (2015) found that sometimes it would need expert knowledge to fully understand the policies because of their vocabulary and methodologies. Even if organizations provide access to the metrics on how the decisions were made or how their data was used, it does not guarantee a meaningful insight for the consumer. This situation is an information asymmetry (Bergh et al., 2019), and it can lead to apparent consent.

Companies also use a lot of legal and technical jargon as well as fine print in their communication, which in the end reduces transparency and trust-building. Christensen and Cheney (2015) also state that consumers struggle to process information when there is too much of it, or it is complex and not presented clearly. If consumers experience information overload, they may not read the policies and simply accept everything. Parris et al. (2016) found that consumers and other stakeholders have become more skeptical towards organizations' communications due to past lack of openness or ethical issues. This makes it challenging for the companies to build trust when they try to be transparent. In addition, if consumers see the company's transparency as inconsistent or self-promotional, it won't build trust towards them.

4.3 How to improve transparency practices to gain consumer trust

Despite the advances in regulations such as GDPR, companies struggle to implement transparency practices that are accessible and understandable for consumers. As said, lack of understanding can lead to scepticism, which reduces the consumer's willingness to purchase items or share data. Luckily, these challenges can be addressed to enhance consumer trust. Martin et al. (2017) state that transparency can be increased with easily understandable and straightforward privacy policies and notifications, which, in a clear way, explain the data collection process. Parris et al. (2016) add that the transparency practices should be designed for consumers to easily learn. First, the companies should think about how the stakeholders want to receive the information. This means that the companies should think about how to share their practices in a clear, easily interpreted, accurate, time-sensitive, and easily accessible way without using legal or technical jargon. Companies should message about their practices in every stage of the customer journey to maximize transparency.

In addition, giving consumers more control of their data can increase their trust. (Martin et al., 2017). This is, for example, raw data from the decisions made from both primary and secondary sources (Parris et al., 2016). Consumers should be able to have control of their data, for example, opt-in or opt-out specific data, storing of the data, or what kind of marketing communications they want to see. Parris et al. (2016) mention that interacting privacy practices in desirable formats can increase trust. These formats could exploit visualization to make it more accessible. For example, companies could use interactive dashboards, where consumers could clearly see how their data is used and why it was needed, where the decisions arise from, and who has access to it. In addition, there should be an option to edit the consent, download the data, and delete it.

In the e-commerce context, improving transparency means having clear and accessible explanations of the personalization in the shopping interface. These are, for example, communicating an explanation of “Why am I seeing this?” along with the product recommendations. Because of the consumer’s purchase-focused motivations, companies should communicate their transparency practices in both the browsing and checkout phases rather than limiting those to cookie banners and privacy policies. Martin et al. (2017) argue that the combination of high control and high transparency is the most effective way to gain high consumer trust, additionally leading to lower levels of violations. They also mention that without control, transparency can lead to negative effects. Liyanaarachchi (2020) argues that building competency in privacy can bring sustainable competitive advantages and shape the corporate strategy. Transparency and ethical data practices can be a core part of the company’s brand.

5 Discussion

The study aimed to examine how AI technologies enable personalization in e-commerce marketing and what kind of ethical and transparency issues arise from it. The study addressed three research questions: RQ1 focused on the role of AI in implementing personalized marketing. In addition, it focused on the benefits and possible risks, and negative impacts. RQ2 focused on the ethical challenges and risks for consumers, and RQ3 focused on transparency and how it can be increased.

RQ1 showed that AI-driven personalized marketing can provide significant benefits for both consumers and businesses in every stage of the customer journey. However, these benefits raise negative impacts and risks. Without responsible practices and effective regulation, the benefits of personalization might move from a competitive advantage to degrading the customer experience. The extensive use of consumer data raises ethical issues.

Based on RQ2, the ethical challenges related to AI-driven personalization arise from privacy concerns, data protection, and biases and discrimination in algorithms. The effectiveness of personalization is linked with extensive data collection and profiling, which creates risks related to privacy and fairness. Algorithms have a key role in personalization and in the decisions of what we see. That is why it is crucial to be transparent about how algorithms make decisions, as they can be discriminatory or have biases. Values such as fairness and transparency should be considered and practiced at all levels.

RQ3 indicated that transparency is the bridge between personalization and consumer trust. Consumer trust is not built only on the regulations, in addition, it requires companies to have active and understandable communication and practices. Clear and accessible transparency practices decrease consumer concerns and help individuals make more informed decisions. Transparency needs to be implemented in a userfriendly manner, considering the diverse levels of stakeholders' knowledge. Enhanced transparency practices bring competitive advantages for the company.

Overall, these results show that the use of AI-driven personalization benefits the company, but it requires ethical responsibility. Even though AI improves the efficiency of marketing practices, not being open and transparent about it can weaken consumer trust, which is linked to consumers' willingness to purchase and share data. Therefore, to succeed, the company needs ethically sustainable and transparent practices as well as technological expertise.

5.1 Limitations

This thesis has several limitations. First, the variety of AI applications is wide, and this thesis was made as a literature review. Some widely used technologies were not mentioned, and those that were were discussed at a general level. This allows to gain a holistic understanding of the subject. In addition, different companies implement AI in different ways, and those were not explored within the thesis. Second, the regulations mentioned in this focused on the widely adopted frameworks based on a European perspective. This means that emerging regulations and industry-specific guidelines were left out. Finally, technologies develop rapidly, as well as the tools that companies can use. This can lead to rapid changes in the ethical landscape and regulatory requirements.

5.2 Conclusions

The purpose of the study was to examine the role of AI technologies in personalized marketing from the perspectives of privacy and transparency. The results show that AI enables effective personalization that benefits both consumers and companies. At the same time, these technologies create ethical challenges related to data collection and processing, algorithmic biases, and consumers' lack of knowledge of their data and its uses.

This study presents that consumer trust is crucial for companies of AI-driven personalization. Trust is not only built on regulation, but it is built on openness, understandable explanations, and clear communication. Companies that focus on transparency, sustainability, and ethical practices gain more trust and can utilize AI better.

In the end, personalized marketing needs both ethically sustainable operations and technological knowledge. Responsible use of AI strengthens customer relationships, increases engagement, and reduces risks. This highlights the need to develop AI applications that are transparent, respectful, and explainable.

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