

The double-edged razor of machine learning algorithms in marketing: benefits vs. ethical concerns

Author: Tanser Karakash
University of Twente
P.O. Box 217, 7500AE Enschede
The Netherlands

ABSTRACT

New advancements in artificial intelligence algorithms contribute to the competitiveness of businesses. However, the increasing use of machine learning algorithms for analyzing customer data in marketing is frequently accompanied by ethical concerns. By using rule utilitarianism theory, the following research aspires to develop guidelines by which machine learning algorithms can create and capture value within the ethical boundaries of customer segmentation and targeting. To accomplish this goal, AI algorithms' benefits and ethical risks are analyzed through a systematic literature review, followed by semi-structured interviews with practitioners and academic researchers. By combining the theoretical and practical insights a total of 4 ethical issues was found, which can be mitigated through 40 guidelines, divided into 6 stakeholder groups. Hence, the model can serve as a framework for ethical marketing and design practices. Because of the fast-changing nature of AI technologies, the exploration of ethics and AI will be a continuous topic, and the outlined guidelines can serve as a starting point for future research.

Graduation Committee members:

1st Examiner: Dr. A.B.J.M. Wijnhoven

2nd Examiner: Dr. M. de Visser

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1. INTRODUCTION

Artificial intelligence is growing steadily, and its market size is expected to amount to 126 billion U.S. dollars by 2025 (S. Liu, 2020). One of its subsets is machine learning, which is "(...) a system's ability to acquire and integrate knowledge through large-scale observations and to improve and extend itself by learning new knowledge rather than by being programmed with that knowledge" (Thomas W. Edgar, 2017, p.224). In this regard, machine learning algorithms are applied in several fields, such as medicine, finance, and criminal justice.

In recent years, the algorithms gained popularity in the marketing and sales area, where they assist in better-segmenting customers based on their interest and demographic characteristics, cheaper personalization of purchase preferences (Zulaikha et al., 2020), and customer profiling (Arco et al., 2019). In this regard, automated recommendation systems employ predictive analytics that accounts for 35% of Amazon's purchases (MacKinzie et al., 2013) and 80% of the movies and series watched on Netflix (Editorial Team, 2020). Owing to the artificial intelligence software, marketers reduce the time spent on segmenting consumers and organizing targeting campaigns, and thus, increase the marketing department's productivity ratio. The general belief is that artificial intelligence algorithms improve business operations and lead to better customer service and personalization. However, this innovative technology raises ethical concerns, and following the Cambridge Analytica - Facebook crisis in 2018, emphasis has shifted to the ethics of algorithms (Confessore, 2018). Further, the adoption of AI technologies for marketing purposes is rising continuously in all industries, and its current rate in marketing and sales is 15% (McKinsey, 2021). Machine learning algorithms' impact on the business, society, and even economy does not go unnoticed (Canhoto & Clear, 2020; Ma & Sun, 2020; Mari, n.d.). Thus, if ethical risks of algorithms in customer segmentation and targeting are not considered by the marketers (Zulaikha et al., 2020), they can damage the brand's reputation or can lead to a huge financial loss for the company. An example is the latest lawsuit against Alphabet Inc. amounting to 5 billion US dollars, where Google is blamed for customer profiling even in "private" mode (Reuters, 2020).

1.1 Objective and research questions

The existing literature lacks providing clear guidance on how the machine learning algorithms can continue to operate both effectively and ethically. The goal of this study is to propose guidelines that will assist marketers, data scientists, and developers in using machine learning algorithms ethically for customer segmentation and buyer targeting while preserving the benefits delivered to customers and businesses. More specifically, the proposed research aspires to address the following research question: **How can the machine learning algorithms create and capture value within the ethical boundaries of customer segmentation and targeting?**

The main research question can be broken down into 4 more specific sub-questions, namely:

1. What are the benefits delivered by algorithms' use in marketing?
2. What are the ethical risks of machine learning algorithms in customer segmentation and targeting?
3. What are the existing guidelines for ethical algorithms (within the EU) and their limitations?
4. What further guidelines are needed for dealing with the ethical issues of machine learning algorithms in segmentation and targeting?

2. METHODOLOGY AND RESEARCH DESIGN

The design of this research is a qualitative explorative study. Hence, the data collection methods chosen are critical literature review and semi-structured qualitative expert interviews. The literature review involves the researcher in a critical thinking process and provides a comprehensive understanding of the status quo (Xiao & Watson, 2019). The semi-structured interviews are chosen as a data collection method to serve as a bridge between the academic and practical perspectives on the researched topic. Thus, the findings from the literature review will be built upon during the interviews.

Determining the optimal number of interviewers is difficult because the literature has not reached a consensus on this topic (Adams, 2015; Baker & Edwards, n.d.). A reasonable number of interviews for qualitative research ranges between 5 and 20, depending on its scope (Adams, 2015; Baker & Edwards, n.d.; Coper Joseph, 2014; Galvin, 2015). Considering the proposed limits in the literature, the total number of interviewees in this study was set to be 7.

2.1 Literature search

In terms of collecting scientific literature and research papers, a systematic literature search is carried out. This method contributes to developing a better understanding of the operation of machine learning algorithms for customer targeting and the associated ethical issues. Scopus and Web of Science are the most used search engines, as they allow for keyword searches relating to the subject as well as back-and-forth movement between different sources (Wijnhoven, 2014). Keywords' combinations used are the following: 'artificial intelligence or machine learning and ethics', 'machine learning algorithms and marketing', 'personalized marketing and privacy', 'ethical issues and algorithms', 'ethical AI', 'GDPR and AI', 'ethical theories and algorithms.' The libraries of Google Scholar, Research Gate, and the university library - FindUT assist for additional literature searches. Snowball sampling for data collection is applied since it is an efficient technique for forwarding searches from already found articles. As the study's scope covers a quickly changing and upgrading technology mainly papers from 2016 onwards are reviewed to ensure the knowledge and data passed to the reader is not outdated.

The literature review in this study is not limited to scientific papers, rather, web-based articles and secondary statistical data are utilized. Statista and Kaggle are used to access secondary quantitative data, such as the adoption rates of ML and AI techniques in the marketing field and public opinion survey results for information privacy concerns. Additionally, the study relied on online blogs and articles, for gathering more detailed exemplified information about the algorithms' application in marketing and the hidden ethical risks of those. The online articles are in help of deriving insights about the companies which have adopted automated targeting and personalization, as well as recent scandals in the media, arising from the data collection and analysis with the ML algorithms.

2.2 Interviews' set-up

The interviewees are chosen based on their area of expertise and current occupation, as well as their research interests and publications. Good expertise in machine learning or digital marketing, as well as ethics and philosophy, are among the selection criteria. The diversity of experts is essential for fully answering the research questions. As a result, researchers, marketing company representatives, data scientists, machine learning, ethics, and marketing professors are interviewed.

As this research is conducted during a global pandemic, protecting the health and safety of participants is amongst the top priorities. Owing to the advances in online communication and technology, the interviews can easily be conducted in a digital environment. First, the interviewees are contacted via email and are given an overview of the research topic, an invitation to the interview, together with a list of the main questions to be asked during the interview (see **Appendix A**). From the 8 companies engaged with digital marketing and data analytics, 3 agreed to contribute to the following research. On the other hand, 14 researchers and university professors are reached, whose interest area is AI and digital marketing or ethics of algorithms. Four of them are willing to contribute to the current study.

To protect interviewees' privacy, personal information such as their names and gender is not shown. However, to demonstrate how they contribute to the following research subject, the current occupation/position of participants is included in the table in **Appendix C**. In the same table, the short interviewees' answers to the posed questions can be found.

3. CONCEPTUALIZATION AND THEORETICAL FRAMEWORK

3.1 AI algorithms benefit automated segmentation and personalization

Artificial intelligence (hereinafter abbreviated as AI) and its components are widely used throughout the customer journey, starting with segmentation, through direct marketing and targeting campaigns, to relying on AI shopping assistants and chatbots. Machine learning (hereinafter abbreviated as ML) algorithms, however, are mainly applied in the stages of segmentation and targeting due to their predictive and optimization capabilities (Ma & Sun, 2020). Despite extensive study on the undermining of social values and ethical concerns posed by chatbots and interactive AI, ML algorithms are sometimes underestimated since they remain quite invisible to the broader audience - users and customers.

3.1.1 Defining AI and Machine learning algorithms

The term artificial intelligence (AI) is being used since the first half of the twentieth century. Various authors, including McCulloch & Pitts (1943), have outlined in their works a technology that mimics the human brain and can perform complex tasks such as information analysis and decision-making. AI has been upgraded and adapted over time to execute more specific functions such as driving a car (Bhalla et al., 2020), playing chess (Buchanan, 2005), and interpreting complex data. Machine learning (ML) is an artificial intelligence subset related to statistics and data analysis (Ongsulee, 2017). ML algorithms, in particular, can learn patterns from training data and apply those patterns to the population. The algorithms are spread widely in the advertisement and marketing area, where they assist throughout the customer journey. Algorithms, like humans, learn more as they absorb more knowledge and thus get "smarter". The more unstructured data the AI algorithms process, the more precise the output they provide to users (Kietzmann et al., 2018).

3.1.2 Machine learning algorithms for customer segmentation and targeting

One reason for introducing machine learning algorithms in marketing is the increasing market competition due to globalization. Businesses seek a way to meet consumer demands while also providing better service. However, understanding customers' needs necessitates increased spending. Hence, the introduction of information technologies

is regarded as a watershed moment in the modern marketing field. According to a recent Kaggle study, nearly 45 percent of global companies have established ML algorithms, while 21 percent are in the learning stage of the algorithms and hope to incorporate them into their businesses sooner or later (Hayes, 2021).

One of the methods by which marketers can better respond to customer needs is segmentation – the process of dividing customers into groups based on demographics, preferences, and purchasing behaviour (Qian & Gao, 2011). Companies profit from vast amounts of data analysis to align marketing decisions with customer demands (Tripathi & Bhardwaj, 2018). Consumers are grouped and profiled, and due to the algorithms, the need to observe each client is reduced (Tripathi & Bhardwaj, 2018); instead, the algorithm learns that, for example, the age group 25-40 is more likely to be interested in sports equipment than older age groups (like 41-55-year-olds). As a result, advertisements for sports equipment will be targeted more frequently at the younger age group. Hence, each consumer category has similar characteristics as well as akin interests and demands (Qian & Gao, 2011).

After segmenting the customer base, the next marketing strategy is targeting, which necessitates the use of "thinking" algorithms (Huang & Rust, 2020). Targeting is the process of selecting the appropriate client segments to emphasize the firm's marketing activities. This strategy requires judgment, knowledge, and decision-making skills, and thus, more complex algorithms, such as recommendation engines or predictive modelling (Huang & Rust, 2020).

3.1.3 ML algorithms' added value to businesses and consumers

Handling an immense amount of unstructured data (like text, video, and images) is the biggest strength of machine learning algorithms (Ma & Sun, 2020). Usually, marketers have to analyze thousands of customer data, to segment them precisely. By using ML algorithms, this process is done *quickly and efficiently*.

Moreover, the significance of *cost reduction* is emphasized during the interviews. The explanation behind this is the decreased need for human intervention and thus, a reduction in labour costs. Currently, there are primarily automated advertisements, email campaigns that are personalized by AI and sent directly to the user, content creation, and curation jobs that are all performed by machines, requiring less human interaction (Levy, 2018). The biggest challenge for marketers is *decreasing the cost per acquisition* while maintaining or increasing the return on investment of the business. One innovative way to achieve this goal through automated targeting was introduced by Amazon, which sends samples of new products to customers, depending on their personal preferences and past purchases (Cavill, 2019; McCabe & Fischer, 2019). Without using those algorithms, the segmentation costs can rise in direct proportion to the quantity of individual data to be evaluated and the various regions for which they must be studied (Zulaikha et al., 2020). As a result, advertisements like Amazon's would have grown prohibitively expensive and ineffective.

Another advantage of algorithms is their *predictive capabilities*; once an algorithm has recognized patterns in trained data, it can quickly forecast customer product or service preferences (Ma & Sun, 2020). This in turn is essential for providing *personalized service* to customers. By modelling a large number of variables, ML algorithms can anticipate human behaviour, resulting in a match between products/services and clients' demands (Kotras, 2020). One such example is Harley-Davidson, which uses its AI

tool, Albert, to identify potential high-value customers and provide them with more personalized service, resulting in a 40% increase in motorcycle sales(Kaplan, 2017).

Thanks to artificial intelligence and machine learning algorithms, the 4Ps of marketing (product, pricing, promotion, and place) can be easily boosted. Marketers improve *content generation* with user data, in addition to analyzing previous purchases, which further increases personalization. Blogs are a recent addition to e-commerce websites that cover a variety of themes, and visitors frequently participate by posting and providing feedback. This in turn allows advertisers to employ machine learning algorithms to *analyze client behaviour on specific blog pages* and learn more about their preferences(Ahuja & Medury, 2011). Such interventions with AI techniques *improve consumer engagement* and make them *loyal* to specific e-commerce platforms. Additionally, it becomes easier for marketers to implement effective customer retention tactics. However, improved profiling raises the question of how far customer data may be utilized ethically.

The interviewed data scientists highlighted that AI systems *boost business management* because they provide a simple metric of success, such as data driven KPIs. Machine learning, on the other hand, leads to *business improvement* by increasing the quality and consistency of results as opposed to human decision-making(Deloitte, 2017). The third pillar is *market expansion*, which is accomplished by real-time automation, resulting in scalability and optimal decisions, thus increasing the business's competitiveness.

3.2 What is considered ethical?

Judging whether the algorithms are ethical and whether the produced decisions regarding customers are morally right or wrong can be accomplished by developing an understanding of the different standpoints of ethics. The philosophy of ethics is divided into four branches – meta-, applied, normative, and descriptive ethics. Meta-ethics is concerned with developing a general understanding of ethics (Allan, 2015), applied ethics targets controversial issues, or so-called practical dilemmas (Attfield, 2006), whereas descriptive ethics covers the topic of people's behaviour and their moral standards (Hämäläinen, 2016). Lastly, the normative ethics branch is responsible for developing moral standards and responsible behaviour (Copp, 2005). The following research will utilize the theories within normative ethics to judge which actions are ethical while answering the research questions. The three general types of normative ethics are consequentialism, virtue ethics, and deontology and although they are within the same branch, each indoctrinates different values and beliefs. Consequentialism holds that an action is ethical when the overall benefits outweigh the overall harm (Mingers et al., 2010), whereas deontology undervalues the outcome and calls the act's morality into question. On the other hand, virtue ethics drives the individual towards achieving the ultimate goal while maintaining high standards of excellence (Gal et al., 2020)and practicing good traits like generosity.

Due to the differing viewpoints of each of the ethical theories, one specific approach was chosen to guide this study - rule utilitarianism, which is part of collective consequentialism. According to this theory, an act must not only maximize the overall good for society but also adhere to certain rules (Harsanyi, 1977). Rule utilitarianism and deontology are both classified as "rule" theories; however, they differ in the reasoning behind following the rules. Deontology is the theory of duty and thus, people have to live by the socially accepted rules(Bonnemains et al., n.d.). From a utilitarian perspective – people do what is right to maximize the overall societal

benefit(Copp, 2005). In other words, the theory holds that the population, in general, will be safer if no one ever crosses over the limit. When rule utilitarianism is applied to AI algorithms, the limits are set by the Charter of Fundamental Rights of the EU, which protects universal values, based on law and democracy. Thus, rule utilitarianism classifies the algorithm as unethical if it either ignores human rights or the benefits it delivers to individuals do not exceed the risks.

3.3 Ethical Issues of AI Algorithms for Segmentation and Targeting in the existing literature

While authors have investigated the ethical risks of AI and algorithms in general (Kritikos, 2018; Magalhães, 2018; Sample et al., 2020; Susser, 2019), the emphasis has not been specifically put on those in marketing. As a result, the literature on ethical issues of machine learning algorithms and how they can emerge in the marketing industry will be addressed in the following sections. The four ethical issues (privacy, bias, autonomy, and opacity) are chosen and evaluated using the rule utilitarian framework as they violate certain human rights (cf. **Table 1**). Furthermore, rule utilitarianism approaches the advantages provided to society holistically, in this case, the benefits generated by automated marketing to clients and businesses. Each of the four concepts of privacy, bias, nudging, and opacity breaches 3-5 human rights (see **Table 1**). The described ethical risks (cf. 3.3.1 – 3.3.4) also are found to be the most mentioned during expert interviews, indicating their prevalence.

Table 1: Violated human rights by each ethical issue

Article №	Fundamental Human Rights	Privacy	Bias	Autonomy and nudging	Opacity
1	Human dignity	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>
3	Right to the integrity of the person	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
7	Respect for private and family life	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>
8	Protection of personal data	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
10	Freedom of thought, conscience and religion	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
21	Non-discrimination	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
23	Equality between men and women	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>

3.3.1 Privacy

AI algorithms work based on input data and can make predictions when they are "fed" with enough data. A large part of AI cannot exist or, at least function, without data. By collecting and analyzing consumer information, algorithms draw better assumptions for individual preferences, allowing advertisers to offer more personalized service. Although e-commerce customers value personalized services, they are frequently confronted with the privacy-personalization conundrum(Zeng et al., 2021). Tracking customers' social and private lives have become the new normal for marketing in the increasingly data-driven world(Kotras, 2020). With their willingness to provide better service and remain competitive, marketers rely on data analytics, which is often privacy invasive. Target, a major US retailer, used big data and predictive analytics to identify pregnant customers by tracking their previous purchases and internet searches, and then sent them booklets containing baby clothes and diapers(Duhigg, 2012; Kuhn, 2020). Clients became irritated by this high personalization, as the shop knew too intimate information about them. As a result, Target's marketing department was

forced to alter its targeting method in order to appear less intrusive on consumers' privacy (Kuhn, 2020).

Nevertheless, collected data can either benefit or harm the customers – personal data can be used to recommend a product that is close to the individual's preferences, but it can also publicize private information, such as an individual's sexual or political preferences. In their study, Kosinski et al. (2013) demonstrate how predictive analytics and a single piece of information – Facebook likes – can be used to create a client profile with a 60% accuracy. Customers' gender, family status, sexual and political orientation, as well as their addictions such as cigarettes, drugs, and alcohol, can be predicted (Kosinski et al., 2013). Such privacy invasion is considered unethical from the standpoint of rule utilitarianism, as it humiliates several human rights, including the right to private life and human dignity (Stahl et al., 2021). The most pressure is exerted on the protection of personal data, as well as its unfair processing and use for commercial purposes (cf. **Table 1**). The stored data may also be outdated or irrelevant for the specific customer. This, in turn, may be a violation of the right to rectification if the individual is denied access to the information collected about him.

3.3.2 Bias

Machine learning bias arises due to heterogeneities in the data, which can lead to inaccurate predictions (Mehrabi et al., 2019). Recently, there have been scandals involving biased artificial intelligence. Amazon's hiring algorithms, for example, were designed to read resumes and select the best-qualified candidates (Dastin, 2018). However, the algorithms were prejudiced against women and exclusively hired men, because the system was built to reproduce the current hiring practices and biases (*5 Examples of Biased Artificial Intelligence*, 2019). Similarly, Wijnhoven & van Haren (2021) discovered that Google suggests primarily female-related employment (such as hairdresser and nurse) to females, a practice known as gender bias. Such biases can also be observed in personalized targeting, income-based segmentation, and credit allowances. The core of this problem is that machines learn from human-provided information, and thus, human biases can be easily transferred to the technology (Baldrige, 2015; Yapó & Weiss, 2018).

Marketers often rely on the internet and social media to gather customer data, as the information there is easy-to-access and free. This data, however, represents only a subset of the population. As a result, when applied to groups that have not been included in the training data, invalid results are being produced (European Union Agency for Fundamental Rights, 2019). Amazon's algorithm in the United States segmented customers based on race, and it did not offer same-day delivery to predominantly black neighborhoods. Amazon was tracking customers' locations based on their ZIP code, and even white residents in predominantly black neighborhoods were experiencing delivery delays (Ingold & Soper Spencer, 2016). This is a typical example of building a racist algorithm by using an irrelevant sample of the population.

Biased algorithms can lead to discriminatory pricing, which is assigning higher charge rates to wealthier customers. Evidence suggests that algorithms can trigger discriminatory pricing if they have access to information like geographic location and purchase history (Gautier et al., 2020; Hannak et al., 2014). Uber is an example of a company that raises its prices when demand outnumbers supply or when the algorithm decides that customers can afford to be charged more (Kominers, 2017). Some booking websites use price discrimination tactics to provide more personalized service to their customers. According to Hannak et al. (2014), there is a difference (though

not a significant one) in the offers displayed to logged-in users on the websites of Cheaptickets and Orbitz (see **Appendix D**). These businesses use algorithmic direct segmentation to reach out to potential customers and give lower rates to those who create an account on their website (Hannak et al., 2014). Acts like this are considered prejudiced and run counter to people's right to equal care (cf. **Table 1**).

3.3.3 Autonomy (decisional privacy) and nudging

Advertising firms began to rely on behavioral economics strategies in order to remain competitive and enhance conversion rates. One such strategy is "nudging", which involves influencing individuals' choices by various means (Thaler & Sunstein, 2008). In marketing terms, this involves giving deceptive options to buyers without forbidding any possibilities. When this definition is applied to computer science, it refers to the setting of defaults when the decision-maker has not specified a requirement (Cronqvist et al., 2018). As algorithms are used to recommend products and services to consumers, they frequently enhance certain types of control over individuals' decisional privacy. Netflix, for example, exerts influence over its customers' tastes by prominently displaying "Netflix Originals" on its home page, minimizing the probability that people will overlook them (Oestreicher, 2017). In case subscribers fail to watch the original series, Netflix's algorithms gently nudge them to do so, regardless of whether those match customers' preferences (Oestreicher, 2017). Although a highly beneficial marketing strategy, nudging can hinder an individual's decision-making capacity and become harmful for his agency and autonomy (Renaud & Zimmermann, 2018; Susser, 2019). These practices are unethical as they are designed to subvert customers' mindsets and challenge their decision-making capacity by exploiting psychological and cognitive vulnerabilities (see **Table 1**).

The nudge, however, can grow into surveillance in some cases. For example, most of the applications used nowadays promise to provide the users with a better service if allowed to access their location. However, this might be a method for controlling people and following their movements. An example is a recent system introduced by the Chinese government, after the outbreak of the coronavirus, the purpose of which is to notify people in need of self-quarantine (Ferreira et al., 2020; Gan & Culver, 2020). The system works with personal QR-codes which track where and when each individual has been. This is somehow similar to the disruptive aspect of dynamic capitalism, which contributes to human exploitation and environmental destruction, but also extends commodification and individual behaviour analysis for business purposes (Zuboff, 2019). The government can easily monitor individuals and gain access to more intimate personal details, whereas marketers and advertisers can openly manipulate consumer data to maximize profits and destroy rivals.

3.3.4 Opacity

Another ethical issue associated with algorithms is opacity – the inability of algorithms to be accountable and transparent (Buhmann et al., 2020; Paudyal & Wong, 2018). Based on this definition, an algorithm is opaque if the path it takes to obtain a result cannot be traced back (Burrell, 2016). Examples of opacity could be the inability to see why the algorithm does not permit a client to receive a credit allowance, or the reasoning behind selecting a specific targeting ad (Canhoto, 2020). Machine learning algorithms are frequently referred to as "black boxes" since the processing of findings and the precise method of computing the output are hidden (Mols, 2017). This metaphor demonstrates the complexity and subjectivity of the automated decision-making process, on

which businesses and marketers rely to provide better customer service.

In marketing, the opacity of algorithms can have profound consequences for the customers, as they cannot provide clear information of how a decision was made (Diakopoulos, 2015). If the algorithms are opaque, developers will be unable to test the results produced, which can potentially lead to a slew of unethical outcomes such as filter bubbles, discrimination, and nudging. According to rule utilitarianism, opacity violates equality rights because the patterns developed by algorithms cannot be challenged, and thus bias may occur even more frequently (Buhmann et al., 2020). Furthermore, consumer and data protection rights may be violated if clients do not consent to the use of their data (see **Table 1**). Additionally, cases like discriminatory pricing and inaccurate profiling can arise, which instead of profiting the customers can harness their rights. That being said, while algorithms may provide the most value and utility to customers, they fail to be transparent for their decision-making and therefore complex to judge whether they meet the ethical requirements and the extent to which the output they produce is accurate (Paudyal & Wong, 2018).

4. APPLYING EXISTING GUIDELINES TO THE IDENTIFIED ETHICAL ISSUES

The General Data Protection Regulation (GDPR) is a law regulation, and its primary goal is implementing uniform data protection legislation across all EU member countries. The GDPR emphasizes the collection of data via internet means like social networks and websites, as well as all offline methods. The legislation is created to protect the fundamental rights and freedoms of the EU citizens and thus fits perfectly within the rule utilitarian approach of this paper.

Although the GDPR is designed as a system for general data security, it has a significant effect on artificial intelligence and algorithms (cf. 4.1, 4.2, 4.3). The applicability of GDPR to resolving the stated ethical difficulties is demonstrated in the following sections. Personal data (4.1), fairness (4.2), and transparency (4.3) are umbrella phrases for the various policies that fall under each of them. A summary of the GDPR guidelines can be found in **Figure 1**. Following that, the application of the GDPR to limit the ethical issues raised in this paper is identified. **Appendix B** provides a more comprehensive analysis of the Articles relevant to resolving the ethical difficulties. A critical review of GDPR's limitations, as well as the potential disadvantages of its use for marketers and businesses, are described in section 4.4. The findings are summarized in **Figure 1**.

4.1 Personal data protection and profiling

Under the GDPR, personal data is defined as "(...) any information relating to an identified or identifiable natural person" (General Data Protection Regulation, 2016, p.33). This definition also includes information that, although pseudonymized, can be traced back to the individual. Returning to one of the previous examples, Amazon's same-day delivery - even if the algorithms do not know the customers' colour and ethnicity, they can automatically guess it based on a ZIP code. Accordingly, the law restricts such invasions of consumer privacy by *banning dissent data collection and analysis*. Thus, information processed for consumer profiling should be obtained with permission. In this regard, the GDPR suggests collecting the data in such a way that the data subject is *consent* (cf. **Appendix B**). To ensure data subjects' security by default, the data protection legislation requires companies to create a *privacy-preserving design* for the technologies they use.

4.2 Fairness

By enforcing fairness and clarity in data analysis, the GDPR limits the "black box" impact of algorithms. The honest portrayal of the processing of customer data is one type of fairness under the GDPR. The law recommends *informing data subjects on how they will be profiled* and what are the accompanying benefits followed by such action (e.g., greater personalization, cheaper service, appropriate targeting). Furthermore, the specialists must be able to access the training set, search for data inconsistencies, validate the dataset, and restrict its obscurity. These inspections can reduce opacity and increase transparency in algorithmic decision-making.

Second, the *fairness of the output* produced by the algorithms should be *evaluated* using a variety of criteria, including acceptability, relevance, and reliability (Sartor, 2020). Because the regulation *prohibits discriminatory decisions* based on race, ethnicity, religion, or political beliefs, such information should be treated as sensitive (General Data Protection Regulation, 2016).

4.3 Transparency

The concept of transparency involves the understandability, explainability, and observability of the algorithmic decision-making by all of the related stakeholders (Shin & Park, 2019). By considering the GDPR, Burrell (2016) develops a framework, which overcomes the opacity of algorithms by various means. For example, eliminating discrimination requires data scientists to have *access to the sample of the training data* set and be able to *validate* ML inferences with the target population (Burrell, 2016). Furthermore, the *source of personal data must be traceable*, and the criteria used to make judgments based on this data must be transparent (Burrell, 2016). The EU regulation recommends that data be *anonymized* to avoid unauthorized usage and to keep the automated decision-making process transparent (cf. **Appendix B**). Marketers must enable data subjects to acknowledge themselves about the utilization and storage of their data to achieve multidimensional transparency. Additionally, establishing an *internal organizational policy* outlining the measures that should be taken during data collection, processing, and storage may be one way to minimize the incidence of ethical issues. The importance of security *certification* should not be undermined. Finally, to achieve accountability, advertisers must enable data subjects to understand the *real purpose of data collection*.

4.4 GDPR limitations and following challenges

The GDPR imposes significant constraints on data analysts and marketers. Even though it does not directly address AI and its subsets, the EU regulation opposes these systems as they deal with massive amounts of personal data. The constraints mentioned in this section are established in part during semi-structured interviews with experts. The existing literature's point of view together with several real-life examples is considered as well.

The first barrier is the *re-identifiability of personal data*. Even if online service users are pseudonymized, they may be re-identified by other means, as was the case with Netflix, which could identify the users, by analyzing the when and how movies were rated (Lemos, 2007). Ergo, details such as birthday, ZIP code, and gender continue to be considered personal data under the GDPR and should be collected and processed accordingly. However, the input data has a big impact on the performance of the AI algorithms, as they learn from patterns and produce an output (Najafabadi et al., 2015). Therefore, the re-identifiability

regulation can have a profound adverse force on both segmentation and personalized targeting. Since the training dataset is insufficient to establish highly accurate consumer profiles, and due to a lack of minority data, other ethical problems like bias and discrimination may arise (Williams et al., 2018). Furthermore, it is unclear to what extent governmental bodies can *regulate profiling* activities of algorithms and how they can ultimately determine and constrain their significance to a person.

The second problem is within the scope of requiring the customers to share their data in an informed way. Usually, the data processing is not easy-to-explain action and requires a lot of effort for the policymakers to describe one such procedure in its full details (Centre for Information Policy Leadership & Lee, 2020). However, researchers argue that a larger part of the population using online services does not have the skills to understand such customer profiling process, and oftentimes people mechanically press the consent button without even reading the privacy policy of the website (Cate et al., 2014). Furthermore, the disclosure of the collected data's potential consequences stifles the development of artificial intelligence and big data. Because of law enforcement, AI technology cannot contribute to game-changing discoveries that will benefit the future (Li et al., 2019). Besides, there is a risk of suppressing advertisers' creativity and decrease the total benefit delivered to the businesses. Apple's iOS 14 privacy updates, which require iPhone and iPad owners' consent to collect and store personal data for advertising and targeting purposes (App Store, 2021), is a recent example. Due to this update, marketing companies that have relied on third-party cookies to run their businesses will be disadvantaged, and their ad power and personalization service level will suffer as a result.

Customers can also be affected by such consent data collection, and even become irritated in some circumstances. Consider opening an e-commerce website that demands your permission to download cookies, a second authorization to monitor your location for better support, and a request for using your email for targeting and recommendation purposes. The problem lies in requirements for consent data collection that have to be applied on every website (Lamb, 2019), independent of the importance of the decision or complexity of action that the individual has to undertake.

Another point of contention raised during the interviews is the lateness of legislation. Typically, the rules apply to a problem that existed at least two years ago, highlighting obsolete or non-applicable to current technology concerns. As a result, in most cases, the legislation is insufficient to address the found ethical problems.

The decision to use AI in marketing, like any other in the business world, necessitates trade-offs. The cost of complying with GDPR is typically very high and unaffordable, particularly for SMEs. Software with cybersecurity capabilities, data classification, and data loss prevention is just a small part of the expensive technologies required (Coos, 2018). On the other hand, the non-European companies stop selling their goods and services within the EU entirely. The rationale behind this is the EU's requirement of compliance with laws and thus, American and Chinese companies must also adhere to the GDPR rules, which usually comes at a high cost and does not pay off (Li et al., 2019). However, people's human rights and the costs of unethical automated processes are still on the other side of the razor.

5. PRELIMINARY FINDINGS

During the first phase of the study – literature analysis – the benefits delivered by the use of machine learning algorithms in

marketing are identified and discussed (cf. 3.1.3). The ability to manage massive amounts of unstructured data can occasionally lead to some hidden ethical difficulties, which marketers and data scientists frequently overlook. Bias, invasion of privacy, nudging, and opacity all run counter to the ethical bounds established by the main theory employed in this study for ethical decision-making, rule utilitarianism (cf. 3.3). **Table 1** shows the violations of human rights caused by the occurrence of the indicated ethical concerns.

Because ethical concerns endanger human rights, the General Data Protection Regulation is applied to explore how it may be utilized by organizations and data scientists to secure the ethical operation of AI. The regulation provides some guidance and suggestions on how to protect customer data and prohibits certain practices such as gender and racial discrimination and the gathering of dissident data. Although EU law is the most powerful regulator, it has some drawbacks, one of which is its late occurrence, which means it does not consider the most recent breakthrough, such as big data and artificial intelligence. During the interviews, digital marketing specialists emphasized the limitations created by GDPR on advertising, like stifling creativity and a high cost of compliance (see **Appendix C**). As a result, the advantages of automated marketing are diminishing (cf. 3.1.3).

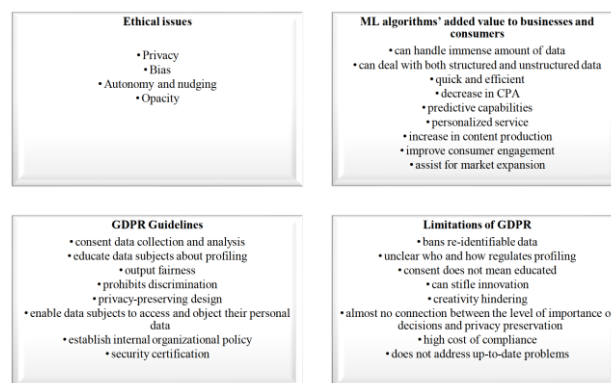


Figure 1: Summary of preliminary findings

Figure 1 summarizes the findings from the literature review and highlights the GDPR's advantages and downsides. Occasionally, it appeared that EU regulation is insufficient to defend human rights and that it partially hampered the capability of online marketing to provide the greatest utility to consumers (cf. 4.4). As a result, the emphasis in the second half of this study is on defining practical rules that prioritize the benefits of automated marketing while minimizing the incidence of ethical issues.

6. IT IS NOT ALL ABOUT LAW

As a second source for building this study, the knowledge of experts in the marketing and data science field is collected through semi-structured interviews. As described above (cf. 4.4), the General Data Protection Regulation hinders the benefits delivered by AI systems. Thus, other methods for ethical customer segmentation and targeting are discussed with data analysts and marketing companies and those are incorporated in the final ethical framework of this study.

When used for marketing purposes, the algorithms can have a profound impact on customers' lives (Kotras, 2020; Magalhães, 2018; Noble, 2018), which can be negative at times, and the responsibility for this innovation should not be disregarded. Therefore, the concept of responsible research and innovation (RRI) states each individual involved in the innovation process, or "stakeholder," should bear specific duties (Owen et al., 2012).

In that way, the responsibility is divided amongst interest parties and errors can be traced back. Ergo, the guidelines in this study are organized by the stakeholders involved in the development, deployment, and use of AI systems. First, the participants from the word go of the automated segmentation and targeting process are briefly analyzed (see 6.1). Following that, a model for overcoming the ethical risks while preserving the outlined benefits is developed (see **Table 2**).

6.1 Stakeholder groups

By building on the work of Resseguier et al.(2021), several stakeholder parties, related to the development and use of ML algorithms for segmentation and targeting are identified. When an artificial intelligence system is built, there is one or a group of *AI system developers*. These individuals may be referred to as IT professionals, hardware technicians, or IT directors, but they may also be organizational units such as colleges or businesses engaged in the development of advanced technology(Resseguier et al., 2021). Those stakeholders are usually in charge of building the AI's functional side. Following that, AI is being integrated into businesses or is simply being used within departments such as marketing, finance, and operations. Thus, the second stakeholder group is uniting *the deployers and users of the AI algorithms*, including data scientists, digital marketers, IT managers. In the case of technologically advanced corporations such as Amazon, both developers and users work within the same organization. As machine learning algorithms necessitate a huge amount of individual data, some businesses may use the services of *big data providers* if they aim to generate precise targeting results or want to rely on certified providers. The *standard setters and governance organizations* constitute the next step, and they are primarily responsible for regulating and enforcing standards or rules(Lütge, 2020). ISO and IEEE are the two most common standards within the European Union(Cihon et al., 2019). It is critical to classify the targeted people (*customers*) or the *broadier public* as stakeholders, as they are the most affected party by the algorithms' immoral decision-making. The final group is made up of *ethics organizations or ethics committees*. These professionals advise marketing enterprises on what is ethical and clarify the uncertainty around the social implications of ML technology, thus reduce the moral gap created by the use of algorithms(Winfield et al., 2019).

6.2 Towards ethical automated marketing

6.2.1 Developers

The construction of an AI system, which is usually developed by an IT firm, is the first step towards automated marketing. At this level, creating an explainable and transparent system is vital. This reduces the chances of algorithms acting as "black box" at later phases(Shin & Park, 2019). Developers must be able to grasp the inner workings of the algorithm; thus, keeping the procedure as basic as feasible may be advantageous for its clarity. Knowing how the system works and understanding the dataset reduces the opacity of algorithms and makes users more trusting of the final output(Centre for Information Policy Leadership & Lee, 2020). Amazon's recommendation system, for example, employs only simple and understandable algorithms, such as Bayesian classifiers or decision trees. Now consider the following scenario: customers want to select a product, based on preferred attributes. Marketers may effectively choose the right data to add to the specification sheet by recognizing the preferred product qualities(Lee et al., 2020). Neural networks are employed for such complicated decision-making and ranking. For a neural network to be explainable, the variables and model must be transparent(Lee et al., 2020) to users (marketers) so that they can understand how the final

output is produced. The model is typically a function $f(x)$, but there are also more sophisticated ones.

Although algorithmic transparency is good, information transparency is considered unethical (cf.3.3.1). There is an approach, which proves to be effective according to several studies(Cavoukian et al., 2010; Chen & Williams, n.d.; Vitale et al., 2017) and the conducted expert interviews, namely privacy-by-design. It requires IS and IT developers to build privacy into technology as a default to decrease the infringement cases and increase informational transparency from the very beginning(Chen & Williams, n.d.). Referring to the case of e-commerce platforms, privacy-by-design means having control over the parties who access data and excluding quasi-identifiers like gender and postcode from the algorithm.

Table 2:Guidelines for ethical automated marketing

AI system developers	Privacy-by-design Algorithmic fairness Explainable AI Team diversity Conduct training courses for ethical AI Make the data protection secure to limit data leaks Establish an honours code
Deployers and users of AI algorithms	Educate platform users: customers' features used for making decisions should be explained When making decisions for minority groups, include representatives of the minority in training data. Use only anonymized clients' data for segmentation and targeting. Align the data analysis process with GDPR requirements. Always work with relevant and recent data. Limit the use of sensitive data for advertisement. Limit the use of third-party cookies; instead, build a data within your company and anonymized first-party tracking and analytical cookies. Expand the ethical circle within the organization – train and educate employees about the importance of ethical business. Regular meetings among departmental representatives: think of possible ethical risks and evaluate the probability of their occurrence. Work in teams to minimize the biases. Develop a code of conduct within each department and one for the whole organization. Ensure stable coordination and communication between departments (especially marketing and R&D). Do not wait for the algorithms/ AI systems to determine what is ethical. Make the right choice of acquisition and deployment. Be mindful to the social and ethical challenges. Know your clients and what they consider (un)ethical.
Big data providers	Privacy preserving data collection. Educate consumers on the benefits of collecting and analyzing their data. Ensure that you collect only needed data. Employ lawyers and ethicists and consult with them. Use the GDPR framework for data collection. Supply marketing companies with the most recent data. Provide anonymized not pseudonymized personal data.
Standard and governance organizations	Regulate the use of ML algorithms with policies and procedures. Develop ethical criteria checklists for companies, which use AI systems. Require/ suggest certification, especially when the algorithms make decisions for humans.
Customers and broader public	Do not automatically accept the privacy policies and cookies of the e-commerce webpages. Make trade-offs between privacy invasion and service level. Clearly define your ethical borders. Educate yourself about the level of privacy protection on social media (e.g. Facebook, Twitter) and how the shared personal information can be used for profiling.
NGOs and ethics committees	Advise companies on ethical marketing, decision-making, and profiling. Do regular check-ups (surveys or questionnaires) to minimize the occurrence of ethical issues. Require auditing of algorithms.
Eliminate the occurrence of privacy invasion, bias, nudging and opacity.	

Other methods for reducing the ethical risks include working in diverse teams and establishing an honors code inside IT departments. Education in AI ethics may help with reducing the transfer of human biases onto technology and with the development of an ethical AI system (Baldrige, 2015). Researchers conclude that biased predictions are primarily generated by imbalanced data, but that engineer demographics also have an impact(Cowgill et al., 2020). As a result, having gender and racial diversity in development teams may contribute to an ethical AI system.

6.2.2 Deployers and users of ML algorithms

The second stakeholder group is ultimately in charge of automated segmentation and targeting. **Table 2** depicts a total of 16 guidelines related to digital marketers, business analysts, advertisers, and all algorithm users. The concept of explainability must be extended from the development stage to the platform clients. For example, a movie-streaming platform like Netflix should be able to explain why particular series are being recommended to the customers (the genre, actors, the plot may be similar to the ones in previously watched series). This, in turn, leads to more individualized service while justifying the recommendations. When it comes to personal data, the law must still be obeyed; consequently, data anonymization and working with relevant and recent data are required (*General Data Protection Regulation*, 2016). According to the GDPR and the EU Charter of Fundamental Human Rights, people should be informed about the data being collected and allowed to object to it. However, the interviewers agreed that restricting the use of sensitive consumer data, such as gender, ethnicity, and religion, may be more beneficial than merely anonymizing it (cf. **Appendix C**). Marketers shared that they could target the relevant consumer categories even without utilizing sensitive data — one method is to create a behaviour-based customer profile. Park & Chang (2009) describe a model, based on clicks, basket insertions, and interest fields, that does not rely on sensitive consumer data, however, shows to be effective.

If marketers are unsure whether the personal data is collected in an ethically safe way, the solution is to build data within the company and use only first-party tracking or analytical cookies. Blocking first-party analytical or tracking cookies may result in a poor user experience and cause the website's operation to be disrupted (Koop et al., 2020). Blocking third-party cookies, on the other hand, decreases the likelihood of hijacking but seems to have no substantial influence on e-commerce. Chrome, for example, is not working with third-party cookies since 2018 but still tops the web browser markets list (Shanhong Liu, 2021). Thus, though not completely safe, first-party cookies are preferable.

A further suggestion is conducting regular inside organization meetings with other departments and ethicists. Consider a large advertising firm with a varied multi-cultural workforce, such as the multinational companies Amazon and Netflix. It is difficult for such businesses to ensure that all of their staff adhere to ethical ideals (Baker-Brunnbauer, 2020). As a result, a code of conduct, supported by at least quarterly meetings may limit using unethical AI. Additionally, it is important to communicate the current social challenges, concerning society. People may value their well-being and privacy more than ever before as a result of technological breakthroughs and media influence. Knowing that the majority of consumers regard the invasion of privacy as a violation of their human rights is critical for selecting the best marketing strategy. The marketing firms interviewed suggested creating a checklist with attributes that consumers may consider unethical. An example is a checklist proposed by the European Commission (2019), which can be adapted to different industries. Other methods include analyzing client behaviour on blogs and considering their complaints, as well as polling customers or getting their feedback for certain campaigns.

6.2.3 Big data providers

The interviewed marketing companies shared that they rely on big data providers to run their businesses. Thus, although not completely part of the AI system development and use, big data providers are included as a stakeholder group due to the value they deliver to marketers. Ensuring privacy-preserving data

collection before transferring the data to the advertisers may reduce unethical work with data. IBM – a big data providing company – has already implemented these privacy-preserving data analysis techniques (so-named differential privacy). The corporation relies mostly on k-anonymity-based algorithms to assure "data sanitization" (Moffie, n.d.). Once used by advertising companies, the anonymized data cannot be linked back to the individual and is thus not intrusive to privacy. Additionally, bias may be decreased, as the data contains no sensitive consumer information (like gender and nationality).

Another consideration is GDPR compliance. When the GDPR was formed, big emailing platforms, like Gmail, were sending an email, informing users about the private data gathered by the company and the objectives for which it was collected. The users were given the option to opt-in or opt-out. Gmail serves as a good illustration of how law regulation may be put into effect and its usefulness for consent data collection.

6.2.4 Standard and governance organizations

Because algorithmic decision-making is used in everyday life and can sometimes influence and impede people's autonomy, governmental institutions must guarantee respect for human rights. As a result, a good framework with norms and standards for the development and application of AI in each area is an excellent place to start. Moreover, cases like discrimination must be considered by the responsible regulatory bodies, so that they are not repeated over time. Also, certification may help reducing information asymmetries and make the AI systems more ethical and identical (Cihon et al., 2021). For example, IBM has ISO certificates for information security for cloud services (ISO27017), privacy information management system, and information security management system. This ISO certificate guarantees the security of IBM company's services¹ to its partners, customers, and clients, as well as to the broader public in 140 countries. The standard and governance organizations should ensure that all e-commerce platforms and data providers follow certification standards. In case of doubt, the GDPR checklist² can be used to evaluate the platforms' compliance.

6.2.5 Customers and the broader public

Using e-commerce and internet services necessitates making trade-offs. The general public must be aware of their ethical boundaries; for example, some people may not consider gender as a discriminatory factor. Another requirement is to educate the larger audience on how consent information sharing on social media accounts (such as Facebook and Instagram) can lead to customer profiling. The GDPR requires each website to have privacy policies in place, and to provide the website visitors with the choice to opt-in or out. A study reveals that most consumers in online environment click "I have read the terms and conditions" or "I agree" with the privacy policy reflexively (Cate et al., 2014). People should recognize that it is in their best interests to read those privacy rules before disclosing any personal information.

On the other hand, using services such as meal delivery usually requests access to customers' current location. The client is given the option to deny, however with the price of not being shown the nearest restaurants. This may result in inferior service delivery. In such circumstances, people should decide for themselves what they value more: their privacy or the level of service they receive.

¹ [Read more](#) about IBM certification.

² [GDPR checklist](#).

6.2.6 NGOs and Ethics committees

Internal governance, such as ethical committees, is essential, particularly for large-scale functioning marketing companies. Not only should these committees be in charge of establishing the ethical standards for AI technology, but should be held accountable in case an unfair decision is obtained by ML algorithms. By employing AI auditing, development firms and users of the technology can work with ethicists to verify that bias and algorithmic nudging are kept to a minimum (Raji et al., 2020). Platforms such as Google Ads, Amazon, and Netflix deal with significant amounts of personal data daily and must be able to do ethical business while protecting human rights. Non-governmental organizations in the EU, on the other hand, are the ones who insist on the EU developing regulations to ensure ethical artificial intelligence. They combat prejudice on all levels and advocate for people's human rights and liberties. Those groups should adhere to the law's requirements and, if there is a significant impact on social well-being, they should disclose it to the court.

7. DISCUSSION AND LIMITATIONS

The following study addresses the research question: **“How can the machine learning algorithms create and capture value within the ethical boundaries of customer segmentation and targeting?”**. To find an answer, rule utilitarianism was used as a framework for ethical decision-making. This theory focuses on preserving the human rights of the society while delivering them the highest value (Copp, 2005; Harsanyi, 1977). The ethical challenges of algorithmic opacity, privacy invasion, bias, and nudging that arise in digital marketing are identified and their effect on people's human rights is observed. The paper demonstrates how the GDPR can be used as a weapon for ethical AI marketing business. Aside from constraining AI systems, the data protection regulation imposes some limitations on advertisers and the general public. The benefits of the ML algorithms are also analyzed, and as a result, a collection of 40 proposals is generated that aims to overcome the ethical challenges. The framework is built by separating responsibilities among stakeholder groups, which allows for a better possibility of tracing ethical concerns back to their source. The proposed rules aim to preserve the benefits of implementing ML algorithms while preventing ethical difficulties from arising.

7.1 Contribution to theory

Through this research, the most common ethical challenges, which can arise in the stages of customer segmentation or personalized targeting, have been structured and presented. The behavioural economics theory of nudging (Acquisti, 2009) is extended to the area of AI marketing and is defined as an ethical risk, arising from the ML algorithms. Additionally, the benefits delivered to the marketing industry and customers by using AI systems are extracted from the most recent literature (2016 onwards). The study allocates the obligation of ethical business to the stakeholders in the digital marketing process using the responsible research and innovation theory (RRI). Moreover, the various interested parties are defined, and their responsibilities are described. Following the multi-stakeholder strategy of Resseguier et al. (2021), guidelines for ethical AI in digital marketing were developed. Although being neglected so far, the big data companies were added as a further stakeholder, due to their huge role in providing customer data to the advertising companies.

The recommendations provided in this study can serve as a new method for analyzing the extent to which a certain business uses its AI technology ethically. Because of the discussed GDPR restrictions, this study should serve as a wake-up call to the

European Union Commission to introduce legislation governing AI. The EU Commission recently announced a series of measures to improve the fairness aspect of online platforms and to address issues such as confusing policies and unclear ranking procedures (European Commission, 2019a). The decision to apply such principles should not be left to enterprises and their moral judgment; consequently, a study must be conducted to identify how standard and regulatory organizations behave when human rights are violated as a result of AI use. Researchers should concentrate on developing a qualitative study that provides insight into how ethical automated businesses might boost the company's KPIs. Furthermore, the ethical implications of using AI for neuromarketing could be investigated, as more and more digital platforms are discovered to rely on neuromarketing combined with AI to remain competitive.

7.2 Contribution to practice

With an increasing interest in preserving society's well-being in general and living a sustainable existence, the ethical aspect of AI is something that corporations should address. The proposed guidelines can be applied by each stakeholder group as indicated. However, due to the focus of this study, we can argue that the adherence of marketers and users of AI systems is extremely important for delivering maximum utility to their customers. This report can contribute to the governmental bodies in the European Union, together with the non-governmental organizations, and provide them with a direction towards what should be regulated in the following years when it comes to algorithmic decision-making. Because of its simplicity, this study is appropriate for educating the general public and users of e-commerce platforms on the possibility of human rights violations and how to limit such situations on an individual level. Last but not least, data providers can benefit from some of the rules given to foster trust in their clients. The primary goal, however, is to raise awareness among all actors in the automated marketing process to secure a robust and ethical business while not jeopardizing the benefits of AI technology.

7.3 Limitations

It is difficult to predict how artificial intelligence will evolve in the upcoming years and what trends will emerge in its application in business. Although the literature examined for this study is from 2016 onwards, it may be out of date due to the ever-changing nature of AI and its subsets. Furthermore, the analyzed legislative regulation – GDPR – is primarily enforced in Europe and seems to be subject to change. Another issue is the inability to demonstrate the impact of applying the given guidelines with figures (e.g., KPIs). Finally, the stated ethical difficulties and associated obstacles may become irrelevant over time as a result of emerging AI development approaches such as explainable AI (XAI), which attempt to remove difficulties from the start.

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10. APPENDICES

Appendix A - Methodology

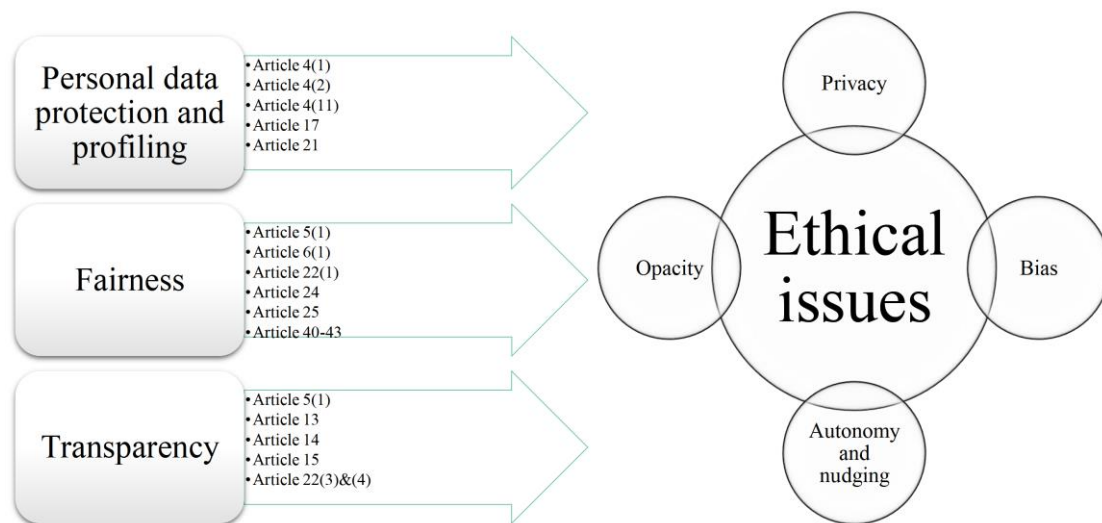
A.1. Main guiding questions during the semi-structured interviews.

Interview questions

1. What are the benefits of using ML algorithms for customer segmentation and targeting?
2. What ethical issues can arise from the usage of automated customer targeting and what could be the negative impact of those issues on the business and customers?
3. Can the ethical issues be traced back to their origin and who is responsible for resolving them?
4. What are the current guidelines which are used by data scientists to limit the moral hazard on people?
5. The EU guidelines for ethical artificial intelligence and the GDPR usually require a high level of compliance. However, what are the limitations of such strict guidelines? Do they limit the marketers to offer better service level and greater personalization to customers?
6. What can be done on an organizational level to avoid the ethical risks? How can companies ensure that they are intrinsically safe from the potential to harm customers on a moral level? Are there any codes of conduct or other written agreements for ensuring ethical businesses, or are the employees e.g., trained to behave morally?
7. What can be done by marketers and/or developers to limit the ethical issues? What technical or ethical guidelines are needed to ensure ethical data analysis?

Appendix B – Existing Guidelines

B.1. Applicable GDPR articles for resolving the identified ethical issues.



Appendix C – Interview results

C.1. – Results from conducted expert interviews in chronological order

Interviewee	Benefits of using algorithms in marketing	Ethical issues in segmentation and targeting	Limitations of the existing guidelines (GDPR)	Guidelines and approaches to minimize the occurrence and adverse effects of ethical risks
1. Assistant professor in data science and big data analytics	<ul style="list-style-type: none"> Decrease the human biases and their impacts on decision-making Reduce the subjectiveness of decisions and convert them into more systematic ones Machines make better and more accurate predictions than humans in some cases Helpful for making difficult decisions, based on complex calculations 	<ul style="list-style-type: none"> Transparency Fairness Accuracy Privacy 	<ul style="list-style-type: none"> Access to personal data becomes harder, and thus the algorithms could produce a vague output, leading to imprecise segmentation 	<ul style="list-style-type: none"> When developing the algorithms for segmenting, the customers' features used for making decisions should be explained. Restrict the use of sensitive attributes (e.g., gender, race, ethnicity, religion). When taking decision for minority groups, include larger part of the minorities in the training data. Privacy preserving data collection.
2. Data scientist from the company LittleRocket (Enschede, Netherlands)	<ul style="list-style-type: none"> Automated – you do not need a human to interfere, rather get the desired outcome only with AI Cost effective – at the beginning it is an investment, later it pays off 	<ul style="list-style-type: none"> When using “creepy” data sources like Whatsapp and Facebook, you may ask whether such action is ethical (privacy invasion) Higher personalization, greater ethical issues Lack of transparency to data subjects 	<ul style="list-style-type: none"> Can hinder the creativity of advertisers In case of third-party cookies – can potentially irritate customers 	<ul style="list-style-type: none"> Build a team of data scientists for bearing the responsibility of constructing algorithms Expand the ethical circle within the organization Educate and provide appropriate training to the developers Limit the use of third-party cookies; instead, build a data which can be used by your company and anonymized first-party tracking and analytical cookies

					<ul style="list-style-type: none"> Plan inspirational meetings, and talk of possible ethical risks The platforms should be responsible of educating their users Prefer anonymized, rather than pseudonymized data
3.	Associate professor of digital marketing <ul style="list-style-type: none"> Research interests: big data, consumer neuroscience, impact of IT on marketing and consumers 	<ul style="list-style-type: none"> ML algorithms are able to analyse a large quantity of data Can deal with both structured and unstructured data The process is real-time Usually more precise and faster than humans 	<ul style="list-style-type: none"> Data protection and privacy issues – hacking and data leak Sometimes mental pressures because of privacy invasion Nudging Discrimination Job loss 	<ul style="list-style-type: none"> Always late and addresses outdated topics; can't cope with the advancement of technologies The more regulation there is, the less you can do with data People provide a lot of information in a consent way on their social media 	<ul style="list-style-type: none"> Educate consumers on the benefits of collecting and analysing their data Create teams of data analysts to minimize the biases Technology companies should make the data protection as secure as possible to limit data leaks to none Marketers can collect data through social media and transactions; no need to have sensitive personal data Be transparent of how the profiling process is done
4.	Assistant professor marketing <ul style="list-style-type: none"> Research interests: digital marketing, big data, machine learning 	<ul style="list-style-type: none"> Personalization of products and services Real-time data analysis Greater precision in customer segmentation Cheaper one-to-one personalization Increase in purchases and engagement Easier customer profiling No need of human assets for 	<ul style="list-style-type: none"> Privacy issues – although partially anonymised, data can be traced back to the individual Bias and discrimination Nudging and manipulation (not new for marketing but even more visible in digital environment) Data leaks and data breach – extreme cases 	<ul style="list-style-type: none"> Requires marketers to make either-or decisions Does not consider psychological profiling; profiling is not only demographics Regulations are usually falling behind the technological advancement 	<ul style="list-style-type: none"> Codes of conduct within each organization; maybe even for each department Honour code of the data analysts and developers – watch beyond the benefits The data providing companies must have departments of lawyers and

		data analysis and thus decrease in labour costs	<ul style="list-style-type: none"> • Job loss 	<ul style="list-style-type: none"> • The non-compliance costs are way too high 	<ul style="list-style-type: none"> • s • ethicists • Ensure that you collect only needed data • Limit the use of sensitive data for advertisement • Customers must be educated • Customers should make trade-off between the better service and privacy invasion • Always work with relevant and recent data
5.	Senior Data Scientist at the company A4E (Sofia, Bulgaria)	<ul style="list-style-type: none"> • Business management: clear measure of effectiveness of AI systems (KPIs based on data); recommendation generated by AI support • Eliminates the human decision-making • Business improvement: increases the accuracy (e.g., more accurate decisions, based on much more data); • consistent results compared with human decisions. • accelerates business processes (e.g., faster decision-making) • cheaper processes (computation cost vs. human cost) • business expansion: automation of decision-making leads to scalability; optimal decisions contribute to greater competitiveness • For customers: receiving 	<ul style="list-style-type: none"> • Data-driven AI systems may have biases if data consists of sensitive information (e.g., race, gender) • Unreliable data (here an a-priori knowledge is implemented in the AI system – an issue may occur, if a-priori logic is not ethical) • Bad reputation for businesses • Violation of the equality rights 	<ul style="list-style-type: none"> • Customers should provide informative agreement, which makes the data collection processes much complicated • Reduces the data quality • Regulations may reduce the accuracy of the AI systems, as they rely on data • The data limitations lead to worse performance for both businesses and for customers 	<ul style="list-style-type: none"> • Avoid non-ethical data (a posteriori information) and a-priori info., which is used to build AI • Be compliant with the regulations • Consult with lawyers – GDPR experts • Technical guidelines regarding the data and business rules • Code of conduct • For SMEs – ensure there is stable coordination between departments • The SMEs can choose a data provider with certification

relevant offers; faster and accurate					
6.	<p>Professor philosophy of technology</p> <ul style="list-style-type: none"> Has developed new approaches in ethics of IT Research interest: RRI, technology for well-being, anticipatory technology ethics 	<ul style="list-style-type: none"> Better and more accurate decisions Can analyze large quantity of data Real-time grouping, based on certain characteristics 	<ul style="list-style-type: none"> privacy, profiling of people and individuals that contain even more info than it is available to their friends algorithmic bias - can treat individual and groups differently and unfairly - qualify for a loan and only consider objective criteria discrimination transparency - black box problem control - algorithms can threaten autonomy; people can be manipulated oppression - algorithms can be used by powerful actors; surveillance like facial recognition and behavioral analytics 	<ul style="list-style-type: none"> always comes late does not address recent problems and technology 	<ul style="list-style-type: none"> for organizations, which develop the AI methods – privacy-by-design, ensure algorithmic fairness, use explainable and transparent AI for companies that use it – make the right choice of acquisition and deployment, regulate its use with policies and procedures, be mindful to the social and ethical challenges good to have design tools, international certification standards for data privacy
7.	<p>Social.inc (Netherlands) – data scientist</p>	<ul style="list-style-type: none"> Less manual ways to optimize the work/outcome Efficiency – how you reach your target in the most efficient way Stay withing targeting budgets Be more precise in targeting 	<ul style="list-style-type: none"> Privacy Oppression Nudging Decisional privacy 	<ul style="list-style-type: none"> Example is the IOS 14 update – you can check which companies have been profiling you Limits the amount of data that companies are even track (esp. from Facebook perspective) 	<ul style="list-style-type: none"> When you start talking with your clients, you should develop an understanding about what is ethically go/no-go for them – what do you need from us, what is the goal and what are the boundaries; before implementing the targeting strategy Think about whether there is really a need to offer this high level of personalization – do you actually need to go that in-depth into tracking


people; there might be another creative way to attract people

- Think about anonymization always\
- Gathering engagement data within the platform itself – when doing campaign with video assets – see how people engage with the assets and then retarget that audience as an interest audience
- The guidelines should be already to the pre-screening and do not wait for the system to determine what is ethically right – before the audience, think first about the client
- The ethical checklist should not be determined by the platform, rather by the agency to make sure both customer and client side is protected from ethical risks

Appendix D – Illustrated examples of ethical risks

D.1. – Biased E-commerce websites

Save 30% Off - 4 Nights Or More



Eden Roc Miami Beach

★★★★★ 4.1 / 5 [192 reviews](#)

Price is 47% less than usual

Miami Beach

Landmark Miami Beach hotel brings on the beachside glamour

Famed architect Morris Lapidus changed the face of Miami Beach with this 631-room hotel, an... [More](#)

There are 6 people viewing this hotel.

Last booked 13 hours ago.

\$25 Elle Spa Credit

\$299

\$209


Avg/night

FREE Cancellation

Best Price Guarantee

See details

MEMBERS ONLY Stay 3 nights, Save 35%



Eden Roc Miami Beach

★★★★★ 4.1 / 5 [192 reviews](#)

Miami Beach

Landmark Miami Beach hotel brings on the beachside glamour

Famed architect Morris Lapidus changed the face of Miami Beach with this 631-room hotel, an... [More](#)

There is 1 person viewing this hotel.

Last booked -12 hours ago.

\$25 Elle Spa Credit

\$299

\$194

Avg/night

FREE Cancellation

Best Price Guarantee

See details

Figure 2: Price discrimination - the top result is shown for Cheapticket users which are not logged in, whereas the bottom is a “Members Only” price (Hannak et al., 2014).

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