Exploring Artificial Intelligence in Marketing Management

Understanding Managers’ Perceptions towards Artificial Intelligence

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List of Abbreviations

Add.	Additional
AI	Artificial Intelligence
AMA	American Marketing Association
B2B	Business-to-Business
Behav.	Behavioral
CEO	Chief Executive Officer
CIMON	Crew Interactive MObile CompanioN
CM	Customer Management
CPU	Central Processing Unit
CSI	Culture, Strategy, and Implementation
d.h.	Das heisst
DACH	Deutschland, Österreich und Schweiz
DME	Decision-Making and Ethics
e.g.	Exempli gratia
eds.	Editors
EMAC	European Marketing Academy Annual Conference
Et al.	Et alii
EU	European Union
GESS	German European School Singapore
GFF	Grundlagenforschungsfonds an der Universität St.Gallen
H	Hypothesis
i.e.	Id est
ICMarkTech'21	2021 International Conference on Marketing and Technologies
Inw.	Inward
IT	Information Technology
KI	Künstliche Intelligenz
M	Mean
M./T.	Methodological/Technological
MA	Massachusetts
M_{age}	Mean age

MIT	Massachusetts Institute of Technology
ML	Machine Learning
n	Number of observations
NJ	New Jersey
NY	New York
Outw.	Outward
P&G	Procter & Gamble
p.	Page
P1-P13	Research Propositions 1-13
Ph.D.	Doctor of Philosophy
pp.	Pages
R&R	Revise and Resubmit
SD	Standard deviation
Strat.	Strategic
US$	United States Dollar
vs.	Versus

List of Symbols

%	Percent
&	Ampersand (and)
b	Regression coefficient
CI	Confidence Intervals
p	Significance level
R^2	Regression coefficient of determination
t	Significance test
β	Regression coefficient
χ^2	Likelihood ratio chi-squared

Executive Summary (English)

Although an increasing number of companies are already using or planning to implement AI for various marketing applications (e.g., managerial decision-making), our understanding of how marketing managers can thrive in the age of AI and cope with the psychological and ethical barriers of managerial decisions induced by AI is still limited. In particular the human factor remains unclear, that is, a marketing manager's perspective amid the interplay of (1) technology (AI), (2) marketing management and managerial decisions, (3) psychology and individual perceptions of AI, and (4) ethics. This dissertation addresses, and seeks to close, this gap through four distinct investigations. Together, these studies aim to better understand managerial decisions, to stimulate further research on this topic, and to apply an interdisciplinary and mixed-methods approach, which is necessary given the complex and constantly evolving nature of the topic.

Moving along the field of marketing (management), the four articles of this dissertation focus on managerial decisions and emphasize the importance of human reactions to AI. The first article uses an exploratory approach to identify opportunities and challenges related to AI in marketing. Building on these findings, and taking a managerial perspective, the second article implements a mixed-methods approach to examine the drivers, barriers, and future developments of AI in marketing management. This article formulates research propositions to stimulate interdisciplinary research (at the intersection of the four fields mentioned above). As a result, the third and fourth articles answer the call for additional research and shed a more nuanced light on two research propositions (i.e., perception of responsibility and explainability) by suggesting important boundary conditions, which need to be taken into consideration to improve AI acceptance.

This research represents a significant advance in the theoretical and practical understanding of the drivers, barriers, and future development of AI in marketing management as well as of the individual managers' perceptions when interacting with AI. Marketing organizations should manage the potential tensions between humans and AI not only internally (i.e., to improve processes, collaboration, and decisions), but also externally (i.e., in interactions with their customers), in order to create competitive advantages. Together, the four articles are intended to close the existing research gap and to initiate further research on the intersection of technology, marketing, organizational behavior, psychology, and ethics.

Executive Summary (German)

Obwohl Unternehmen vermehrt Künstliche Intelligenz (KI) für verschiedene Marketinganwendungen (z. B. zur Entscheidungsfindung von Managern) einsetzen, ist das derzeitige Verständnis immer noch begrenzt. Es besteht eine Wissenslücke, wie Marketingmanager im Zeitalter der KI erfolgreich sein können und mit den psychologischen und ethischen Herausforderungen von KI umgehen können. Insbesondere ist der menschliche Faktor, der die Perspektive eines Marketingmanagers im Zusammenspiel von (1) Technologie (KI), (2) Marketingmanagement und Managemententscheidungen, (3) Psychologie und die individuelle Wahrnehmung von KI und (4) Ethik betrachtet, noch wenig erforscht. Die vorliegende Dissertation untersucht diese Forschungslücke durch vier Untersuchungen. Die resultierenden Artikel zielen gemeinsam darauf ab, Managemententscheidungen besser zu verstehen, weitere Forschung zu diesem Thema anzuregen und einen interdisziplinären sowie Mixed-Methods Ansatz anzuwenden. Dies ist angesichts der komplexen aber auch sich ständig weiterentwickelnden Natur des Themas notwendig.

Die vier Artikel dieser Dissertation befassen sich mit Entscheidungen von Führungskräften und betonen die Bedeutung menschlicher Reaktionen auf KI. Der Erste nutzt einen explorativen Ansatz, um Chancen und Herausforderungen im Zusammenhang mit KI im Marketing zu identifizieren. Basierend auf diesen Erkenntnissen und im Hinblick auf eine Management-Perspektive, untersucht der zweite Artikel die Treiber, Herausforderungen und zukünftige Entwicklungen von KI im Marketingmanagement. Er formuliert Ansätze zur Anregung interdisziplinärer Forschung in der Schnittstelle der vier genannten Disziplinen. Die Artikel drei und vier greifen diese Ergebnisse auf und werfen ein differenzierteres Licht auf zwei Einflussfaktoren: Individuelle Wahrnehmung von Verantwortung und Erklärbarkeit von KI. Sie zeigen wichtige Randbedingungen auf, um die Akzeptanz von KI zu verbessern.

Diese Forschung stellt einen bedeutenden Fortschritt im theoretischen und praktischen Verständnis der Treiber, Herausforderungen und der zukünftigen Entwicklung von KI im Marketingmanagement, sowie der individuellen Wahrnehmung der Manager im Umgang mit KI dar. Die vier Artikel dieser Dissertation zielen gemeinsam darauf ab, diese Forschungslücke zu schließen und weitere Forschung in der Schnittstelle von Technologie, Marketing, Organisationsverhalten, Psychologie und Ethik anzustoßen.

1. Introduction to Artificial Intelligence in Marketing Management

Artificial Intelligence (AI) has received widespread attention, particularly since its potential to generate favorable outcomes has been recognized in diverse sectors and industries, such as financial services, healthcare, commerce, and marketing (Huang & Rust, 2018). In the public sector, the most prominent and latest examples include healthcare, where AI is being deployed to manage the Covid-19 pandemic (e.g., Bragazzi et al., 2020) or to monitor and to improve mental health (D'Alfonso, 2020; Kim, Ruensuk, & Hong, 2020). Additionally, AI is used in education, where it serves to enhance learning (e.g., Kumar, 2019; Mirchi et. al., 2020). Great potential for implementing AI also exists within the private sector, especially in businesses with direct customer interfaces. Among others, there are plenty of opportunities in marketing and sales (Grewal et al., 2020). Product enhancement via AI-based technologies has already simplified consumers' life in many ways. Today, consumers can interact directly with various AI tools, such as chatbots, which facilitate online shopping or choosing between financial investments (Maedche et al., 2019; Grewal et al., 2020). Overall, AI enhances customer experience, satisfaction, and loyalty (Kumar et al., 2019).

Deploying various AI applications has provided marketers with new and more reliable information on process automation and market forecasting, among others (Huang & Rust, 2021). For instance, newly generated information can be used to create value by providing real-time personal recommendations (Davenport et al., 2020), by improving services, and by responding to constantly shifting customer needs (Rust, 2020). Ever-changing customer needs, combined with continuously increasing customer data, make AI in marketing not only relevant for business, but also a highly promising field of study (Timoshenko & Hauser, 2019; Huang & Rust, 2021).

AI technologies not only serve to deal with external challenges and opportunities (e.g., on the customer-side). They can also be applied within companies (e.g., to improve managerial decision-making) (Prahl & Van Swol, 2017; Paschen, Kietzmann, & Kietzmann, 2019). This area of AI application can be used for several marketing fields within managerial decision-making (Huang & Rust, 2021). Examples include dynamic price setting (Bauer & Jannach, 2018), customer segmentation or targeting (Drew et al., 2001; Simester, Timoshenko, & Zoumpoulis, 2020), planning product ranges (Kawaguchi, 2020), as well as product development (Wierenga, 2010; Soltani-Fesaghandis & Pooya, 2018). Expanding AI to decision-making has numerous advantages, such as increasing decision speed, and hence leading to competitive advantages (Stone et al., 2020). In addition, as demand rises or falls, decisions can be scaled up or down, which can ultimately lead to higher profits (Davenport et al., 2020). As a result, AI is developing from a previous "nice-to-have technology to a have-to-have technology" for marketing managers (Kreutzer & Sirrenberg, 2020; Preface p. viii).

Despite the mentioned benefits for marketing (management), AI has also attracted critical voices. For instance, Stephen Hawking (2016) observed that it remains unclear whether AI is the best or worst thing to have happened to humanity (Saffell, 2016). It has also been shown to have adverse consequences, such as concerns about data privacy (e.g., Martin & Murphy, 2017), the fear of jobs being replaced (Granulo, Fuchs, & Puntoni, 2019; Huang & Rust, 2018), or even reduced well-being (Etkin, 2016). As a result, these negative consequences also raise ethical questions about the "right" interaction with AI technologies. Thus, a positive net effect of AI appears to depend on determining what AI *should* do rather than what it *can* do, as Satya Nadella, the CEO of Microsoft (2018), pointed out: "We need to ask ourselves not only what computers can do, but what computers should do—that time has come" (Bittu, 2018; p. 1). This ethical perspective is necessary to ensure AI implementation and use evolve positively in the future. As stated by the EU Commission (2019), several ethical questions (e.g., Explainable AI, Responsible and Accountable AI) need to be addressed in order to build and maintain users' trust in AI (EU Commission, 2019). This statement calls for further investigating how to minimize the potential negative perception of AI and to enhance its positive aspects.

Despite the extant research on AI in marketing (management), little is known about the human perspective, particularly from the marketing manager's point of view. Research is still needed to understand how marketing managers can thrive in the age of AI and cope with the associated psychological and ethical barriers. To really benefit from AI, it is therefore crucial to work between and across disciplines and to consider psychology and ethics along with technology. Considering the particular challenges facing marketing managers resulted in the four articles making up this cumulative dissertation.

1.1 AI in Marketing Management

This section introduces the theoretical background of this thesis and summarizes information that is relevant to AI in marketing (management).

Understanding AI

Despite AI's long history, which began as early as the 1956 Dartmouth Summer Conference, there is no universal definition of the term Artificial Intelligence (Russel & Norvig, 2019). A categorization of AI capable of nurturing interdisciplinary research needs to differentiate three distinct capabilities:

(1) *Understanding* is the human perception and interpretation of environmental information, for instance, via natural language processing and computer vision (Daugherty & Wilson, 2018; Russel & Norvig, 2019).

(2) *Reasoning* can be seen as a model that gives a certain probability of occurrence to make informed decisions or recommendations in order to optimize different actions (Bellman, 1978; Albus, 1991; Kolbjørnsrud, Amico, & Thomas, 2017).

(3) *Learning*, finally, means that AI has the ability to acquire knowledge from different kinds of information and to adapt to an environment exhibiting intelligent behavior (McCarthy et al., 1955; Kurzweil, 1990; Kaplan & Haenlein, 2019).

These three aspects combine different capabilities of AI that are intended to support human thought and action. The latter two criteria can also be used to define AI in terms of whether a system thinks (Bellman, 1978) or acts (Kurzweil, 1990) like a human, or whether it thinks (Charniak & McDermott, 1985) or acts (Nilsson, 1998) rationally. These criteria share either a technological or a human focus: A technological focus depends on the ability of computers, machines, algorithms, or robots to perceive the environment and therefore to solve complex tasks independently (McCarthy et al., 1955; Nilsson, 1998). A human focus requires a certain intelligence of technical systems to perform tasks as expected of humans (Kurzweil, 1990). These different points of view demonstrate the difficulty of formulating a universal definition of AI. Hence, AI can be defined based on the three previously mentioned capabilities:

> *Artificial intelligence is a branch of science and technology that is capable of intelligently performing various tasks, detecting errors, and learning from them. Thus, AI has the ability to act reasonably in a real-world environment according to intelligent behavior.*

This definition presents AI as a multidisciplinary scientific field that intersects with various disciplines, including marketing (management).

The Role of AI in Marketing Management

AI is becoming increasingly important for marketing (managers) and seems to offer infinite opportunities (Abubakar et al., 2019; Paschen, Kietzmann, & Kietzmann, 2019). So far, however, marketing success has always depended on managers' ability to create personal experiences (van Osselaer et al., 2020). This makes using AI in marketing management a particularly promising, yet (also) challenging area of research. AI helps marketing managers to identify and understand existing customers (Huang & Rust, 2021), to segment as well as target new customers (Jabbar, Akhtar, & Dani, 2020), and to generate insights based on customer purchasing data (Wright et al., 2019). It can enable marketing managers to better identify themes and patterns that will increase the efficacy and efficiency of their marketing strategies (Paschen, Kietzmann, & Kietzmann, 2019). It also supports marketers in analyzing large amounts of data deriving from various media (e.g., textual, visual, or verbal) and sources (web, mobile, in person) (Du & Xie, 2021). AI's generated insights support marketing managers in improving their decision-making capabilities (Paschen, Kietzmann, & Kietzmann, 2019), which is a critical success factor (Abubakar et al., 2019). Consequently, marketing managers can achieve a strong competitive advantage over other companies with AI technologies (Huang & Rust, 2021).

Using AI in decision-making has been a major accomplishment in recent years (Duan, Edwards, & Dwivedi, 2019). AI systems are technically capable of improving decision quality by complementing human decision-making capabilities (Jarrahi, 2018). Thus, this dissertation uses a modified marketing decision model based on the managerial decision-making process in marketing (Lilien, 2011) and on AI-driven decision-making (Colson, 2019). Thus, the input for a (marketing) management problem can be provided either by a human or by AI. Managers, then, take decisions based on recommendations and their managerial judgment, in order to solve a managerial problem.

While AI has the potential to improve managerial marketing decisions, managers are concerned about using AI exclusively to augment human knowledge. The challenge remains whether managers should trust decisions and recommendations derived from AI (Davenport & Kirby, 2016). Research suggests that humans tend to be adverse to using AI, especially when an algorithm makes a mistake (Moon, 2003; Dietvorst, Simmons, & Massey, 2015). Hence, they accept algorithmic advice only in very specific situations, such as for performing objective or numerical tasks (Castelo, Bos, & Lehmann, 2019; Logg, Minson, & Moore, 2019; Newman, Fast, & Harmon, 2020). Consequently, many marketing managers remain concerned about fully utilizing AI in decision-making despite its potential (Davenport & Kirby, 2016).

Overall, marketing organizations should manage the potential tensions between humans and AI not only internally (i.e., to improve processes, collaboration, and decisions), but also externally (i.e., in customer interactions). The particular challenges facing marketing managers are discussed in the four articles of this cumulative dissertation. Their common objective is to understand how marketing managers can thrive in the age of AI and hence cope with the associated psychological and ethical barriers.

1.2 Relevance of the Dissertation

While the technological possibilities of AI in marketing have been (and continue to be) researched, little is known about the human perspective, particularly from a marketing manager's point of view. Thus, this dissertation focuses on understanding how marketing managers can thrive in the age of AI and cope with the psychological and ethical barriers of AI-based managerial decisions. The four articles gathered here address this research gap by examining the interplay between (1) technology, specifically AI, (2) marketing management and managerial decisions, (3) psychology and individual perceptions of AI, and (4) ethics. This research thus heeds the calls of prior research to better understand managerial decisions (Wierenga, 2011), to stimulate further research on ethics and AI (Baker-Brunnbauer, 2020), and to apply an interdisciplinary and (exploratory) mixed-methods approach, which is needed given the complexity and constant evolution of the topic (Keding, 2020).

The first major topic of this dissertation is *technology,* specifically *AI.* AI has revolutionized countless of fields over the past years and is constantly evolving (Daugherty & Wilson, 2018; Torra et al., 2019), resulting in AI applications being implemented in different industries, including financial services, healthcare, and marketing (Huang & Rust, 2018). AI can take on certain tasks and surpass human performance (Davenport & Ronanki, 2018), for example, processing large amounts of data (Du & Xie, 2021). It can also take on repetitive tasks, which humans are often not pleased about doing or are time-consuming. Contemplating the ways and means of enhancing human capabilities raises questions about how to ensure transparent and beneficial human–machine collaboration (Jarrahi, 2018) and how to reduce human errors (Logg, Minson, & Moore, 2019). Given efforts to gain a competitive advantage via AI (Huang & Rust, 2021), the question is no longer whether or not to employ AI, but to what extent (Lilien, Rangaswamy, & De Bruyn, 2017).

The second major topic *is marketing (management)*. Especially in marketing (management), using different AI applications has provided marketers with various opportunities, such as creating additional value by providing real-time personal recommendations (Davenport et al., 2020), by improving services, and by responding individually to customer needs (Rust, 2020) as well as by improving process automation, market forecasting, and (managerial) decision-making (Paschen, Kietzmann, & Kietzmann, 2019; Huang & Rust, 2021). Indeed, AI-based technologies are predicted to keep disrupting managerial decision-making even further (Davenport et al., 2020). Utilizing AI to make decisions has been a major accomplishment in recent years (Duan, Edwards, & Dwivedi, 2019). Today's AI systems are technically capable of improving decision quality by complementing human decision-making abilities (Jarrahi, 2018). Nonetheless, one of the most challenging issues is trusting AI decisions and recommendations. Managers, who work on highly confidential and strategic issues, will have difficulties in trusting AI recommendations without further analysis (Kolbjørnsrud, Amico, & Robert, 2016). The main reason being that AI does not explain its decisions on its own without further programming. Therefore, computers might perform very well—but for the wrong reasons. Data may "inherit" an unknown bias, or the model used may be suitable only for certain tasks and will fail at the slightest deviation from routine (Ransbotham et al., 2017). Thus, trusting AI recommendations without further examining or questioning its advice can be dangerous.

Two minor fields—*psychology* and *ethics*—complete the intersection of the four topics of this dissertation. Psychology plays an important role not only in the intersection with marketing management (e.g., trust, acceptance, and individual perception of AI), but also with AI technologies when exploring managerial reactions to AI. Even though AI systems have become more popular in recent years, the ethical debate remains about whether AI is entirely beneficial or should be seen as a threat (Daugherty & Wilson, 2018). Among other topics, this debate covers Explainable AI, Responsible and Accountable AI or Transparent AI, which the EU Commission lists as AI ethics guidelines for ensuring trustworthy AI (EU Commission, 2019). Thus, ethics (i.e., ethical AI) completes the intersection of AI, marketing management, and psychology.

Ethical questions arise when AI systems are included in the decision process, which makes it harder to hold managers accountable for their decisions (De George, 2008). Especially when AI makes mistakes, individuals tend to trust humans rather than AI (Moon & Nass, 1998; Moon, 2003; Dietvorst, Simmons, & Massey, 2015), and therefore tend to reject responsibility and blame AI for negative outcomes (De George, 2008). In addition, the lacking transparency of AI systems also complicates understanding the reasoning behind AI-based decisions. It is important to incorporate a certain level of explainability in AI reasoning, in order to maximize transparency (Brewer, Chinn, & Samarapungavan, 1998; EU Commission, 2019). Thus, future research needs to evaluate the ethical dimension of AI, and to minimize negative perceptions, in order to guarantee favorable developments in the coming years.

The identified research gaps highlight several ways in which our understanding of the human perspective in the intersection of technology (AI), psychology and individual perceptions of AI, and ethics remain limited, especially in the field of marketing management. This dissertation contributes to filling these gaps with four investigative studies.

1.3 Research Objectives and Overall Goal of this Dissertation

To fully benefit from AI, marketing management (strategy), psychology, and ethics, need to be considered in close association with technology. This, moreover, requires interdisciplinary cooperation and rethinking the roles and responsibilities of humans and machines (Hoffman & Novak, 2018). Building on this idea, the goal of this dissertation is to combine these four fields and thus to shed a more nuanced light on the human factor in AI in general and on the role of marketing managers in particular.

Collectively, the four articles cover the field of marketing (management). In doing so, they focus on managerial decisions and emphasize the importance of human reactions to AI. *Article 1* uses an exploratory approach to identify and discuss opportunities for and the challenges of AI in marketing (management). Building on these findings, and taking a managerial perspective given managers' boundary-spanning role, *article 2* combines a mixed-methods approach to examine the drivers, barriers, and future developments of AI in marketing management. It formulates research propositions to stimulate interdisciplinary inquiry across marketing, organizational behavior, psychology, and ethics. Consequently, *articles 3* and *4* answer the call for additional research and more closely illumine two research propositions (i.e., perception of responsibility and explainability) by suggesting important boundary conditions, which need to be taken into consideration to improve AI acceptance.

1.4 Methods

This section outlines the research methodologies used in this dissertation. What follows provides a brief overview of the data collection methods and analysis techniques used in each of the articles.

Article 1 adopted an exploratory approach to identify current and future challenges of AI in marketing. The selected experts represented a heterogeneous set of participants with vast expertise in marketing and AI. These experts were recruited from the following areas: research and academia, marketing, technology, and management consulting. At least two technology experts represented each AI technology, as defined in the AI framework. The interviews followed a semi-structured guideline and began with general questions about industry trends, opportunities, and challenges regarding AI in the context of marketing. This was followed by factors (including ethical issues) influencing managers' decision-making. The resulting data were analyzed based on inductive coding, in order to develop categories (Gioia, Corley, & Hamilton, 2013) and to group interviewees' ideas into an efficient number of categories (Weber, 1990). Based on this category-building process, the opportunities and challenges relating to the application of AI in marketing in various industries were analyzed, as well as the factors influencing marketing managers' expectations, decisions, and implementation of AI technologies.

Article 1 served as a basis for the second article. *Article 2* applied a mixed-methods approach in order to derive research propositions about organizational drivers and barriers to deploying AI in marketing, to outline future developments, and to suggest boundary conditions. Evidence came from three distinct investigations: a two-round Delphi study, a quantitative survey, and two focus groups. Starting with interviews (see article 1) in the first round of the Delphi study, the potential of AI in marketing (management) was explored and 30 statements from selected experts were gathered. In the second round (online questionnaire), the compiled statements were evaluated and discussed by the same experts. This procedure generated additional statements based on expert ratings and comments (Brady, 2015). After categorizing the statements according to three overarching themes, a quantitative survey with other experienced marketing managers was conducted to evaluate these statements and to generate dimensions and research propositions. Finally, two focus groups were implemented (Prince & Davies, 2001) with marketing managers possessing experience in AI projects to further refine our research propositions, to exclusively link these propositions to AI, and to enhance the contributions by making these propositions testable, and thus to open up a promising avenue for further research. Overall, 13 research propositions were derived as a starting point for further research.

Article 2 served as a basis for the *articles 3* and *4*. These addressed specific research propositions, which were discussed during personal interviews as well as with focus groups (see article 2, studies 2 and 3) and needed to further define boundary conditions. Hence, experimental studies were explicitly chosen for these two articles, in order to investigate the cause-and-effect relations implied by managers' perception of AI based on the derived research propositions. Both articles used the same scenario,[1] marketing decisions in product development (Kotler, 1967). According to Huang and Rust (2021), product development can be categorized as a strategic decision area in marketing. They argue that this decision field requires a combination of both qualitative and quantitative skills, making product development a promising management scenario in marketing (Huang & Rust, 2021). To further conduct these experiments, online experiments were utilized to allow timely independence of the individual answers (Reips, 2002). This method was chosen because of the challenges involved in convincing the desired population (managers with direct responsibility for at least one employee) to participate in laboratory experiments due to time and location constraints.

Article 3 investigates managers' perceived responsibility in the decision-making process (see article 2, research proposition P10). This paper linked managers' individual perception of responsibility with their willingness to accept a recommendation and compared their perception of AI- or human-generated recommendations. To examine this relationship, two experiments with experienced managers were conducted. First, the effect between perceived responsibility and willingness to accept a recommendation and how the source of advice moderates this relationship were examined. Second, to understand this effect a mediator, sense of ownership, was included in the model. A pre-study (with 50 managers) was conducted as a first step so as to select the products

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[1] Participants had to take the role of a product manager in a fictitious company, which produces and sells consumer products. They had to choose between two products and to decide which one to launch in a test market.

for the two experimental studies. The first study collected data from 300 managers for the moderation effect while the second recruited 350 managers for the moderated mediation effect. Bootstrapping was used to investigate the moderated mediation effect and utilized Hayes' (2017) PROCESS Model 14. In addition, further drivers for accepting or discounting the recommendation were investigated by including an open question. The content analysis showed that failing to explain the recommendation plays a major role in discounting the advice (especially in the AI condition). These findings illustrate the impact of a manager's perceived responsibility on their willingness to accept a recommendation by comparing human- and machine-made decision inputs.

Building on article 2, and on the findings of the open question in article 3, *article 4* analyzed managers' perception of the explanation quality of an advice and whether this differs between a human or an AI-generated recommendation. Based on research proposition P9 from the second study, an online experiment was conducted with 250 managers. The results show that managers who received a human recommendation perceived the explanation as less satisfying and as less good compared to an AI-generated advice. In order to understand the effect of the source of advice on the perceived explanation quality, the mediator, decision evaluation (perceived informed decision), was included in the model. To examine this relationship, bootstrapping was used to investigate the mediation effect and utilized Hayes' (2017) PROCESS Model 4. These results contribute to understanding managers' perceptions of the explanation quality of AI-generated recommendations and why such advice is discounted more often.

The methodological approaches adopted in the four articles examine AI in marketing (management) from different yet complementary perspectives. This mixture (and combination) of approaches ensures methodological independence, prevents methodological bias, and enables obtaining (and thus including) qualitative and quantitative results. The mixed-methods approach also permits enhancing the research results and analyzing more complex research problems (Lund, 2012). It provides a more holistic perspective and thus gives a strong foundation for future research. Table 1 summarizes the methodological approaches used in each article for the purpose of data analysis.

Table 1: Methodological Approaches

Article	Research Method	Sample	Software
Article 1: Artificial Intelligence in Marketing: Opportunities and Challenges			
1	Interviews	39 interviews with experts from academia, technology, and marketing management	Atlas.ti
Article 2: Artificial Intelligence and Machine Learning: Exploring Drivers, Barriers, and Future Developments in Marketing Management			
2	Delphi Study (2 Rounds)	Round 1: Interviews 39 selected experts from academia, technology, and marketing management	Atlas.ti
		Round 2: Questionnaire 25 experts (based on the same expert panel as the first round, interviews)	Excel, R
2	Quantitative Questionnaire	204 marketing managers from the alumni panel of a major European business school	Excel, R
2	Focus Groups	11 participants with proven experience in both marketing and AI; two focus groups (focus group I: n = 5; focus group II: n = 6)	Excel
Article 3: Artificial Intelligence in Managerial Decisions: Understanding Perceived Responsibility and Willingness to Accept Recommendations			
3	Pre-study	50 managers with managerial responsibility (effective sample size after manipulation checks)[2]	R
3	Experiment 1	258 managers with managerial responsibility (effective sample size after manipulation checks)[3]	R
3	Experiment 2	331 managers with managerial responsibility (effective sample size after manipulation checks)[3]	R
Article 4: Managerial Decisions in Marketing: The Individual Perception of Explainable Artificial Intelligence			
4	Experiment	207 Managers with managerial responsibility (effective sample size after manipulation check)[4]	R

Table 2 provides an overview of the key variables that were used in the four research articles.

[2] Participants had to indicate their company business (Oppenheimer, Meyvis, & Davidenko, 2009) as well as state for how many employees they have direct managerial responsibility to.
[3] Participants had to first recall the source of recommendation and second, their attention was tested by asking to leave a question blank. In the last part of the study, participants had to describe their perceived goal of study to control for demand characteristics (Orne, 1962). In addition, they had to indicate their company business (Oppenheimer, Meyvis, & Davidenko, 2009) and the number of employees under their direct responsibility.
[4] Attention was tested by adding attention check items, such as asking participants to identify their company business (Oppenheimer, Meyvis, & Davidenko, 2009). Additionally, participants had to indicate the number of employees under their direct responsibility.

Table 2: Main Variables

Variable Name	Variable Measurement	Reference
Article 1: Artificial Intelligence in Marketing: Opportunities and Challenges		
Chances	This article defined the opportunities for AI in marketing by using a category-building process that served to identify the following categories: • Efficiency • Objectivity • Quality • Customer Satisfaction • Applications in Marketing	Authors' items based on inductive coding (Gioia, Corley, & Hamilton, 2013)
Challenges	Similar to AI-related opportunities, this paper identified and categorized the challenges associated with AI in marketing: • Acceptance • Data • Ethics • Implementation • Interaction • Knowledge • Strategy • Corporate Culture • Trust	Authors' items based on inductive coding (Gioia, Corley, & Hamilton, 2013)
Article 2: Artificial Intelligence and Machine Learning: Exploring Drivers, Barriers, and Future Developments in Marketing Management		
Culture, Strategy, & Implementation	This variable serves as an overarching theme and can be further defined by five derived dimensions[5]: • Avoiding a Blame AI Culture • Recommendation Output • Decision Frame • Objectivity versus Human Bias • Expectation Management & Strategy	Authors' item
Decision-Making & Ethics	This overarching theme can be further specified by four derived dimensions[5]: • Humans in the Loop • Understandability • Decision Explainability • Responsibility & Accountability	Authors' item
Customer Management	This variable can be defined by two dimensions[5]: • AI & Customer Experience • Customer Data	Authors' item

[5] Each dimension defines further research propositions for future research.

Table 2 (continued)

Variable Name	Variable Measurement	Reference
Article 3: Artificial Intelligence in Managerial Decisions: Understanding Perceived Responsibility and Willingness to Accept Recommendations		
Outcome Responsibility	Outcome responsibility was measured by using the scale developed by Botti & McGill (2006). More specifically, all participants were asked to assess their perceived responsibility when making the decision as a manager based on a 7-point Likert scale (1 = Not at all; 7 = Extremely).	Botti & McGill (2006)
Willingness to accept a recommendation	This variable is a dummy variable that assumed a value of one if participants changed their decision and zero otherwise. Advice acceptance was measured by determining the difference between pre- and post-advice decision.	Sniezek & Buckley (1995)
Sense of Ownership (Perceived)	Perceived sense of ownership was assessed when making the decision as a manager by asking participants to indicate the degree to which they felt this task was entirely their decision (7-point Likert scale, 1 = Not at all; 7 = Extremely).	Peck & Shu (2009)
Reasons for accepting or discounting the recommendation	Participants were asked to explain their reasons for accepting or discounting the advice with the question "Why did you [follow]/[not follow] the recommendation you received from the [other employees/managers]/[algorithm]?"	Authors' item
Article 4: Managerial Decisions in Marketing: The Individual Perception of Explainable Artificial Intelligence		
Explanation Quality	This variable represents how well participants perceived the explanation quality by assessing whether they felt the need to ask further questions about the received recommendation.	Dijkstra (1999)
Decision Evaluation	To capture an individual's decision evaluation and whether they perceived having made an informed decision, a 4-item scale was used (with a 7-point Likert scale, 1 = I do not agree at all; 7 = I fully agree). Participants had to indicate whether they were satisfied with the recommendation, for instance, or felt they had made a well-informed choice.	Stalmeier et al. (2005)

1.5 Structure of the Dissertation

The structure of this dissertation is based on four related studies that investigate different perspectives on AI in marketing (management). Section 1 introduces AI in marketing management and briefly summarizes the theoretical background, relevance of the topic, and the research objectives. It provides a methodological overview and illustrates the structure of the articles and how they relate to each other. The first section provides the conceptual background, which forms the basis for the four individual articles. Section 1 concludes with the publication strategy and the publication status.

Article 1, co-authored by Sven Reinecke and Peter M. Fischer, examines the opportunities for and the challenges of applying AI in marketing (management) in various industries. This paper also discusses those factors that influence managers' expectations, decisions, and implementation of different AI technologies. It serves as a basis for the second article by including the interviews conducted during the first round of the Delphi study.

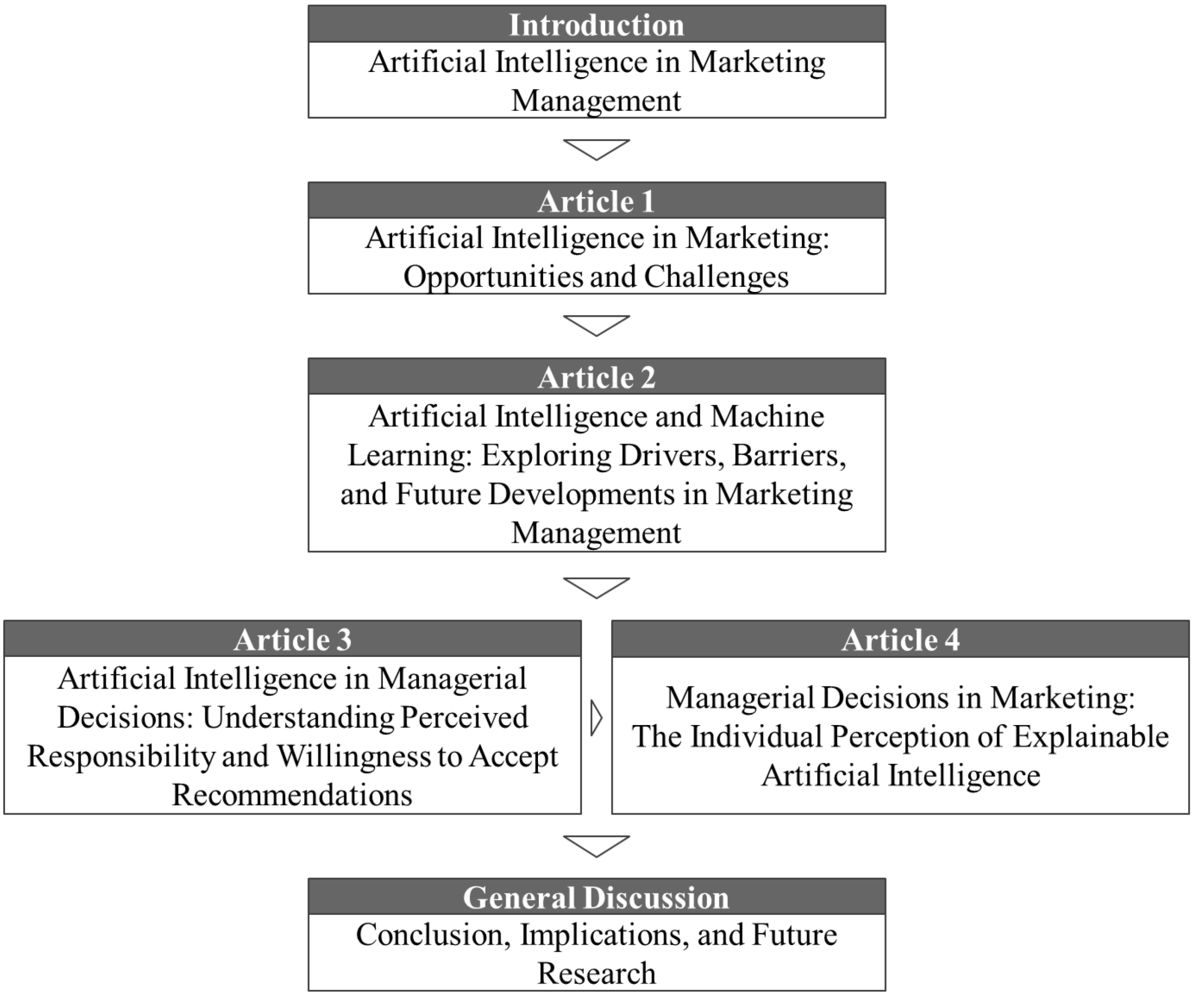
Article 2, co-authored by Peter M. Fischer and Sven Reinecke, further explores the drivers, barriers, and future developments of AI in marketing management. It expands the personal interviews conducted in article 1 by deriving expert statements and by combining these results with a questionnaire designed to evaluate the statements by the same expert panel (Delphi study). The results of the Delphi study were further evaluated by a quantitative survey to generate research propositions. As a final step, two focus groups were implemented to refine the research propositions, to specifically link these to AI, to make these propositions testable, and thus to open up a promising avenue for further research. The main result of this paper is 13 research propositions that can be grouped into three overarching themes (Culture, Strategy, and Implementation; Decision-Making and Ethics; Customer Management). These propositions form the basis for the empirical research conducted in both articles 3 and 4.

Articles 3 and *4* are single-author papers. Based on the research propositions derived in article 2, these articles answer the call for further research. They examine two research propositions from within the overarching theme Decision-Making and Ethics, since this topic was not only frequently discussed during the personal interviews, but also attracted the largest number of comments during the second round of the Delphi study. In addition, the two selected propositions were discussed in the focus groups and served to further define boundary conditions. *Article 3* examines managers' perceived responsibility (Research Proposition P10) and how including AI in managerial decision-making influences the acceptance of recommendations compared to human advice.

Based on the results of the open question, which was used to analyze the reasons for accepting or discounting the advice, decision explicability played an important role in advice discounting and required further exploration. This was the second reason for studying decision explicability (Research Proposition P9) in *article 4*. Hence, the final article investigates how marketing managers' perception of the explanation quality of an advice differs between AI and human recommendations and what reasons might account for this difference. An experiment served to answer the call for future research issued in article 2, in order to define more detailed boundary conditions.

The last section of this dissertation discusses the collective insights of the four articles and concludes with a summary of the key findings. It also provides an overview of the main theoretical and managerial implications, points out and discusses the limitations, and opens up directions for future research. Figure 1 shows the structure of this dissertation.

Figure 1: Structure of Dissertation



The following section will provide an overview of the four articles in this dissertation.

1.5.1 Overview of Article 1

Title

Artificial Intelligence in Marketing: Opportunities and Challenges

Abstract

Artificial Intelligence (AI) is becoming increasingly important in solving many tasks that were previously performed by humans. Many companies are planning to introduce AI applications in the near future, but tend to neglect the holistic implementation in their corporate strategy.

As part of an international, qualitative trend study on “Artificial Intelligence in Marketing”, the possibilities and challenges of AI in its application in marketing were examined. For this purpose, 39 interviews with experts from academia, technology, and management were carried out. On the one hand, possibilities and limits as well as challenges relating to the application of AI in marketing in various industries were explored. On the other hand, factors were discussed that influence management in terms of expectations, decisions, and implementation of AI technologies. In the following, the main results of the study regarding the challenges and possibilities of AI in marketing are revealed.

Authors

Gioia Volkmar, Sven Reinecke, Peter M. Fischer

1.5.2 Overview of Article 2

Title

Artificial Intelligence and Machine Learning: Exploring Drivers, Barriers, and Future Developments in Marketing Management

Abstract

Companies neither fully exploit the potential of Artificial Intelligence (AI), nor that of Machine Learning (ML), its most prominent method. This is true in particular of marketing, where its possible use extends beyond mere segmentation, personalization, and decision-making. We explore the drivers of and barriers to AI and ML in marketing by adopting a dual strategic and behavioral focus, which provides both an inward (AI and ML for marketers) and an outward (AI and ML for customers) perspective. From our mixed-method approach (a Delphi study, a survey, and two focus groups), we derive several research propositions that address the challenges facing marketing managers and organizations in three distinct domains: (1) Culture, Strategy, and Implementation; (2) Decision-Making and Ethics; (3) Customer Management. Our findings contribute to better understanding the human factor behind AI and ML, and aim to stimulate interdisciplinary inquiry across marketing, organizational behavior, psychology, and ethics.

Authors

Gioia Volkmar, Peter M. Fischer, Sven Reinecke

1.5.3 Overview of Article 3

Title

Artificial Intelligence in Managerial Decisions: Understanding Perceived Responsibility and Willingness to Accept Recommendations

Abstract

The paper focuses on understanding the perceived responsibility of marketing managers, and how Artificial Intelligence (AI) influences the acceptance of recommendations during the managerial decision process. AI's impact is compared to the influence of human advice. Two experiments differentiate AI-based vs. human recommendations: The first study extends prior research on managerial decision-making by showing that managers, who feel highly responsible for decisions, are less likely to accept recommendations in general. Interestingly, this effect differs between the source of recommendation. Managers tend to accept an algorithmic recommendation less when their perceived responsibility is high. In contrast, human recommendations do not differ by the degree of responsibility. The second study analyzes this moderation effect by including sense of ownership as a mediator. Results show a significant indirect interaction between perceived responsibility and managers' willingness to accept a recommendation through sense of ownership and source of recommendation. Overall, these findings contribute to understanding the psychological mechanism underlying the individual perception of responsibility and the acceptance of AI-derived recommendations. Thus, this paper offers valuable insights into improving AI acceptance.

Author

Gioia Volkmar

1.5.4 Overview of Article 4

Title

Managerial Decisions in Marketing: The Individual Perception of Explainable Artificial Intelligence

Abstract

This paper examines how marketing managers` perception of the explanation quality of an advice differs between Artificial Intelligence (AI) and human recommendations. The results of this experimental study extend previous findings on managerial decisions by demonstrating that managers' perception of the explanation quality differed between AI and humans. Explanations behind human advice were perceived as less satisfying, as needing more information about the recommendation. In contrast, receiving an AI-generated advice positively changed managers' perception of the explanation quality. They perceived explanations as more sufficient without the need for further clarification. These findings contribute to understanding managers perceptions of the explanation quality of AI-generated recommendations. Including explanations of AI-based recommendations in the decision process is important for building user trust. Thus, this paper is intended to stimulate interdisciplinary research on using AI in managerial decisions in marketing. Particularly, this study aims to encourage further research to examine the importance of explanations in the decision process to improve AI acceptance.

Author

Gioia Volkmar

1.5.5 Summary of Research Projects

Table 3 summarizes the four articles, including research questions, hypotheses and main findings.

Table 3: Summary of Articles, Research Questions, Hypotheses, and Main Findings

Authors	Research Question / Hypotheses	Main Findings
Article 1: Artificial Intelligence in Marketing: Opportunities and Challenges		
Gioia Volkmar Sven Reinecke Peter M. Fischer	What are the current and future trends as well as opportunities and challenges relating to the application of AI in marketing?	• Based on the results of the conducted interviews, this paper illustrated five central topics of AI in marketing (Data, Ethics, Applications in Marketing Management, Decision-Making, Management) that need to be addressed. • This article combined current AI applications with fields of use of AI in marketing (e.g., Sales, Product Management) and included recent examples provided by experts. • Further, the identified current opportunities and challenges are enriched with examples from different industries.
Article 2: Artificial Intelligence and Machine Learning: Exploring Drivers, Barriers, and Future Developments in Marketing Management		
Gioia Volkmar Peter M. Fischer Sven Reinecke	How can marketing managers thrive in the age of Artificial Intelligence and benefit from its potential to create value?	• The article illustrates organizational drivers and barriers to deploying AI in marketing, outline future developments, and suggest boundary conditions. • The paper derived research propositions to contribute to theory and practice by analyzing empirical evidence obtained from thought leaders and experienced AI users from three investigations. • It focuses on the role of AI in marketing both in strategic and in behavioral terms, as well as from an internal and an external perspective.

Table 3 (continued)

Authors	Research Question / Hypotheses	Main Findings
Article 3: Artificial Intelligence in Managerial Decisions: Understanding Perceived Responsibility and Willingness to Accept Recommendations		
Gioia Volkmar	How does the perceived responsibility of marketing managers affect their willingness to take AI-generated compared to human advice? H_1: Managers have a greater willingness to accept a recommendation with a decreasing perceived responsibility. H_2: The source of recommendation moderates the relationship between a manager's perceived responsibility and willingness to accept a recommendation. H_3: The indirect effect of a manager's perceived responsibility on their willingness to accept a recommendation through sense of ownership is contingent on the source of recommendation.	• The results suggest that managers are less likely to accept a recommendation when they feel responsible for a decision. • This paper analyzes the moderating role of the source of advice and finds that a lower perceived responsibility in the algorithmic condition increases the tendency to accept a recommendation (compared to the human condition). • Including sense of ownership as a mediator demonstrates that perceived responsibility positively influences sense of ownership. The source of recommendation moderates this effect by decreasing sense of ownership resulting in a higher tendency to accept a recommendation (especially in the algorithmic condition).
Article 4: Managerial Decisions in Marketing: The Individual Perception of Explainable Artificial Intelligence		
Gioia Volkmar	How do managers perceive a certain explainability of AI-based decision input? H_1: Managers' perception of the explanation quality differs depending on the source of advice (human vs. AI). H_2: The effect of the source of advice (human vs. AI) on the explanation quality is contingent on the decision evaluation.	• The article illustrates the significant relationship between the source of advice and perceived explanation quality: Managers receiving a human recommendation perceive the explanation as less satisfying and as less good compared to an AI-generated advice. • This effect was analyzed by including decision evaluation as a mediator. Receiving an AI-generated recommendation resulted in a more informed and more satisfied perception of the explanation, which positively affected the perceived explanation quality. In contrast, managers in the human condition displayed the need for further information and rated the explanation as inferior.

1.6 Paper Publication Strategy

Article 1 ("Artificial Intelligence in Marketing: Opportunities and Challenges") was published in a renowned Swiss management journal (*Die Unternehmung: Swiss Journal of Business Research and Practice*) and was written in German. Article 2 ("Artificial Intelligence and Machine Learning: Exploring Drivers, Barriers, and Future Developments in Marketing Management") was recently published in the *Journal of Business Research* in a special issue on "Machine Learning in Marketing." Article 3 ("Artificial Intelligence in Managerial Decisions: Understanding Perceived Responsibility and Willingness to Accept Recommendations") was presented at the 2022 AMA Winter Academic Conference as a competitive paper. Article 4 ("Managerial Decisions in Marketing: The Individual Perception of Explainable Artificial Intelligence") was presented at the Conference ICMarkTech'21 – The 2021 International Conference on Marketing and Technologies and has been published in the Conference Proceedings *Marketing and Smart Technologies: Smart Innovation, Systems and Technologies*. My paper was selected as one of the two best conference papers, and I was invited to submit an extended version to the peer-reviewed journal *Cogent Business & Management*. The extended version is currently under review. See Table 4 for the current publication statuses.

Table 4: Paper Publication Strategy

Article	Article Title	Authors	Publication Status
1	Artificial Intelligence in Marketing: Opportunities and Challenges	Gioia Volkmar Sven Reinecke Peter M. Fischer	• Published in *Die Unternehmung – Swiss Journal of Business Research and Practice*
2	Artificial Intelligence and Machine Learning: Exploring Drivers, Barriers, and Future Developments in Marketing Management	Gioia Volkmar Peter M. Fischer Sven Reinecke	• Published in the *Journal of Business Research*
3	Artificial Intelligence in Managerial Decisions: Understanding Perceived Responsibility and Willingness to Accept Recommendations	Gioia Volkmar	• Presented at the *2022 AMA Winter Academic Conference*
4	Managerial Decisions in Marketing: The Individual Perception of Explainable Artificial Intelligence	Gioia Volkmar	• Presented at the *ICMarkTech'21 – The 2021 International Conference on Marketing and Technologies* • Published in *Marketing and Smart Technologies: Smart Innovation, Systems and Technologies* • Under review at the *Journal of Cogent Business & Management* (extended Version)

Section 2 to section 5 of this dissertation contain the four research articles.

2. First Dissertation Article

Künstliche Intelligenz im Marketing: Möglichkeiten und Herausforderungen

(Artificial Intelligence in Marketing: Opportunities and Challenges)

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2.1 Abstract

Artificial Intelligence (AI) is becoming increasingly important in solving many tasks that were previously performed by humans. Many companies are planning to introduce AI applications in the near future, but tend to neglect the holistic implementation in their corporate strategy.

As part of an international, qualitative trend study on “Artificial Intelligence in Marketing”, the possibilities and challenges of AI in its application in marketing were examined. For this purpose, 39 interviews with experts from academia, technology, and management were carried out. On the one hand, possibilities and limits as well as challenges relating to the application of AI in marketing in various industries were explored. On the other hand, factors were discussed that influence management in terms of expectations, decisions, and implementation of AI technologies. In the following, the main results of the study regarding the challenges and possibilities of AI in marketing are revealed.

Keywords: Artificial Intelligence, Marketing, Management, AI Implementation, AI Trends, AI Challenges, AI Opportunities, AI Ethics

2.2 Zusammenfassung

Künstliche Intelligenz (KI) gewinnt an Bedeutung bei der Lösung vieler Aufgaben, die früher von Menschen ausgeführt wurden. So planen viele Unternehmen in naher Zukunft KI-Anwendungen einzuführen, vernachlässigen aber dabei die ganz-heitliche Implementierung in die Unternehmensstrategie.

Im Rahmen der internationalen, qualitativ ausgerichteten Trendstudie "Künstliche Intelligenz im Marketing" wurden Möglichkeiten und Herausforderungen der KI in ihrer Anwendung im Marketing untersucht. Zu diesem Zweck wurden 39 Interviews mit Experten aus den Bereichen Wissenschaft, Technologie und Management durchgeführt. Zum einen wurden Möglichkeiten und Grenzen sowie Herausforderungen bezüglich der Anwendung von KI im Marketing unterschiedlicher Branchen ausgelotet. Zum anderen wurden Faktoren diskutiert, die das Management in ihrer Erwartungshaltung, ihren Entscheidungen und der Implementierung von KI-Technologien beeinflussen. Nachfolgend werden die zentralen Ergebnisse der Studie hinsichtlich der Herausforderungen und Möglichkeiten der KI im Marketing aufgezeigt.

Stichwörter: Künstliche Intelligenz, Marketing, Management, KI-Implementierung, KI-Trends, KI-Herausforderungen, KI-Möglichkeiten, KI-Ethik

2.3 KI als multidisziplinäres Thema

In Zukunft wird künstliche Intelligenz (KI) zu starken Veränderungen in vielen Lebensbereichen führen (Wolan, 2020). KI hat bereits mehrere Branchen vorangebracht (Torra et al., 2019). Ihr Einsatz umfasst sowohl verschiedene Verbraucheranwendungen als auch verschiedene industrielle Anwendungen, einschliesslich Gesundheitswesen, Handel, Finanzdienstleistungen und Marketing (Huang & Rust, 2018).

Die KI-Revolution wird durch den Einfluss von immer grösseren Datenmengen sowie einer steigenden Rechenleistung zur Verarbeitung von Daten in Echtzeit vorangetrieben (Gentsch, 2019). KI-Anwendungen ermöglichen besonders im Marketing Erkenntnisse aus den umfassenden Informationen zu gewinnen. Diese Informationen sind auf unterschiedlichen Kanälen (Web, Mobil oder persönlich) verteilt und umfassen verschiedene Formen (Kommentaren oder Blogs) (Kietzmann et al., 2018). Mit Hilfe dieser Informationen kann KI genutzt werden, um zum Beispiel personalisierte Empfehlungen (in Bezug auf Produkte oder den optimalen Preis) in Echtzeit zu liefern (Davenport et al., 2020). Dadurch können Unternehmen ihren Service verbessern und personalisiert auf die individuellen Kundenbedürfnisse eingehen (Rust, 2019). Der Einsatz verschiedener KI-Anwendungen ermöglicht es Marketingführungskräften, neue und zuverlässigere Informationen zur Prozessautomatisierung, Marktprognose und Entscheidungsfindung zu nutzen (Colson, 2019).

Um ein bestmögliches Ergebnis zu erzielen, sollten Mensch und KI allerdings zusammenarbeiten. Damit stellt sich die Frage, wie eine solche Zusammenarbeit aussehen könnte (Traumer et al., 2017). Ein kritischer Aspekt besteht darin, dass Menschen häufig das grundlegende Verständnis fehlt, was KI bedeutet und welche Potentiale diese Technologie mit sich bringt (Davenport & Kirby, 2016).

2.4 Künstliche Intelligenz verstehen

Trotz einer langen Geschichte der KI, die ihre Anfänge bereits 1956 auf der Dartmouth Summer Conference hatte, gibt es bis heute keine universelle Begriffsdefinition (Russel & Norvig, 2019). Zahlreiche Forscher definieren KI nach den Kriterien, ob ein System wie ein Mensch denkt (Bellman, 1978), wie ein Mensch reagiert (Kurzweil, 1990; Rich & Knight, 1991) oder ob Systeme rational denken (Charniak & McDermott, 1985) beziehungsweise rational agieren (Nilsson, 1998). Es lassen sich aber auch Gemeinsamkeiten in den Definitionen finden:

(1) *Technologischer Fokus:* Ob Computer, Maschinen, Algorithmen oder Roboter: Alle sind in der Lage, zu denken, zu handeln, die Umgebung wahrzunehmen und daher komplexe Aufgaben selbständig zu lösen (McCarthy et al., 1955; Nilsson, 1998; Kaplan & Haenlein, 2019).

(2) *Menschlicher Fokus:* Es wird eine gewisse Intelligenz von technischen Systemen verlangt, um eine Aufgabe auszuführen, wie es auch von einem Menschen erwartet wird (Kurzweil, 1990; Wilson & Daugherty, 2018).

Da es sich bei der KI um ein komplexes Thema handelt und sich die Technologie dynamisch entwickelt, hat sich noch keine einheitliche Definition durchgesetzt. Eine Möglichkeit besteht darin, drei Schlüsselaspekte ins Zentrum zu stellen:

(1) *Verstehen* ist die menschliche Wahrnehmung und Interpretation von Umweltinformationen, beispielsweise mittels natürlicher Sprachverarbeitung und Computer Vision (Russel & Norvig, 2019).

(2) *Schlussfolgern* lässt sich als Modell interpretieren, das eine bestimmte Eintrittswahrscheinlichkeit angibt. Dies wird genutzt, um fundierte Entscheidungen zu treffen oder Empfehlungen abzugeben (Bellman, 1978; Kolbjørnsrud et al., 2017).

(3) *Lernen* bedeutet, dass die KI die Fähigkeit besitzt, aus verschiedenen Arten von Informationen Rückschlüsse zu ziehen und sich an die jeweilige Umgebung anzupassen, was intelligentes Verhalten aufzeigt (McCarthy et al., 1955; Kurzweil, 1990).

Diese drei Aspekte kombinieren unterschiedliche Fähigkeiten von KI, die den Menschen hinsichtlich seines Denkens und Handelns unterstützen sollen. Mangels Verfügbarkeit einer allgemeingültigen Definition des Begriffs KI, definieren wir diese anhand der drei Schlüsselaspekte:

> *Künstliche Intelligenz als Zweig der Wissenschaft und Technik ist in der Lage, unterschiedliche Aufgaben intelligent zu erfüllen, Fehler zu erkennen und aus diesen zu lernen. Somit besitzt KI die Fähigkeit, in einem unsicheren Umfeld intelligentes Verhalten anzunehmen und angemessen zu handeln.*

Diese Definition zeigt, dass KI eine multidisziplinäre Wissenschaft ist.

2.5 Methodische Vorgehensweise im Rahmen der KI-Trendstudie

2.5.1 Datenerhebung

Zielsetzung

Das Ziel der Studie bestand darin, aktuelle und zukünftige Trends sowie Herausforderungen der Anwendung von KI im Marketing zu identifizieren. Aus diesem Grund wurde eine Trendstudie mit 39 ausgewählten Experten aus Wissenschaft, Technologie und Management durchgeführt, die fundierte Kenntnisse über KI-Fähigkeiten und -Anwendungen haben. Die internationale qualitative Studie fokussierte schwerpunktmässig, aber nicht ausschliesslich, auf den deutschsprachigen Raum.

Selektion der Experten

Gemäss Liebold und Trinczek (2009) verfügt ein Experte über spezifische Kenntnisse in einem abgegrenzten Wissensgebiet. Somit erfolgte die Auswahl der Experten in drei Schritten. Im *ersten Schritt* wurden selektiv Experten anhand vorher festgelegter Kriterien ausgewählt:

(1) *Geschäftsgebiete:* Die Interviewpartner sollten relevante Branchen repräsentieren. Darunter fallen Technologiekonzerne, Unternehmensberatungen, Wissenschaft und Forschung.

(2) *Technologie:* Zu jedem KI-Technologiebereich gemäss der Technologiegrafik (siehe Abbildung 2) sollten mindestens zwei Experten befragt werden.

(3) *Marketing Management:* Experten sollten Manager aus dem Bereich Marketing sein, welche Kenntnisse über KI besitzen.

Diese Kriterien waren wichtig, um das Forschungsfeld zu strukturieren und anschliessend einen umfassenden Einblick zu KI im Marketing zu erhalten (Wassermannn, 2015). Im *zweiten Schritt* wurde das Schneeballverfahren angewandt. Die Experten wurden gebeten, weitere Interviewpartner zu benennen, welche denselben Kriterien entsprechen (Palinkas et al., 2015). Im *dritten Schritt* wurden solange Interviews geführt, bis eine Saturation der Erkenntnisse eintrat, welche gemäss Morse et al. (2002) ein Indikator für die Reliabilität der Daten darstellt.

Insgesamt lag die Antwortrate im europäischen Raum bei 77% und im asiatischen Raum bei 13%. Die Rückmeldequote der Grundlagenwissenschaftler war dabei erwartungsgemäss geringer als jene der anwendungsorientierten Wissenschaftler. Um eine mögliche Verzerrung zu vermeiden, wurde beim Ausfall eines Experten ein anderer Interviewpartner explizit aus demselben Bereich rekrutiert. Insgesamt wurden Experten aus den folgenden Bereichen interviewt: Wissenschaft und Forschung (6 Teilnehmende), Marketing (9), Technologie (14) und Unternehmensberatungen (10). Die Experten wurden auch zu Trends und Beispielen in Bezug auf KI befragt, die für sie aus subjektiver Perspektive interessant waren. Sie galten nicht als stellvertretend für das Unternehmen, sondern lediglich als Experten für eine KI-Technologie (vgl. Abbildung 2). Es wurden keine expliziten persönlichen Fragen gestellt, um die Offenheit und Flexibilität der Experten nicht zu gefährden.

Datenerhebung

Die Daten wurden mittels Telefon- und Skype-Interviews erhoben. Die Interviews folgten einem semi-strukturierten Leitfaden, um die neuen Ideen und Themen innerhalb der Gesprächsdauer (30-90 Minuten) zu ermöglichen (Jaeger & Reinecke, 2009). Es kamen drei Interviewer zum Einsatz, die über verschiedenes Hintergrundwissen zu KI verfügen (Betriebswirtschaftslehre, Psychologie und Ingenieurwesen/Technologie). Unser Ziel war es, dadurch den Einfluss von Suggestivbefragungen und/oder einen Interviewer Bias zu minimieren. Zudem wurde anhand einer Literaturanalyse sichergestellt, dass alle Interviewer über eine ausreichende inhaltliche Kompetenz verfügten. Die Interviews begannen mit Fragen zu Trends, Chancen und Herausforderungen der KI im Marketing. Der zweite Teil konzentrierte sich auf Faktoren, die den Entscheidungsprozess von Führungskräften beeinflussen, einschliesslich ethischer Aspekte.

Methode

Alle Interviews wurden mit Zustimmung der Teilnehmenden aufgezeichnet und transkribiert. Aufgrund des explorativen Charakters wurde der Begriff KI nicht vorgängig spezifiziert und für die Interpretation durch die Teilnehmenden bewusst offengehalten. Vorläufige Themenbereiche wurden basierend auf den gewonnenen Daten und den von den Teilnehmenden gelieferten Informationen generiert. Der Schwerpunkt jedes Interviews wurde durch die Antworten der einzelnen Experten bestimmt und angepasst. Zusätzlich wurde eine Grafik (vgl. Abbildung 2) der relevantesten KI-Technologien als Orientierungshilfe für die Experten zur Verfügung gestellt.

2.5.2 KI-Technologiegrafik

Wie bereits im *Kapitel 2.4* diskutiert, gibt es zahlreiche Definitionen der KI, die sowohl Unterschiede als auch Gemeinsamkeiten aufweisen. Aus diesem Grund und angesichts des explorativen Charakters der Studie wurde den Teilnehmenden vor dem Interview bewusst keine Definition vorgegeben. Dadurch blieben die Experten unvoreingenommen und konnten ihre eigene Definition von KI äussern und begründen.

Auf der Grundlage einer disziplinenübergreifenden Literaturrecherche wurde eine Technologiegrafik (vgl. vereinfacht Abbildung 2) entwickelt und den Experten als Orientierungshilfe bereitgestellt.[6] Auf dieser Basis wurden die Interviewfragen von den Teilnehmenden beantwortet. Der Grounded Theory (Glaser & Strauss, 1967) folgend wurde ein iteratives Vorgehen gewählt, bei welchem die Grafik basierend auf dem Expertenfeedback kontinuierlich angepasst und validiert wurde.

Abbildung 2: KI-Technologiegrafik[7]

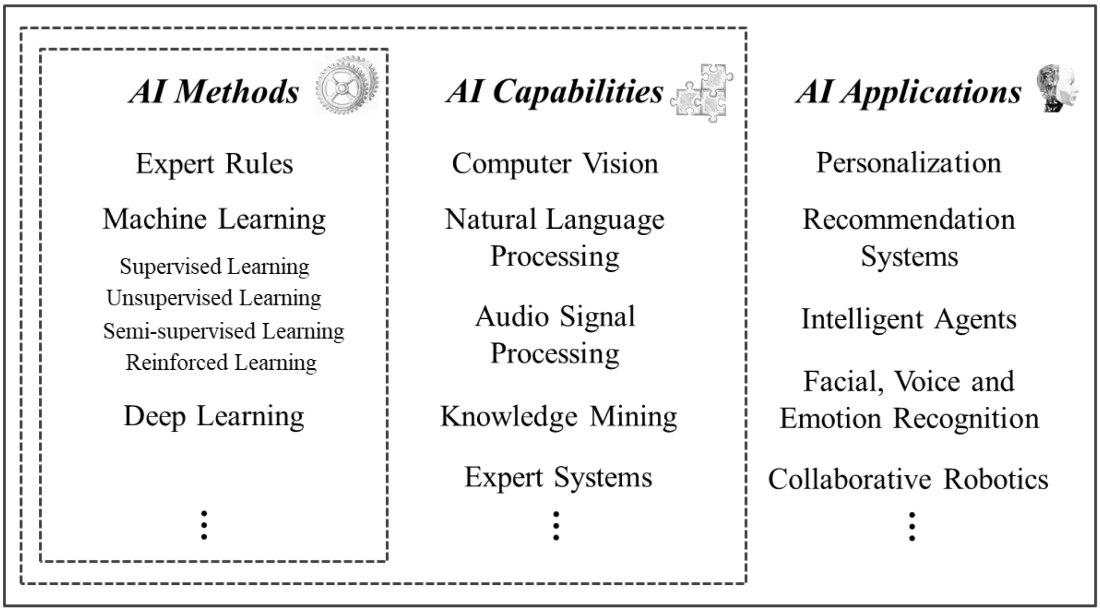

Abbildung 2 illustriert einen Ausschnitt relevanter KI-Technologien.[8] Diese lassen sich in drei Bereiche gliedern: (1) *KI-Methoden* (AI Methods), (2) *KI-Fähigkeiten* (AI Capabilities) und (3) *KI-Anwendungen* (AI Applications).

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[6] Die Technologiegrafik wurde in englischer Sprache allen Experten vorgelegt.
[7] Eigene Darstellung basierend auf Russel & Norvig (2009); Daugherty & Wilson (2018); Gentsch (2019).
[8] Die aufgelisteten Aspekte repräsentieren einen Teil von KI-Methoden, KI-Fähigkeiten und KI-Anwendungen, die heute verwendet werden.

KI-Methoden dienen dazu, unterschiedliche Arten von Daten zu verarbeiten und zu strukturieren. Dabei stellen Machine Learning und Deep Learning Teilbereiche der KI dar. Sie verwenden statistische Methoden, um Systeme mit der Fähigkeit zum Lernen auszustatten (Torra et al., 2019). Abbildung 3 zeigt verschiedene Machine Learning-Methoden.

Abbildung 3: Unterteilung der Machine Learning-Methoden[9]

	Description	Type of Data	Method
Supervised Learning	It learns by following a predetermined target pattern	Labeled data	Maps the labeled input to the known output
Unsupervised Learning	The system acts on unsorted input data without guidance	Unlabeled data	Understands patterns and discovers the unknown output
Semi-supervised Learning	It learns from labeled data while classifying unlabeled data	Combination of labeled data and unlabeled data	Use of existing, assigned data to label unlabeled data
Reinforced Learning	It learns based on the feedback from its environment	No predefined data	Follows the trial and error method

KI-Fähigkeiten basieren auf KI-Methoden und ermöglichen Systemen, die Umwelt zu verstehen. Bekannte Beispiele für KI-Fähigkeiten sind unter anderem Computer Vision oder Natural Language Processing. Mittels Computer Vision kann die Umgebung visuell erkannt werden. Dies ermöglicht Objekterkennung und Bildanalyse durch visuelle Daten aus der Umgebung. Natural Language Processing ermöglicht es der KI, die natürliche Sprache zu verstehen (Gentsch, 2019).

KI-Anwendungen basieren auf KI-Methoden und/oder KI-Fähigkeiten und beschreiben Applikationen in der Praxis. Diese Anwendungen können dann vom Endnutzer genutzt werden, seien es Führungskräfte, Mitarbeitende oder Kunden. Darunter fallen zum Beispiel Intelligente Agenten, Personalisierung und Empfehlungssysteme. Intelligente Agenten (Intelligent Agents) interagieren mit dem Menschen und verstehen Anfragen mit Hilfe von Natural Language Processing. Bekannte Beispiele sind Alexa oder Siri (Gentsch, 2019). Personalisierung (Personalization) ordnet Merkmale einem Nutzer zu und passt im Anschluss Programme, Dienste oder Informationen an die persönlichen

[9] Eigene Darstellung basierend auf Russel & Norvig (2009); Daugherty & Wilson (2018); Torra et al. (2019).

Vorlieben, Bedürfnisse und Fähigkeiten des Nutzers an (Daugherty & Wilson, 2018). Empfehlungssysteme (Recommendation Systems) schlagen dem Kunden neue Produkte vor. Die empfohlenen Produkte basieren dabei auf vergangenen Interaktionen mit dem System und ermöglichen eine zielgerichtete Empfehlung. Bekannte Anwendungen sind Netflix oder Spotify (Gentsch, 2019).

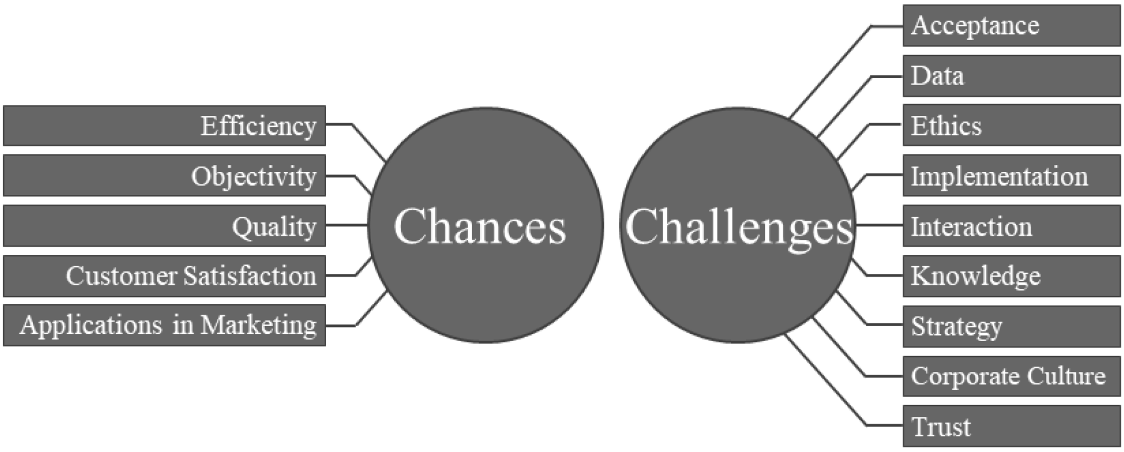
Der bereits in Abbildung 2 eingeführte Zusammenhang zwischen KI-Methoden, KI-Fähigkeiten und KI-Anwendungen ist jedoch nicht trennscharf zu unterscheiden, sondern ist abhängig von den unterschiedlichen Einsatzfeldern. Grundsätzlich bilden die KI-Fähigkeiten den Transmissionsriemen zwischen KI-Methoden und KI-Anwendungen (Russel & Norvig, 2009; Daugherty & Wilson, 2018; Gentsch, 2019).

2.5.3 Kodierung der Experteninterviews

Die Transkripte, die zusammengefassten Erkenntnisse aus den Interviews sowie die zur Verfügung gestellten Informationen wurden analysiert und nach der von Gioia, Corley und Hamilton (2013) vorgeschlagenen Vorgehensmethodik kodiert. Basis für das Kodierungsschema waren die Interviewfragen sowie ausgewählte Aussagen der Experten. Dieses Schema ermöglichte eine offene Kodierung und diente als Bezugsrahmen, um eine systematische Auswertung der Ergebnisse sicherzustellen.

Die Aussagen der Experten wurden im ersten Schritt als Konzepte erster Ordnung zusammengefasst. Auf diese Weise liessen sich im Anschluss die Themen zweiter Ordnung identifizieren und entsprechend klassifizieren (zum Beispiel: “Efficiency” oder “Acceptance”). Diese Kategorien wurden dann zu übergeordneten Dimensionen “Chances” und “Challenges” aggregiert. In diesem Artikel werden wir den Fokus auf die Möglichkeiten sowie die Herausforderungen der KI legen (vgl. Abbildung 4).

Abbildung 4: Kodierungsschema der Möglichkeiten und Herausforderungen der KI[10]



Nach Gioia, Corley und Hamilton (2013) erfolgte im nächsten Schritt die Untersuchung der daraus entstehenden Themen und Konzepte. Dabei diente die Kodierung der Ergebnisse als Basis für die Identifizierung der als relevant eingeschätzten Themenschwerpunkte. Im Zuge der Typenbildung erfolgte eine fokussierte, systematische Betrachtung einzelner Aspekte. Es wurden anhand dieser Gruppierung fünf Kategorien entwickelt. Im nächsten Kapitel wird detailliert auf die identifizierten Themenfelder der KI eingegangen.

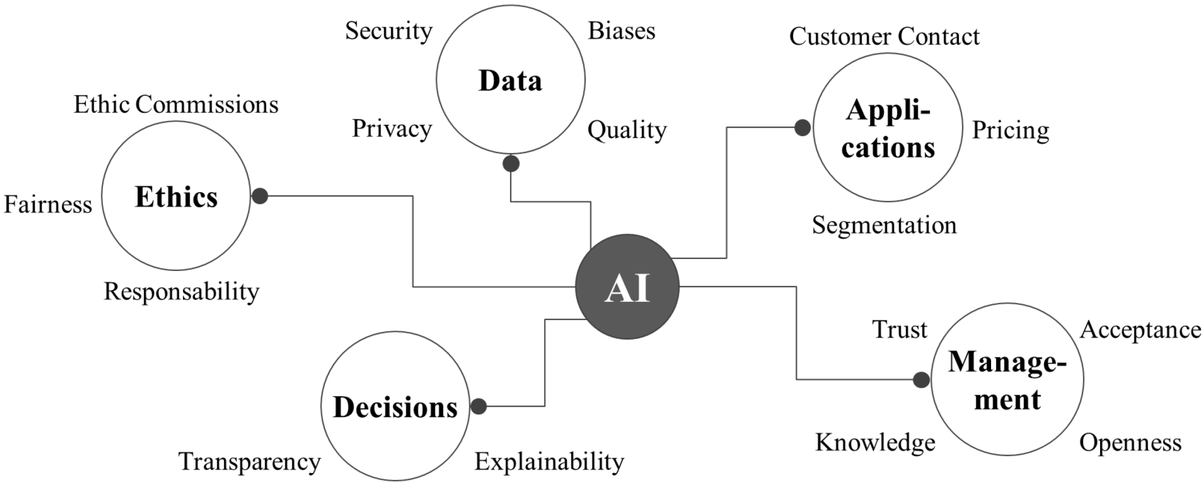
2.6 Zentrale Ergebnisse der KI-Trendstudie

2.6.1 Themenfelder der KI im Marketing

Auf Grundlage der Ergebnisse der Experteninterviews (vgl. Kapitel 2.5.3) wurden fünf Themenfelder der KI identifiziert (vgl. Abbildung 5).

[10] Die Auswertung sowie die Kodierung erfolgten auf Englisch.

Abbildung 5: Identifizierte Themenfelder der KI



Daten

Bezüglich der Datenbasis werden Herausforderungen der KI sowohl bei der Datenerhebung als auch bei der -verarbeitung gesehen. Eine mögliche Gefahr liegt in einer zu geringen Quantität und Qualität der Daten. Dadurch besteht die Möglichkeit, dass die KI Falsches lernt und somit verzerrte Ergebnisse produziert. Ein Beispiel hierfür ist das Unternehmen *Amazon*, das mithilfe von KI den Bewerbungsprozess effizienter gestalten wollte. Da die KI mit den Lebensläufen der derzeitigen und mehrheitlich männlichen Angestellten geschult wurde, waren die Daten verzerrt (biased data), so dass die KI Bewerbungen von Frauen überwiegend ablehnte.

Des Weiteren sind Datenschutz und Privatsphäre der Nutzer grosse Herausforderungen, welche auch einen Bezug zu ethischen Fragen aufweisen. Ein Beispiel hierfür ist der *Roboter CIMON* (Crew Interactive MObile CompanioN) von *IBM*. Dieser ist ein persönlicher Assistent für Astronauten, der zur Dokumentation der Experimente und zum Small Talk verwendet wird. Dabei stellte sich aber die Frage, wie mit den persönlichen Daten umzugehen ist. Um die Privatsphäre der Astronauten zu schützen, wurde vereinbart, die Daten aus persönlichen Gesprächen nicht weiter zu verwenden. Hier lassen sich Analogien zum Marketing bezüglich der Nutzung von Kundeninformationen ziehen.

Ethische Fragen

Da durch die KI immer mehr Daten gesammelt werden, werden Nutzer zunehmend “gläserner”. Es ist deshalb nach Ansicht der Experten zwingend erforderlich, die Privatsphäre der Nutzer zu schützen und vertrauensvoll mit den Daten umzugehen. Ein weiterer Aspekt besteht darin, dass Menschen einer KI keine Fehler verzeihen: Sie sind gegenüber anderen Personen meist wesentlich nachsichtiger. Jedoch stellt sich die Frage, wer für falsche Entscheidungen verantwortlich ist: die KI oder der Mensch. Ein bekanntes Beispiel ist das *Autonome Fahren*. Die Debatte der Schuldfrage im Falle eines Unfalls ist nach wie vor nicht gelöst. Die Auswirkung einer Entscheidung ist entscheidend und muss deshalb differenziert werden.

Entscheidungen

Die Experten sind sich weitgehend einig, dass die Verantwortung für falsche Entscheidungen letztlich immer beim Menschen liegt, da KI lediglich die Entscheidungsfindung unterstützt. Führungskräfte müssen somit gewährleisten können, dass sie alle relevanten Informationen in ihre Entscheidung einbezogen haben. Dies ist weitaus einfacher, wenn die KI transparenter und erklärbarer wird. Ein Beispiel ist *Procter & Gamble (P&G)*. Sie nutzen KI bei der strategischen Entscheidungsfindung zur Analyse der meistverkauften Produktvarianten für jedes Geschäft und jedes Land. So können Finanz- und Verkaufsdaten kombiniert werden, um eine ganzheitliche und transparente Entscheidungsfindung zu ermöglichen.

Management

Führungskräfte sollten über ein grundsätzliches Verständnis von KI verfügen sowie offen gegenüber Innovationen sein. Dies erfordert, dass Manager ihr Entscheidungsverhalten auf einen stärker datengestützten Entscheidungsprozess anpassen. Die *Deutsche Bahn* nutzt KI zur Unterstützung der Verwaltung für operative Prozesse. Der Verkehr wird immer komplexer und KI erleichtert es, Probleme an den Schienen festzustellen und die weitere Vorgehensweise zu planen.

Durch mehr Wissen und Transparenz bezüglich KI wird Vertrauen in diese Technologie gestärkt, wodurch die Akzeptanzwahrscheinlichkeit steigt. *IBM* ermöglicht es, durch ihre KI-Anwendung Verzerrungen der Daten (biased data) zu überprüfen und eine gewisse Erklärbarkeit zu schaffen. Infolgedessen wird die Transparenz darüber erhöht, warum Entscheidungen in welcher Weise getroffen wurden.

Applikationen im Marketing

KI wird im Marketing bereits sehr häufig eingesetzt, insbesondere in der operativen Segmentierung von Kunden und im Rahmen der direkten Kundenansprache. Zumeist handelt es sich (noch) um automatisierte, operative Prozesse. Dahingegen findet KI bei strategischen Marketingentscheidungen bislang noch selten Anwendung.

Die Experten wurden im Rahmen der Studie ferner nach den grössten Schwierigkeiten, Potentialen und Herausforderungen im Umgang mit KI-Technologien gefragt, die nachfolgend kurz dargestellt werden.

2.6.2 Möglichkeiten der KI im Marketing

Die Hauptmöglichkeiten lassen sich hinsichtlich *Effizienz, Produkt- und Dienstleistungsqualität, Kundenzufriedenheit* und *Marketingmassnahmen* differenzieren.

Effizienzsteigerung durch KI

Die grösste Chance in Bezug auf den Einsatz von KI besteht in der Effizienzsteigerung. Dies wurde nahezu von allen Experten bestätigt. Der Einsatz von KI bietet Unternehmen die Möglichkeit, die Effizienz bei der Arbeit vor allem durch Automatisierung zu steigern. So können sehr präzise Vorhersagen und Prognosen in Echtzeit erstellt werden. Dies basiert auf der Fähigkeit der KI, eine sehr grosse Datenmenge zu verarbeiten und zu analysieren. Dadurch können Unternehmen effizienter in ihren Entscheidungsprozessen unterstützt werden.

> *"Call Center […], relevante Informationen bereitzustellen, egal welche Aktion sie gerade starten. […] Aktuelle Nachrichten auswerten, social listening (d.h. Social Media Auswertungen), alle relevanten Informationen mit hinein zu nehmen. Und das bezieht sich meistens nicht nur auf Text, sondern man kommt sehr schnell auch in die Auswertung von Bildmaterial. Und wenn es richtig umfangreich betrieben wird, dann geht es auch in die Auswertung von Videomaterial."* (Experte 19)

Streng genommen bezieht sich KI allerdings nicht nur auf die Effizienz, sondern auch auf die Effektivität, da gewisse Datenauswertungen erst durch den Einsatz von KI möglich werden. *P&G* nutzt zur Entscheidungsunterstützung einen intelligenten Agenten namens *SAMANTHA*. Dadurch ist es erst möglich, die Menge an Verkaufsdaten zu analysieren und Prognosen über Verkaufszahlenänderungen in Echtzeit zu erstellen.

Qualitätsoptimierung durch KI

Die Qualität von Produkten und Dienstleistungen kann deutlich verbessert werden, weil Fehler minimiert werden und eine effizientere sowie präzisere Arbeitsweise sichergestellt wird. Dadurch wird auch die Beziehung zwischen dem Unternehmen und seinen Stakeholdern, wie etwa Kunden, verbessert, da ihre Qualitätsansprüche besser erfüllt werden können. Unternehmen, die in der Lage sind, Kunden und deren Verhalten zu antizipieren, können ihr Leistungsangebot und die Servicequalität gezielter optimieren.

> *"Derjenige, der den Kunden am besten kennt und sein Verhalten antizipieren kann, der hat gewonnen, der kann sein Unternehmen besser steuern, der kann sein Produktsortiment, seine Servicequalität anpassen und personalisierte Kundenansprache betreiben."* (Experte 5)

Höhere Kundenorientierung durch KI

Eine weitere Chance besteht in einer Verbesserung der Kundenorientierung. Da KI es ermöglicht, Kunden schneller, umfassender und personalisierter anzusprechen, können individuelle Bedürfnisse antizipiert und befriedigt werden. Unternehmen können sich kundenorientierter ausrichten und das Kundenerlebnis (Customer Experience) verbessern.

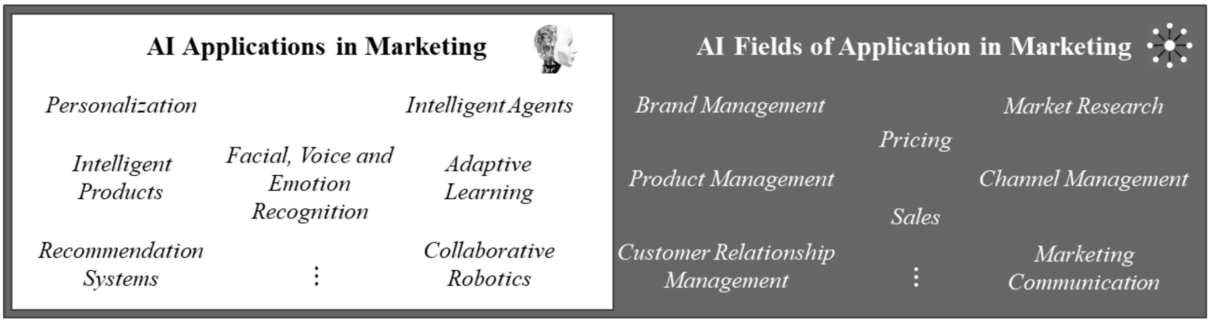
> *"Man versucht nicht nur unbedingt den User zu identifizieren, sondern es geht mehr darum herauszufinden, was gerade jemand liest und was ihn beschäftigt und basierend auf diesem Wissen werden Datenbotschaften ausgespielt. Das ist nur mit KI möglich."* (Experte 5)

Unternehmen wie *Amazon* oder *Spotify* setzen dabei auf Empfehlungssysteme, um die Kundenzufriedenheit zu erhöhen. Anhand vorheriger Präferenzen wird ein geeignetes Produkt vorgeschlagen. Eine höhere Kundenorientierung kann auch durch eine *vorausschauende Wartung* (Predictive Maintenance) erreicht werden. Dabei gibt die KI-Anwendung im Vorfeld an, wann die nächste Reparatur notwendig ist.

Anwendungen und Einsatzfelder von KI im Marketing

Es gibt zahlreiche Anwendungsfälle, die von den Experten für das Marketing erwähnt wurden (vgl. Abbildung 6).

Abbildung 6: Anwendungen und Einsatzfelder von KI im Marketing[11]



Unter den Anwendungsgebieten im Marketing wurden drei KI-Anwendungen von den Experten hervorgehoben.

Intelligente Agenten können als Verkaufsassistenten eingesetzt werden, die dem Verkaufspersonal während des Kundengesprächs Empfehlungen und Informationen bereitstellen. Hierbei sind Chatbots eine stark verbreitete Anwendung. Sie können rund um die Uhr über die Website des Unternehmens mit dem Kunden kommunizieren. Bei der *INTER Versicherung* erhalten Kunden per Chatbot Antworten auf Ihre Fragen zu Versicherungspolicen.

Personalisierung wird auf Basis der KI intensiv eingesetzt. Dabei geht es um die individuelle Ansprache von Kunden. Zum Beispiel werden Kunden individualisierte Werbebotschaften auf Webseiten oder in Apps präsentiert. *P&G* nutzt KI, um Kunden online sowie offline mit individuellen Nachrichten anzusprechen, indem eine Botschaft entsprechend des jeweiligen Benutzerprofils personalisiert wird.

Empfehlungssysteme werden häufig eingesetzt, um Kunden bestimmte Produkte oder Dienstleistungen vorzuschlagen, die ihren bisherigen Präferenzen entsprechen. Dies lässt sich insbesondere zur Kundenbindung im Onlinehandel einsetzen. *IBM* nutzt eine KI-Anwendung (Watson Personality Insights), um Produktempfehlungen auf der Grundlage des Persönlichkeitsprofils eines Benutzers zu geben.

Im Marketing gibt es zahlreiche *weitere Einsatzfelder* von KI-Applikationen:

Eine eher neue Technologie, die im Marketing eingesetzt wird, ist *Computer Vision*. Im Einzelhandel wird sie verwendet, um das Kundenverhalten im Geschäft zu analysieren

[11] Die aufgelisteten KI-Anwendungen und KI-Einsatzfelder im Marketing repräsentieren einen Ausschnitt der Anwendungen, die heute verwendet werden.

und individuelle Botschaften auf Bildschirmen anzuzeigen, um sowohl Cross- als auch Up-Selling zu ermöglichen.

> *"Computer Vision wird bei der Produkterkennung, bei der Personenerkennung, bei "Mood"-Sentiment und so weiter eingesetzt. Gerade im Online-Commerce."* (Experte 7)

Darüber hinaus können mittels KI Marktanalysen schneller und effizienter durchgeführt werden. Darunter fallen zum Beispiel *Kunden- und Zielgruppensegmentierung*, aber auch die *Erstellung von Benutzerprofilen*.

> *"I think from a usage level, machine learning applications are the ones that are being mostly used in the context of marketing [...]. One big use of it, is better understanding the markets and the consumers. So, what these models allow you to do is to have both a more sophisticated perspective about their consumer needs and how they change, but also have a more life perspective about it."* (Experte 31)

Dynamische Preis- und Marketingkampagnen können durch den Einsatz von KI optimiert werden. *Videoanalysen* lassen sich einsetzen, um zu analysieren, wie Kunden Produkte wahrnehmen und konsumieren. Dies wird genutzt, um Potenziale für Produktverbesserungen zu identifizieren. Ausserdem werden Kundenbeschwerdedaten mit Hilfe von *Text Mining* (Textanalysen) analysiert, um den gesamten Prozess zu beschleunigen.

Für die Kundeninteraktion werden vermehrt *kollaborative Roboter* (Collaborative Robotics) eingesetzt. Ein bekanntes Beispiel ist der Roboter Pepper von *Softbank Robotics*. Darüber hinaus wird die *Stimmungsanalyse* (Voice and Emotion Recognition) auf Grundlage natürlicher *Spracherkennung* auf Kundenrezensionen angewandt, um ein besseres Verständnis der Kundenhandlung zu erhalten. Ein weiteres Anwendungsgebiet im Marketing-Management ist die Produktentwicklung. Einige Unternehmen setzen KI ein, um neue Produkte zu entwickeln. Der Parfümhersteller *Symrise* verwendet KI als Assistenten bei der Entwicklung neuer Düfte, die auf spezielle Zielgruppen ausgerichtet sind. Dabei schnitt der von KI produzierte Duftstoff auf dem Markt am besten ab. Darüber hinaus ermöglicht *Augmented Reality* den Kunden, Produkte virtuell zu Hause auszuprobieren. Ein Beispiel ist das Testen von Make-up.

2.6.3 Herausforderungen der KI im Marketing

Bei den Hauptherausforderungen für die KI ist zwischen dem *Einsatz* und der *Implementierung von KI* zu unterscheiden.

2.6.3.1 Implementierung von KI im Marketing

Eine zentrale Herausforderung besteht darin, die richtigen Handlungsfelder für die jeweilige Unternehmenssituation auszuwählen und anschliessend erfolgreich zu implementieren.

Fehlende Umsetzungsstrategie

Viele Unternehmen besitzen keine klare Strategie bezüglich der Implementierung der KI. Sie wollen aufgrund des derzeitigen "Hypes" KI implementieren, ohne im Vorfeld einen expliziten Anwendungsfall identifiziert zu haben. Diesen suchen Unternehmen häufig erst im Anschluss nach der Einführung. Diese Strategie wird jedoch laut der Experten nicht zum Erfolg führen.

> *"Once you start introducing a technology, start from the simplest thing. So, the concrete example would be, don't start by saying we're going to need to build up our own neural net-based decision prediction machines from first principles. Pick something off the shelf and see how well that works for you."* (Experte 20)

Eine klare Strategie und ein fokussierter, abgegrenzter Anwendungsfall erhöhen die Erfolgswahrscheinlichkeit einer Implementierung. Es empfiehlt sich, die relevanten Mitarbeitenden in den Entscheidungsprozess bezüglich KI zu integrieren, um die Akzeptanz zu fördern.

Unternehmenskultur und Managementsupport spielen eine wichtige Rolle

Darüber hinaus kann die Unternehmenskultur für den Einsatz von KI eine Herausforderung sein. Eine risikoscheue und konservative Kultur hemmt die Implementierung. Somit sollte ein gewisses Mass an Risikobereitschaft, Agilität und Innovationsfähigkeit in der Unternehmenskultur und im Management verankert sein.

> *"I think the biggest difficulty today is the organizational and human factors of technology. Of course, you have the technology aspect, too. The technology works and so we are still improving the technology, which will improve over time. But then what prevents a lot of companies from leveraging this technology, it's more the fact that they're not organized for it."* (Experte 36)

Ethische Herausforderungen sind komplexer als technologische Probleme

Alle Experten sahen bezüglich des Einsatzes von KI im Marketing den Bereich der Ethik als eine äusserst schwierige und ernstzunehmende Herausforderung an. Verantwortlichkeit, Entscheidungstransparenz und Datenschutz sind diesbezüglich kritische Aspekte.

> *"Sie haben in komplexen Systemen, insbesondere in maschinellen Systemen, ein riesiges Komplexitätsproblem, ein riesiges Transparenzproblem und daher auch ein Erklärbarkeitsproblem. Das ist nicht mehr lösbar und dadurch, dass sie jetzt den Begriff KI für alles verwenden, überträgt das alles auf andere Bereiche."* (Experte 6)

Ein negatives Beispiel ist der *Microsoft Bot Tay*. Der Bot hat sich bereits nach wenigen Stunden politisch extrem rechts orientiert und musste nach nur 16 Stunden abgeschaltet werden.

2.6.3.2 Einsatz von KI im Marketing

Wissen über KI ist der Schlüssel

Viele Marketingführungskräfte und -mitarbeitende verstehen nicht, wie KI-Technologien funktionieren. Sie sind daher verunsichert und skeptisch bezüglich der KI-Anwendung im Marketing. Dies wirkt sich negativ auf ihr Vertrauen in die KI aus. Viele Unternehmen sind aber auch naiv bezüglich der KI-Potenziale. Sie überschätzen das Potenzial deutlich und halten KI für eine universale Lösung, die alle Probleme auf Anhieb ohne Anstrengung lösen kann.

> *"Es gibt viele Unternehmen, die sagen: „Wir wollen KI einführen, was auch immer das bedeutet."* (Experte 11)

> *"Die Leute glauben, sie kriegen eine Wunderkiste."* (Experte 33)

Wenn die Ergebnisse des KI-Einsatzes letztlich diese häufig unrealistischen Erwartungen nicht erfüllen, wird die KI-Technologie wieder schnell abgeschafft.

> *"Die Erwartungen sind einfach zu hoch und führen dann natürlich dazu, dass man sagt: so sehr hilft das nicht. […] Man erkennt nicht, dass KI mehr als eine situative Projektrelevanz hat, sondern eine Relevanz darüber hinaus. Diese muss man mittelfristig sehen, und die Möglichkeiten und Chancen auch geistig erschließen können. Und ich glaube, da fehlt es noch ein bisschen an der Transparenz im Markt."* (Experte 34)

Daten als grösste Herausforderung beim Einsatz von KI im Marketing

Nach Meinung der Experten sind Datenzugang und -nutzung die grösste Herausforderung für Unternehmen. Dazu gehören die *mangelnde Qualität der Daten*, eine *unzureichende Quantität der Daten* und die *ungenügende Datenaufbereitung und -verarbeitung*. Daten sind die Quelle aller KI-Technologien: Der Output hängt daher massgeblich vom Input ab. Daten sind demzufolge laut den Experten der entscheidende Faktor für den Erfolg der Technologie.

> *"Die Grundlage ist bei den meisten eigentlich das Schwierigste: Dafür das Bewusstsein zu schaffen, die Daten von Anfang an richtig zu sammeln."* (Experte 8)

Eine weitere Herausforderung ist das Risiko, dass KI aufgrund *verzerrter Daten* scheitert. In diesem Fall wird das Modell mit falschen Daten trainiert und "lernt" falsche Dinge, was wiederum zu unzweckmässigen Empfehlungen und Entscheidungen führen kann. Zum Beispiel suchen einige Kunden online nach Produkten und vergleichen lediglich die Preise. Das ausgewählte Produkt wird aber nicht online gekauft, sondern im klassischen Einzelhandel. Dennoch erhalten sie personalisierte Onlinewerbung für das gesuchte Produkt. Diese Datenlücke wirkt sich somit auf das Marketing negativ aus.

> *"Dann gibt es das Thema Bias, wie stelle ich sicher, dass ich die Modelle richtig trainiere, dass ich nicht ein Bias reinkriege."* (Experte 2)

Datensicherheit und Datenschutz sind weitere wichtige Herausforderungen. Durch die zunehmenden Möglichkeiten der Datenerhebung gewinnt der Verbraucherschutz für Unternehmen an Bedeutung. Es ist anspruchsvoll, sicherzustellen, dass keine Datenschutzprobleme auftreten und auch international alle Rechte der Verbraucher eingehalten werden.

> *"Ein Aspekt zum Marketing, was natürlich interessant ist, ist das Targeting von bestimmten Personen. Bei solchen Systemen sollte man immer auf die Persönlichkeitsrechte der Personen achten, die dort angesprochen werden. Es kann aber dazu führen, dass die Personen durch dieses gezielte Targeting ihrer eigenen Person abgeschreckt sind und explizit nicht bei diesem Hersteller kaufen. Das ist ein zweischneidiges Schwert."* (Experte 21)

Im Marketing gibt es durch KI ein hohes Potenzial bei der direkten Kundenansprache und der Personalisierung. Allerdings besteht die Gefahr, Kunden durch zu präzise Zielgruppenansprache abzuschrecken, indem beispielsweise Produkte vorgeschlagen werden, über die kürzlich gesprochen wurde. Aus diesem Grund ist es nicht immer ratsam, alle gesammelten Daten zu nutzen. Häufig erhöht eine vertrauliche Behandlung der Daten aufgrund des dadurch gesteigerten Kundenvertrauens den Mehrwert für den Kunden.

2.7 Fazit und Ausblick

Die Möglichkeiten und die Potenziale der KI im Marketing sind enorm. In den nächsten Jahren wird es noch deutlich mehr marketingrelevante KI-Applikationen geben. Im Rahmen dieser Trendstudie konnten praktische Erkenntnisse hinsichtlich der Möglichkeiten und Herausforderungen der KI in ihrer Anwendung im Marketing gewonnen werden. Dabei konnten schwerpunktmässig Experten aus der DACH-Region befragt werden, was eine regionale Limitierung der Aussagekraft der Studie zur Folge hat.

Aus Sicht der Experten bestehen jedoch nach wie vor zahlreiche Herausforderungen, die nicht nur Unternehmen und Führungskräfte, sondern die Gesellschaft im Allgemeinen betreffen. Nur wenn diese bewältigt werden, kann das volle Potential von KI ausgeschöpft werden. KI erfordert neue Kompetenzen, Vertrauen in die Technologie und eine grosse Veränderungsbereitschaft. Ungeachtet dieser neuen Mensch-Maschine-Interaktion bleiben noch zahlreiche Fragen offen, wie eine transparente Zusammenarbeit gewährleistet werden kann. Zudem bedürfen die ethischen Fragen einer Antwort, zum Beispiel bezüglich Verantwortung für und Erklärbarkeit von KI-basierten Entscheidungen. Aus Sicht der Forschenden sind somit weitere Forschungsanstrengungen insbesondere in den Geistes- und Sozialwissenschaften erforderlich, damit KI das volle Potenzial zum Nutzen der Gesellschaft entfalten kann.

Aus diesen Ergebnissen leiten die Autoren Folgendes ab: Sollte KI ohne die richtigen Voraussetzungen eingesetzt werden, kann der Einsatz dazu führen, dass Mitarbeitende der Technologie nicht vertrauen oder sogar Angst davor entwickeln. Insbesondere wenn sie befürchten, dass ihre Arbeitskraft durch KI ersetzt werden könnte, werden sie den persönlichen Nutzen nicht erkennen. Dies könnte dazu führen, dass Mitarbeitende gegen die Implementierung intervenieren und somit das Unternehmen in seiner Entwicklung behindern. Werden hingegen die Mitarbeitenden in ihren Bedenken ernst genommen, ausreichend geschult und in den Implementierungsprozess integriert, kann Effektivität und Effizienz für das Unternehmen sowie der Nutzen für Kunden gesteigert werden.

3. Second Dissertation Article

Artificial Intelligence and Machine Learning: Exploring Drivers, Barriers, and Future Developments in Marketing Management

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3.1 Abstract

Companies neither fully exploit the potential of Artificial Intelligence (AI), nor that of Machine Learning (ML), its most prominent method. This is true in particular of marketing, where its possible use extends beyond mere segmentation, personalization, and decision-making. We explore the drivers of and barriers to AI and ML in marketing by adopting a dual strategic and behavioral focus, which provides both an inward (AI and ML for marketers) and an outward (AI and ML for customers) perspective. From our mixed-method approach (a Delphi study, a survey, and two focus groups), we derive several research propositions that address the challenges facing marketing managers and organizations in three distinct domains: (1) Culture, Strategy, and Implementation; (2) Decision-Making and Ethics; (3) Customer Management. Our findings contribute to better understanding the human factor behind AI and ML, and aim to stimulate interdisciplinary inquiry across marketing, organizational behavior, psychology, and ethics.

Keywords: Artificial Intelligence, Machine Learning, Marketing Management, Decision-Making, Delphi Method, Ethics

"We need to ask ourselves not only what computers can do, but what computers should do—that time has come!"

—Satya Nadella, CEO of Microsoft (Bittu, 2018, p. 1)

3.2 Introduction

Due to its potential to generate favorable outcomes in diverse sectors and industries, Artificial Intelligence (AI), and especially Machine Learning (ML), is attracting widespread attention. Frontlines include health care, where AI and ML are being deployed to manage the COVID-19 pandemic (e.g., Bragazzi et al., 2020) and to monitor and improve mental health (D'Alfonso, 2020; Kim, Ruensuk, & Hong, 2020); education, where they can enhance learning (e.g., Kumar, 2019; Mirchi et al., 2020); and agriculture, where they help improve harvests and thus fight starvation (Dharmaraj & Vijayanand, 2018). Along with their benefits, AI and ML have also been shown to have adverse effects: violations of data privacy (e.g., Martin & Murphy, 2016), fear of job replacements (Granulo, Fuchs, & Puntoni, 2019; Huang & Rust, 2018), or even reduced well-being (Etkin, 2016). Thus, a positive net effect of AI and ML appears to depend on determining what they *should do* rather than what they *can do* (Bittu, 2018). AI and ML need to be implemented to augment instead of replace human capabilities, and must ultimately serve users' needs (Jarrahi, 2018).

Thus, AI and ML in marketing, defined as the "activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large" (AMA, 2017), is a promising field of study. Deploying AI and especially ML applications provides marketers with ample opportunities to improve process automation, market forecasting, and (managerial) decision-making (Paschen et al., 2019; Huang & Rust, 2021). Further, applications can be used to create value by providing real-time personal recommendations (Davenport et al., 2020), by improving services, and by responding individually to customer needs (Rust, 2020). Despite this extant research on the technological possibilities of AI and ML in marketing, little is known about the human perspective, particularly from a marketing manager's viewpoint. Hence, we ask: How can marketing managers thrive in the age of AI and benefit from its potential to create value?

We explore this question by examining the interplay between (1) marketing management and managerial decisions, (2) psychology and individual perceptions of AI/ML, (3) technology, and (4) ethics. We thus heed calls of prior research to better understand managerial decisions in addition to consumer behavior (Wierenga, 2011), to stimulate further research on the topic of ethics and AI (Baker-Brunnbauer, 2020), and to apply an interdisciplinary and exploratory approach, that is needed given the complexity of this constantly evolving topic (Keding, 2020).

Our research makes two main contributions. *First*, based on a literature review, we propose a revised technological framework for using AI and ML in marketing. Our framework holistically links AI methodology (specifically ML) to AI capabilities and applications. We validate and expand this framework with marketing and technology experts from both academia and practice. *Second*, we develop research propositions on the scarcely explored human factor, especially the role of marketing managers in successfully implementing AI and ML to benefit (marketing) managers and consumers. We thereby aim to stimulate scholarly and interdisciplinary inquiry into how marketing managers should employ AI and ML internally and externally (i.e., in customer interactions), and how obstacles to adequate utilization might be overcome. On this basis, we identify influential research on AI and ML in marketing. In doing so, we distinguish a *strategic* and a *behavioral* focus, and consider an *inward* and an *outward* perspective (see Table 5).

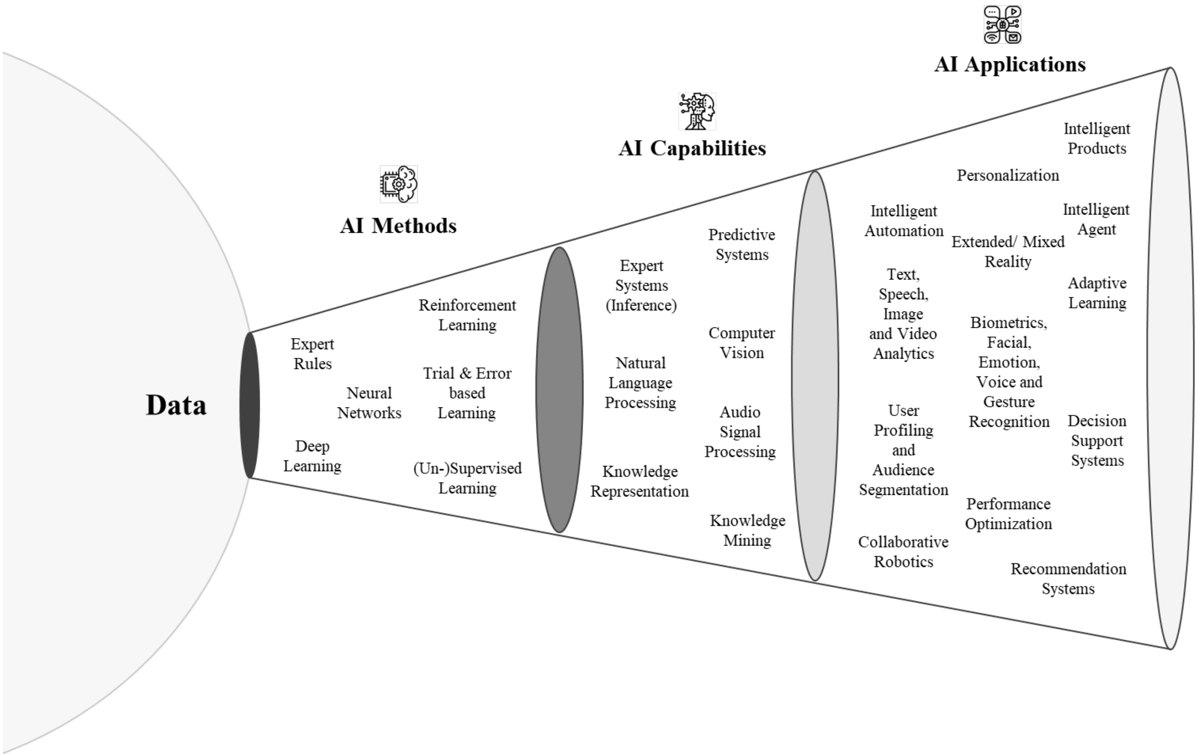
Using a mixed-methods approach, we build on evidence from three distinct investigations: a two-round Delphi study, a quantitative survey, and two focus groups. Round 1 of our Delphi study (based on personal interviews) explored the potential of AI and ML in marketing management and gathered 30 statements from carefully selected technology experts and marketing managers with profound knowledge of AI and ML. In Round 2 (online questionnaire), the compiled statements were evaluated and discussed by the same experts, and additional statements were generated based on expert ratings and comments. After categorizing the statements according to three overarching themes, we conducted a quantitative survey with additional experienced marketing managers to evaluate these statements and themes, and to generate dimensions and research propositions. We implemented two focus groups with marketing managers (previously involved in AI and ML projects), in order to (1) further refine our research propositions, (2) exclusively link these to AI and ML, and (3) enhance our contributions by making these propositions testable and thus a promising avenue for future research. After triangulating the results, we present theoretical and managerial implications, discuss the inherent limitations of our study, and outline future research directions.

3.3 Theoretical Background

3.3.1 Understanding AI and ML

Despite their long history, which began as early as the 1956 Dartmouth Summer Conference, there is no universal definition of Artificial Intelligence and Machine Learning (Torra et al., 2019). Even worse, as the terms are often used interchangeably (e.g., Camerer, 2019), definitions remain rather vague (De Bruyn et al., 2020; van Giffen, Herhausen, & Fahse, 2022). We follow Ma & Sun's (2020) well-established distinction: AI refers to machines that perform human intelligence tasks while ML denotes computer programs that can learn without following strict human instructions. Following this differentiation, and as machines can perform intelligent tasks (primarily) based on trained computer programs, we integrate ML into a comprehensive AI framework. Extending Daugherty and Wilson's (2018) AI framework, we understand ML as the predominant *AI method* for building *AI capabilities*, and ultimately *AI applications* (see Figure 7 and Section 3.5.2). We thus follow extant research in regarding ML as an essential subdomain of AI (e.g., Mitchell, 1997; Goodfellow, Bengio, & Courville, 2016).

Figure 7: AI and ML Framework



Note: Developed Framework, based on Russell & Norvig (2010) and Daugherty & Wilson (2018), and enhanced in round 1 of our Delphi study.

Another categorization of AI well-suited to stimulating interdisciplinary research distinguishes AI's distinct capabilities: *understanding*, *reasoning*, and *learning* (Russell & Norvig, 2010). *Understanding* is the human perception and interpretation of environmental information via, for example, natural language processing and computer vision (Daugherty & Wilson, 2018). *Reasoning* means that informed decisions or recommendations will likely be made to optimize courses of action (Bellman, 1978; Albus, 1991; Kolbjørnsrud, Amico, & Thomas, 2016). *Learning* means that AI and ML acquires knowledge from distinct information and adapts to an environment exhibiting intelligent behavior (McCarthy et al., 1955; Kurzweil, 1990; Kaplan & Haenlein, 2019). These three aspects combine AI capabilities designed to support human thinking and action.

Researchers have defined AI in terms of whether a system *thinks* (Bellman, 1978) or *acts* (Kurzweil, 1990) like a *human,* or whether a system *thinks* (Charniak & McDermott, 1985) or *acts* (Nilsson, 1998) *rationally*. These definitions have either a *technological* or a *human focus*. A *technological focus* emphasizes the ability of computers, machines, algorithms, or robots to think, to recognize their environment, and thus to solve complex tasks independently (McCarthy et al., 1955; Nilsson, 1998; Kaplan & Haenlein, 2019). A *human focus* means that technical systems require a specific intelligence to perform tasks as humans would (Kurzweil, 1990; Daugherty & Wilson, 2018).

Despite their capabilities and multidisciplinary appeal, AI and ML continue to attract skepticism and concern, as Satya Nadella's words (quoted at the beginning) illustrate: "We need to ask ourselves not only what computers *can do*, but what computers *should do*—that time has come" (Bittu, 2018, p. 1). Considering how to enhance human capabilities raises questions about how to ensure transparent and beneficial human-machine interaction (Jarrahi, 2018). We thus focus on *human reactions* to AI. Taking a *managerial* perspective, we investigate the drivers and barriers for executives when AI and ML proliferate in firms. Given their boundary-spanning role, we focus on marketing managers and explore how they can thrive in the age of AI.

3.3.2 The Role of AI and ML in Marketing Management

AI and specifically ML seem to offer infinite opportunities in marketing. Yet marketing success per definition has always depended on creating human and personal experiences (Schmitt, 1999; van Osselaer et al., 2020). This makes studying AI and ML in marketing management highly promising yet challenging. Both can significantly improve marketing performance (Wright et al., 2019). Ample opportunities exist for using AI technologies in marketing: for instance, to identify and understand existing customers (Loureiro, Guerreiro, & Tussyadiah, 2021); to generate insights from customer purchasing data (Wright et al., 2019); to identify current competitors (Huang & Rust, 2021); and to segment and target new customers (Martínez-López & Casillas, 2013; Jabbar, Akhtar, & Dani, 2020). AI, ML, and robotics have been shown to encompass all 4 Ps of marketing (Xiao & Kumar, 2021): (1) product (e.g., Google Home or Amazon Echo) and service (e.g., Walmart's autonomous shopping cart Dash); (2) price (e.g., Ebay's auction sniper); (3) place (e.g., Tesla's driverless semi-truck or Softbank Robotics' Pepper); and (4) promotion (e.g., Nike's Chalkbot).

AI and ML help to analyze large amounts of data from various media (e.g., textual, visual, verbal) and sources (web, mobile, in-person) to gain extensive knowledge (Du & Xie, 2021). These insights support marketers in improving their decision-making capabilities (Paschen, Kietzmann, & Kietzmann, 2019)—a critical factor for firm success (Abubakar et al., 2019). In the last two decades, using AI and ML in decision-making has been a major achievement (Duan, Edwards, & Dwivedi, 2019) and will further disrupt marketers' decision-making (Davenport et al., 2020). Today's AI systems are capable of improving decision quality by complementing human decision-making (Jarrahi, 2018) and by reducing human error (Logg, Minson, & Moore, 2019). Gaining competitive advantage through AI and ML (Huang & Rust, 2021) is no longer about whether to employ them, but to what extent (Lilien, Rangaswamy, & De Bruyn, 2017).

Nevertheless, research shows that humans tend to reject algorithms and AI, in particular when mistakes occur (Moon, 2003; Dietvorst, Simmons, & Massey, 2015) or when humans feel less responsible (Promberger & Baron, 2006; Dietvorst, Simmons, & Massey, 2015). Humans tend to prefer algorithmic advice over human judgment only in certain situations such as objective or numerical tasks (Castelo, Bos, & Lehmann, 2019; Logg et al., 2019; Newman, Fast, & Harmon, 2020). Unsurprisingly, therefore, many marketing managers remain concerned about fully utilizing AI and ML in decision-making (e.g., automated decisions; Davenport & Kirby, 2016), despite their potential.

Some marketing managers have difficulty trusting AI and ML recommendations because machines do not explain their decisions (Kolbjørnsrud et al., 2016). Computers might perform very well—but for the wrong reasons. Data may "inherit" an unknown bias, or the model may fail at the slightest deviation from routine (Ransbotham et al., 2017). Further, as evidenced in a marketing context, extensive and disproportional use of AI, ML, and big data by senior managers can generate tensions between AI and subordinate managers, who may feel less valued and understood (Wortmann, Fischer, & Reinecke, 2018). Ultimately, such reactions to AI and ML may even elicit fears of robotic job replacement (Granulo et al., 2019).

While these examples highlight concerns about using AI and ML *internally* (to improve processes, collaboration, and decisions), marketing needs to find ways of using AI and ML *externally* (customer interactions). As marketing seeks to establish unique, value-creating experiences through personal relationships (Schmitt, 1999), there is an ongoing debate on whether automation and AI technologies augment rather than dilute customer experience (Waytz, 2019). There is an inherent danger that such technologies objectivize customers, and thereby damage the customer-employee relationship (Fuchs, Schreier, & van Osselaer, 2015; van Osselaer et al., 2020). For example, an identical computer-based message is evaluated as significantly more pleasurable if deemed human-generated (Gray, 2012), highlighting the importance of human interactions in a service context. Further, consumers may resist automated and AI-based products if they identify strongly with a product and if automation prevents them from demonstrating their skills (e.g., robotic advisory for experienced financial investors; robotic surgery). This raises questions about whether and when AI/ML and automation make companies lose their most valuable customers (Leung, Paolacci, & Puntoni, 2018). Finally, if AI and ML are utilized to identify, target, and retain key customers through personalized offers, companies must adapt their activities to avoid violating data privacy (Leslie, Kim, & Barasz, 2018).

Marketing organizations, then, need to manage potential tensions between humans and AI/ML both *internally* and *externally*. To fully benefit from AI, marketers need to consider strategy, ethics, and psychology alongside technology. This requires interdisciplinary cooperation and rethinking the roles and responsibilities of humans and machines (Hoffman & Novak, 2018). To explore the role of AI and ML in marketing, we therefore apply both a dual (*strategic* and *behavioral*) focus and a dual perspective (*inward* and *outward*). We used both criteria to identify influential research on AI and ML in marketing and to extend existing results (Table 5). We examined managerial tasks and explored managerial reactions to AI and ML to derive research propositions designed to stimulate further research intended to help organizations overcome the current challenges of AI and ML.

Table 5: Influential[a] Empirical Research on AI and ML in Marketing

Authors (Year)	**Focus[b]**	**Perspective[c]**	**Key Findings**
Dietvorst, Simmons, & Massey (2015)	Behav.	Outw.	• Shows the tendency of people to dismiss algorithms and have less confidence in them when algorithms make a mistake.
Huang & Rust (2018)	Strat.	Inw.	• Specifies four intelligences required for service tasks. Lays out the way firms should decide between humans and machines.
Leung, Paolacci, & Puntoni (2018)	Behav.	Outw.	• Demonstrates consumers' resistance to automation/automated products if identity-relevant processes are being automated.
Castelo, Bos, & Lehmann (2019)	Behav.	Outw.	• Shows consumers' perception of algorithms as being less useful for subjective tasks. This effect is reduced when algorithms are considered as human-like.
Duan, Edwards, & Dwivedi (2019)	Strat.	Inw.	• Addresses how humans and AI can be complementary in decision making. Derives research opportunities on designing information systems.
Granulo, Fuchs, & Puntoni (2019)	Behav. & Strat.	Inw.	• Shows human preference for being replaced by robots rather than by other humans due to self-threat.
Logg, Minson, & Moore (2019)	Behav.	Outw.	• Demonstrates human reliance on algorithmic advice over advice from other humans (i.e., algorithm appreciation).
Davenport et al. (2020)	Behav. & Strat. & M./T.	Inw. & Outw.	• Focuses on a conceptual paper resulting in a framework helping customers and firms anticipate how AI is likely to evolve and derives a general research agenda.
Hildebrand et al. (2020)	M./T.	Outw.	• Develops a conceptual framework and illustration of linking vocal features in human voices to experiential outcomes and emotional states.
Loureiro, Guerreiro, & Tussyadiah (2021)	Behav. & Strat.	Inw. & Outw.	• Provides an AI literature overview in the business context and derives research questions for various domains.
Makarius et al. (2020)	Strat. & M./T.	Inw.	• Develops a model to efficiently integrate AI within an organization.
Newman, Fast, & Harmon (2020)	Behav.	Inw.	• Shows the perception of people when being evaluated by an algorithm as less fair if employees perceive it as reductionistic.
Rai (2020)	Strat.	Inw.	• Explores Explainable AI as critical to making AI more transparent within organizations.
Rust (2020)	Strat.	Inw. & Outw.	• Explores the nature of change of technological trends and examines the implications for marketing managers, marketing education, and academic research.
Du & Xie (2021)	Strat. & M./T.	Inw.	• Develops a model for managers to categorize AI-enabled products.
Dwivedi et al. (2021)	Strat.	Inw. & Outw.	• Shows AI's challenges and future opportunities for business and management, government, public sector, and technology.
Huang & Rust (2021)	Behav., Strat. & M./T.	Inw. & Outw.	• Develops a three-stage framework for AI-based strategic marketing planning: Mechanical AI, Thinking AI, Feeling AI.
Kumar, Ramachandran, & Kumar (2021)	Strat.	Inw. & Outw.	• Focuses on four technologies – the Internet of Things, AI, ML, and Blockchain, and their roles in marketing, and formulates research questions.
Perez-Vega et al. (2021)	Strat. & M./T.	Inw. & Outw.	• Develops a conceptual framework on how firms and customers can enhance the outcomes of firm-solicited and firm-unsolicited online customer engagement behaviors and derives five propositions.
Shah & Murthi (2021)	Strat.	Inw.	• Examines the transforming role of marketers and describes challenges by developing a model on how technology expands the scope and role of marketing.
Sowa, Przegalinska, & Ciechanowski (2021)	Strat. & M./T.	Inw.	• Explores synergies between human workers and AI in managerial tasks by distinguishing levels of proximity between AI and humans in a work setting.
Stahl et al. (2021)	Strat.	Inw. & Outw.	• Categorizes ethics into three areas: (1) issues related to ML, (2) social and political issues, and (3) metaphysical questions.

[a] Given the high number of studies on AI in marketing, we focused on publications in more prestigious journals and/or highly cited papers.

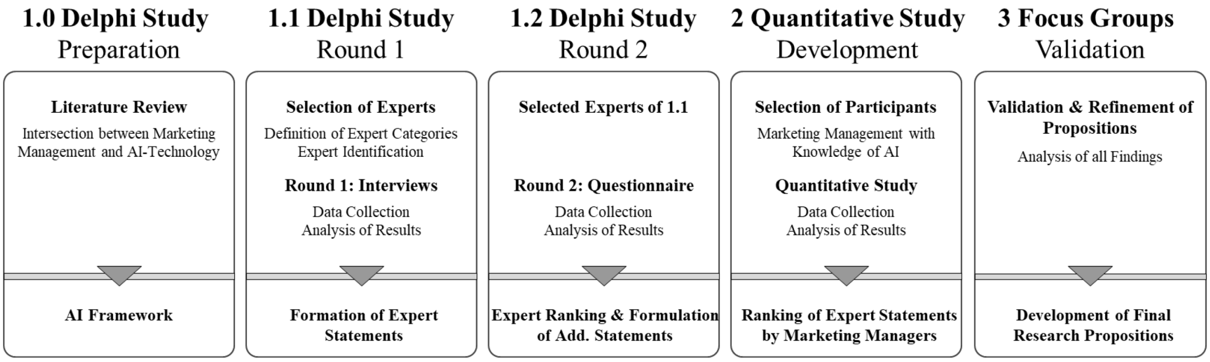
[b] Behav. = Behavioral; Strat. = Strategic; M./T. = Methodological/Technological

[c] Inw. = Inward; Outw. = Outward

3.4 Overview of Studies

To generate research propositions on the AI and ML challenges facing marketing managers and firms, and to stimulate future research, we used a mixed-methods approach (Figure 8). We first conducted a two-round Delphi study (comprising expert practitioners and academics). Round 1 aimed to capitalize on expert knowledge to identify meaningful themes and novel statements on AI and ML in marketing. Round 2 sought to validate statements as well as stimulate additional ones based on those made in Round 1. Having achieved broad expert consensus after our Delphi study, we launched a survey with experienced managers working at the intersection of marketing and AI/ML. We aimed to validate expert views from the practitioner and user perspectives. Marketing managers' assessment of experts' themes and statements led to dimensions and testable research propositions via exploration and interpretation. To evaluate its appropriateness, we conducted two focus groups involving additional marketers with experience in AI and ML. Discussions sharpened dimensions and propositions in an AI and ML context, and provided vivid examples.

Figure 8: Research Plan



3.5 Delphi Study: Generating and Validating Statements on AI and ML in Marketing

3.5.1 Methodological Introduction and Procedure

Delphi studies iteratively collect and summarize participants' opinions and knowledge and share these with a peer group (Brady, 2015). Through multiple data collection and feedback rounds, expert panels can revise their initial ideas and opinions (Dalkey & Helmer, 1963). Anoymizing experts prevents opposing views from clashing and enables gaining multiple perspectives on a specific topic (Rowe, Wright, & Bolger, 1991). After every round, the researcher updates and aggregates experts' answers, evaluations, and reasons (Linstone & Turoff, 1975). This serves to gather expert thoughts and insights and to elicit novel, yet converging perspectives on an interdisciplinary issue (Rowe & Wright, 1999). Thus, Delphi studies, suited to multifaceted exploratory research (Okoli & Pawlowski, 2004), open up multiple perspectives without allowing one opinion to dominate—all being critical requirements of our investigation.

Delphi studies have become popular among marketing scholars and have recently been used to study diverse topics: how to identify and combat fake news and communication (Flostrand, Pitt, & Kietzmann, 2019); challenges to organizations' social media activities (Poba-Nzaou et al., 2016); the economic power of B2B transactions (Cortez & Johnston, 2017); and managers' appreciation of big-data analytics (Côrte-Real et al., 2019). There are four types of Delphi studies (Paré et al., 2013): (1) Ranking-type Delphi studies (which seek to rank identified key factors); (2) Classical Delphi studies (which attempt to reach a consensus); (3) Policy Delphi studies (which define different views in social and political contexts); and (4) Decision Delphi studies (which define future directions based on a small group with decision-making power). To prioritize key statements, and to validate these and generate research propositions for our next studies, we used the ranking-type method (Poba-Nzaou et al., 2016; Côrte-Real et al., 2019).

3.5.2 Development of an AI and ML Framework

To avoid misconceptions, Delphi study informants should have at least a common understanding of the core concepts. We therefore extended Daugherty and Wilson's (2018) AI framework, made this available to each expert, and used it as a starting point for our Delphi study without narrowing the topic. The framework comprises and interrelates *AI methods*, *AI capabilities*, and *AI applications* (Figure 7). *AI methods* are used to process and structure different types of data. Based primarily on ML as an essential subdomain of AI (Goodfellow, Bengio, & Courville, 2016), AI methods encompass statistical methods to endow systems and computer programs with the ability to learn (Ma & Sun, 2020).

The literature distinguishes three broad subcategories of ML as AI methods intended to create AI capabilities: supervised learning, unsupervised learning, and reinforcement learning (Bonaccorso, 2017). While training data are labeled in supervised learning (e.g., a picture of a human is categorized as a human being), computer programs independently look for patterns in unlabeled training data, with reinforcement learning providing systems with constant feedback on whether a decision or categorization was correct or not. *AI capabilities*, then, mostly result from ML-based AI methods—enabling systems to understand the environment (e.g., through computer vision). Finally, *AI applications* are derived from AI capabilities, and culminate in use cases (e.g., facial recognition based on computer vision). Common to AI applications is direct employment by end-users (e.g., marketing executives or customers) (Rai, 2020).

We extended Daugherty and Wilson's (2018) model in three ways: First, to update their model according to recent developments, we included expert rules, neural networks, as well as trial-and-error-based learning as *AI methods*; natural language processing and knowledge mining as *AI capabilities*; and user profiling and audience segmentation, mixed reality, emotion and voice recognition, performance optimization, adaptive learning, and decision support systems as *AI applications*. Second, to illustrate the exponential growth of applications, we represented the model as a funnel instead of as a circle. Third, we included a data cloud to visualize the available information in our environment and to illustrate that the data used in ML methods and AI applications are only a fraction of the data cloud.

3.5.3 Delphi Study: First Round

3.5.3.1 Experts Selection and Participants

Carefully selecting experts is critical to establishing validity in Delphi studies (Møldrup & Morgall, 2001). This requires recruiting *heterogeneous* participants with vast *expertise* in distinct domains of *immediate relevance* to the topic (Caley et al., 2014). To meet these requirements, participants, besides in-depth AI knowledge, needed to represent one of four diverse areas: research and academia, marketing, technology, consultancy. We further ensured that at least two technology experts represented each AI technology, as per the AI and ML framework (see Figure 7). Recruited experts had the opportunity to nominate potential candidates who had to meet our predefined criteria—to achieve a balanced set of experts.

We conducted interviews until findings reached saturation—an indicator of data reliability (Morse et al., 2002). In total, n = 39 experts (response rate: 77%) from the following areas were successfully recruited to identify current and future challenges to AI in marketing: research and academia (6 participants), marketing (9), technology (14), and management consulting (10). Table 6 shows the selected experts. So as not to jeopardize their openness, experts were not asked direct personal questions.

Table 6: Overview of Expert Panel Characteristics – Delphi Study

Expert Panel Characteristics			
Business Areas		**USA**	3
Research & Academia	6	**Asia**	
Marketing	9	China	2
Technology	14	Hongkong	1
Consultancies	10		
Job Position			
Chief Marketing Officer	3		
Chief Executive Officer	1		
Chief Technical Officer	2		
Data Protection Officer	1		
Managing Director	8	**Companies**	*Microsoft, Accenture, Echo Novum, AI Zürich, Echo Novum, 1plusX AG, IBM, avantgarde labs, DATAREALITY VENTURES, digitaladservices, Deutsche Bahn, Axel Springer AI, PROS, Squirrel AI, Greenshots Labs, McKinsey, le ROI Consulting, ITyX Group, IBOT Control Systems AG, Procter & Gamble*
Partner	3		
Head of Development	1		
Founder	2		
Researcher	6		
Head of AI	1		
Division Leader/Manager	3		
Chief Strategist/ Expert/Data Scientist	3		
Solution Specialist/ Architect/Consultant	4	**Academia**	*University of Lübeck, University of St.Gallen, University of Hongkong, Erasmus University of Rotterdam, German Research Center for Artificial Intelligence*
Technical Sales Manager	1		
Geography			
Europe			
Belgium	1		
Germany	17		
Great Britain	3		
Netherlands	1		
Switzerland	9		

3.5.3.2 Data Collection and Procedure

Interviews lasted 30 to 90 minutes (M = 42 minutes, SD = 15.39). They followed a semi-structured guideline to enable novel ideas and themes to surface (Jamshed, 2014). Three interviewers from different backgrounds (business administration, psychology, and engineering/ technology) were employed to minimize interviewer bias (Qu & Dumay, 2011). Interviewers received our literature review to ensure content-specific competence (Meuser & Nagel, 2009). Interviews began with general questions about industry trends, opportunities, and challenges regarding AI and ML in marketing. Next, they focused on the factors (including ethical issues) influencing managers' decision-making.

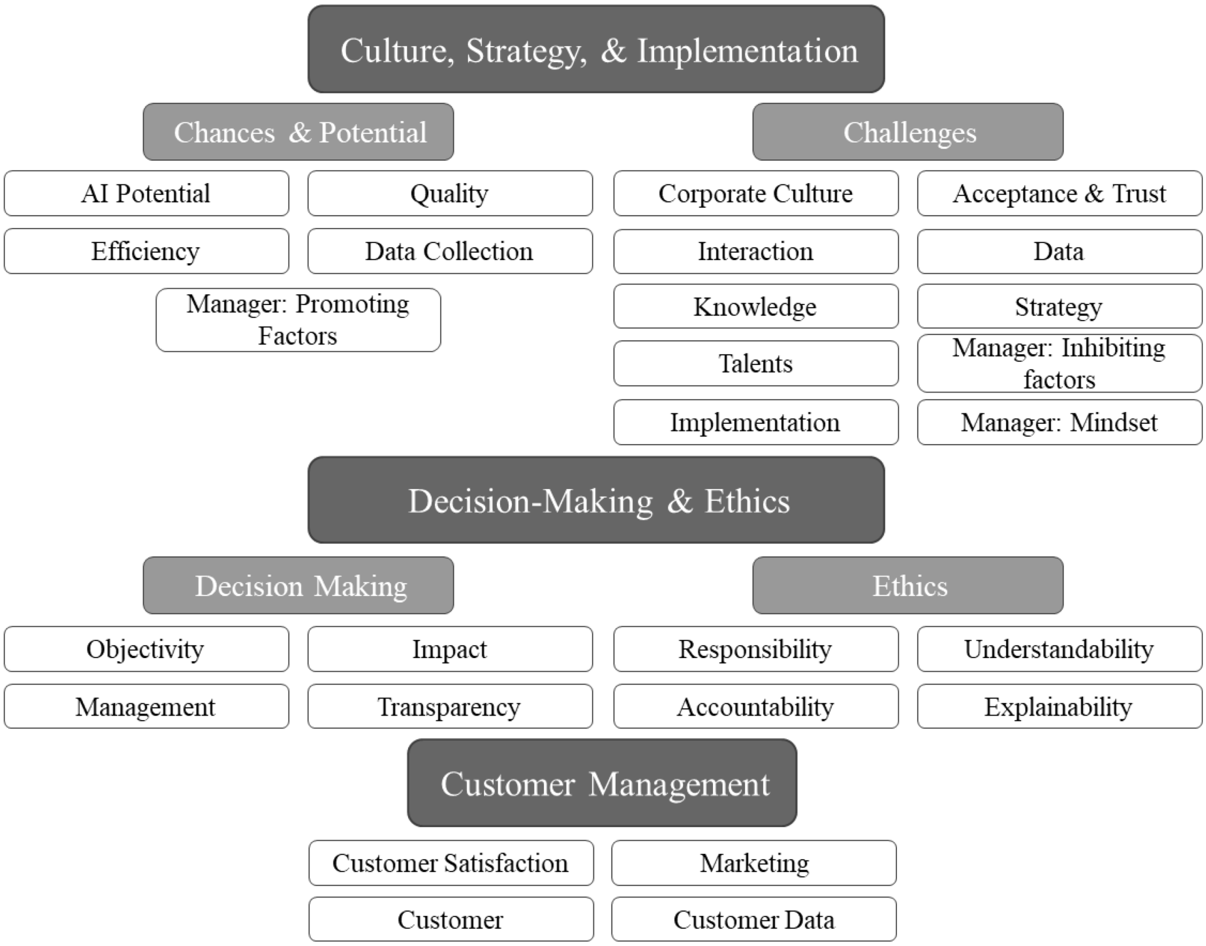
Experts were shown the extended AI and ML framework, which served as a common basis for discussion. Interviews were recorded with participant consent (revocable post-interview) and transcribed. Their focus varied based on responses, as is usual with semi-structured qualitative approaches. To reflect the generated insights, we modified the interview guide and the AI and ML framework as data collection proceeded.

3.5.3.3 Coding of Expert Interviews and Results

Following grounded theory (Strauss & Glaser, 1967), we transcribed and analyzed interviews using inductive content analysis (Mayring, 2014). We used inductive coding to develop categories (Gioia, Corley, & Hamilton, 2013) and to classify interviewees' ideas into an efficient number of categories representing similar thoughts (Weber, 1990). The coding scheme was based on the interview questions and the selected expert statements. This scheme enabled open coding and ensured systematically evaluating results (Corbin & Strauss, 2014). Two researchers independently performed open coding using the transcripts, primary findings, and participant information (Charmaz, 2014). They reproduced category-building with similar outcomes and confirmed the intercoder reliability of the content analysis.

First, we summarized and categorized experts' statements. Following an iterative process, we identified and classified second-order topics (e.g., "Efficiency" or "Corporate Culture"). *Second*, we aggregated these categories to form two superordinate dimensions: "Chances and Potential" and "Challenges." *Third*, we examined the resulting topics and concepts, which involved systematically considering individual aspects (typification). Given this grouping and thematic overlaps, we developed three final overarching themes to categorize the derived statements: (1) Culture, Strategy, and Implementation (CSI); (2) Decision-Making and Ethics (DME); (3) Customer Management (CM) (see Figure 9).

Figure 9: Coding Categories



We derived 30 statements (see Table 7). Each code represents at least one statement. A statement can reflect more than one code due to overlapping themes. Statements form a basis for exploring drivers, barriers, and future developments of AI and ML in marketing management.

3.5.4 Delphi Study: Second Round

Round 2 had two goals: (1) to determine the importance of each of the 30 statements developed in Round 1; (2) based on experts' reasons for their assessment (Brady, 2015), to generate additional statements on AI and ML in marketing, and thus to benefit from experts' broad knowledge of the field.

3.5.4.1 Experts Selection and Participants

The same expert panel was invited to participate in a second round (five participants admitted having language problems, which decreased interview quality in Round 1). Of 34 selected experts, we received valid responses from 25, yielding a response rate of 74%.

3.5.4.2 Procedure and Results

Applying the ranking-type Delphi method (Paré et al., 2013), experts rated statements via 7-point Likert scales (1 = I do not agree, 7 = I fully agree) and gave reasons for their evaluations (von der Gracht, 2012). They were shown the statements with no additional information on the source(s), in order to preserve anonymity and to limit potential evaluation bias (e.g., bandwagon effect; Winkler & Moser, 2016). Ratings were calculated, and experts' reasons for their evaluations were further analyzed to generate additional statements (O'Connor & Joffe, 2020).

Combining two established criteria, consensus on a statement was achieved when it was rated as 5, 6, or 7 by at least 70% of the expert panel (Hsu & Sandford, 2007), and when its standard deviation was below the upper quartile (in our case: < 1.72) of the standard deviations of all 30 statements (Holey et al., 2007). General consensus was relatively high (see Table 7 for consensus rates). Experts agreed on 17 statements. Five statements were agreed on by at least 60% of experts, with a standard deviation below the upper quartile. For one statement (CM2), consensus was obtained by experts agreeing to disagree (83% assigned a 1, 2, or 3; SD = 1.43). The remaining seven statements generated relatively low consensus and insightful comments.

Table 7: Derived Statements of First-Round Delphi Study and Statements Ranked in Second-Round

Items	Expert Statements	5, 6 & 7	Mean	SD
CSI1	AI enables humans to focus on tasks of higher value.	88%	6.16	1.08
CSI2	Most companies start with the technology and then look for a use case for AI.	48%	4.44	1.55
CSI3	Lack of knowledge of AI is the biggest obstacle to leveraging AI.	56%	4.56	1.77
CSI4	Market pressure is forcing companies to implement AI.	84%	5.56	1.5
CSI5	Automating administrative management tasks can create enormous added value for companies.	92%	6.58	0.86
CSI6	Most people think that implementing AI will work miracles and solve everything without any effort.	64%	4.8	1.62
CSI7	Most AI pilot projects fail—not because of technological issues but because of overly high expectations of the management.	67%	4.83	1.28
CSI8	It is important to establish a culture of trial and error in the company to learn from mistakes.	96%	6.52	0.94
CSI9	When humans interact with AI, they do not tolerate failure.	68%	4.76	1.48
CSI10	AI is not allowed to make mistakes, humans are.	64%	4.76	1.92
CSI11	Without transparency, AI won't be accepted.	63%	5.04	1.84
CSI12	Online marketing can be automated, as it is technically feasible.	91%	5.82	0.94
CSI13	It will take longer to solve the ethical questions than to develop the technology and to make it feasible.	63%	5.42	1.71
DME1	With AI, subjective decisions based on gut feeling can be avoided, and objectivity can be increased.	72%	5.08	1.62
DME2	AI makes decisions, but people have the choice.	61%	4.83	2.26
DME3	If the manager makes the decision based on bad AI advice, the manager is responsible.	76%	5.24	1.5
DME4	Managers should demand that AI reasoning is made transparent to them.	84%	6.16	1.32
DME5	The more transparent the decision-making, the less accountability needs to be discussed.	56%	5.04	2.13
DME6	The riskier a decision becomes regarding ethical and moral values; the less people will hand over decision-making to AI.	76%	5.24	2.12
DME7	The biggest obstacle is the predictability and understandability of AI systems.	71%	5.13	1.39
DME8	If managers understand the functionality of AI, they are willing to give up control.	60%	4.92	1.57
DME9	People are very skeptical of AI, because they don't understand it.	76%	5.36	1.69
DME10	Managers have to be able to deal with the consequences of AI.	92%	6.36	1.2
CM1	Having (structured) access to a lot of data will be an important source of competitive advantage in the age of AI.	96%	6.4	1.1
CM2	If you want competition in the market, you can't have customer data privacy.	9%	1.96	1.43
CM3	Using AI for personalized customer contact can increase customer satisfaction.	75%	5.58	1.5
CM4	Sometimes it is better not to use the gathered customer data but to treat it confidentially, because trust in the relationship has greater value.	92%	6.33	0.94
CM5	Users should be given higher rewards by companies using their data.	58%	5.25	1.83
CM6	Customers are getting closer to the company through AI.	75%	5.25	1.79
CM7	Explaining the decision-making process to customers is very important.	72%	5.68	1.38

One author and an independent experienced researcher separately analyzed all comments, starting with the statements with the lowest level of expert consensus (i.e., most contested points of view). As a result, 82 potential additional statements were formulated and presented to the other two authors. They independently evaluated each potential statement, with a recommendation to add it or not. Both authors agreed to reject 31 statements and accept 22 statements (the latter were included in our pool; Table 8). Since all original statements yielded at least moderate consensus among experts, we conducted a second study (i.e., quantitative survey) with experienced marketing managers to evaluate their agreement with the 30 original statements and the 22 newly developed statements. We thus sought to assess the appropriateness of experts' identified overarching themes and statements from practitioner and user perspectives. The survey also served to structure statements aiming to develop testable research propositions.

Table 8: Specified Statements – Derived from Second-Round Delphi Study

Items	Additional Statements		
CSI5_a	Some areas of online marketing can be automized, but others require human creativity.		
CSI9_a	Human tolerance of failure when interacting with AI is lower when the task is perceived as easy.		
CSI9_b	People tend to be less tolerant with AI decisions when choosing between different options ("Choose product A") rather than providing an estimate ("Choose 90% product A").		
CSI9_c	People are more forgiving with other humans who makes mistakes than with AI.	People are more forgiving with AI making mistakes than with other humans.	
CSI9_d	People blame other humans less for making mistakes compared to AI.	People blame AI less for making mistakes compared to other humans.	
CSI10_a	A greater sense of responsibility is required because AI has a much more systemic impact than what humans can do on their own.		
CSI10_b	The fact that AI clearly states probabilities ("the result is 90% product A") as decision output instead of merely stating the result ("the result is product A") will help users to better understand AI.		
CSI10_c	The fact that AI clearly states probabilities ("the result is 90% product A") as decision output instead of merely stating the result ("the result is product A") will increase user acceptance.		
CSI10_d	Humans will be held responsible for mistakes because AI has no agency of its own (yet).		
CSI10_e	AI should be allowed to make more mistakes than humans, so they can learn from them rather than make the same mistake again.		
DME1_a	AI cannot substitute for human decision-making.		
DME1_b	AI cannot be completely objective because of the inherent human bias that is programmed within it.		
DME2_a	AI makes decisions, but people have the final choice, provided the decision-making process has a certain transparency.		
DME3_a	If the manager makes a decision based on bad AI advice, AI is responsible.	If the manager makes a decision based on bad AI advice, both the AI and the manager are responsible.	If the manager makes a decision based on bad AI advice, he or she is responsible.
DME4_a	Explainability of AI reasoning is key.		
DME5_a	Accountability in the decision-making process is more important than transparency.	Transparency in the decision-making process is more important than accountability.	
DME6_a	The riskier a decision becomes regarding ethical and moral values; the less people would leave the decision to AI.	The riskier a decision becomes regarding ethical and moral values; the more people would leave the decision to AI.	
DME6_b	The riskier a decision becomes regarding ethical and moral values; the less people would hand over decision responsibility to AI.	The riskier a decision becomes regarding ethical and moral values; the more people would hand over decision responsibility to AI.	
DME8_a	If managers are able to understand the functionality of the AI, they are most likely to use the technology but will never give up its control.		
DME8_b	Managers do not need to understand AI systems, but should trust AI in order to use it.		
CM3_a	AI can decrease the customer experience, without an effective combination of AI and humans.		
CM6_a	AI brings companies closer to their customers.		

3.6 Quantitative Survey: Cross-Validating Statements and Deriving Propositions

3.6.1 Sampling and Procedure

3.6.1.1 Sampling

Via the alumni panel of a major European business school, we recruited 204 marketing managers (mean age: 50 years; 75% male) for a study titled "Artificial Intelligence in Marketing." In return, participants received an executive summary of the study and a digital presentation of results. We also raffled prizes worth US$500. Because marketing managers came from various levels (middle and top management), and because their self-rated knowledge of AI differed ("*How would you personally rate your experience of using AI?*"; 1 = very low, 7 = very high; M = 3.20, SD = 1.57), we qualified our sample to ensure (externally) valid responses. We chose our final sample based on two predetermined criteria, including prespecified cutoff values: First, marketing managers needed to be in a leadership role, with direct responsibility for at least one subordinate manager. Second, they were required to have a minimum self-rated AI knowledge of 3. These requirements resulted in a sample of 101 marketing managers (mean age: 50 years, SD = 10.18; 84% male), who on average had direct responsibility for 38 subordinate managers (SD = 120) and a moderate knowledge of AI (M = 4.29, SD = 1.16).

3.6.1.2 Procedure

Respondents were briefly introduced to the study and given an overview of the participants of the Delphi study (experts and thought leaders). They read that they would evaluate the generated statements from the expert panel through a practitioner lens, thereby implementing a reality check. They were informed that their assessments of statements as consumers and users of AI and ML would be critical to developing meaningful research propositions, thus highlighting their pivotal role in our research. To ensure a common understanding of AI among participants, we presented our definition: "AI is a science and technology capable of implementing various tasks intelligently, of recognizing errors, and of learning from these—thereby having the capability to act adequately and intelligently in uncertain environments."

After some introductory questions about their previous AI experience, marketing managers were asked to rate their level of agreement with (1) the original 30 statements from Round 1 of the Delphi study and (2) the 22 newly developed statements from Round 2 (1 = I do not agree, 7 = I fully agree). Statements were categorized by three themes: (1) Culture, Strategy, and Implementation; (2) Decision-Making and Ethics; (3) Customer Management. To avoid cognitive load confounding ratings, respondents received randomized statements from each theme. Finally, they were asked to provide demographics, were thanked, and could sign up for the executive summary, the virtual results presentation, and the raffle.

3.6.2 Results and Interpretation

We analyzed respondents' evaluations of statements in four steps. *First*, we considered their *average* assessment of statements and accordingly assigned statements to one of four categories: (1) reject ($M \leq 3$); (2) tend to reject ($3 < M \leq 4$); (3) tend to accept ($4 < M \leq 5$); (4) accept ($M > 5$). Two statements were fully rejected, five were categorized as tend to reject, 16 as tend to agree, and 23 as fully agree (including six statements with a semantic differential). *Second*, identical to the Delphi study, we calculated a consensus percentage of the assessments, thus determining consent if at least 70% of the respondents rated a statement with 5, 6, or 7 (Hsu & Sandford, 2007). If, however, at least 70% rated a statement with 1, 2, or 3 (i.e., they agreed to disagree), we reverse-coded the statement. *Third*, we combined the two criteria to determine whether a statement was accepted overall or not.

Fourth and finally, categorizing statements as accepted or not accepted served as a basis for further interpretation. We retained statements meeting both criteria but did not eliminate those not categorized as accepted. This information instead formed the basis for in-depth discussion on why statements did not elicit agreement. From this exploratory process, we derived 27 topic areas to detect commonalities and differences between statements, and to better understand and refine them. Identifying and merging similar topic areas produced 10 aggregated dimensions: *Avoiding a "Blame-AI" Culture; Recommendation Output and Decision Frame; Objectivity versus Human Bias; Expectation Management and Strategy; Humans in the Loop; Understandability; Decision Explainability; Responsibility and Accountability; AI and Customer Experience; Customer Data.*

Appendix A.1 shows (1) the categorization of the 10 generated dimensions into our three overarching themes and (2) the topic area from which a dimension emerged. Each dimension is backed by several statements, resulting in 19 propositions on AI in marketing. All propositions comprise several statements and are based on respondents' assessments of these statements.

We note that both dimensions and propositions were derived via interpretation, after considering marketing managers' assessment of statements. Hence, the generated dimensions and propositions require more formal evaluation. To verify whether propositions and dimensions are adequate, to make them more AI-specific, and to collect vivid examples, we implemented two focus groups (each comprising additional marketing managers with AI and ML experience).

3.7 Focus Groups to Validate Dimensions and Research Propositions

Focus groups enable (usually 6–12) participants to jointly discuss a problem (Prince & Davies, 2001), and thereby explore a topic in-depth (Byrne & Rhodes, 2006) and offer rich comments (Al-Qirim, 2006), while providing a more comprehensive view of the collected data (Newby, Watson, & Woodliff, 2003). Given the methodological benefits, we conducted two focus groups with experienced managers at the intersection of AI, ML, and marketing to verify and refine our derived dimensions and propositions.

3.7.1 Study Context and Methodology

3.7.1.1 Sampling

Via LinkedIn, we invited managers to take part (free of charge) in a focus group on AI, ML, and marketing management. We selectively recruited 11 participants with proven experience in marketing and AI (a prerequisite of our study). Participants represented diverse industries (e.g., Banking/Insurance, IT/Technology, Pharmaceutical) and held various executive positions (e.g., Global Vice President for Marketing & Consumer Intelligence). This served to ensure that our propositions and dimensions were appropriate, to refine our propositions, and to provide current examples.

We conducted our focus groups (focus group I: n = 5, one female; focus group II: n = 6, two females) (1) to determine whether participants' views converged or diverged, (2) to focus discussion on our propositions (heavily debated in the first focus group) and (3) to foster intense interaction through a limited number of participants (Prince & Davies, 2001). While participants could indicate their preferred meeting date, we took care that groups were sufficiently heterogeneous, without heterogeneity hampering free-flowing discussions (Morgan, 1996). Discussions lasted 93 (64) minutes for focus group I (II).

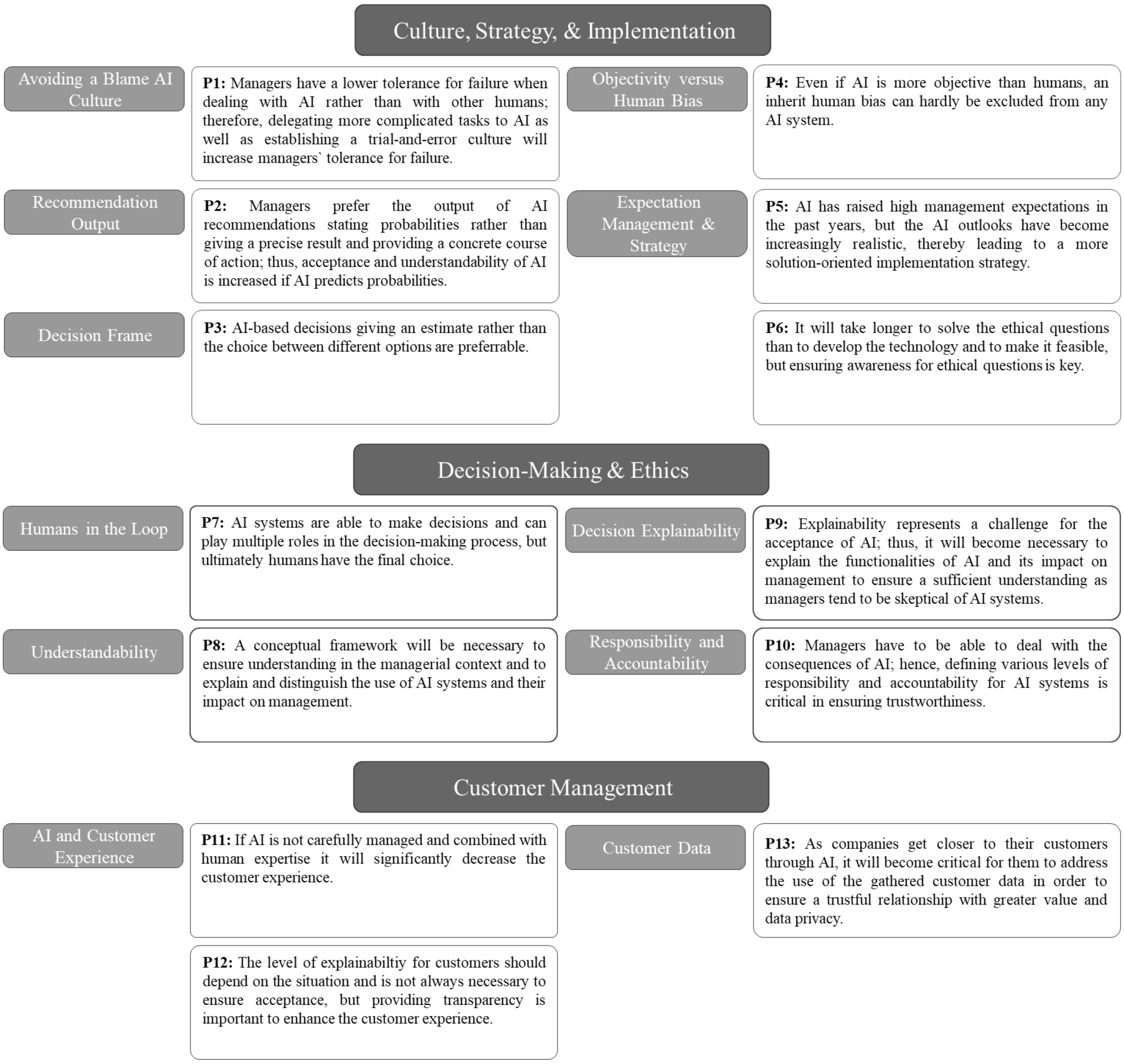
3.7.1.2 Procedure

Two authors served as moderators, with the third obtaining the role of an observer. Moderators followed a guideline comprising our 10 dimensions and 19 research propositions (Appendix A.1). They read and elaborated on the propositions. We strongly emphasized active discussion, as well as making participants feel comfortable, to ensure they would openly share their views (e.g., Malhotra, 2019). Discussions were recorded with participants' permission, transcribed, and subjected to thematic analysis (Braun & Clarke, 2006).

3.7.2 Results

We reduced the number of final propositions from 19 to 13. Following participants' recommendations, we disentangled *Recommendation Output* and *Decision Frame* into two separate dimensions (see Figure 10). Participants largely agreed on the remaining dimensions and their labels, and propositions were categorized into various dimensions and overarching themes.

Figure 10: Research Propositions



3.7.2.1 Culture, Strategy, and Implementation

The overarching theme of Culture, Strategy, and Implementation encompasses five dimensions: (1) *Avoiding a "Blame AI" Culture*, (2) *Recommendation Output*, (3) *Decision Frame*, (4) *Objectivity versus Human Bias*, and (5) *Strategy and Expectation Management*.

Avoiding a "Blame-AI" culture proved to be a major topic and was confirmed as an independent dimension by both focus groups. They agreed that people tend to blame humans less than AI, and are more tolerant of "mistakes" committed by humans compared to AI. Implementing a trial-and-error culture, although considered very difficult, was seen as potentially effective in preventing a "Blame-AI" culture. Calibrating management expectations upfront thus was confirmed as a critical starting point.

> *"We require for image recognition [...] 100% accuracy. Even a human cannot reach this level, but he [the superior] demanded 100% accuracy. The comparability with humans is sometimes totally disconnected."*

The dimension *Recommendation Output* and *Decision Frame* sparked vivid debate in both focus groups and resulted in two separate dimensions. Participants disagreed on the proposition related to *Recommendation Output*. According to participants, marketing managers prefer AI to provide clear recommendations instead of estimates.

> *"You do not expect a human being to give a finite answer, so human beings can say, e.g., 70%, 30%. However, from an AI system you expect to get an answer on every single question."*

The dimension *Decision Frame* also triggered lively discussion. Participants argued both in favor of and against its related proposition, highlighting the need to further investigate how to define the ideal decision frame for AI recommendations.

> *"I would go for the estimate, because I would always ask why I should choose A or B. This is why we use AI because we want numbers to support our decision."*

> *"I would clearly say A or B. Top management has no time and [...] they want a clear road to follow."*

All participants agreed with *Objectivity vs. Human Bias* and its proposition.

> *"I am sure there is a human bias that affects the AI somehow, either due to training or the judgment that comes at the end."*

Regarding *Strategy and Expectation Management*, participants partially agreed on the first proposition, that companies are now pursuing a more solution-oriented AI strategy. They noted that companies are now aligning technology with use cases to achieve direct benefits. Participants agreed that while management expectations are still high, they are gradually becoming more realistic.

> *"There are still high expectations. If there weren't any, a lot of companies wouldn't invest that much. But at the same time, it's balanced by being more realistic."*

Participants fully agreed on the second proposition of *Strategy and Expectation Management* and emphasized the importance of raising awareness of ethical issues.

> *"Developing technology is quite steep but, once you get there, you get there. I think ethics involves lots of soft skills, lots of nuances and consideration of cultural differences. So, it's a bit more complex."*

3.7.2.2 Decision-Making and Ethics

This theme consists of four dimensions: (1) *Humans in the Loop*, (2) *Understandability*, (3) *Decision Explainability*, and (4) *Responsibility and Accountability*.

Humans in the Loop addresses the need to include human judgment in the decision process, thus sparking further lively debate. Opinion was divided in both focus groups. Agreement on this proposition appeared to depend on both the use case and the ethical and moral components of a decision.

> *"There are so many options that we can design [...] how we get to a decision. It might be different for all the systems and you as a user might not have the final choice, but the designer had a choice."*

> *"For certain cases when you use AI, you're not the final decision-maker in the end. This is exactly the problem where ethics come into play."*

Understandability highlights the difficulties of implementing AI systems not fully understood by managers and customers. Participants agreed that marketing managers should possess a basic understanding of AI to justify their decisions.

> *"I think this is really needed. Decision-makers don't understand what they decide, that's a big problem."*

> *"They think they understand it. This is called the Dunning Kruger effect. [...] I'm confronted with some hilarious requirements and projects because they don't understand what they want and the impact."*

The dimension *Decision Explainability* is crucial for understanding the AI model and for ensuring transparency. Participants agreed on the related proposition, highlighting the need to enable a basic understanding of AI functionalities and thus a certain explainability. However, the level of explanation seemed to depend on the use case and the end-user.

"Who of us knows how a CPU works? I guess, nobody. Yet we are using it all day long via our smartphone and computer. Basically, everybody should know how a transistor works but the CPU is a complex system of a lot of transistors and so on, and it's the same with AI. Maybe we all just need to get used to it."

The challenges of the dimension *Responsibility and Accountability* emerge from the complexity of AI systems. Participants agreed with the dimension and noted various levels of responsibility (i.e., shared responsibility)—with managers being ultimately involved. Thus, responsibility and accountability point to statutory issues, which must be addressed and regulated to ensure transparent AI implementation.

"When we think of advertising, maybe it's easier, because it's neither critical nor life-threatening. But when it's life-threatening and life-changing, then it's hard to go to the judge and say, well, it's not my fault, the machine gave the wrong recommendation. In my mind, this connects the discourse on explainability. Managers need to understand the impact because this is not just experimenting or child's play but could have far-reaching consequences."

3.7.2.3 Customer Management

This theme comprises (1) *AI and Customer Experience* and (2) *Customer Data*.

AI proliferation can both increase and diminish *customer experience*. Participants agreed with the first proposition, stating that if AI and humans are not properly combined, this may adversely affect customer experience.

"We're at the stage where I don't think we have fully explored the full potential [of AI]. Depending on specific use cases, we may not need human intervention, but at the same time, depending on certain use cases, I think we'll need human intervention, because if AI is left alone it will decrease the customer experience."

The second proposition received no full agreement. While agreeing that transparency is key to *customer experience*, participants identified a tension between a seamless experience on the one hand and transparency on the other. Deciding which steps need to be explained to the customer, and in which detail, appears to significantly challenge marketing managers.

"I don't think customers necessarily want to understand the whole process. People want to have a smooth and seamless experience. They want to know that their data isn't being mishandled, that they have control over their own data,

but what then happens, and how that's used, whether it's an AI system or someone manually changing things. I don't think people necessarily want to think about those things too much either."

The dimension *Customer Data* outlines the potential of generating insights through AI to enable better understanding customers. Managers agreed but were unsure how companies can move closer to their customers through AI without engaging in personal relationships.

"This [focus group] will be treated with discretion. That immediately made me feel at ease. [...] I think that it's the right thing to do, to be fully transparent and to tell your audience how their data will be managed."

"I think we are all obliged to make it as easy as possible for customers to understand and to gather data."

3.8 General Discussion

According to Katrina Lake, the celebrated founder and former CEO of Stitch Fix, her company, which sends consumers personalized parcels matching their fashion style (based on insights generated from both AI/ML and human stylists), is successful because it does not train "machines to behave like humans and certainly not [...] humans to behave like machines" (2018, p. 40). Instead, she highlights the importance of acknowledging that "we are wrong sometimes—even the algorithm" (p. 40), and that her company's most critical success factor is to keep learning. Our investigation supports Lake's view by identifying challenges of working with AI and ML, not being limited to profit-seeking organizations, but also encompassing NGOs.

We employed a dual strategic and a behavioral focus on the role of AI and ML in marketing, as well as an inward and an outward perspective. We examined the organizational tasks of marketing managers, how firms might strategically use AI and ML to improve internal processes and reach out to customers, and how both marketing managers' and customers' reactions may influence AI and ML effectiveness and hence strategy. Our findings are based on responses from a panel of experts and from experienced AI and ML users (i.e., marketing executives working with AI/ML). We thus contribute to valuable conceptual research focusing either on a single perspective (Duan, Edwards, & Dwivedi, 2019), or on deriving research questions (Davenport et al., 2020; Loureiro, Guerreiro, & Tussyadiah, 2021; Huang & Rust, 2021) by identifying and structuring research propositions from both perspectives based on empirical research. Our derived propositions (Figure 10) thus contribute to theory and practice.

3.8.1 Theoretical Contributions

3.8.1.1 *Inward* Perspective

From an *inward* perspective, our results illustrate organizational drivers of and barriers to deploying AI and ML in marketing, outline future developments and suggest boundary conditions. Consistent with previous research (Moon, 2003; Dietvorst, Simmons, & Massey, 2015) and Katrina Lake's statement, we suggest that managers tend to be less tolerant of failure when dealing with AI than with humans. As humans favor algorithmic advice on objective or numerical tasks (Castelo, Bos, & Lehmann, 2019; Logg, Minson, & Moore, 2019; Newman, Fast, & Harmon, 2020), managerial expectations about AI and ML are likely even higher with such tasks, making managers less tolerant of errors. While our participants confirmed this boundary condition, we also found that managers' tolerance of AI/ML relative to human failure may be even lower when tasks are perceived as easy. This finding was also confirmed by one focus-group participant, whose superior expects AI image recognition to be 100% accurate, a succees rate unattainable for human beings.

Whether low failure tolerance of AI and ML results mainly from an inherent Blame-AI culture or unrealistic management expectations is a critical question, in theory and practice. It highlights the need to tackle the challenge at its root. If expectations about AI and ML become increasingly realistic (as our study suggests), the former mechanism may prevail. Thus, less tolerance of AI and ML failure would be a novel manifestation of defensive decision behavior (Ashforth & Lee, 1990) rather than a consequence of unrealistic expectations.

The dimensions *Recommendation Output* and *Decision Frame* deserve further attention. While respondents in our quantitative survey confirmed that managers prefer AI and ML to provide estimates rather than make a choice, this proposition was heavily debated in both focus groups. Some participants agreed that estimates are preferable because decision-makers want to know why or by which margin AI and ML prefer a certain course of action. Others simply preferred AI to make a clear recommendation. Supporters of the latter view argued that top managers either lack the time to discuss possibilities or prefer AI not to behave like humans. This discussion illustrates the topic's relevance and implies that preferring AI recommendation output and decision frames is contingent on various factors (e.g., hierarchy level).

Across our studies, participants agreed that excluding human bias seriously challenges any AI system, highlighting the importance of the dimension *Objectivity versus Human Bias*. Du and Xie (2021) have addressed these biases on the product level when customers interact with AI. In addition, we find that these biases can occur on different levels and involve various factors: training data, system design, human use of a system, and human judgment. Surprisingly, focus-group participants were skeptical about this pivotal issue: They observed some human bias will always exist, either in developing an AI system (e.g., selecting biased training data; Buolamwini & Gebru, 2018) or subsequently in interpreting an AI and ML outcome.

As long as AI systems are fallible and involve human bias, delegating decisions to AI and ML has a strong ethical component. As part of our overarching theme Decision-Making and Ethics, we identified the dimension *Humans in the Loop* as critical. Across all three studies, we consistently found that managers prefer AI systems that theoretically give them the final choice. This does not imply they always want to have a final choice, but rather the chance to decide, depending on the situation. Further, the dimension *Responsibility and Accountability* revealed a moderating variable. While humans may not need to make the final decision in domains such as personalization or (programmatic) advertising, delegating the final choice to humans is critical in life-threatening decisions or with decisions having a strong ethical component (Dwivedi et al., 2021). Whether the importance of having humans in the loop decreases as AI/ML improve is both an empirical and a relevant question.

In line with the EU Commission (2019), that decision explicability is crucial for building and maintaining user trust in AI, two further dimensions proved relevant from an inward perspective: *Understandability* and *Decision Explainability*. Participants agreed that decision-makers need to understand an AI system in the managerial context. While this acknowledges that expert knowledge is not required, a gap currently exists between perceived and actual understanding. Participants not only complained that superior managers tend to display overconfidence but also noted that working with AI and ML on a too superficial level may increase confidence but not actual knowledge (i.e., Dunning–Kruger effect; Kruger & Dunning, 1999). Whether and to what extent an AI system explains its decision again depends on the specific context, essential from both an inward and an outward perspective. When receiving an AI-based recommendation, consumers may want to know why they have received it. Finding the right level of explanation is challenging, as evidenced by companies reluctant to share data of their algorithms (e.g., Facebook), hence weakening a primary competitive advantage.

3.8.1.2 *Outward* Perspective

From an *outward* perspective, our findings relate to the overarching theme Customer Management. They imply that AI and ML can increase customer experience and alert companies that they need to set clear goals and thoroughly understand consumer behavior. Ideally, AI and ML facilitate understanding customer needs, which enables companies to address needs faster and in a more personalized way, and thus improving customer experience (Kumar, Ramachandran, & Kumar, 2021). However, if AI and ML are not used correctly or for the wrong customer (Loureiro et al., 2021), efforts may backfire, and customer experience decreases. Examples include a formerly human customer service now operating as a chatbot failing to benefit customers (Khan & Iqbal, 2020); or an identity-relevant product (e.g., cooking device) that is fully automated and denies passionate chefs the possibility to demonstrate their skills (Leung, Paolacci, & Puntoni, 2018). In both cases, AI and ML diminished customer experience, suggesting that rather than focusing on external, customer-related goals, companies focused on their own goals or targeted the wrong customers.

Similarly, whether *customer data* and AI systems help companies move closer to customers was heavily debated in our focus groups. Participants agreed that companies need a clear strategy to be effective in this regard, in particular if data privacy is concerned. While customers need to be convinced to disclose their data, future research needs to center on strategies for transparently obtaining data and for using such data for the benefit of companies and customers alike. Even though exploiting customers' ignorance about their digital footprints may be alluring (i.e., "privacy paradox"; see Kokolakis, 2017), educating customers on how to handle their data carefully is an alternative path, one leading to trustful and sustainable relations.

3.8.2 Managerial Contributions

3.8.2.1 *Inward* Perspective

Organizations should recognize that managers tend to be less tolerant of AI/ML versus human failure, and that lower tolerance is not limited to objective and numerical tasks. To successfully tackle managers' strict assessment of AI/ML, organizations need to evaluate whether this is due to unrealistically high expectations about AI/ML or whether managers are simply waiting for AI/ML to fail. The two mechanisms require distinct strategies to achieve a more balanced view of AI/ML. Regarding the former, organizations are advised to launch training programs that increase AI/ML literacy among managers (Long & Magerko, 2020), in order to understand the limitations, reduce unrealistic optimism, and manage expectations. Regarding the latter, organizations are likely to have cultural issues. Like Stitch Fix, they need to foster fruitful human-machine interaction (Lake, 2018), in order to regard AI/ML as augmenting rather than threatening managers' work, and to ultimately prevent defensive decision-making, which reflects a blame AI decision-making culture.

Further, our results illustrate that organizations need to carefully consider the extent of information given to decision-makers. AI/ML output should be personalized. While preferences are individual, our results point to the importance of hierarchy level in this regard: Top managers prefer clear decisions and middle managers favor probabilities and reasoning potential courses of action. Finally, organizations should be aware that most algorithms involve a human bias, which most likely unfolds already when developing AI systems (i.e., selecting biased training data) and intensifies when interpreting AI/ML outcomes. Thus, particular emphasis should be placed on receiving objective training data and on rationally evaluating AI/ML decisions.

3.8.2.2 *Outward* Perspective

While AI and ML aim to increase operational excellence and efficiency from an inward perspective, they should enhance customer experience from an outward perspective. Firms must understand that operational efficiency and enhanced customer experience can create tensions, leading to delicate tradeoffs. For example, as illustrated, AI- and ML-based chatbots should not be exclusively regarded as a means of alleviating employee's workload but of (1) enhancing customer experience via a novel channel and

(2) improving critical face-to-face customer touchpoints by enabling employees to invest more time in such interactions. Thus, companies need to consider both the inward and outward perspectives of AI and ML from a holistic strategic angle. Similarly, as data availability is a prerequisite of successful ML and AI, a key challenge for companies will be to treat and store data responsibly and safely (Rauschnabel et al., 2022), and to convince customers to grant access to their data. Our research shows companies need a transparent strategy in this regard (Brough et al., 2022).

3.8.3 Limitations, Conclusions, and Future Research

Consistent with our research design, our findings are interpretative. Our propositions should therefore be seen as potentially fruitful research directions derived from experts and confirmed by users. To represent the multifaceted domain of AI and ML in marketing, we embraced both inward and outward perspectives by employing a strategic and behavioral focus. This should not imply that our themes, dimensions, perspectives, and focuses are independent. On the contrary, they are profoundly interrelated. For example, Waymo, a subsidiary of Google's parent company Alphabet Inc. developing autonomous driving technologies, is keen to avoid a *Blame-AI* culture from an outward (i.e., the customer's) perspective. With their business resting entirely on *AI and customer experience*, they try to find the right amount of *decision explainability*, so as not to alienate their customers, while gathering as much *customer data* as possible to prevent system failure. In case of failure, it is critical to have human support as close as possible (i.e., *humans in the loop*). Hence, further research should not view our propositions as separate but further explore when and how themes and dimensions are interrelated.

We aimed to identify overarching themes and dimensions, and ultimately research propositions, in order to stimulate further innovative research seeking to improve organizations' approach to AI. While our 13 research propositions should be seen as providing directions for further research, four concrete research questions may be particularly and immediately relevant: First, given that managers appeared less tolerant of AI and ML failure, and given that this is likely due to defensive decision-making than unrealistic expectations (as AI and ML become increasingly advanced), further research could investigate whether providing managers with more autonomy or allowing them to make wrong decisions reduces a Blame-AI culture and boosts tolerance of AI and ML failure. Second, the fact that experts remained skeptical of reducing human bias in AI and ML illustrates the need for psychologists, AI technology experts, and data scientists to jointly address this multifaceted challenge. Third, future research would need to explore the roles of humans and AI in important topics such as decision-making: Do we want AI to play a low or a high agentic role, and what might be critical contextual factors in this regard (e.g., Novak & Hoffman, 2019)? Finally, future investigations should raise awareness of and uncover conflicts between inward and outward goals, as well as investigate how to mutually achieve superior operational excellence and customer experience using AI and ML.

3.9 Appendix

Appendix A.1: Research Propositions Derived Based on Results of the Quantitative Study

Culture, Strategy, & Implementation		Decision-Making & Ethics		Customer Management	
Dimension	**Research Propositions**	**Dimension**	**Research Propositions**	**Dimension**	**Research Propositions**
Avoiding a Blame-AI Culture **Topics:** Mistakes & Failure, Culture, Blame, Tasks	1. Managers have a lower tolerance for failure when dealing with AI than with other humans; therefore, a trial-and-error culture is needed to learn from the mistakes. **Propositions:** CSI8, CSI9, CSI9_c, CSI9_d, CSI10, CSI10_d, CSI10_e 2. Managers' tolerance of failure when interacting with AI is lower when the task is perceived as easy. **Propositions:** CSI9_a, CSI9_d	**Humans in the Loop** **Topics:** Humans in the loop, Control, Decision-making	1. AI systems are able to make decisions and can play multiple roles in the decision-making process, but ultimately humans have the final choice. **Propositions:** DME1_a, DME2, DME2_a 2. The riskier a decision becomes regarding ethical and moral values; the less people will hand over decision making to AI. **Propositions:** DME6, DME_6a	**AI & Customer Experience** **Topics:** Customer experience, Customer satisfaction	1. If AI is not carefully managed and combined with human expertise to enhance the customer experience, it will significantly decrease the customer experience. **Propositions:** CM3, CM3_a 2. Explaining the decision-making process to customers will become very important to enhance the customer experience and increase the transparency. **Propositions:** CM7
Recommendation Output and Decision Frame **Topics:** Decision Output, Decision Frame	1. Managers prefer the output of AI recommendations stating probabilities rather than giving a certain result; thus, increasing the acceptance and understandability of AI. **Propositions:** CSI10_b 2. AI-based decisions giving an estimation rather than the choice between different options are preferable. **Propositions:** CSI9_b	**Understandability** **Topics:** Understandability, Transparency, Trust	1. A conceptual framework will be necessary to ensure understanding in the managerial context and to explain and distinguish the use of AI systems and their impact on management. **Propositions:** DME8, DME8_a, DME8_b 2. Managers will need to demand that AI reasoning is made transparent to them in order to ensure the right understanding. **Propositions:** DME4, DME8_a	**Customer Data** **Topics:** Data privacy, Data, Competition	1. As companies get closer to their customers through AI, it will become critical for them to address the use of the gathered customer data in order to ensure a trustworthy relationship with greater value and data privacy. **Propositions:** CM4, CM6_a 2. Having access to a lot of (structured) customer data will be an important source of competitive advantage in the age of AI. **Propositions:** CM1
Objectivity vs. Human Bias **Topics:** Human Bias	1. Even as AI is more objective than humans, an inherent human bias can hardly be excluded from the equation. **Propositions:** DME1, DME1_b	**Decision Explainability** **Topics:** Explainability, Acceptance, Implementation	1. Explainability represents a challenge for the acceptance of AI and is crucial for ensuring transparency. **Propositions:** DME4_a, CSI11 2. It will become necessary to explain the functionalities of AI and its impact on management to ensure a sufficient understanding, as managers tend to be skeptical of AI systems. **Propositions:** DME4_a, DME9		
Expectation Management & Strategy **Topics:** Strategy, Knowledge, Expectation Management	1. AI has raised high management expectations in the past years, but the AI outlooks have become increasingly realistic thus leading to a more solution-oriented implementation strategy. **Propositions:** CSI6, CSI2, CSI7 2. It will take longer to solve the ethical questions than to develop the technology and to make it feasible. **Propositions:** CSI13	**Responsibility & Accountability** **Topics:** Responsibility, Accountability, Consequences	1. Managers have to be able to deal with the consequences of AI; thus defining the degree of responsibility and accountability for AI systems is critical in ensuring trustworthiness. **Propositions:** CSI10_a, DME3, DME3_a, DME10 2. Defining an ethical framework for AI systems will be important, as accountability and transparency are both equally important in the decision-making process. **Propositions:** DME5_a		

4. Third Dissertation Article

Artificial Intelligence in Managerial Decisions: Understanding Perceived Responsibility and Willingness to Accept Recommendations

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4.1 Abstract

The paper focuses on understanding the perceived responsibility of marketing managers, and how Artificial Intelligence (AI) influences the acceptance of recommendations during the managerial decision process. AI's impact is compared to the influence of human advice. Two experiments differentiate AI-based vs. human recommendations: The first study extends prior research on managerial decision-making by showing that managers, who feel highly responsible for decisions, are less likely to accept recommendations in general. Interestingly, this effect differs between the source of recommendation. Managers tend to accept an algorithmic recommendation less when their perceived responsibility is high. In contrast, human recommendations do not differ by the degree of responsibility. The second study analyzes this moderation effect by including sense of ownership as a mediator. Results show a significant indirect interaction between perceived responsibility and managers' willingness to accept a recommendation through sense of ownership and source of recommendation. Overall, these findings contribute to understanding the psychological mechanism underlying the individual perception of responsibility and the acceptance of AI-derived recommendations. Thus, this paper offers valuable insights into improving AI acceptance.

Keywords: Marketing, Marketing Management, Decision-Making, Artificial Intelligence, Perceived Responsibility

4.2 Key Contributions

This research contributes to both academia and marketing practice. The two experimental studies make several important contributions to the literature on managerial decisions, AI, and psychology. They examine the impact of a manager's perceived responsibility on their willingness to accept a recommendation by comparing human and machine decision inputs. This paper highlights the importance of integrating both perceived responsibility and AI into managerial decision-making in order to better assess managers' willingness to accept a recommendation. Further, rather than simply trusting AI recommendations as a black box, it is paramount to properly explain the recommendations obtained through AI—otherwise, positive decision outcomes cannot be assured. Hence, a clear understanding of the decision background is crucial to ensuring transparency and thus to increasing its acceptance.

These two studies also make an important practical contribution to marketing. AI systems are capable of improving decision processes, and hence performance, by complementing human decision abilities. Especially in the field of marketing, using different AI applications has provided marketers with new and more reliable information on process automation, market forecasting, and decision-making. Marketing managers must be aware of both the added value and the potential opportunities arising from AI. Thus, managers at all levels will need to be willing to include AI tools in their daily work and, most importantly, must be willing to accept their recommendations. Providing transparency and explanations were found to increase managers' acceptance of AI and proved crucial to ensuring trust, effectiveness, and efficiency. Therefore, it is important to better integrate the factors influencing decision responsibility as well as to examine how sense of ownership potentially impacts managerial decision-making. This will enable increasing the acceptance of AI recommendations.

4.3 Introduction

Additional information can be included in a decision-making process by using a recommendation (Sniezek & Buckley, 1995; Yaniv, 2004). Managers tend to seek advice to be able to make more accurate decisions and to improve their decision-making (van Bruggen, Smidts, & Wierenga, 1998; Bonaccio & Dalal, 2006). This enables managers to make better-informed decisions, which are likely to be closer to optimal decisions (Sniezek & Buckley, 1995; Yaniv, 2004). The additional value of any recommendation is to provide new information, to initiate a change in perspective (Bonaccio & Dalal, 2006), or to provide orientation on unfamiliar topics (Yaniv, 2004). Moreover, managers can profit from the insights gained from people possessing greater expertise (van Bruggen, Smidts, & Wierenga, 1998). Beyond these practical reasons, managers may also seek recommendations from others in order to share their responsibility for the decision outcome (Harvey & Fischer, 1997). Botti and McGill (2006) define responsibility as “the extent to which decision-makers feel a sense of ownership of the outcome and so may credit themselves for good and blame themselves for bad outcomes” (Botti & McGill, 2006; p. 212). In the managerial context, the attribution of responsibility has been examined both on the company and on the individual level. This paper focuses on the individual perception of responsibility, which has been investigated concerning the specific consequences for managers (e.g., accountability for the decision process). Managers must be accountable for both their decisions and their actions (Hales, 1986). Wierenga (2011) addressed this lack of research in the field of marketing managers’ decision-making.

The deployment of AI applications provides marketing managers with new information on market forecasting, process automation, and decision-making (Huang & Rust, 2021). AI’s abilities to analyze large amounts of data help managers to gain extensive knowledge. These insights support marketing managers in making better decisions and more generally in improving their decision-making capabilities (Paschen, Kietzmann, & Kietzmann, 2019). These two factors are critical for an organization’s success (Abubakar et al., 2019). Indeed, AI-based technologies are predicted to keep disrupting managerial decision-making even further (Davenport et al., 2020). Using AI in decision-making has been a major accomplishment in recent years (Duan, Edwards, & Dwivedi, 2019). In particular, today’s AI systems are technically capable of improving decision quality by complementing human decision-making abilities (Jarrahi, 2018). However, research has largely explored how people perceive AI- or human-generated managerial decisions rather than (also) considering how managers’ perceived responsibility and its drivers (e.g., sense of ownership) influence managers' willingness to accept a recommendation (e.g., Kyung Lee, 2018; Newman, Fast, & Harmon, 2020).

Specifying the source of recommendation (human vs. non-human, i.e., AI) might play an important role in managers' perceived responsibility and the willingness to accept a recommendation. Based on the managerial decision-making process in marketing (Lilien, 2011), and on AI-driven decision-making (Colson, 2019), this paper uses a modified marketing decision model. The input for a (marketing) management problem can be provided either by a human or by AI. While previous literature employs statistical models and basic decision rules performed by a computer (e.g., Dawes, Faust, & Meehl, 1989), the current understanding of learning algorithms and their fields of application dominate recent works (e.g., Castelo, Bos, & Lehman, 2019; Burton, Stein, & Jensen, 2020). They refer to applications that support, for instance, decision-making as a functionality of AI systems which are based on algorithms (Burton, Stein, & Jensen, 2020). Thus, managers take decisions based on recommendations (human vs. algorithm[12]) and their managerial judgment, in order to derive a decision to solve a managerial problem.

Based on prior research, the two experimental studies presented here investigate how marketing managers' perceived responsibility affect their willingness to accept algorithmic or human recommendations. More specifically, the proposed model integrates various factors, including sense of ownership and how this influences marketing managers' perception of responsibility and their willingness to accept a recommendation. Both studies provide evidence for the indirect effect of perceived responsibility on the willingness to accept a recommendation through sense of ownership, which is contingent on the source of recommendation. The results indicate that executives are less willing to accept a recommendation when their perceived responsibility is high. This relationship was identified to be particularly strong for an algorithmic recommendation and to be independent of human advice. What follows considers the theoretical foundations of the findings, presents the results, and elaborates on the implications and limitations of this empirical research.

[12] In the two studies presented here, AI was further specified by using the term algorithm.

4.4 Theoretical Background and Hypotheses

One way of improving managerial decision-making is by accepting recommendations (van Bruggen, Smidts, & Wierenga, 1998; Bonaccio & Dalal, 2006). However, managers must still be accountable for their decisions and actions (Hales, 1986). The higher the impact of a decision, the more responsible decision-makers feel (Harvey & Fischer, 1997). Franklin and Guerber (2020) demonstrated that managers less concerned about the ethical implications of the decision outcomes are more likely to accept a recommendation, and thereby reduce their perceived responsibility. According to Palmeira, Spassova, and Keh (2015), a person's responsibility also rests on their advisor's responsibility. Advisors receive more responsibility for a successful decision outcome compared to a negative one. This shift in responsibility is rooted in the perception of the advisor having a certain control over the decision. Managers also tend to share responsibility in order to avoid emotional distress as well as uncertain and potentially negative outcomes. Thus, sharing their responsibility may serve as protection against bad outcomes (El Zein, Bahrami, & Hertwig, 2019).

The decision process including a recommendation can be described as an expert suggesting a course of action or a decision (Bonaccio & Dalal, 2006). In the end, the manager chooses whether or not to follow the recommendation. Thus, the decision-maker prefers not to bear full responsibility for the decision outcome, which leads them to seek advice (Harvey & Fischer, 1997). Thus, it is hypothesized:

H_1: *Managers have a greater willingness to accept a recommendation with a decreasing perceived responsibility.*

Recent research has found that people prefer algorithmic advice over human judgment, although only in very specific situations such as objective or numerical tasks (Castelo, Bos, & Lehmann, 2019; Logg, Minson, & Moore, 2019; Newman, Fast, & Harmon, 2020). Nevertheless, many people still mistrust algorithms and prefer human recommendations (e.g., Dietvorst, Simmons, & Massey, 2015; Yeomans et al., 2019). Decision-makers often reject algorithms when they can actively choose between human and algorithmic recommendations (e.g., Eastwood, Snook, & Luther, 2012).

Decision-making is usually connected with a direct perceived responsibility by the decision-maker (Neri et al., 2020). However, using an AI system makes it harder to hold managers and businesses responsible and accountable for their actions (De George, 2008). Especially when an algorithm makes mistakes, individuals tend to trust humans rather than AI (Moon & Nass, 1998; Moon, 2003; Dietvorst, Simmons, & Massey, 2015). Thus, the greater autonomy of an algorithm tends to make humans attribute negative outcomes to a machine while taking the credit for successful outcomes (Jörling, Böhm, & Paluch, 2019). In the medical field, for instance, studies show that participants favor a physician's advice over a computer program's. This effect was demonstrated by participants' diminished sense of responsibility when accepting the physician's advice (Promberger & Baron, 2006). According to Bonaccio and Dalal (2006), the motivation to seek advice is to share responsibility. Thus, in the algorithmic condition managers are more likely to discount a recommendation when their perceived responsibility is high, because the responsibility cannot be shared. Thus, the following hypothesis can be formulated:

H_2: *The source of recommendation moderates the relationship between a manager's perceived responsibility and willingness to accept a recommendation.*

One keyword emerges from the definition of perceived responsibility (Botti & McGill, 2006): sense of ownership. Beggan (1992) suggested that ideas or thoughts are seen as positive when people have a feeling of ownership about them. This feeling may arise for both physical and nonphysical objects, such as ideas or decision output (Beggan, 1992). Hence, a feeling of ownership may be positively linked to perceived responsibility (Furby, 1978). According to Jörling, Böhm, and Paluch (2019), sense of ownership is directly linked to a higher perceived responsibility. Baer and Brown (2012) demonstrated that having a sense of ownership negatively affects the acceptance of a recommendation when the advice is contrary to one's own beliefs, triggering feelings of anger. Therefore, sense of ownership may mediate the relationship between the perception of responsibility and the willingness to accept a recommendation and is contingent on the source of recommendation. Accordingly, it is hypothesized:

H_3: *The indirect effect of a manager's perceived responsibility on their willingness to accept a recommendation through sense of ownership is contingent on the source of recommendation.*

4.5 Experimental Studies - Design, Methodology, Results

4.5.1 Sample and Research Procedure

Data Collection and Sampling

First, an online pre-study was conducted with 50 managers (M_{age} = 36, SD = 11.73, 54% female), who were asked to select two out of three ice cream products for the main studies (see Appendix 1: Product Choice in the Pre-study). The products were displayed in random order, controlling for question order effects (Blankenship, 1942). As a result, overperforming or underperforming ice creams were excluded[13] to control for a social desirability bias (Nederhof, 1985). *Second*, data were collected from 300 managers (M_{age} = 38, SD = 11.06, 41% female) for the first online experiment to examine the proposed moderation effect. *Third*, a second experiment with 350 managers (M_{age} = 37, SD = 10.36, 43% female) was conducted to investigate the moderated mediation effect by including sense of ownership as a mediator. To ensure a high-quality marketing management sample in both studies, participants without employee responsibility were excluded. Their attention was further controlled by including attention check items,[14] resulting in an effective sample size of n = 258 (study 1) and n = 331 (study 2) (Oppenheimer, Meyvis, & Davidenko, 2009).

Method

The two experiments were conducted in the field of marketing decisions: Decision fields can be distinguished in communication management, price management, and product development (Kotler, 1967). Using forecasting information technologies is highly relevant for marketing decisions, especially in developing a new product with high uncertainty (Polat, 2008). The studies were constructed by including an active product choice.[15] In both studies, marketing managers chose between different products and had to decide which one to launch into a test market (see Appendix 2: Product Choice for the Experimental Studies). After their first choice, they received either an

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[13] Using a chi-square independence test, one product was found to be significantly different from the other two ice creams ($p < 0.1$), leading to the product being excluded. Thus, two products with similar results ($p > 0.1$) were chosen for the experiment.

[14] Participants had to first recall the source of recommendation and second, their attention was tested by asking them to leave a question blank. In the last part of the study, participants had to describe their perceived goal of the study to control for demand characteristics (Orne, 1962).

[15] Research suggests that including an active choice option increases the feeling of perceived responsibility, resulting in more realistic experimental results (Botti & Lyengar, 2004; Botti & McGill, 2006).

algorithmic or a human recommendation. The experiments manipulated the advice to produce an opposite recommendation to managers' previous choice. The between-subjects design assigned managers randomly to one of two conditions (see Appendix 3: Scenario for both Experiments).

Measuring Scales

At the end of both experimental studies, participants were asked to complete a short questionnaire measuring their perceived responsibility and how this affected their willingness to accept a recommendation. *First*, the willingness to accept a recommendation was measured by comparing the final choice with the initial opinion and whether managers changed their decision (e.g., Sniezek & Buckley, 1995). *Second*, the degree of perceived responsibility was measured by adapting the items developed by Botti and McGill (2006). In addition to the first experiment, one open question was included to determine the reasons for accepting or discounting the recommendation. The proposed mediator, sense of ownership, was measured by adapting the items developed by Peck and Shu (2009). For an overview of all measures used in both experiments, see Appendix 4: Measuring Scales.

4.5.2 Results

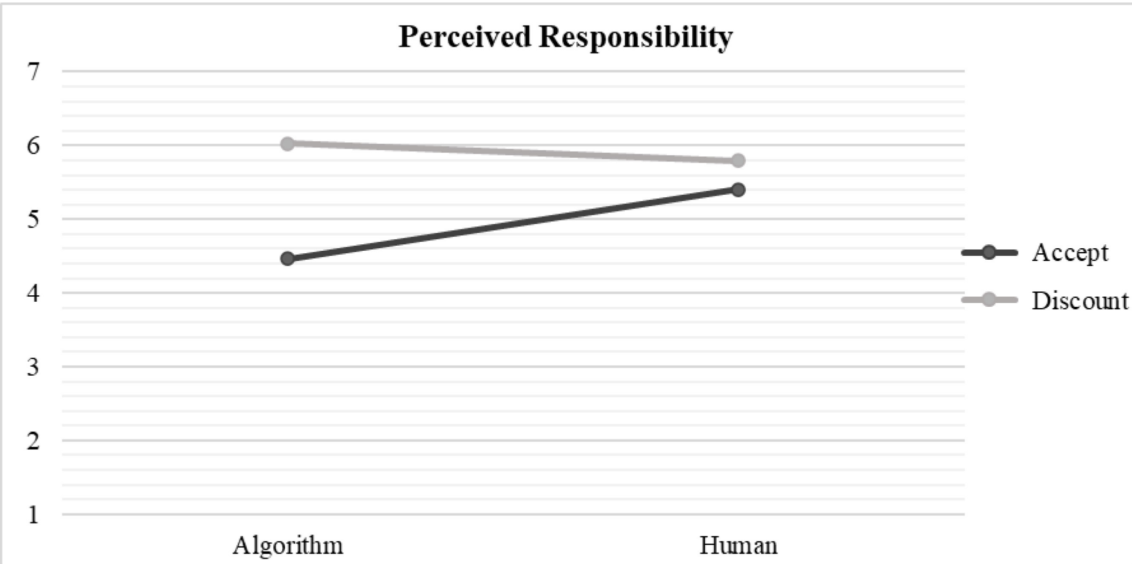
Hypothesis Tests

The first study examined Hypotheses 1 and 2. *First*, the relationship between perceived responsibility and willingness to accept a recommendation was tested (H_1). The regression results show that a manager's perceived responsibility significantly affects the willingness to accept a recommendation (β = -.13, t = -6.12, $p < .001$). Hence, the willingness to accept a recommendation increases with a decreasing perceived responsibility, thus supporting the first hypothesis.

Second, in order to test the moderating effect (H_2) of the source of recommendation between a manager's perceived responsibility and the willingness to accept a recommendation, Hayes' (2017) PROCESS was applied. Basic moderation model number 1 was used with 10.000 bootstrapped samples. The results showed that the interaction of the source with perceived responsibility impacted the willingness to accept a recommendation, adding 13% (R^2 = .13, $p < .001$) of the variance explained. The source of recommendation significantly moderated this relationship (b = -.81, 95% CI [-1.48, -.28]). In order to further understand the nature of this relationship, two analytical approaches were applied: (1) simple slope analysis (to differentiate different levels of the moderator); and (2) line graphs of the slopes (to illustrate the moderating role).

The results of the simple slope analysis revealed no significant effect between perceived responsibility and willingness to accept a recommendation (b = -.25, 95% CI [-.56, .05]) in the human condition. In contrast, a significant effect (b = -1.01, 95% CI [-1.48, -.65]) was found in the algorithmic condition. According to the line graph (see Figure 11), the human source does not change the perceived responsibility, and thus does not affect the willingness to accept a recommendation. Interestingly, when a manager's perceived responsibility is lower for an algorithmic recommendation, the tendency to accept a recommendation is higher—compared to greater responsibility, which leads to more recommendation discounting. Additionally, the perceived responsibility differs significantly between the human and the algorithmic condition when managers accept the recommendation. These results show the moderation effect in the algorithmic condition, and thus support Hypothesis 2.

Figure 11: Results of the Moderated Effect



The second study examined Hypothesis 3 by using bootstrapping with the PROCESS macro to investigate the moderated mediation effect. This study utilized Hayes' (2017) PROCESS Model 14, where the effect of a manager's perceived responsibility on the willingness to accept a recommendation via sense of ownership is moderated by the source of recommendation. The results demonstrate that perceived responsibility positively influences sense of ownership (b = .95, SE = .05, p < .001). Further, sense of ownership (b = -.46, SE = .15, p < .01) directly impacts the willingness to accept a recommendation. The interaction effect of sense of ownership and the source of recommendation on the willingness to accept a recommendation was significant (b = -.43, SE = .19, p < .05). The indirect effect was significant for both the human (b = -.43, 95% CI [-.75, -.15]) and the algorithmic (b = -.84, 95% CI [-1.29, -.53]) condition. However, the findings show that the indirect effect becomes stronger with an algorithmic recommendation. As hypothesized, a significant indirect interaction between perceived responsibility and the willingness to accept a recommendation through sense of ownership is contingent on the source of recommendation (b = -.41, 95% CI [-.81, -.09]). Therefore, the proposed moderated mediation hypothesis (H_3) is supported. This model is able to account for a large portion of the overall variance (R^2 = .55, p < .001).

Content Analysis

An open question captured why participants accepted or discounted the recommendation. Inductive coding was used to categorize participants' answers (Gioia, Corley, & Hamilton, 2013). In order to increase coding reliability, another researcher coded and confirmed the intercoder reliability of the content analysis (Charmaz, 2014). The results show eleven codes, which are categorized into two main dimensions: Reasons for accepting and discounting the recommendation.

Reasons for accepting the recommendation: Managers were unsure about their choice (low confidence), or thought that the advisor had more information or expertise than they did (advisor expertise). Some managers mentioned that including multiple perspectives was better than basing their decision only on a single opinion (include other perspectives), whereas others felt they had to appreciate the recommendation (value the opinion of others). Some participants believed that the advisor was competent or that the advice was accurate (positive advisor reputation).

Reason for discounting the recommendation: Managers used opposing arguments, such as being very confident with their decision (high confidence) or that they doubted the advisor's intentions and competence (negative advisor reputation). In addition, their argumentation included their reliance on their gut feeling (reliance on intuition) or that it was their decision to make (decision ownership). The greatest issue causing advice discounting was the lack of explanation of the recommendation (no explainability). This reason was mentioned by 23% of managers in the algorithmic condition, compared to roughly 10% in the human condition. More specifically, most managers failing to follow the algorithmic advice (48%) used this reason to justify their decision.

4.6 Implications and Future Research

These results show that including AI and a manager's perceived responsibility in the decision process strongly affects the acceptance of a recommendation. In the first experimental study, H_1 and H_2 were examined while H_3 was analyzed in the second study. *First*, the results demonstrated that when confronted with recommendations for action, a manager's perceived responsibility powerfully influences the willingness to accept a recommendation. Managers who feel responsible for a decision are less likely to accept a recommendation (H_1). *Second*, as a result, when specifying the source of recommendation this effect differs in the human and in the algorithmic condition. These results illustrate this moderating role in the algorithmic condition: A manager's low perceived responsibility when receiving an algorithmic advice increases the tendency to follow a recommendation, whereas high perceived responsibility lowers advice acceptance, thus discounting the recommendation (H_2). *Finally*, to understand the mechanism underlying the moderation, sense of ownership was included as a mediator. The results demonstrated that perceived responsibility positively influences sense of ownership, and thus affects the willingness to accept a recommendation. The source of recommendation moderates this effect by decreasing sense of ownership, resulting in a stronger tendency to accept a recommendation. This effect is greater in the algorithmic condition compared to the human one (H_3).

Beyond these three hypotheses, additional drivers for discounting the recommendation were investigated. The content analysis offered insights into the importance of explainability. Many managers had an issue with the low explainability of the recommendation, and led them to discount the advice. The black box algorithm used in the experiment and the related lack of transparency, which is often associated with algorithms (Davenport & Ronanki, 2018; Burton, Stein, & Jensen, 2020), could account for the lower explainability. Further, managers who discounted the recommendation were more likely to accept the advice with more detailed explanation. In addition, decision ownership, high confidence, and reliance on intuition play further an important role. According to Yaniv and Kleinberger (2000) and Krueger (2003), the egocentric bias, that people favor their own opinion in general due to assumed superiority, might be a possible reason for these three arguments.

Given these results, this paper has important implications for both researchers and practitioners. *First*, for researchers, it makes several important contributions to the literature on managerial decisions, AI, and psychology. In particular, it highlights the importance of combining managers' perceived responsibility and AI in the decision process to better assess the willingness to accept a recommendation. Further, rather than simply trusting AI recommendations as a black box, it is paramount to clearly understand the decision background in order to ensure transparency and thus increase acceptance. *Second*, for practitioners, an increasing number of companies are already using or planning to implement AI in their work structures. Managers at all levels will need to be willing to include AI tools in their daily work, and hence to accept their recommendations for action. Algorithm transparency and explanations were identified as driving advice acceptance and serve several key purposes, among others, ensuring trust, effectiveness, and efficiency. It is therefore crucial to better integrate the factors influencing decision responsibility and how a sense of ownership impacts the decision-making process in order to increase the acceptance of AI recommendations.

However, the studies also have limitations and therefore open up opportunities for future research. *First*, the sample used in both studies might have included participants who did not reflect the desired population (managers with direct responsibility for at least one employee). There is a danger that participants gave wrong information on their personal background, so they could participate in the online study (Buchanan & Scofield, 2018). Further research could, therefore, replicate these studies in a field experiment, in order to increase external validity and to ensure a representative sample. *Second*, the scenario refers to a specific marketing task in product management. Hence, it is uncertain whether the same results would be obtained with different marketing tasks. These studies could be replicated with other marketing tasks, derived from the "4 Ps," for instance, in pricing, promotion, or placement. *Third*, the recommendation was presented without any reasoning. As the findings show that higher explainability positively affects the willingness to accept a recommendation, further research could include a detailed explanation of the advice. By taking into account the requirements for good advice, different levels of explainability could be included (black box vs. explainable AI). *Finally*, in these two studies participants received a recommendation by default. However, it would be interesting to investigate the effect when managers have to actively request a recommendation.

Without doubting the relevance of AI and managers' perceived responsibility, this paper has shown that it can change existing patterns of managerial decision-making. In particular, managers need to realize that they may perceive AI- or human-generated recommendations significantly different, which may result in various consequences as far as acceptance is concerned.

4.7 Appendix

Appendix 1: Product Choice in the Pre-study

The Honest Ice Cream

Delicious Low Calorie Ice Cream

Traditional Homemade Ice Cream

Chi Square Test: Homemade vs. Low Calorie: $\chi^2(1) = 15.152$, $p = 0.0000992$
Homemade vs. Honest: $\chi^2(1) = 0.89084$, $p = 0.3452$ (not significant)
Low Calorie vs. Honest: $\chi^2(1) = 17.87$, $p = 0.00002366$

Appendix 2: Product Choice for the Experimental Studies (Studies 1 and 2)

Product A:

<u>Traditional Homemade Ice Cream</u>

Product B:

<u>The Honest Ice Cream</u>

Appendix 3: Scenario for both Experiments

Please imagine you are the **product manager** at **Delicia,** a well-known consumer goods manufacturer. Overall, the company generates an annual turnover of $5 billion and employs 3,000 people worldwide. Among other responsibilities, you are the main decision-maker for product management and product development.

Delicia is planning to introduce a new ice cream in a test market. Among two alternatives, you need to select the **most promising ice cream product** to launch in a **representative test market**.

Please imagine yourself in this role for 1-2 minutes as vividly as possible.

Appendix 4: Measuring Scales

Measures	Scale	Items/Description
Outcome Responsibility (Botti & McGill, 2006)	7-point Likert scale *1 = Not at all* *7 = Extremely*	When making the decision as a manager …I felt responsible for the outcome of my choice. …I felt accountable for the outcome of my choice. …I felt in control of the outcome of my choice.
Willingness to accept a recommendation (Sniezek & Buckley, 1995)	Dummy Variable (Binary) *0 = Participants sticked to their decision* *1 = Participants changed their decision*	Advice acceptance was measured by determining the difference between pre- and post-advice decision.
Sense of Ownership (Perceived) (Peck & Shu, 2009)	7-point Likert scale *1 = Not at all* *7 = Very much so*	I feel like this was entirely my decision. I feel a very high degree of personal ownership for this decision.
Reasons for accepting or discounting the recommendation	Open Question	Why did you [follow]/[not follow] the recommendation you received from the [other employees/managers]/[algorithm]?

5. Fourth Dissertation Article

Managerial Decisions in Marketing: The Individual Perception of Explainable Artificial Intelligence

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5.1 Abstract

This paper examines how marketing managers` perception of the explanation quality of an advice differs between Artificial Intelligence (AI) and human recommendations. The results of this experimental study extend previous findings on managerial decisions by demonstrating that managers' perception of the explanation quality differed between AI and humans. Explanations behind human advice were perceived as less satisfying, as needing more information about the recommendation. In contrast, receiving an AI-generated advice positively changed managers' perception of the explanation quality. They perceived explanations as more sufficient without the need for further clarification. These findings contribute to understanding managers perceptions of the explanation quality of AI-generated recommendations. Including explanations of AI-based recommendations in the decision process is important for building user trust. Thus, this paper is intended to stimulate interdisciplinary research on using AI in managerial decisions in marketing. Particularly, this study aims to encourage further research to examine the importance of explanations in the decision process to improve AI acceptance.

Keywords: Marketing, Marketing Management, Decision-Making, Artificial Intelligence, Explainable Artificial Intelligence

5.2 Introduction

Artificial Intelligence (AI) has revolutionized countless fields over the past years and is constantly evolving (Torra et al., 2019). AI is being applied not only in consumer applications but also in various industries, such as financial services, healthcare, commerce, and marketing (Huang & Rust, 2018). Its greatest potential lies in enhancing human abilities. As such, it will enable human-machine collaboration that is capable of solving various problems (e.g., complex situations with a lot of data available, which humans can hardly master). Only through such collaboration can trust in AI systems be established (Jarrahi, 2018).

Not only benefits are associated with AI. It also attracts widespread criticism, primarily due to serious implementation risks. According to Stephen Hawking, for instance, it is still unclear whether AI is the best or worst thing for humanity (Saffell, 2016). This points to conflicting attitudes toward AI. On the one hand, researchers are questioning the ethicality of enhancing human capabilities. On the other, AI has unquestionable potential in various business contexts, including managerial decisions (Edwards, Duan, & Robins, 2000).

However, it is crucial that marketing managers do not rely blindly on AI decisions, especially when decision outcomes are undesirable. One dimension in particular plays an important role in building and retaining trust in AI: Decision explicability. According to the EU Commission (2019) a certain explicability should be embedded in decision-making processes in order to ensure transparency (EU Commission, 2019). Thus, future research needs to evaluate the ethical dimension of AI, and to minimize negative perceptions, to assure favorable developments in the coming years.

Based on prior research and aimed at shedding a more nuanced light, an experiment was conducted with marketing managers to establish whether perceived explicability differs between AI and human decision input. More concretely, it is assumed that managers perceive the recommendations generated either by a human or AI in a different way and thus, evaluate the explanation quality differently.

This paper hence combines a theoretical background with empirical findings, derives implications for practitioners (marketing managers) and researchers and suggests opportunities for future research.

5.3 Theoretical Background

A growing number of companies are considering possibilities of implementing AI in their organizations (Kolbjørnsrud, Amico, & Robert, 2016). While AI is said to potentially improve organizational efficiency and productivity (Paschen, Kietzmann, & Kietzmann, 2019), significant skepticism remains about whether AI technologies will transform the workflow and its processes or should be seen as a threat (Daugherty & Wilson, 2018).

In recent years, AI has shown enormous potential in decision-making (Duan, Edwards, & Dwivedi, 2019). Especially in marketing, implementing AI is bearing fruit due to its ability to generate increasingly affordable and accessible data (Conick, 2017). However, combining these two fields shows that marketing managers are as yet unable to tap the potential of AI technologies (Davenport et al., 2020).

A core issue of human-AI interaction is managing and maintaining trust in its decision-making (Davenport & Kirby, 2016). As managers tend to work on highly sensitive issues, a lack of trust will most likely prevent them from using AI without their supervision (Kolbjørnsrud, Amico, & Robert, 2016). The lacking transparency of AI systems also complicates understanding the reasoning behind AI-based decisions (Jarrahi, 2018). In addition, AI output is based entirely on its input, making the data sets used crucial for the desired outcome. If it picks up on a biased view, AI could perform well for the wrong reasons (Ransbotham et al., 2017). Therefore, including transparency in decision-making is critical to successfully use AI (Jarrahi, 2018). Thus, incorporating a certain level of explainability in AI reasoning is important for maximizing transparency (Brewer, Chinn, & Samarapungavan, 1998). Explanations can be seen as making a word, an idea, or a concept understandable to others (Kim, 1995).

When looking on prior research, two prominent and yet divergent bodies of literature can be distinguished: One research stream states that people prefer human recommendations since they are easier to understand. If an algorithmic recommendation were presented with a certain explanation, individuals would be less averse to following it. In this case, the explainability and understandability, then, are key rather than the ability of a recommendation system to outperform humans (Yeomans et al., 2019). Any such system must also be understandable in a way that managers can be certain AI is being used as intended (Harrell, 2016).

Another research stream argues that lay persons prefer an AI advice compared to human recommendations (Logg, Minson, & Moore, 2019). Such individuals tend to perceive the advice of an expert system as more rational and as more objective than human advice (Dijkstra, 1999). Thus, blindly trusting recommendations without closer scrutiny or questioning the advice can be very dangerous. Especially, when AI makes a mistake individual tend to trust humans rather than AI (Dietvorst, Simmons, & Massey, 2015). Doing so hence may result in failing to notice errors in an expert system (Dijkstra, Liebrand, & Timminga, 1998).

Most research on AI still focuses predominantly on the transformation of unstructured and structured data into Smart Data (e.g., Wedel & Kannan, 2016) or on implementing Smart Technologies in consumer environments (e.g., Novak & Hoffman, 2019; Kietzmann, Paschen, & Treen, 2018). However, little research has investigated how managers perceive a certain explainability of AI-based vs. human decision input.

Hence, the two following hypotheses were derived to shed light on this unresearched topic:

H_1: *Managers' perception of the explanation quality differs depending on the source of advice (human vs. AI).*

H_2: *The effect of the source of advice (human vs. AI) on the explanation quality is contingent on the decision evaluation.*

5.4 Experimental Study: Research Procedure and Results

The experimental study tested the explicability of managerial decisions in a marketing context, taken either by AI or by humans, by identifying the decision attributes involved. This experimental study investigates how far explicability plays a role in the decision process.

5.4.1 Research Procedure

This section outlines the research procedure of the experiment and presents the data collection and sampling, conceptual framework, method and measuring scales used in this paper.

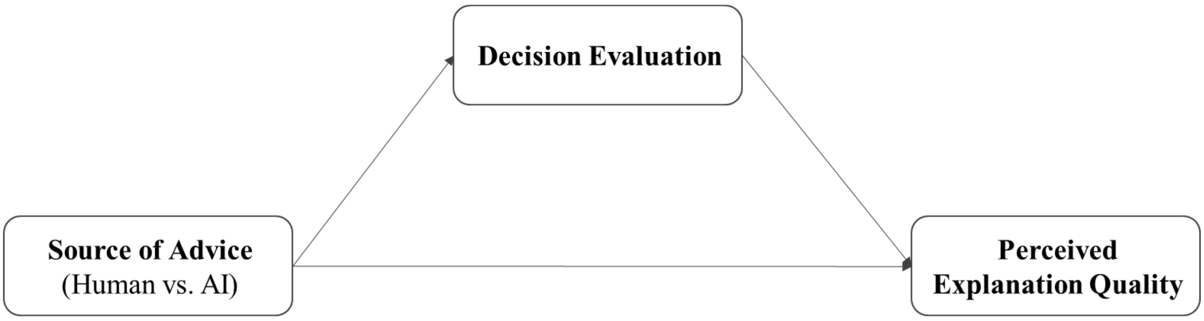
Data Collection and Sample

An online experiment was conducted with 250 managers (M_{age} = 40, SD = 10.04). As this paper focuses on managerial decision-making in marketing, managers formed the population of interest. In order to ensure a management sample, participants with no employee responsibility were eliminated. Their attention to the scenario in the experiment was further tested by adding attention check items, such as asking about the company's fictitious business (Oppenheimer, Meyvis, & Davidenko, 2009). The effective management sample size was thus reduced and resulted in n = 207.

Conceptual Framework

Based on the theoretical background and the formulated hypotheses (H_1 and H_2), the following conceptual framework was derived (see Figure 12).

Figure 12: Conceptual Framework



Method

A scenario-based approach was chosen for the experiment, using a common decision-making situation in marketing, more specifically in product development. This enables drawing conclusions about real-life behavior (Woods et al., 2006).

The scenario was designed, so that participants had to take the role of a product manager in a fictitious company, which produces and sells consumer products. Ice cream was chosen as consumer product, as it represents a product, which everyone is familiar with and does not require further explanation (Shukla, 2004). In their position as product manager, they had to evaluate the company's latest product innovation idea and to choose which of the two products to launch in a test market. The main manipulation consisted of participants receiving either an AI-generated or human recommendation for the product choice. In both conditions, there was no explanation given for the recommendations. These two sources of recommendation served as the independent variable in this study. The experimental scenario is provided in Figure13.

Figure 13: Experimental Scenario

> Please imagine you are the **product manager** at **Delicia,** a well-known consumer goods manufacturer. Overall, the company generates an annual turnover of $5 billion and employs 3,000 people worldwide. Among other responsibilities, you are the main decision-maker for product management and product development.
>
> Delicia is planning to introduce a new ice cream in a test market. Among two alternatives, you need to select the **most promising ice cream product** to launch in a **representative test market**.
>
> Please imagine yourself in this role for 1-2 minutes as vividly as possible.

The second part of the study began by asking participants follow-up questions about the experiment and included measurements to further analyze managers' perception of the scenario. These measurements are presented in the following paragraph – Measuring Scales.

Measuring Scales

In order to measure perceived explanation quality, Dijkstra's (1999) item regarding the need to ask further questions about the received recommendation was adapted. Further, Stalmeier et al.'s (2005) items were used to evaluate the decision in regards of managers' perception of having made an informed decision and their satisfaction with the explanation quality. For a summary of all measurements used in the experiment, see Table 9.

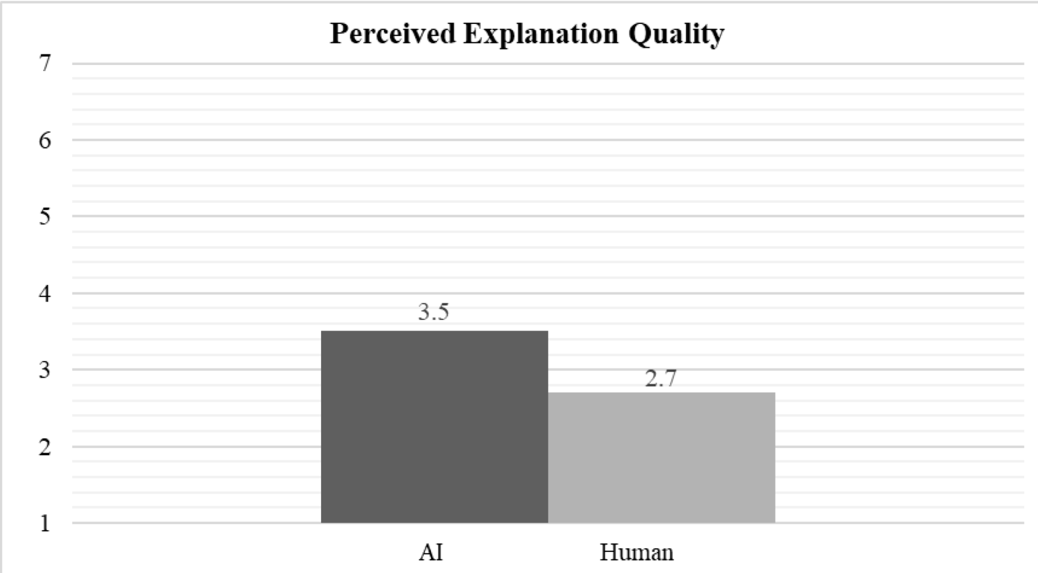
Table 9: Measuring Scales

Variable Name	Scale	Variable Measurement	Reference
Explanation Quality	7-point Likert scale *1 = I do not agree at all* *7 = I fully agree*	This variable represents how well participants perceived the explanation quality by assessing whether they felt the need to ask further questions about the received recommendation.	Dijkstra (1999)
Decision Evaluation	7-point Likert scale *1 = I do not agree at all* *7 = I fully agree*	To capture an individual's decision evaluation and whether they perceived having made an informed decision, a 4-item scale was used. Participants had to indicate how much the agree with the following statements: • I am satisfied with the explanation of the recommendation I received • I want more information about the product decision • I want a clearer recommendation • I made a well-informed choice	Stalmeier et al. (2005)

5.4.2 Results

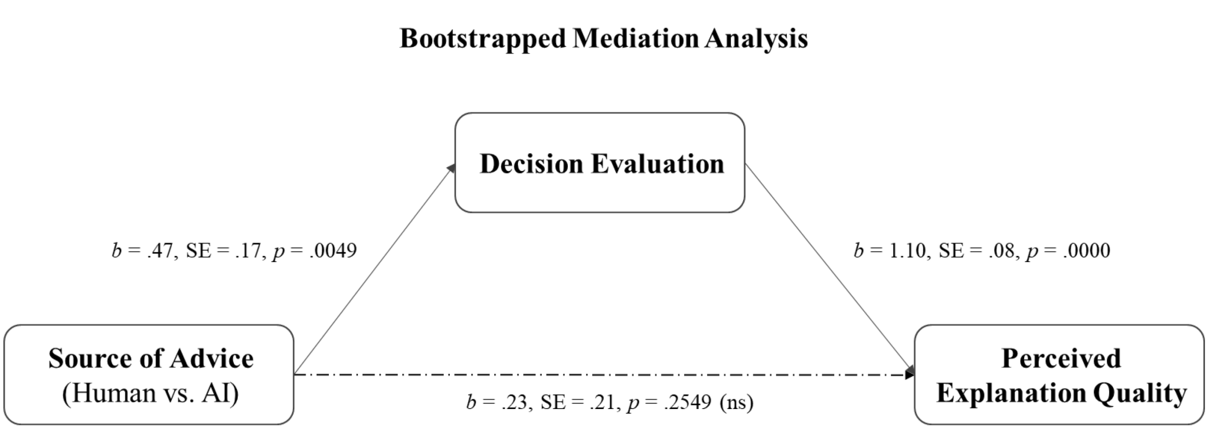
First, the relationship between the source of advice (human vs. AI) and perceived explanation quality (no explanation was given in both conditions) was tested (H_1). The regression results show that the source of advice significantly affects the perceived explanation quality of that advice (β = .75, t = 2.78, p < .01). Participants who received a human recommendation perceived the explanation as less satisfying and as less good compared to an AI-generated advice. Figure 14 shows the differing perceptions of the explanation quality depending on the source of advice.

Figure 14: Perceived Explanation Quality Depending on the Source of Advice



Second, in order to understand the effect of the source of advice on the perceived explanation quality, decision evaluation (perceived informed decision) was included as a mediator (H_2). The bootstrapping method, based on 5.000 bootstrap samples (Hayes, 2017), was used to test the relationship between the source of advice and perceived explanation quality through decision evaluation. The source of advice significantly affected managers' decision evaluation (b = .47, SE = .17, p < .005), which in turn significantly affected the perceived explanation quality (b = 1.10, SE = .08, p < .0001). The conceptual framework including the results to answer the second hypothesis, can be derived from Figure 15.

Figure 15: Overview of the Bootstrapped Mediation Analysis
(by using Hayes (2017) Model 4)



After decision evaluation (perceived informed decision) was included as a mediator, the direct effect of the source of advice on the explanation quality became nonsignificant (b = .23, SE = .21, p > .10). Thus, decision evaluation fully mediated the impact of the source of advice on the perceived explanation quality. Further mediation analysis, based on the bootstrapping method, indicated that the effect of the source of advice on the perceived explanation quality is mediated by decision evaluation (b = -.52, 95% CI [.17, .87]). This means that in the human condition, participants felt less informed about the received recommendation and thus were not satisfied with the explanation. In comparison, when receiving an AI-generated advice, managers felt more informed and hence perceived the explanation as having better quality.

5.5 Implications and Future Research

This study aims to initiate further research on the benefits of using AI in managerial decisions in marketing, especially the importance of explainability in the decision process. *First*, the results show that even though no explanation was given, participants' perception of the explanation quality differed between both conditions (human vs. AI). The explanation of the human advice was perceived as less satisfying, and participants therefore felt they needed more information about the recommendation. In contrast, receiving an AI-generated advice significantly changed participants' perception of the explanation quality. Managers perceived the explanation as more sufficient and felt no need to ask further questions. *Second*, the results demonstrate the mediating role of decision evaluation (perceived informed choice). When receiving the AI-generated recommendation, participants felt more informed and were more satisfied with the explanation, which positively affected the perceived explanation quality. In contrast, this effect was significantly weaker with human advice. Participants wanted more information about the recommendation and thus rated the explanation quality as inferior.

The results of the experimental study have important implications for practitioners and researchers. For *practitioners*, they indicate that since marketing managers are required to both take and deal with many strategic and highly sensitive decisions, a certain transparency is crucial to ensuring a desired decision outcome. Thus, blindly trusting AI recommendations is not sufficient in itself. Rather, recommendations must include a certain degree of explainability of AI-generated recommendations in order to increase the acceptance of AI. For *researchers*, these results make important contributions to the literature on managerial decisions, AI, and psychology. In particular, they show that the differing perceptions of explainability in the decision process depend on the source of advice. These individual impressions of managers should be actively used in order to increase the acceptance of AI.

This paper serves as a starting point for further studies and thus has further research potential. *First*, since the recommendation was presented without context, participants did not receive an explanation. Future research could manipulate this by providing different levels of explainability. As a result, the decision-making process could for example be further differentiated: For human recommendations, the scenario could include a differentiation between intuitive versus analytical reasoning, whereas for the AI-generated recommendation a distinction between AI as a black box versus an explainable AI could be implemented. *Second*, additional measurements of explainability should be incorporated in subsequent studies. These scales could include how objective, logical, relevant, useful, and reliable the explanation was perceived between the two conditions (human vs. AI). These measurements can help to further examine the reasons underlying the results presented in this study. *Third*, the number of recommendations could be additionally manipulated to examine the effect of one compared to multiple successive recommendations from the same source. Thus, the difference of anchoring and egocentric bias could be further analyzed. *Finally*, future studies could include different levels of urgency or impact of the decision outcome and analyze whether and, if so, how this changes the results depending on the source of recommendation.

5.6 Conclusion

This paper aims to explore how marketing managers perceive the explanation quality and how it differs between human and AI-based recommendations. Therefore, the results of this experimental study seek to contribute to the existing literature on managerial decision-making in marketing, psychology and AI technology. Until now, there has been no comparable study that successfully links these three topics and examines the difference between the source of advice (human vs. AI) and the perceived explanation quality.

The findings of the experimental study provide evidence that the perception of the recommendation differs when generated by AI or a human and should play an important role in the decision-making process. These results can lead to various consequences especially relevant in the managerial context. It is hence important to understand managers' individual perceptions when interacting with AI and to include these in the managerial decision-making in order to increase the acceptance of AI.

6. Conclusions and Implications

This section presents the overall conclusions and contributions to both research and practice based on a summary of the key findings of the four articles that constitute this dissertation. It also discusses the limitations of this study and makes suggestions for future research.

6.1 Summary of Key Findings

This dissertation began by considering the lack of research on AI in marketing (management). It has examined how marketing managers can thrive in the age of AI and cope with psychological and ethical barriers. The four articles gathered here have investigated the human factor, specifically marketing managers, and have interrelated four fields: AI, marketing management (strategy), psychology, and ethics.

Article 1 discussed the five central topics of AI in marketing (Data, Ethics, Applications in Marketing Management, Decision-Making, Management). On this basis, it identified current applications of AI within marketing as well as the manifold opportunities and challenges that influence marketing managers' expectations, decisions, and implementation of AI technologies. It enriched this discussion with a number of industry examples provided by the experts. The interviewed experts agree that AI continues to challenge not only companies and managers in various ways, but also society in general. Moreover, various ethical questions still need to be addressed in order to ensure a transparent collaboration between humans and AI. Thus, further research efforts are required, so that AI can develop its full potential.

Article 2 first extended an AI framework established by Daugherty and Wilson (2018) by advancing their model according to recent developments and expert comments (made during personal interviews). Second, it examined organizational drivers of and barriers to AI in marketing (management), outlined future developments, and suggested boundary conditions. Based on empirical evidence from three distinct investigations, this paper derived several research propositions in order to contribute to theory and practice. The propositions have a strategic and a behavioral focus, as well as an inward (i.e., internal challenges and opportunities in companies) and outward perspective (i.e., external issues, e.g., on the customer-side). The results offer a holistic view of the role of AI in marketing management and stimulate further research that is intended to help organizations overcome the current challenges of AI.

Article 3 highlighted the importance of including managers' decision responsibility and the factors driving responsibility in the decision process to increase the acceptance of AI recommendations. In particular, managers are less likely to accept an algorithmic recommendation when their perceived responsibility is high. In contrast, human recommendations do not differ by the degree of responsibility. This relationship was explained by including sense of ownership in the model. Managers' perceived responsibility positively influences sense of ownership, and affects the willingness to accept a recommendation. The source (human vs. AI) moderates this effect by decreasing sense of ownership, resulting in a stronger tendency to accept an advice. To further define more specific boundary conditions, I used an open question to analyze the reasons for accepting or discounting the advice. The results demonstrate the need to further examine why decision explicability plays an important role in discounting the advice, which was particularly prominent in the AI condition.

Article 4 demonstrated that blindly trusting AI recommendations is not sufficient to increase advice acceptance. Rather, recommendations must include a certain degree of explainability in order to improve managers' acceptance of AI. The results show the important role of the source of advice, which significantly affects the perceived explanation quality. In the human condition, managers therefore feel less informed about the received recommendation and rate the explanation quality as inferior. By comparison, an AI-generated advice results in a more informed decision, which also has better explanation quality. These findings contribute to understanding managers' perceptions of the explanation quality of AI-generated recommendations and why this leads to discounting such advice more often.

Together, the four articles sought to close the existing gap and to initiate further research on the intersection of AI, psychology and individual perceptions of AI, and ethics, especially in marketing management. Researchers and practitioners have already benefitted significantly from these findings and will continue to do so.

6.2 Theoretical Implications

This dissertation makes several important contributions to the literature on ethics, managerial decisions, AI, and psychology.

First, it links these four research fields by understanding the human factor and hence the perception of marketing managers when engaging with AI. In particular, it has examined how marketing managers should employ AI internally, in their organizations, as well as externally, in customer interactions. Thus, this dissertation contributes to previous conceptual work, which either focused on a single perspective (Duan, Edwards, & Dwivedi, 2019) or merely derived research questions (Davenport et al., 2020; Huang & Rust, 2021; Loureiro, Guerreiro, & Tussyadiah, 2021). It does so by identifying and structuring relevant and timely research propositions from both internal and external perspectives based on empirical research. The empirical evidence, obtained from experienced marketing managers, thought leaders, and experienced AI users (based on a mixed-methods approach), has enabled deriving research propositions that address marketing managers' and organizations' challenges when interacting with AI across three domains: Culture, Strategy, and Implementation; Decision-Making and Ethics; Customer Management. These propositions contribute to understanding the human factor in order to improve AI acceptance and to pursue further research across marketing, organizational behavior, psychology, and ethics.

Second, this dissertation highlights the importance of including an ethical point of view in the managerial decision process as well managers' individual perceptions. This approach is in line with observations made by the EU Commission (2019) about the crucial role of decision explicability and perceived responsibility in building and maintaining trust in AI. Based on these two critical ethical issues, this study has found that managers' perception of the explanation quality of recommendations differs strongly depending on the source of advice. Managers' willingness to accept a recommendation depends further on the perceived responsibility. Studies on the intersection of these four fields are scarce and have so far not highlighted the need to include the human perspective, mainly marketing managers. Thus, this dissertation provides a starting point for further closing the existing research gap in this context. Hence, managers' individual perceptions of AI should be actively used and included in the decision process. Further, rather than simply trusting AI recommendations as a black box, it is paramount to clearly understand the decision background, in order to ensure transparency and thus increase AI acceptance.

Third, this dissertation provides valuable insights into algorithm aversion (e.g., Dietvorst, Simmons, & Massey, 2015) versus appreciation (e.g., Logg, Minson, & Moore, 2019) in marketing management. The findings shed a more nuanced light on the mechanism underlying managers' perception and willingness to accept a recommendation. Advice utilization can be examined by looking at the drivers of advice taking and discounting (Yaniv, 2004; Bonaccio & Dalal, 2006). For this purpose, articles 3 and 4 analyzed managers' perceptions when engaging with AI and thus include an ethical perspective. Article 3 demonstrated managers' tendency to accept AI-based recommendations with lower perceived responsibility compared to a non-significant difference for human recommendations. Content analysis further identified the importance of receiving explanations for an advice (especially for AI-derived recommendations). Many managers mentioned this reason for discounting advice and that they would more likely accept a recommendation if it were explained in detail. Article 4 showed that managers' perception of the explanation quality significantly differs between AI-generated and human advice (even though no explanation was given). Human advice was perceived as less satisfying, with respondents (i.e., experienced marketing managers) demanding more information, whereas an AI-based recommendation was considered more self-sufficient (i.e., did less require asking further questions). One possible explanation for these partly contradictory findings might be that managers interact differently with AI compared to humans (Ryan, 2020). They are less likely to consider asking further questions when engaging with AI and thus may rate the explanation quality higher compared to human advice. Managers (and people in general) can always ask other humans for more information, and therefore can question the advice. Overall, these findings demonstrate that further research is needed to identify more potential boundary conditions.

Finally, and more generally, this dissertation has tackled the existing research gap concerning AI in marketing management and should be considered as a starting point for closing this gap. The topic is constantly evolving, meaning that many studies become outdated within a few years (Keding, 2020). Hence, the derived propositions (article 2) need to be continuously revaluated with the right sample to address the current situation. Researchers can benefit from these results in order to formulate hypotheses for future studies. In articles 3 and 4, hypotheses were developed based on two specific research propositions (i.e., Decision Explainability (P9) and Perceived Responsibility (P10)). Together with the conducted experiments, these propositions highlight the research potential in this area and help to understand how marketing managers can thrive in the age of AI and cope with psychological and ethical barriers to fully benefit from AI's potential for managerial decisions in marketing.

6.3 Managerial Implications

Besides offering valuable insights for research, this dissertation will also benefit managers and top executives.

First, managers can deepen their understanding of AI by using the extended conceptual AI framework. They can link AI methods to AI capabilities and AI applications in order to realize the possibilities and limitations of AI systems in marketing. Hence, marketing managers should possess a basic understanding of AI systems and the gathered data. For example, it is paramount to understand consumer behavior, in order to derive correct implications for further marketing activities, which in turn will deepen consumer relationships. Consequently, companies can reduce the negative perception of AI and unfold its potential in order to transform data into insights.

Second, the findings presented here can help managers better understand the value created by AI by addressing and discussing current managerial issues. This dissertation has developed research propositions about the little explored human factor in general and about the role of marketing managers in particular, in order to successfully implement AI for the benefit of (marketing) managers and consumers. In addition, by examining the tasks of marketing managers and by exploring managerial reactions to AI, this dissertation opens up avenues for further research. On the foundation established here, such research can help organizations overcome the current challenges of AI and improve its acceptance.

Third, the results demonstrate the particular relevance of ethical issues, such as transparency, responsibility, and explainability in managerial decisions. Managers need to stay in the loop to take final decisions—which may change in the next few years and thus need to be further evaluated. Ensuring a high degree of transparency requires properly explaining the decisions obtained through AI. The lack of explainability not only of AI reasoning but also of AI-generated recommendations are a main reason why managers discount an AI-based advice. Therefore, it is important to include more information of AI-based recommendations so that managers are able to justify their decisions. Otherwise, positive decision outcomes cannot be assured. Especially if the decision output turns out to be negative, marketing managers would be ultimately held responsible and accountable for any resulting errors. This perspective underscores the need to further include a robust ethical perspective, so as to ensure greater acceptance and utilization of AI in managerial decision-making.

Fourth, including AI systems in managerial decision-making in marketing requires considering various factors when implementing AI. Essential is a supportive corporate environment. The decision to implement AI should be taken top-down, and thus be leadership-supported. Additionally, the environment should be set up to overcome possible skepticism and thus to avoid a "Blame AI" culture. Implementing a trial-and-error culture could be potentially effective. As a starting point, it may help to calibrate management expectations upfront. In addition, businesses should also ensure that their managers do not blindly rely on the given advice. AI decision-making should be overseen in order to avoid biases or misguiding information (Dijkstra, 1999).

Lastly, not every digitization process needs AI. It is therefore crucial to examine whether a company really needs to implement AI tools. Further, the purpose of AI should depend on the goals set (i.e., the goals a company wants to achieve) and on whether AI is suitable to solve the existing problem. Hence, the optimal use of AI in marketing management should first be evaluated, with a view to achieving competitive advantages and benefitting from the initial investments. Whether AI is really necessary should be assessed based on the types of interaction (structured vs. open-ended) and their purposes (task-oriented vs. social-oriented). Businesses should optimize their strategy and hence be pursuing a more solution-oriented AI strategy today, thus seeking to better align technology with their specific use cases.

6.4 Methodological Limitations

As with all research, the limitations of this dissertation need to be discussed in order to highlight avenues for future research. This dissertation has limitations due to the chosen research design.

First, article 2 aimed to identify overarching themes and dimensions, and ultimately research propositions, in order to stimulate further research on timely and relevant domains aimed at improving organizations' approaches to AI. While the findings are based on three distinct studies, it is important to note that these are interpretative, which was essential for the research design. In addition, both an internal and external perspective were combined by applying a strategic and behavioral focus. This, however, should not imply that the themes, dimensions, perspectives, and focuses discussed in this dissertation are independent. On the contrary, they are profoundly interrelated. Thus, the identified propositions should be interpreted as potentially fruitful research directions derived from experts and confirmed by users for businesses to improve AI acceptance.

Second, given the need to investigate managers' reactions to AI, and given the relatively scant knowledge about applying AI methods, this dissertation drew on Daugherty and Wilson's (2018) model and used an exploratory approach to advance and to further establish an AI framework. During personal interviews (first round of the Delphi study), experts critically evaluated this framework, in order to identify current challenges and value-enhancing research propositions. The aim, therefore, was not to advance AI methods but to investigate the human perspective, so as to identify potential challenges and to convert these into useful AI capabilities and applications in marketing.

Third, to gain insights from multiple perspectives, a mixed-methods approach consisting of three distinct investigations was implemented: a two-round Delphi study, a quantitative survey, and two focus groups (article 2). The first study (Delphi study) involved heterogeneous participants from various fields and industries. While this approach is recommended for Delphi studies (Powell, 2003), the selection of experts always influences the interpretation of the results. To limit heterogeneity, and to avoid results being affected by larger cultural differences, the main focus was on experts from Western countries (Germany and Switzerland). In addition, Delphi studies utilize a lower sample size, complicating representativeness and thus generalizability. As a result, for this study a relatively large number of participants (n = 39) was recruited, in line with recent recommendations (e.g., Strohmeier, 2020). To address the limitations of the Delphi study, a second study (quantitative survey) was applied to validate experts' views from a practitioner and from a user perspective. These results led to dimensions and testable research propositions via exploration and interpretation with a more representative sample of experienced marketing managers (n = 101). To ultimately evaluate the appropriateness of the derived dimensions and propositions, two focus groups consisting of further marketing managers possessing sufficient AI experience were set up. These experts discussed the research propositions, further sharpened these in an AI context, and, if applicable, provided vivid examples in support of or against the propositions. As a result, and based on previous limitations, the research propositions were further refined, specifically linked to AI, and made testable, with a view to opening up promising avenues for further research.

Finally, to examine the cause-and-effect relations proposed by the formulated research proposition, experimental studies were employed (articles 3 and 4). Both articles referred to a specific marketing task in product development (Kotler, 1967). This task was chosen specifically to represent a strategic decision area in marketing (Huang & Rust, 2021). Hence, the results might differ depending on the selected marketing task. Consequently, other marketing tasks derived from the "4 Ps" (e.g., pricing, promotion or placement) should be examined further to analyze potential deviations in the results. Also, ice cream was chosen for the scenario. This particular consumer product was selected because it represents a low involvement product that everyone has been in contact with and that requires no further explanation (Shukla, 2004). In the scenario, products were shown as visual elements, in line with previous research, which has identified hedonic products[16] as better suited for generating visual attention for products (Feiereisen, Wong, & Broderick, 2008). This product choice may have included a biased view due to managers' personal consumption preferences during product selection and evaluation (Bettiga et al., 2020). Consequently, only one flavor, vanilla, was used, in order to minimize any potential personal and emotional consumption bias. The rationale underlying flavor selection was that vanilla ranks first in America's[17] top 10 favorites (International Dairy Foods Association, 2021).

6.5 Future Research Opportunities

This dissertation provides a starting point for future research and thus opens up manifold avenues for further research in various areas.

First, researchers can benefit from the derived research propositions (article 2) to formulate hypotheses for future studies. For example, the propositions should be seen as a starting point for conducting experiments aiming to test the proposed cause-and-effect relations. Hence, the experimental studies conducted (articles 3 and 4) should be considered as a basis for future research. Following this notion, subsequent studies might extend the data sample by assessing more cultural variations. Follow-up studies considering the views of other cultures and regions would be fruitful. One area could

[16] Ice cream products are categorized as a hedonic product, compared to a utilitarian product, such as milk (Maehle et al., 2015).

[17] Participants were explicitly chosen based on their native language (English) as a prerequisite for the desired population used in the two articles leading to have mainly American participants.

be to look at various AI possibilities and their individual perceptions in marketing (management). For instance, Asian countries are faster than European ones at developing new AI applications. One example is facial recognition, currently being used in various applications in Asia, such as malls, complexes, and office buildings or even in public bathrooms to stop toilet paper theft (Dou, 2021). In contrast, some of these applications are considered highly controversial ethically in western countries and therefore in need of regulation.

Second, it is critical not to consider the generated propositions as separate but to further explore when and how themes and dimensions are interrelated. Future studies could find further intersections between the research propositions (e.g., regarding ethical AI) and formulate additional research questions. Particularly, since the topic is still relatively novel and constantly evolving, many research studies become outdated within a few years (Keding, 2020). Hence, future studies need to continuously revaluate the derived propositions with the right sample so as to address the current situation.

Third, in regard to the conducted experimental studies (articles 3 and 4), the sample used might have included participants without the desired characteristics (i.e., managers with direct responsibility for at least one employee). Online experiments always involve the risk of participants giving wrong personal information to ensure participation in the study (Buchanan & Scofield, 2018). Future studies could replicate the experiments conducted here in field experiments, in order to first ensure a representative sample and second to increase external validity.

Fourth, additional experimental measurements and factors influencing managerial perceptions of and decisions for engaging with AI could be assessed in subsequent studies. Similar to other studies on advice taking (e.g., Van Swol & Sniezek, 2005), the advisor's confidence, authenticity, and credibility could be measured and compared depending on the source of recommendation. These scales could include as how objective, logical, relevant, useful, and reliable a recommendation is perceived. These measures could help to further examine the reasons underlying the presented results.

Finally, the received recommendation was presented in both experimental studies without any reasoning. Given that higher explainability was found to positively affect advice taking, subsequent research could include a more detailed advice explanation. Hence, future studies could analyze whether advice is more likely taken when managers receive more information, including different levels of explainability (e.g., Explainable AI vs. Black Box AI). In addition, managers received a recommendation by default.

However, it would be interesting to investigate the effect when managers need to actively request a recommendation. Yet another way of conducting such experiments would be to examine different levels of urgency as well as the impact (positive or negative) of the decision outcome. Based on Botti and McGill's (2006) definition of perceived responsibility, the degree of responsibility and blame can vary when using a positive or negative decision outcome (Botti & McGill, 2006). Future studies could hence adjust the manipulation and analyze whether and, if so, how this changes the results depending on the source of advice.

6.6 Conclusion

This dissertation has examined the human perspective at the intersection of technology (AI), psychology and individual perceptions of AI, and ethics. It has focused on marketing managers and their perception of AI by applying different lenses (strategic and behavioral focus from internal and external perspectives). This study contributes to understanding how marketing managers can thrive in the age of AI and cope with psychological and ethical barriers.

This dissertation significantly advances theoretical and practical understanding of the drivers, barriers, and future development of AI in marketing management as well as of managerial perceptions when interacting with AI. It has shown how to ensure transparent collaboration between humans and AI. However, numerous questions about this collaboration remain unanswered and require further investigation. In particular ethical questions need to be answered, for example, regarding responsibility for and the explainability of AI-based decisions. Further research is thus required, so that AI can unfold its full potential for the benefit of marketing managers. I am confident that this study will serve as a basis for future research, which will hopefully further refine the findings presented here and contribute to filling the remaining research gaps in the future.

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8. Resume Gioia Volkmar

Education

2018 – 2022	Ph.D. in Management (Area of concentration: Marketing Management, Artificial Intelligence, Psychology, Ethics) at the University of St.Gallen (Switzerland)
2012 – 2015	M.Sc. in Mechanical Engineering and Business Administration at the Technical University of Darmstadt (Germany)
2007 – 2012	B.Sc. in Mechanical Engineering and Business Administration at the Technical University of Darmstadt (Germany)
2010 – 2011	Student Exchange in Mechanical Engineering at the Thammasat University in Bangkok (Thailand)
2005 – 2007	Abitur at the German European School Singapore, GESS (Singapore)

Work Experience

2018 – Present	Research Associate at the Institute for Marketing and Customer Insight (University of St.Gallen, Switzerland)
2016 – 2017	Product Specialist (Sales Engineer) at JOTEC GmbH (Germany)
2011 – 2015	Student Assistant in the fields of International & External Relations and Law & Economics at the Technical University of Darmstadt (Germany)
2010 – 2016	Various internships at LESER GmbH & Co. KG – Sales/Export (Germany), Manufacturing Technology Ltd. – Quality Control and Maintenance (Singapore), PTS Progressive Co. Ltd. – Manufacturing and Machining Techniques (Thailand).

Honorary Activities

Since 2020	Reviewer for the European Marketing Academy (EMAC) Annual Conference
Since 2020	Scientific Committee Member for ICMarkTech International – Conference on Marketing and Technologies
Since 2009	Member of the Network TU 9 DANA – Graduate Network for German Schools abroad
2011 – 2015	Member of the Universities Student Council of the Faculty "Law & Economics"

Publication and Conference Contributions

2022	**Volkmar, G., Fischer, P. M., & Reinecke, S.** (2022). Artificial Intelligence and Machine Learning: Exploring Drivers, Barriers, and Future Developments in Marketing Management. *Journal of Business Research*, 149(10), 599-614.
2022	**Volkmar, G.** (2022). Managerial Decisions in Marketing: The Individual Perception of Explainable Artificial Intelligence. *Smart Innovation, Systems and Technologies*, 279(1), 15-21.
2022	**Volkmar, G.** (2022). Artificial Intelligence in Managerial Decisions: Understanding Perceived Responsibility and Willingness to Accept Recommendations. *Proceedings of the American Marketing Association*, 33(1), 571-582.
2021	**Volkmar, G.** (2021). Managerial Decisions in Marketing: The Individual Perception of Explainable Artificial Intelligence. *ICMarkTech'21 - International Conference on Marketing and Technologies of 2021*, Tenerife.
2021	**Volkmar, G., Reinecke, S., & Fischer, P. M.** (2021). Künstliche Intelligenz im Marketing: Möglichkeiten und Herausforderungen. *Die Unternehmung: Swiss Journal of Business Research and Practice*, 75(3), 359-375.
2020	**Volkmar, G.** (2020). Intelligent Systems: Towards Understanding the Perceived Responsibility for Managerial Decisions in Marketing. *Proceedings of the European Marketing Academy*, 49, (64541).
2020	**Volkmar, G.** (2020). How Can Marketing Managers Thrive in the Age of Artificial Intelligence? *Marketing and Smart Technologies,* 167(1), 444-448.
2019	**Volkmar, G.** (2019). How Can Marketing Manager Thrive in the Age of Artificial Intelligence? *ICMarkTech'19 - International Conference on Marketing and Technologies of 2019*, Porto.
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