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Artificial Intelligence and Machine Learning: Exploring drivers, barriers, and future developments in marketing management

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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.

"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).

1. 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).

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Table 1
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.

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 1).

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.

2. Theoretical Background

2.1. 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 Fig. 1 and Section 4.2). We thus follow extant research in regarding ML as an essential subdomain of AI (e.g., Mitchell, 1997; Goodfellow, Bengio, & Courville, 2016).

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.

2.2. 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,

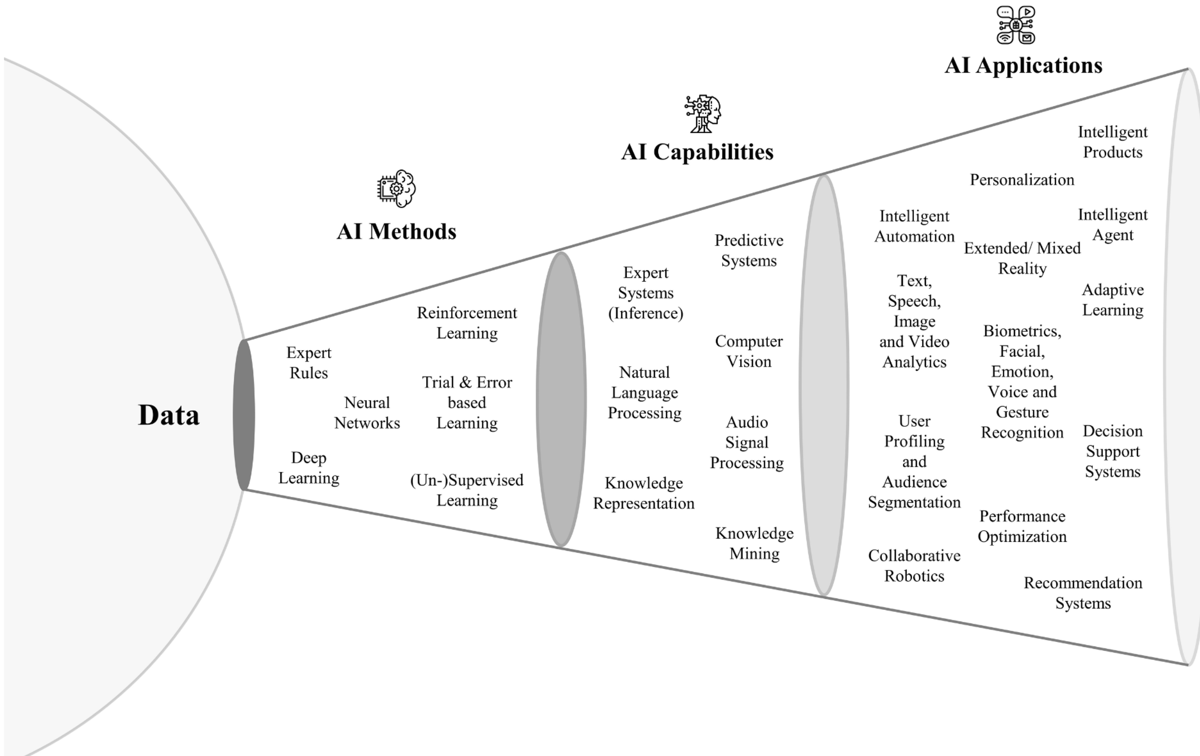

Fig. 1. AI and ML Framework. Developed framework, based on Russell & Norvig (2010) and Daugherty & Wilson (2018), and enhanced in Round 1 of our Delphi study.

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

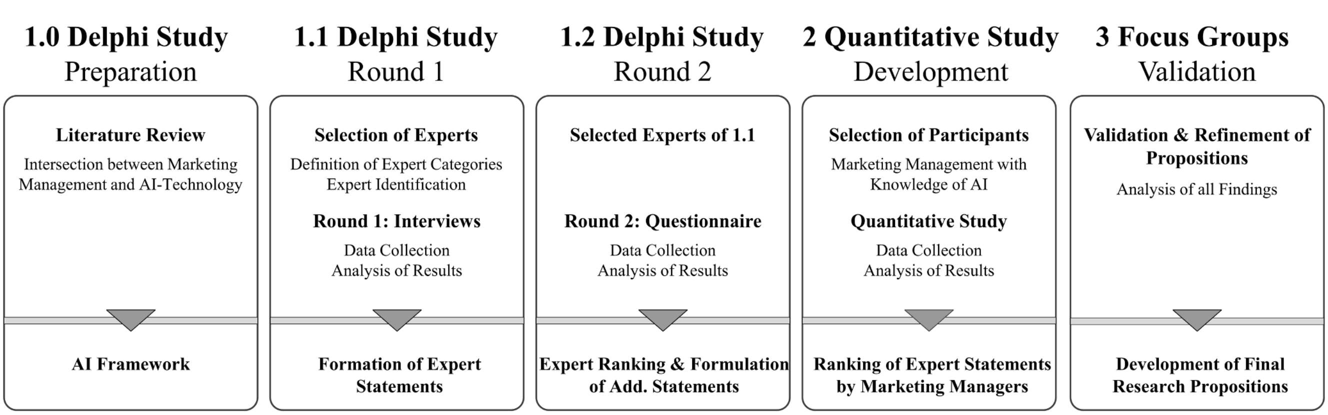

Fig. 2. Research Plan.

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 1). 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.

3. 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 (Fig. 2). 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.

4. Delphi Study: Generating and validating statements on AI and ML in marketing

4.1. 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).

4.2. 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* (Fig. 1). *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

Table 2
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		

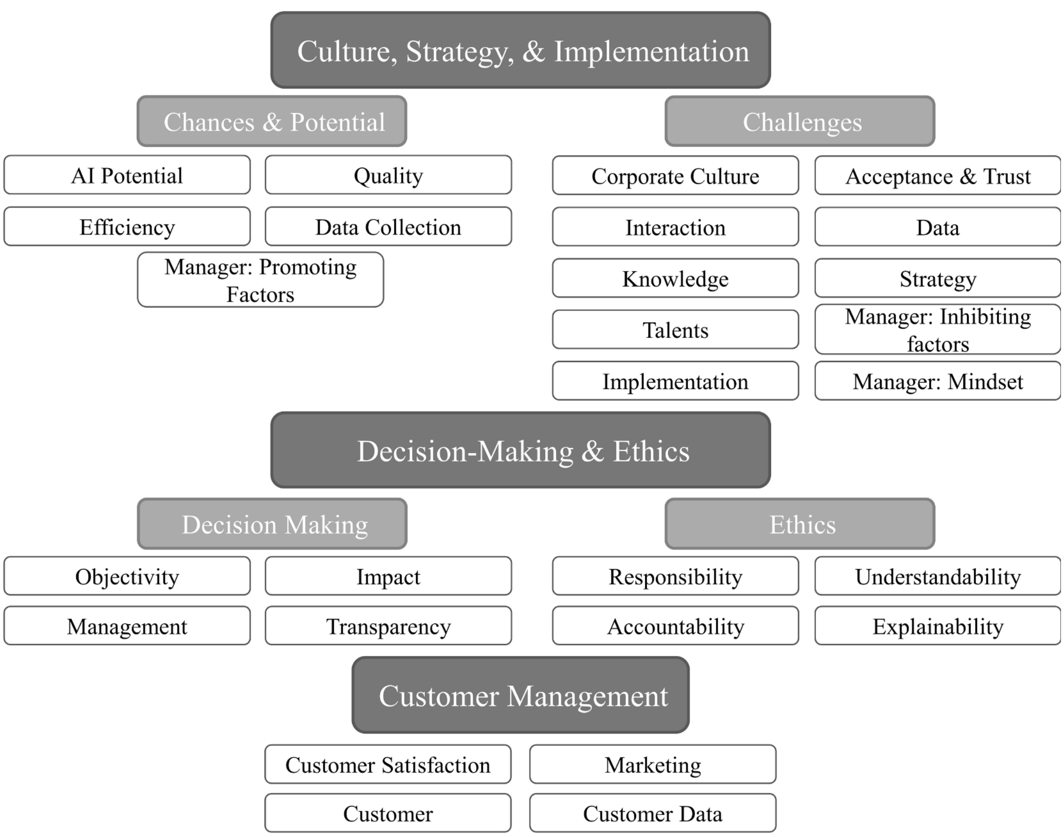

Fig. 3. Coding Categories.

Table 3
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

only a fraction of the data cloud.

4.3. Delphi Study: First round

4.3.1. Expert 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 Fig. 1). 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 2 shows the selected experts. So as not to jeopardize their openness, experts were not asked direct personal questions.

4.3.2. Data collection and procedure

Interviews lasted 30 to 90 min ($M = 42$ min, 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.

4.3.3. 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

Table 4
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 probabilites (“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 probabilites (“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.		

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 Fig. 3).

We derived 30 statements (see Table 3). 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.

4.4. 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.

4.4.1. Expert 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%.

4.4.2. 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 3 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.

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 4). 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.

5. Quantitative Survey: Cross-Validating statements and deriving propositions

5.1. Sampling and procedure

5.1.1. 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).

5.1.2. 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.

5.2. 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).

6. 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.

6.1. Study context and methodology

6.1.1. 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).

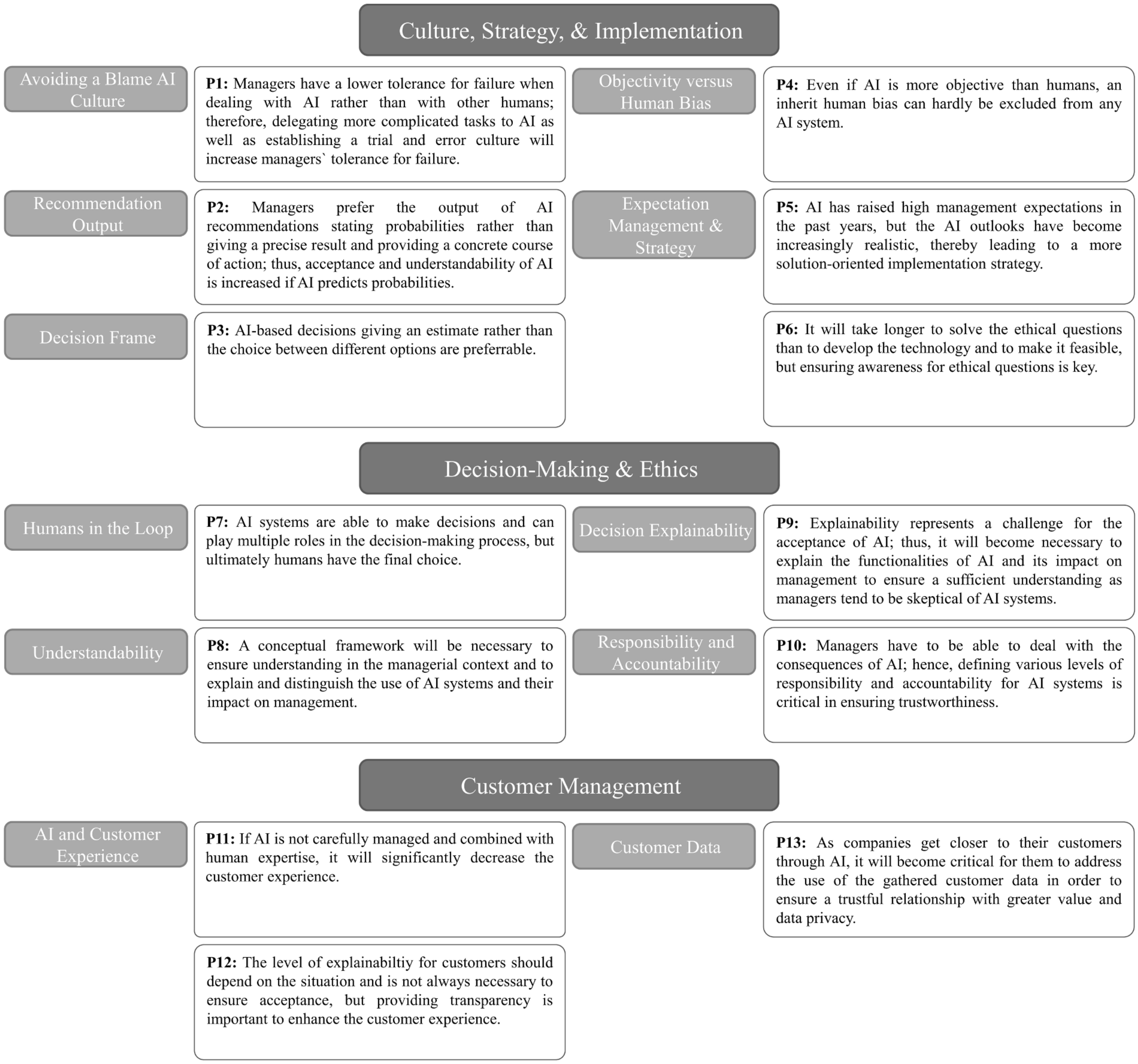

Fig. 4. Research Propositions.

6.1.2. 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).

6.2. 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 Fig. 4). Participants largely agreed on the remaining dimensions and their labels, and propositions were categorized into various dimensions and overarching themes.

6.2.1. 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* vs. *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.

> *"For image recognition we require […] 100% accuracy. Even a human cannot reach this level, but he [the superior] demanded 100% accuracy. 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 AI somehow, either due to training or the judgment in 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."

6.2.2. 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."

6.2.3. 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."

7. 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 (Fig. 4) thus contribute to theory and practice.

7.1. Theoretical Contributions

7.1.1. 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.

7.1.2. 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.

7.2. Managerial Contributions

7.2.1. 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.

7.2.2. 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).

7.3. 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.

CRediT authorship contribution statement

Gioia Volkmar: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Funding acquisition, Data curation, Conceptualization. **Peter M. Fischer:** Writing – review & editing, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sven Reinecke:** Conceptualization, Resources, Validation, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A1. 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		

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