

# Does AI control or support? Power shifts after AI system implementation in customer relationship management

Emmanuel Monod<sup>a</sup>, Raphael Lissillour<sup>b</sup>, Antonia Köster<sup>c</sup> and Qi Jiayin<sup>d</sup>

<sup>a</sup>Emmanuel Monod, UCMT Shanghai, China, Paris-Dauphine University, France and Case Western Reserve University, USA; <sup>b</sup>IPAG Business School, Paris France; <sup>c</sup>Antonia Köster, Weizenbaum Institute for the Networked Society, University of Potsdam, Chair for Business Informatics, esp. Social Media and Data Science, Germany; <sup>d</sup>Institute of AI and Change Management, Shanghai University of International Business and Economics, Shanghai, China

## ABSTRACT

Many companies are currently investing in artificial intelligence (AI) because of its potential to increase customer satisfaction or financial performance. However, the success rates in implementing AI systems are low, partly due to technology-centric approaches that neglect work practices. This study draws on Bourdieu's theory of practice to highlight the potential power shift related to AI in customer relationship management, based on the concepts field, capital, and habitus. Two longitudinal case studies were conducted to understand the power shift related to AI implementation. These two AI systems were designed with the objective to support employees. However, subsequently, their implementation changed the balance of power with a significant shift towards more management control, resulting in a devaluation of employees' work practices. The paper discusses implications for theory and practice in terms of the discrepancies and power shifts following the introduction of AI systems to support customer relationship management.

## ARTICLE HISTORY

Received 30 September 2021  
Accepted 11 April 2022

## KEYWORDS

Artificial intelligence; Customer relationship management; Theory of practice; Field of power; Social capital; Economic capital; Cultural capital; Symbolic capital; Habitus

## 1 Introduction

Artificial intelligence (AI) systems are increasingly implemented in customer relationship management (CRM), resulting in changes to work practices in this area (Frick et al., 2021). Indeed, CRM is currently one of the largest and growing market segments for AI applications (IDC, 2020).

AI has the potential to improve salespersons' and customer service representatives' work by facilitating different tasks, such as price optimisation, forecasting, up-selling, cross-selling, lead scoring, and performance management (Antonio, 2018; Benbya et al., 2020). At the same time, such AI implementation could also have unintended consequences related to a shift in power relations within the workplace (Conboy et al., 2021; Manley & Williams, 2019).

**CONTACT** Antonia Köster  [antonia.koester@uni-potsdam.de](mailto:antonia.koester@uni-potsdam.de)  Weizenbaum Institute for the Networked Society, University of Potsdam, Germany

This article has been republished with minor changes. These changes do not impact the academic content of the article.

© 2022 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.

This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives License (<http://creativecommons.org/licenses/by-nc-nd/4.0/>), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited, and is not altered, transformed, or built upon in any way. The terms on which this article has been published allow the posting of the Accepted Manuscript in a repository by the author(s) or with their consent.

Numerous publications about the use of AI in companies focus either on robotics and process automation (Adam et al., 2021) or on the link with data analytics in marketing (Davenport et al., 2020). However, little attention has been paid to AI's potential impact on the work of salespersons and customer service representatives. Prior research on CRM systems has focused on customer data quality (Alshawi et al., 2011), online trust (Khosravifar et al., 2012), customer knowledge (Khodakarami & Chan, 2014), infrastructure capability (Chuang & Lin, 2013), and organisational learning (Peltier et al., 2013). With the rising implementation of AI in CRM, research related to AI's impact on CRM practices is needed (Soltani & Navimipour, 2016). Specifically, research identifying barriers and unintended consequences associated with AI-induced changes in organisations is scarce (Conboy et al., 2021; Frick et al., 2021). This research gap is significant because AI implementation tends to shape new practices that lead to organisational change (Benbya et al., 2021) and, in turn, potentially impose impersonal discipline and greater control within the workplace (Manley & Williams, 2019; Markus, 1983; Zuboff, 2015).

Previous literature has noted that organisations embed technology adoption in a situated context (Ellway & Walsham, 2015; Orlikowski, 2000). In organisations, the employees are part of a larger social system, and their work practices are intertwined with the organisation's specific characteristics. In this study, we focus on the power change that stems from introducing an AI system to understand to which degree this technology facilitates work or reinforces management control over the workers. Therefore, this study raises the following research question: *What shifts in power relationships result from implementing AI systems in sales and customer service practices?*

To answer this question, we conducted two case studies examining the implementation of two different AI systems in different companies to understand the unintended consequences of AI implementation. These companies were selected to highlight the challenges of AI implementation in the context of CRM. The first company, a large telecommunication company in China (anonymously called Alpha), introduced an AI system for its own customer service department. The second company (Sennsee), a high-tech start-up, implemented an AI system for sales in three different mid-size client companies representing car retailers and real estate companies. These case studies were then analysed by drawing on Bourdieu's theory of practice (Bourdieu, 1998). The theory provides a comprehensive practice-oriented lens that considers power relations in organisational settings (Kumar et al., 2021; Levina & Orlikowski, 2009). We used this theoretical basis to examine the impact of introducing a new AI system in the two cases by considering the relative power positions and emerging work patterns of managers and their employees.

This study makes several contributions to research and practice. First, this study contributes to prior literature in extending our understanding of how AI is implemented. By considering the socio-technical context in which AI is deployed (Benbya et al., 2021; Frick et al., 2021), we find that power-related issues can hinder the successful implementation of AI systems in CRM or can affect the intended objectives. The proposition that AI systems can lead to unintended consequences has been demonstrated in practice (Manyika & Sneider, 2018) and received extensive support in the literature related to the impact of AI (Benbya et al., 2020; Strich et al., 2021). Researchers seeking to understand the drivers of unintended consequences for companies in the context of AI systems will find our study's insights fruitful. Second, we find how implementing new AI systems leads to shifts in power relations between the CRM workforce and the management. This shift can involve different

kinds of employees' resources, including their social, economic, cultural, or symbolic resources. Therefore, this study contributes to the emerging body of research that explores the concept of algorithmic management and its possible relation to extended control over employees (Hughes et al., 2019; Manley & Williams, 2019; Schafheitle et al., 2020). Companies struggling to capitalise on AI implementation (McKinsey & Company, 2020) could use these insights to clarify AI design objectives and to ensure consistency between such design and the subsequent implementation and use of AI.

The paper is organised as follows: First, we discuss the existing literature on AI and power relations. Second, we relate these discussions to Bourdieu's practice theory. Third, the study introduces the methodology of the field research, and the fourth part gives a discussion of the findings. Finally, implications from these findings are outlined for both theory and practice.

## 2 Theoretical background

### 2.1 Artificial intelligence and power relations

Many companies are interested in implementing AI systems in CRM because they expect a positive impact on their growth and profitability (Antonio, 2018; Benbya et al., 2020; Von Krogh, 2018). Although CRM systems and automation have been widely studied in information systems (IS) literature, AI systems' unique characteristics distinguish them from typical CRM systems used in the sales and customer service domains (Chatterjee et al., 2019). First, AI systems have the potential to substitute entire workflow processes, not only specific tasks (Strich et al., 2021). Second, an AI system's ability to learn allows it to potentially process more information and derive decisions beyond the employee's cognitive ability (Chatterjee et al., 2019; Faraj et al., 2018). Third, AI systems can lack transparency (Bayer et al., 2021) due to the high complexity of the underlying algorithmic layers, so that the recommendations or even decision outcomes can remain a 'black box' to employees (Benbya et al., 2020; Schmidt et al., 2020).

Even if employees appreciate their organisations' efforts to be at the cutting edge in technological advancement and implementing innovative work practices, organisational research finds that employees often believe their companies seek to use AI in labour substitution rather than in work enhancement (Amis et al., 2020; Markus, 1983). Therefore, power is a relevant concept in the AI context because it can capture whether and to what extent an AI system is used according to a substitution or enhancement perspective, in other words, for either controlling or empowering workers (Cattaneo & Chapman, 2010).

Through automation and, therefore, labour substitution AI can potentially increase managers' control over workers by structuring hierarchies (Benbya et al., 2020; Manyika & Sneider, 2018), especially by establishing enhanced supervision and monitoring (Amis et al., 2020; Manley & Williams, 2019). Such control might result in an inequality gap between high-skilled and low-skilled workers (Amis et al., 2020; Craypo & Cormier, 2000). However, AI can also potentially empower CRM workers.

## 2.2 A practice-based perspective

The concept of practice is often used in IS independently from exercising power, for instance, by Orlikowski (2002), who defines practice as a 'recurrent, materially bounded and situated action engaged in by members of a community' (Orlikowski, 2002, p. 256). In Bourdieu's theory of practice, the actions actors perform are related to power through the concepts of field, capital, and habitus. In this theory, the field is used to conceptualise organisations as spaces of relative social positions, in which actors struggle to maintain or improve their positions vis-a-vis other actors (Bourdieu, 1998). The field is a conflictual and competitive space where 'hierarchy is continually contested' by actors depending on their power (Bourdieu, 1985, p. 52). In the context of this research, actors include managers and their employees,<sup>1</sup> whereas the field is the company's organisational setting.

In Bourdieu's practice theory, power is assigned to a higher position in the field. Such a higher position might be reachable through resources that are conceptualised as different forms of capital. In other words, power relies on the relative endowment of different forms of capital unequally distributed in the field. Capital endowment is both the means to exert power and the stake in the field by which to obtain more influence over the other actors. The highest power position is achieved when capital is 'appropriated on a private, i.e. exclusive, basis by agents or groups of agents' (Bourdieu, 1986, p. 241). The field is divided into two categories: those endowed with the right types of capital for a particular use and those who are not. The concept of capital, therefore, includes the principles of inclusion and exclusion of the field, as actors 'constantly work to differentiate themselves from their closest rivals' (Bourdieu & Wacquant, 1992, p. 100). Thus, power relations are a form of social structure generated and reproduced through the everyday practices of actors in the field (Levina & Orlikowski, 2009).

Bourdieu's practice theory identifies four types of capital, namely economic, cultural, social, and symbolic capital. *Economic capital* relates to the relative control afforded by physical and financial resources such as money, access to technology, and time. *Cultural capital* refers to cultural skills such as professional expertise, ownership of information, and a university degree (Bourdieu, 1986). *Social capital* can be defined as actors' ability to draw resources from their networks of interpersonal relations inside or outside organisations, including hierarchical positions, friends, family or distant acquaintances (Bourdieu & Wacquant, 1992). Finally, *symbolic capital* refers to the ability to ponder the value of other types of capital in the field. It also encompasses the power to classify the social world and impose one's classification principles. Thus, *symbolic capital* depends on actors' status and 'the degree of accumulated prestige, consecration, or honor' each has (Bourdieu, 1993, p. 7).

In addition to field and types of capital, a third concept related to power is called *habitus*, which Bourdieu defines as 'an acquired system of generative schemes objectively adjusted to the particular conditions in which it is constituted; the habitus engenders all the thoughts, all the perceptions, and all the actions consistent with those conditions, and no others' (Bourdieu, 1977, p. 95). Habitus can be understood as a representation of a specific field and its social hierarchy inside an organisation (Kumar et al., 2021). This theory understands an individuals' practices within a given context as influenced by the power structures within the specific field, the person's habitus, and the capital with which the individual is endowed (Kumar et al., 2021).

Therefore, Bourdieu's practice theory allows us to understand AI implementation in the context of a field of power, the relative endowments of the different types of capital, and how AI might influence the habitus of both employees and managers. Specifically, considering the habitus of employees and managers, AI could change the different capital endowments and thereby transform the respective power positions, in other words, the field of power.

### 3 Research method

This section describes the research method, giving an overview of the case studies, the research design and process, data collection, data analysis, and data trustworthiness.

The case study approach is well established in the IS literature and a preferred way of investigating organisational experience (Tsang, 2014). Case studies have already provided many answers in the management context (Eisenhardt & Graebner, 2007) and are particularly suitable for answering why and how questions. They provide researchers with insight into new research areas and enable unravelling of underlying dynamic processes (Siggelkow, 2007). Accordingly, we chose a case study approach to investigate our research question developed in response to the lack of prior research on AI-induced power changes in CRM. In the two case studies, the first exploratory phase was conducted in an inductive mode, following a qualitative case study design (Eisenhardt & Graebner, 2007). Our cases are intended to be illustrative (Siggelkow, 2007), particularly considering that Bourdieu's (1977) practice theory is an interpretative framework.

#### 3.1 Introduction of the cases

Due to a dearth of deductive studies in AI and CRM, the companies we studied were not chosen to replicate previous cases or extend emergent theory; rather, they were selected to fill theoretical categories. Therefore, the choice of each case relied on theoretical sampling, not statistical sampling (Glaser & Strauss, 1967). Beyond theoretical sampling, the choice was also influenced by the opportunity to access one of the first AI implementation cases in China in a CRM context. The two cases implemented AI systems in different sales process stages, namely for supporting sales and customer services. Thus, the analysis of two cases enabled us to match findings across cases and to better understand the overall context. Before describing the data collection and analysis, we provide an overview of each case company and its corresponding AI system.

##### 3.1.1 Alpha

The first case, Alpha, is a large telecom company in China. Alpha strategically decided to implement an AI Customer Service Assistant (AI-CS) to improve customer relations. Specifically, Alpha focuses on after-sales services, which were suboptimally provided via an Internet platform and call centres before the AI-CS introduction. In 2015, the Alpha company integrated its initial AI-CS mobile app. It was a semantic algorithm designed to help the customer service section solve customer issues through human-machine interaction. New AI features were added in 2017, namely the Internet AI, the SMS AI, and a physical robot. In early 2018, speech recognition was added, and the complete app migrated to a service cloud platform. Later in 2018, the company gradually started to

initiate interactive voice response and SMS functionality. By December 2018, nearly 200 service contact points throughout the country used AI-CSs (Internal technical document, Alpha). In 2020, Alpha's AI technology was a cloud platform built on natural language understanding, a sub-technology of Natural Language Processing (NLP), speech recognition, as well as text to speech technology, artificial assisted training, training sharing, tier-based authorisation systems, vendor management, and service policy management.

### **3.1.2 Sennsee**

The second case comprises an AI system called Sennsee, which is the company's real name derived from the words 'sense and see'. This study encompasses the AI provider and three use cases, i.e. companies using this AI solution. The provider, Sennsee, is a small high-tech company in Changsha, Hunan province, China, that develops AI solutions for sales management. Their business concept is based on NLP, natural language generation, social semantics, mobile internet, cloud computing, and big data. When it was founded in 2018, Sennsee made a strategic decision to develop an AI Sales Assistant (AI-SA) to improve the performance of the sales staff from their client companies. Sennsee's initial AI solution design includes hardware and software components. Even though the software is Sennsee's core capability, the hardware is instrumental to the AI-SA's success. The hardware is a customised smartphone manufactured in cooperation with Xiaomi, a leading Chinese mobile phone producer. The sales department's compulsory use of this smartphone for all customer communication enables the automatic collection of telephone conversations, WeChat messages, and other interactions. All audio data is converted into text and parsed with conversations and chat texts. AI models trained for prediction modelling continuously analyse the accumulated data and gradually enhance the system's ability to 'understand' complex sales situations, which improves prediction accuracy in providing sales support. After the data analysis, Sennsee's AI-SA solution provides algorithmic support for sales employees and management, such as delivering increasingly accurate reports, automatically allocating business opportunities, and showing total sales positions. These support features include call reminders, automatically generated plans and reports, and sales leads identified and created with potential customers. Notably, the AI-SA design relies on support from the top management at client companies since sales employees' ability to effectively use the smartphone is a necessary requirement to successfully implement the AI.

## **3.2 Research process**

The research process included purposeful sampling, multiple investigators, and multiple data collection techniques. We chose informants following the guidelines for purposeful sampling (Lincoln & Guba, 1985). In the case of Alpha, the informant's status included different hierarchical levels, and in the case of Sennsee, we considered different companies using the AI system (see, Table 1 and Table 2). Additionally, the study followed the principle of data triangulation, combining multiple data collection techniques (Yin, 2009), including (1) face-to-face interviews, (2) digital interviews, (3) archival documentation analysis, and (4) field observation. The face-to-face interviews were the primary data source, with the documentation, phone interviews, and direct observation serving as supplementary sources in the triangulation towards a better understanding of the phenomena. The following section describes how data was collected.

**Table 1.** Interviews related to the Alpha system.

Position	Number of years in the position	Number of years of experience (estimation)	Schedule	Number of interviews
Project manager	8	12	May 2019, face-to-face	7
Operation manager	5	5	May 2019, face-to-face	6
Product manager	7	10	May 2019, face-to-face	5
Vice product manager	2	5	May 2019, face-to-face	3
SMS robot manager	2	5	May 2019, face-to-face	1
IVR robot product manager	3	8	May 2019, face-to-face	1
IVR robot operation manager	4	10	May 2019, face-to-face	1
Real robot product manager	5	8	May 2019, face-to-face	1
Real robot operation manager	6	7	May 2019, face-to-face	1
Database manager	9	12	May 2019, face-to-face	1
CS robot product manager	6	10	May 2019, face-to-face	1
CS robot operation manager	10	17	May 2019, face-to-face	1
Text parsing and QC robot product manager	3	7	May 2019, face-to-face	1
Text parsing and QC robot operation manager	4	7	May 2019, face-to-face	1
CS manager	10	15	April 2020, digital	1
CS manager	8	8	April 2020, digital	1
CS manager	5	7	April 2020, digital	1
CS manager	3	4	April 2020, digital	1
CS manager	2	10	April 2020, digital	1
				Total: 36

### 3.3 Data collection

#### 3.3.1 Semi-structured interviews

The primary source of data was semi-structured face-to-face, one-to-one interviews conducted on the companies' premises. These premises included the Alpha company's headquarters and, in the case of Sennsee, their headquarters, and different customers' premises. The interviews were conducted by various investigators (Eisenhardt & Graebner, 2007). In the beginning, multiple semi-structured face-to-face interviews were conducted on site. The interviews were structured according to an interview guideline that we modified as the research progressed. The initial interview protocol was largely standardised across informants, with some adaptation to accommodate different hierarchical levels. Subsequent interviews, especially the follow-up digital interviews, became progressively more structured as themes emerged in the data. One such theme was the system's failure to deliver on its promises. These progressively focused interviews allowed for targeted data collection in our attempts to identify patterns across informants, as well as tentative relations between concepts. In later interviews, we asked informants about AI system use dimensions that had developed through the initial interviews. Thus, the content of subsequent interviews focused on categories and themes represented in the emerging data structure. Table 1 and Table 2 present the list of the respondents. In all, we conducted 36 interviews at Alpha and 34 at Sennsee.

In the case of Sennsee, the face-to-face interviews were conducted during a five-day period in the city of Changsha (Hunan, China). During the first two days, interviews were conducted at the AI technology provider, Sennsee, with managers and employees ranging from the CEO and the CTO to a number of salespersons. During the next three days, the CEO and CTO drove the research team of two investigators to the settings of their

**Table 2.** Interviews related to the Sennsee system.

Company	Position	Number of years in the position	Number of years of experience (estimation)	Schedule	Number of interviews
AI provider: Sennsee	Chief Executive Officer (CEO), one of the Sennsee founders	1	12	January to April 2018: digital May 2018, face-to-face	10
AI provider: Sennsee	Chief Technology Officer, R&D (CTO), one of the Sennsee founders	1	16	January to July 2021: digital May 2018, face-to-face	12
AI provider: Sennsee	Salesperson	1	7	May 2018, face-to-face	1
AI provider: Sennsee	Salesperson	1	8	May 2018, face-to-face	1
Customer 1: Real Estate	CEO	5	9	May 2018, face-to-face	1
Customer 1: Real Estate	Chief Marketing Officer (CMO)	4	4	May 2018, face-to-face	1
Customer 1: Real Estate	Salesperson	2	5	May 2018, face-to-face	1
Customer 2: Suzuki Car Retailer	CEO	6	10	May 2018, face-to-face	1
Customer 2: Suzuki Car Retailer	CMO	4	7	May 2018, face-to-face	1
Customer 2: Suzuki Car Retailer	Salesperson	2	3	May 2018, face-to-face	1
Customer 2: Suzuki Car Retailer	Salesperson	1	4	May 2018, face-to-face	1
Customer 3: Bentley Car Retailer	CEO	7	15	May 2018, face-to-face	1
Customer 3: Bentley Car Retailer	Salesperson	2	3	May 2018, face-to-face	1
Customer 3: Bentley Car Retailer	Salesperson	3	5	May 2018, face-to-face	1
<b>Total:</b>					<b>34</b>

clients, all still located in the city of Changsha. At each client's premises, the executive manager welcomed the research team in his office, where an initial interview of 60 to 90 minutes was conducted. Next, the executive team introduced salespersons who used the AI system to the researchers. Whereas some executives left the research team during the interview with the salespersons, in other cases, such as at the Bentley car dealer, the executives remained present during this interview. The research team relied on the same interview guideline in all cases, starting with open questions and moving to more closed questions towards the end of the interview. In the case of Alpha, these face-to-face interviews took place during a three-day period in the company's main building in China. After a welcoming meeting that included all the IT team workers, each team member met the investigators individually for 60 to 90 minutes in a company office set aside for the research project.

Semi-structured interviews were conducted in Chinese by a team of two interviewers in the case of Sennsee and a team of three interviewers in the case of Alpha. In each case, one researcher handled the interview questions, whereas the other kept a more distant view while taking notes and making observations. A third researcher conducted preparatory and follow-up interviews before and after the field visit by telephone and WeChat. The face-to-face interviews were audio-recorded and transcribed verbatim by the research team. In the case of Alpha, the third researcher provided a translation from Chinese to English, while a third party provided these translations in the case of Sennsee.

The non-recorded interviews were captured by one researcher making detailed notes after the interview. Informants varied in both functional areas and hierarchical levels. To minimise an informant's bias towards our evolving interpretations that could arise from interview questions in follow-up interviews, we structured later interviews by identifying issues other informants had raised and used terms informants had generated to frame questions or general terms.

### **3.3.2 Documentation and observation**

To supplement the primary data source of face-to-face interviews, we collected secondary data from other sources. Through archival documentation analysis, we could double-check findings against multiple sources and different modes of evidence (Eisenhardt & Graebner, 2007; Jick, 1979). In the case of Alpha, the documents included an internal description of the system gathered in a PowerPoint document (54 pages) and a description of the system's intended design collected from other complementary documents. In the case of Sennsee, the first documentation source was the description of the system on the company's website. Such description was not available in the case of Alpha, as they considered their system to be a competitive advantage that they wanted to remain secret. In contrast, Sennsee was a start-up eager to promote its AI solution. The Sennsee executives provided an additional marketing PowerPoint (15 pages) describing the system's design in detail. This marketing PowerPoint evolved during the study period. Also, the CEO and the CTO orally presented this document to the interview team. In both cases, all these documents were in Chinese and had to be translated into English by one of the researchers. Archival documents also included systems artefacts, such as screenshots of the real system, and other contextual material, such as electronic documents related to strategic and operational aspects of the company. Our observations were very limited despite notes we took during the field visit.

Overall, the multiplicity of data sources enabled us to compare different constituencies and discrepancies among informants to gain additional perspectives on key issues (Huberman & Miles, 1994). Specifically, such comparisons revealed the discrepancies between the design and the actual use of the AI system on the one hand and between the managers' use as opposed to the salespersons' and customer service representatives' uses on the other hand.

### 3.4 Data analysis

In both cases, we conducted data analysis and data collection concurrently, which is in accordance with the guidelines established for constant comparison techniques (Glaser & Strauss, 1967). Although our study did not achieve an overlap comparable to grounded theory, which would have involved a joint collection, coding, and data analysis, we maintained such an overlap during the study. Thanks to overlap during data collection and data analysis, the analysis could start early in the research process and allowed the investigators to adapt to specific themes that emerged during the data collection process. Additional adjustments were made to the data collection instruments, such as adding questions to the interview protocol related to the emerging themes we discovered mainly through interviews with clients (corporate customers). This flexibility through controlled openness allowed the investigators to take advantage of the uniqueness of a specific case and the emergence of new themes (Eisenhardt & Graebner, 2007). These principles provided the basis for clearly delineating themes and aggregate dimensions that were not obvious from the beginning. The analytic process consisted of three steps, which were to identify first-order concepts, to define theoretical categories and subcategories, and to aggregate theoretical dimensions (Corley & Gioia, 2004). The data coding is illustrated in [Figure 1](#) and [Figure 2](#) in the appendix, which summarises the dimensions, on which we built our results.

#### 3.4.1 First-order concepts

First-order concepts consist of statements and descriptions drawn from the interviews and documentation analysis through identifying initial concepts in the data and grouping them into categories (Yin, 2009). At this initial stage, the focus was on identifying consistent issues and relationships across the data sources (Corley & Gioia, 2004). This phase relied on the principle of open coding, using the language informants used or simple descriptive phrases as often as possible (Glaser & Strauss, 1967). The next step of this iterative process was to systematically compare the emergent frame of the first-order concepts with evidence from the field to assess how well it fits with the case data. We followed a two-part process involving (1) building evidence that measures the construct in each case and (2) refining the definition of the construct. This occurred through comparing data and concepts so that accumulated evidence from diverse sources, such as face-to-face interviews, digital interviews, and documents on a single, well-defined concept, converged (Glaser & Strauss, 1967).

#### 3.4.2 Second-order concepts

In the next stage, the numerous dimensions related to power, as suggested in the first-order concepts, are described. This is justified by our reliance on Bourdieu's practice theory (Bourdieu, 1977) as an emergent theoretical framework. Therefore, whereas the

first-order concepts were inductive, the second-order concepts were framed by this theoretical framework; however, they remained consistent through a rewording of the first-order concepts.

### **3.4.3 Theoretical dimensions**

Finally, we aggregated the second-order concepts into theoretical dimensions included in Bourdieu's practice theory, gathering similar themes into several overarching dimensions that make up the basis of the theoretical interpretation. These techniques were not linear; instead, they formed a recursive, process-oriented, analytic procedure (Locke, 1996) that continued until we had a clear grasp of the emerging theoretical relationships, and additional interviews failed to reveal new data relationships (Corley & Gioia, 2004).

### **3.5 Data trustworthiness**

We checked the trustworthiness of our data through two processes. First, the data, including contact records, interview transcripts, and documents, were stored in a database that included the source and type of information. Second, we used peer debriefing, which entailed the field researchers engaging the co-authors not involved in the field study to discuss emerging data patterns, serving as a sounding board for evolving propositions, and soliciting critical questions about the data collection and analysis procedures. This provided a means for the field researchers to vet their ideas through another researcher, thereby also gaining an outsider's perspective (Corley & Gioia, 2004).

### **3.6 Overall research process**

Despite the consistency of the data gathering with some aspects of grounded theory (Corley & Gioia, 2004; Glaser & Strauss, 1967), the overall research process was not inductive beyond the first-order concepts, thus it moved towards a positivist case study (Yin, 2009) framed by the theoretical concept of Bourdieu's practice theory (Bourdieu, 1977). However, throughout the research process, the principles of multiple data collection techniques and multiple investigators helped us to view evidence from diverse perspectives. These principles kept the investigators from premature closure in case of conflicting perceptions (Eisenhardt & Graebner, 2007). Also, the research process was strikingly iterative. It required frequent iteration backward and forward between steps. The investigators who conducted interviews on site moved back to redefine the research question and gathered additional evidence by means of digital interviews (telephone and social media), as well as from additional archived material. Also, the process was characterised by a tension between divergence into new ways of understanding the data and convergence into the final single theoretical framework of Bourdieu's practice theory. The process centred on the juxtaposition of contradictory or paradoxical evidence in an attempt to reconcile evidence across types of data and different investigators to limit bias towards investigators' preconceptions.

## 4 Findings and analysis

In this section, we present the results of each case separately. Specifically, the case descriptions provide the overall context by illustrating how the AI was implemented in each case, focusing on (1) the narrative of AI implementation to enhance the work practices of sales and customer service employees, as well as their managers; (2) how the AI system was used to monitor and track work practices, and (3) the organisational consequences that were reported subsequent to AI implementation.

### 4.1 Case 1: Alpha

#### 4.1.1 Artificial intelligence and support

The executives claimed that they expected the AI system to empower customer service representatives. Thus, the AI-CS's main objectives were to provide employees with suggestions, improve efficiency, and enhance service quality (Internal technical document, p. 9). *'When the customer calls, the call is connected both to the human customer service representative and the AI. The AI will push some knowledge to the customer service people for them to provide good support to the customer'* (AI-CS database manager, Alpha). This knowledge included a description of the company's products relevant to the customer's inquiry. As the voice conversation is converted into text, the system is able to suggest the response most relevant to the customer. The users are expected to indicate whether the recommendation was suitable or not. Therefore, the AI-CS suggestions do not overtly impose any imperatives because accepting or rejecting the AI suggestions remains the employee's decision. Based on historical purchasing and consumer behaviour, the system provides predictive insight into which products might appeal to the customer. The customer's acceptance or rejection of the predictive insight is then recorded by the customer service employee, which enables continuous training of the AI-CS.

#### 4.1.2 Artificial intelligence and control

The objectives of implementing the AI were *'to monitor the customer service employees. This includes the speed of speech, the attitude of the employees, and their emotions during the calls with the customers'* (CS manager, Alpha). Insufficient contextualisation is evident in the automatic control: *'The system can automatically monitor the service quality of the human'* (CS manager, Alpha). Indeed, they created 'attitude' as a measure by combining the employee's voice speed and indicators of their emotional presence during the call. One of the managers stated, *'Thanks to the AI, a part of the operations can be tracked [. . .]. If the customer service employee's attitude is not good in all aspects, the AI can send them a warning in real time'* (CS manager, Alpha).

The AI-CS helps the management to identify good performers among the customer service representatives, as to track their behaviour. The recurrent AI-CS use is related to quantifying performance: *'The AI system can make the employees' work more quantitative'* (CS manager, Alpha). More precisely, the AI-CS is perceived to be *'helpful for performance*

appraisal' and 'Key Performance Indicators (KPIs) are created from the data collected from each customer service employee' (CS manager, Alpha). Therefore, KPIs facilitate automatic performance appraisal.

#### 4.1.3 Organisational consequences

The AI-CS project manager noted: *'Between what the design intended to achieve and the usage, there was a gap, a big gap'* (AI-CS project manager, Alpha). All managers agreed that the goal of AI-CS is to reduce the number of employees and thereby promote cost-saving: *'To lift performance by decreasing the number of employees'*. One manager explained: *'The objective is to reduce dependence on customer service employees to make up for the [customer] loss rate'* (CS manager, Alpha). We found that only cost saving was mentioned as a means of improving performance, with no reference to growth or innovation: *'for the moment the AI requires a lot of manpower for training. We increase such investment to meet the requirement of reducing the number of customer service representatives'* (CS manager, Alpha). The primary imperative seems to be a capital-labour substitution, as *'AI can replace customer service representatives at the front-end and in steps toward self-service'* (CS manager, Alpha). The manager's perspective is to gradually cover each step of the process with AI, from 'front-end steps' to 'self-service steps'. The 'steps' of the process take the place of situated practices and embodied know-how.

The structural change generated by implementing the AI-CS produced a conflict of interests that materialised as user resistance. Managers associate this employee resistance with a lack of knowledge, holding that they *'don't have enough perception and understanding [...] of the bugs AI generates, which cause extra burdens for them'* (CS manager, Alpha). This result suggests that limited consultation took place and managers, therefore, possess strategic knowledge about the AI system's design that employees do not have. The AI brought a shift that put managers in a position with a high level of information about the AI system.

## 4.2 Case 2: Sennsee

### 4.2.1 Artificial intelligence and support

Sennsee's board of directors predominantly described their AI-SA as providing technological support for *'the sales team, the service team, especially through the mobile hardware'* (CEO, Sennsee). Sennsee's CTO confirmed that *'the final aim of our product is to support salespersons'* rather than giving more control to the top management. Sennsee's promotional material explicitly states that the AI-SA intention is to support salespersons by providing *'guidance to employees and improving the employees' work efficiency in a sales scenario'* (Marketing document, p. 6). The AI system is *'a complement, not a substitute for the human connection'* (Bentley retailer, salesperson), indicating that the salesforce would still enjoy the freedom to overrule or alter the AI-derived outcomes and continue their preferred practices to achieve their sales goals. Further, Sennsee AI-SA *'supports phone call recording, WeChat public account recording, QR codes, face-to-face scanning, in-batch importing, automatic lead collecting and generating, and turns confirmed leads into business opportunities'* (Marketing document, p. 7). This feature arguably provides benefits and supports salespersons as it optimises the sales pipeline. Also,

the AI-SA is designed to optimise the salespersons' follow-up of each business opportunity through its tracking and learning features: *'The system helps me to look deeply into every customer clue'* (CEO, Bentley retailer). To optimise business opportunities, the system can issue reminders: *'The database will automatically provide the sales team with assignments and send reminders'* (CMO, Real estate client), while to customers: *'The system assigns the leads from customer calls to the salespersons'* (CEO, Suzuki retailer). Managers particularly valued this feature: *'The automatic task assignment to each salesperson presents a real benefit'* (CEO, Bentley retailer).

From the manager's perspective, AI-SA generates benefits provided the sales employees use the Xiaomi phone for all communication. Therefore, they contributed to developing a robust data repository that avoids bias and ensures accuracy, a feature which managers appreciated because *'if salespersons enter the data by themselves, there will be subjectivity. Now, Xiaomi records its customer conversations'* (CEO, Suzuki retailer). The transcribed recordings are entered directly into the database without alterations of any kind.

Another feature of the AI-SA includes customer ratings of the sales experience and the company: *'The customer rating is not only useful for the salespeople but also beneficial for me'* (CEO, Bentley retailer). Customer evaluations of the salesperson and the company and its products are also more reliably stored by AI than by humans: *'Each employee has their individual rating system, especially for the intention to buy, which can be strong or weak, and for the planned purchasing time, which can be urgent or reasonable'* (CEO, Bentley retailer). This greater accuracy and objectivity support organisational needs for understanding sales situations more clearly. However, because the companies implementing the AI-SA were fairly small, the data created on evaluations was not large enough for the AI's predictive analytics.

#### 4.2.2 Artificial intelligence and control

The AI-SA enables managers to track their salespersons' performance. For instance, managers are able to determine whether their employees follow up with customers as expected and whether or not they follow the appropriate procedures. Overall, the system performs an active algorithmic control of the sales workforce: *'The system supervises the salespersons' behaviours. Did they call or not? Did they follow the required process to talk to their customers?'* (CEO, Suzuki retailer). *'The database is always related to the control process'* (CEO, Real estate client). Tracking employees' activities does not require a large dataset for predictive analysis; rather, simple counts of numbers of phone calls, to whom they were directed, and how long they lasted are needed. Thus, the AI-SA supports tracking, even in the absence of a large dataset for advanced predictive analytics. The new system gave managers privileged insight into the work processes: *'The major merit of the system for me [the CEO] is that, within a few minutes, I know what happened and what the salespeople talked about [. . .] every day at 6 pm'*. (CMO, Suzuki retailer). This enhanced visibility is related to performance measurement: *'The system is used for recording all phone calls, in-coming and out-going. Our KPIs depend on this record'* (CMO, Real estate client). Because AI-SA tracks multiple behaviours, such as sales figures, transaction numbers, call numbers, and frequencies, the system helps identify good performers: *'The system can help the management staff to identify good sales employees'* (CEO, Suzuki retailer).

Managers began to value data stability, which enabled them to track and protect data, even after employees' departure. Indeed, they justified the AI investment by arguing that *'the key issue is to enter the customer information in the database to guard against the risk of the employee being hired by competitors'*. (CMO, Real estate client). Creating a database with proprietary information was considered to add value to the company: *'The purpose is to forbid salespersons to leak their customers to the competitors'* (CMO, Real estate client). If employees left the company, they would have to return the Xiaomi phone and all data in its storage, such as information about customers and purchase histories.

#### 4.2.3 Organisational consequences

Employees appreciated the automatic data entry and report generation; however, they were resistant to the AI-SA system because they perceived it primarily as intended to track and monitor their behaviour. Their perception was that management was gathering data to prevent them from retaining their customers' knowledge, if they were to leave the company. In general: *'The salespersons [did] not like this system'* (CEO, Suzuki retailer). For this reason, they were not using the system and therefore also not building the large dataset required for the AI system's predictive analytics. This led to weak AI performance that could not provide accurate data or appropriate reminders. Further, as the NLP application was not able to transcribe phone conversations accurately, this inability to parse the audio from the sales calls accurately enough to create a repository of historical interactions, contributed to the weak dataset. Part of the reason for this failure was that employees often made customer calls from public spaces. Background noise prevented the NLP from identifying voices accurately and then to add them to the database in text format. Therefore, design features of reasonable data quality and usefulness that were the managers' simple monitoring tools brought about employees' rejection of the tool. Because of the AI's inadequacy, managers experienced no improved sales performance that could be ascribed to implementing this AI-SA, therefore, they let their AI-SA contracts expire.

### 4.3 Cross-Case analysis

This section provides a cross-case analysis based on the theoretical perspective of Bourdieu's theory of practice. This theory includes the dimensions of field, capital, and habitus (see, [Table 3](#)).

#### 4.3.1 Field

In both cases, the field of power was structured through the second-order concept of information asymmetry. Whereas managers have access to a higher level of information on their employees' work, employees do not have access to the same information about themselves. The managers in Alpha explain that the AI system *'can make work more quantitative'* (Manager, Alpha) and this system can *'automatically monitor the service quality'* (Manager, Alpha). Such an information asymmetry also occurs in the case of the Sennsee system, but through another aspect, namely through data entry. The Sennsee system allows managers to directly access the salespersons' conversations through an automatic recording of their voice on the Xiaomi cellphone, which is then automatically

**Table 3.** Cross-case analysis.

Concept	Similarities and Differences	Alpha	Sennsee
<i>Field</i>	Information asymmetry	The AI provides managers with information about their employees, to which the employees do not have access.	
	Diverging interests	Labour substitution: replacing employees with the AI system.	Process standardisation: controlling, but not replacing the employees with the AI system.
<i>Capital</i>	Symbolic capital	All managers evaluate the employees, rating them in terms of the measurable quality of their work.	
	Social capital	Both social capital and cultural capital are less important than economic capital.	Social capital in the form of customer data collected by the employees is the most valuable asset to be stored in the AI system.
	Cultural capital	Both social capital and cultural capital are less important than economic capital.	Cultural capital in the form of skills or qualifications is neglected compared to social capital (customer relationships).
	Economic capital	The AI system is aimed to provide savings by replacing employees with the system's functions.	No discussion of cost saving through employee replacement.
<i>Habitus</i>	Control	Managers' habitus to control employees.	
	Value of employees	Managers' habitus to not consider employees as valuable in comparison to other assets.	

transcribed into text and then converted to quantitative data. One of the clients claimed that the system reduces the 'subjectivity' compared to the previous situation in which salespersons 'enter the data by themselves' (CEO, Suzuki retailer). In both cases, this information asymmetry, where the AI system reinforces the visibility of employees for managers while creating opacity between employees and managers, contributes to increasing power asymmetry. This, in turn, contributes to increasing tensions between employees and managers in the field.

In contrast, a distinction between the two cases is introduced through the second-order concept of diverging interests versus the second-order concept of process standardisation. In Alpha, the manager indicated their interest in the AI was to 'decrease the number of employees' and to 'replace the customer service representatives at the front-end' by the AI. Such a divergence of interests between managers and employees reinforced the tensions in the field of power. For the Sennsee system, however, no manager of a user company expressed such an interest. Rather, they all indicated an objective of the system was to force the employees to 'follow the required process' (CEO, Suzuki retailer) or to relate the AI database to 'the control process' (CEO, Real estate client).

### 4.3.2 Capital

The similarity between the two cases lies in the symbolic capital AI could bring. In both cases, managers use the AI system for classifying employees and evaluating what and who the good practices and/or the good employees are. In the case of Sennsee, these employees are believed to be the 'good sales employees' (CEO, Suzuki retailer), or in the case of Alpha, they recognised such employees through right 'attitudes' and 'emotions during a call with a customer' (Manager, Alpha).

The difference between the two cases is related to social capital, cultural capital, and economic capital. In Alpha, the social capital, i.e. the data from customers, is the most valuable asset. Yet, both social capital and cultural capital are less important than economic capital. The aim of the AI is to reduce the number of customer service representatives, regardless of their competence in the cultural capital perspective or their customer connections in the social capital perspective. Only economic capital matters, represented in this case by cost savings. In contrast, the Sennsee AI system remains devoted to 'identify the good sales employees' (CEO, Suzuki retailer), and them being hired by a competitor would represent a loss for the client companies.

### 4.3.3 *Habitus*

The habitus is similar in the two cases. Both for Alpha and Sennsee, the AI is used for monitoring or recording the workers, either by 'monitoring the service quality' (Manager, Alpha) or 'recording all phone calls' (CMO, real estate client); therefore, by reproducing the managers' habitus to control the workers. Also, both cases use the AI either for 'reducing the dependence on customer service representatives' (Manager, Alpha) or for conducting 'automatic task assignment to each salesperson' (CEO, Bentley retailer).

## 5 Discussion, implications, and future research

This study's objective was to investigate the change in power relations that occurs due to the implementation of an AI system. Narratives related to the implementation of two AI systems in different companies that used the AI system in CRM have been collected and represented. We identified a discrepancy between the AI systems' objectives and their actual use. The AI objectives were related to the design of the system, either in design documents at Alpha or according to the AI provider for the Sennsee system. Although these objectives were purported to support employees, either salespersons at Sennsee or customer service representatives at Alpha, their actual use by the managers increased management's control over employees. Therefore, in both cases, the AI implementation resulted in a power shift from employees to managers.

The case studies provided insight into the unintended consequences AI systems have in facilitating sales and customer services. Initially, the AI systems were introduced as a tool for enhancing and supporting work practices, such as automating technical and repetitive tasks so that employees could focus on more value-adding actions such as communicating with customers, either for selling or for solving customers' problems. However, the analysis of managers' and employees' practices in the post-implementation period revealed that the AI implementation strengthened managers' authority and control.

The theory of practice provided a conceptual framework for interpreting this power shift. The cases point to unintended consequences of introducing AI systems, namely a power imbalance and an unwanted authority shift due to reinforcing management control. Indeed, the AI system allowed managers to automatically send feedback to their employees (Morris & Venkatesh, 2010) and flag those who caused bottlenecks or who were underperforming (Faraj et al., 2017). Consequently, the AI system enhanced managers' symbolic capital. They could then set even more

detailed assessment criteria according to which work performance would be measured. Hence, the AI feedback could be based on analysing how fast employees talked and displayed emotions during their interaction with the customer. Thus, they were assessed according to criteria beyond their control (Bajwa et al., 2018). This asymmetrical endowment of symbolic capital produced a loss of employees' autonomy and motivation in the CRM departments as they faced constant pressure to maintain high ratings (Ellmer & Reichel, 2018).

Further, the case studies provide an example of organisational consequences consistent with the concept of the datafication related to AI (Schafheitle et al., 2020; Zuboff, 2015). However, this concept was developed at the individual level, while it was applied at the organisational level in this study. As employees' skills are gradually converted into data, AI facilitates work becoming a commodity that can be outsourced. In the case of Sennsee, datafication created a power imbalance as employees' social capital (contact with customers) was considered the main asset AI had to protect. Therefore, AI neglected the cultural capital related to the employees' skills. At Alpha, both cultural and social capital were neglected in comparison to a unique focus on economic capital. Using the system was related to cost reduction through substituting labour with AI (Amis et al., 2020). Because of their reduced power in the field, employees had no choice but to consent to the information asymmetries and the monitoring embedded in the AI system (Anderson, 2017). The impersonal control enabled by AI algorithms reinforces this information asymmetry by providing additional affordances to managers. Thus, in our case studies, managers found AI to be ideal for strengthening their authority since their focus is to monitor and control employees' activities.

Managers perceived AI as a potential instrument to reduce the value of the workforce. Through the AI system, a part of the CRM work becomes a commodity (Schultze & Boland, 2000), and employees become fungible human capital, who are legible, controllable, and available on-demand (Aneesh, 2009). As the AI system undermined employees' ability to maintain social and cultural capital in the field, this inevitably led to low acceptance of the system, low participation in training the new AI, and ultimately to failure of the implementation. To reduce the implementation failure risk, managers could openly state their implementation objectives (Schmidt et al., 2020). Questions arise as to whether the organisation seeks to reduce the workforce or to empower it. Although AI is often understood as a substitution for workers, another perspective refers to symbiosis or enhancement based on the assumption that AI can support rather than replace workers (Winograd, 2006). As the case studies illustrate, AI seems to be better indicated for work enhancement than for labour substitution. However, such an enhancement view of AI should also be shared by managers, whose interests may, opposingly, be oriented towards substitution. Therefore, Bourdieu's practice theory might bring a promising perspective to better understand power relationships and ultimately improve AI implementation success.

### **5.1 Implications for research**

This study's major contribution is its description of how different AI implementations contribute to power shifts between managers and employees in the workplace. From a theoretical standpoint, this research contributes to introducing the concepts of

field, capital, and habitus in the study of AI implementation. Our first contribution to research is to highlight the way the concept of field might help to better understand AI implementation. In this study, information asymmetry is understood as related to power differences between different actors involved in AI implementation, here between employees and the management team. The field of power includes different aspects, such as either diverging interests or process standardisation to control the employees. The second contribution this research makes, is to show how different types of capital might or might not be involved in AI implementation. Whereas symbolic capital is common in the two cases through the power of naming that the management team uses for classifying and evaluating the employees, the other types of capital differ across the two cases. In one case, social capital, related to customer information owned by the salespersons, is considered the company's most valuable asset. This leads to neglect of the cultural capital represented in the salespersons' skills. In the other case, the most important capital seems to be the economic capital gained by using the AI system for cost reduction through labour substitution. This focus on economic capital eclipsed the value assigned to both the social capital and the cultural capital of the employees. Our third research contribution is to show how the concept of habitus enables a better investigation of managers' behaviour during AI implementation. In both cases, the managers' habitus is reflected in the use of AI, which shows up their lacking consideration for employees and how the managers control them.

## **5.2 Implications for practice**

From a practical standpoint, these cases suggest we should reconsider the concept of resistance to change when it comes to AI implementation. Since a common reason for IS failure is low levels of user participation, managers should encourage participation by their understanding of employees' perceptions and behaviour, which could anticipate implementation problems (Huang et al., 2001). The first practical contribution is an indication that AI implementation teams should highlight how, compared to systems mainly oriented towards control, such as ERPs (Kumar et al., 2021; Lapointe & Rivard, 2005), AI has the potential either to control, or in contrast, to support employees. The second practical contribution is to underline that the distinction between AI and Enterprise Systems lies in the AI potential for labour substitution that can result in massive workforce reduction, as described in the literature related to the dark side of AI (Benbya et al., 2020; Conboy et al., 2021; Frick et al., 2021). In both case studies, considering the AI implementation based on Bourdieu's practice theory allowed us to relate the success or failure of AI implementation not to resistance to change, but to power shifts. The third practical contribution is to illustrate that if the initial AI system's design is maintained throughout the implementation, the system has the potential to enhance the employees' work, reducing their resistance to change in such situations. The fourth practical contribution is our indication that the AI design teams or AI providers should attempt to avoid the effect of the management team's habitus that seeks to control employees. Such habitus seemed to emerge during the implementation in both cases, either in the Alpha company or in the Sennsee customer companies.

### 5.3 Limitations and further research

This research was limited to the description of two case study companies. These companies and their client companies were all based in China, currently described as an 'AI superpower' (Milmo, 2022) and the potential global leader in AI (Li et al., 2021). Hence, our conclusions might not apply to other organisations or contexts. However, we believe that the lessons learned in this study could also be useful to other organisations seeking to embark on developing and implementing AI systems. Since AI is a highly progressive research field, organisational approaches and employees' reactions are likely to be dynamic. Therefore, this work suggests research directions by relying on Bourdieu's concepts of field, capital, and habitus to understand the practices embedded in complex settings in which actors are competitively involved in power distribution. Thus, further research should expand the study to investigate AI implementation considered as a power shift. Including the analysis of field, capital, and habitus prior to implementation could contribute to increasing AI implementation success and, hopefully, to empower employees through AI.

## 6 Conclusion

The two cases show that managers could use AI within a control perspective and even a substitution perspective, which was quite unexpected as the design narrative highlighted empowerment and enhancement. The incongruence between the AI system's design and its implementation to monitor and track employees led to user resistance. An analysis based on Bourdieu's theory of practice might highlight these potential incongruences at the design stage and hopefully avoid them during the implementation.

### Note

1. In this paper we use the term employee to refer to subordinates, whereas the term manager and management is used to indicate their higher hierarchical position within the organisation.

### Acknowledgments

This work was supported by the Federal Ministry of Education and Research of Germany (BMBF) under Grant 16DII127. The research is supported by Sino-German Research Network: Digitalization and Aging (GZ1507).

### Disclosure statement

No potential conflict of interest was reported by the author(s).

### Funding

This work was supported by the Federal Ministry of Education and Research of Germany (BMBF) under Grant 16DII127. The research is supported by Sino-German Research Network: Digitalization and Aging (GZ1507).

## References

- Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, 31(2), 427–445. <https://doi.org/10.1007/s12525-020-00414-7>
- Ågerfalk, P.J., Conboy, K., Crowston, K., Lundström, J., Jarvenpaa, S., Ram, S., & Mikalef, P. (2021). Artificial intelligence in information systems: State of the art and research roadmap. *Communications of the Association for Information Systems*, 1–21 (forthcoming).
- Alshawi, S., Missi, F., & Irani, Z. (2011). Organisational, technical and data quality factors in CRM adoption. SMEs perspective. *Industrial Marketing Management*, 40(3), 376–383. <https://doi.org/10.1016/j.indmarman.2010.08.006>
- Amis, J.M., Mair, J., & Munir, K.A. (2020). The organizational reproduction of inequality. *Academy of Management Annals*, 14(1), 195–230. <https://doi.org/10.5465/annals.2017.0033>
- Anderson, E. (2017). *Private government: How employers rule our lives (and why we don't talk about it)*. Princeton University Press.
- Aneesh, A. (2009). Global labor: Algoratic modes of organization. *Sociological Theory*, 27(4), 347–370. <https://doi.org/10.1111/j.1467-9558.2009.01352.x>
- Antonio, V. (2018). How AI is changing sales. *Harvard Business Review*. <https://hbr.org/2018/07/how-ai-is-changing-sales>
- Bajwa, U., Gastaldo, D., Di Ruggiero, E., & Knorr, L. (2018). The health of workers in the global gig economy. *Globalization and Health*, 14(1), 1–4. <https://doi.org/10.1186/s12992-018-0444-8>
- Bayer, S., Gimpel, H., & Markgraf, M. (2021). The role of domain expertise in trusting and following explainable AI decision support systems. *Journal of Decision Systems*, 1–29. <https://doi.org/10.1080/12460125.2021.1958505>
- Benbya, H., Davenport, T.H., & Pachidi, S. (2020). Special issue editorial: Artificial Intelligence in organizations: Current state and future opportunities. *MIS Quarterly Executive*, 9(4), 1–15. <https://aisel.aisnet.org/misqe/vol19/iss4/4>
- Benbya, H., Pachidi, S., & Jarvenpaa, S. (2021). Special issue editorial: Artificial Intelligence in organizations: Implications for Information Systems research. *Journal of the Association for Information Systems*, 22(2), 1–25. <https://doi.org/10.17705/1jais.00662>
- Bourdieu, P. (1977). *Outline of a Theory of Practice*. Cambridge University Press.
- Bourdieu, P. (1985). The market of symbolic goods. *Poetics*, 14(1–2), 13–44. [https://doi.org/10.1016/0304-422X\(85\)90003-8](https://doi.org/10.1016/0304-422X(85)90003-8)
- Bourdieu, P. (1986). The forms of capital. In J. G. Richardson (Ed.), *Handbook of theory and research for the sociology of education: Bd. Handbook of theory and research for the sociology of education* (pp. S. 253). Greenwood Press.
- Bourdieu, P. (1993). The field of cultural production. In R. Johnson (Ed.), *The field of cultural production: Essays on art and literature: Bd. The field of cultural production: Essays on art and literature* (pp. S. 29–114). Columbia University Press.
- Bourdieu, P. (1998). *Practical reason: On the theory of action*. Stanford University Press.
- Bourdieu, P., & Wacquant, L.C.D. (1992). *Invitation to reflexive sociology*. University of Chicago Press.
- Cattaneo, L.B., & Chapman, A.R. (2010). The process of empowerment: A model for use in research and practice. *American Psychologist*, 65(7), 646–659. <https://doi.org/10.1037/a0018854>
- Chatterjee, S., Ghosh, S.K., Chaudhuri, R., & Nguyen, B. (2019). Are CRM systems ready for AI integration?: A conceptual framework of organizational readiness for effective AI-CRM integration. *The Bottom Line*, 32(2), 144–157. <https://doi.org/10.1108/BL-02-2019-0069>
- Chuang, S.H., & Lin, H.N. (2013). The roles of infrastructure capability and customer orientation in enhancing customer-information quality in CRM systems: Empirical evidence from Taiwan. *International Journal of Information Management*, 33(2), 271–281. <https://doi.org/10.1016/j.ijin fomgt.2012.12.003>
- Corley, K.G., & Gioia, D.A. (2004). Identity ambiguity and change in the wake of a corporate spin-off. *Administrative Science Quarterly*, 49(2), 173–208. <https://doi.org/10.2307/4131471>
- Craypo, C., & Cormier, D. (2000). Job restructuring as a determinant of wage inequality and working-poor households. *Journal of Economic Issues*, 34(1), 21–42. <https://doi.org/10.1080/00213624.2000.11506242>

- Davenport, T.H., Guha, A., & Grewal, D. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24–42. <https://doi.org/10.1007/s11747-019-00696-0>
- Eisenhardt, K.M., & Graebner, M.E. (2007). Theory building from cases: Opportunities and challenges. *Academy of Management Journal*, 50(1), 25–32. <https://doi.org/10.5465/amj.2007.24160888>
- Ellmer, M., & Reichel, A. (2018). *Crowdwork from an HRM perspective—Integrating organizational performance and employee welfare* (University of Salzburg: Working Paper, S. 1–27) [Working Paper, HRM Group].
- Ellway, B.P.W., & Walsham, G. (2015). A doxa-informed practice analysis: Reflexivity and representations, technology and action: A doxa-informed practice analysis. *Information Systems Journal*, 25(2), 133–160. <https://doi.org/10.1111/isj.12041>
- Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization*, 28(1), 62–70. <https://doi.org/10.1016/j.infoandorg.2018.02.005>
- Faraj, S., Sayegh, K., & Rouleau, L. (2017). Knowledge collaboration in organizations: From information processing to social knowing. In D.G. Robert & S. Mari-Klara (Eds.), *The Routledge companion to management information systems* (pp. S. 370–386). Routledge.
- Frick, N.R.J., Mirbabaie, M., Stieglitz, S., & Salomon, J. (2021). Maneuvering through the stormy seas of digital transformation: The impact of empowering leadership on the AI readiness of enterprises. *Journal of Decision Systems*, 30(2–3), 235–258. <https://doi.org/10.1080/12460125.2020.1870065>
- Glaser, B.G., & Strauss, A.L. (1967). *Discovery of grounded theory: Strategies for qualitative research*. Routledge.
- Huang, J.C., Newell, S., Pan, S.-L., & Poulson, B. (2001). ERP systems implementation: A knowledge-focused perspective. *Journal of Decision Systems*, 10(1), 99–117. <https://doi.org/10.3166/jds.10.99-117>
- Huberman, A., & Miles, M. (1994). Data management and analysis methods. In N. Denzin & Y. Lincoln (Eds.), *Handbook of Qualitative Research* (pp. S. 428–444). Sage Publications.
- Hughes, C., Robert, L., Frady, K., & Arroyos, A. (2019). Artificial intelligence, employee engagement, fairness, and job outcomes. In *Managing technology and middle- and low-skilled employees* (pp. S. 61–68). Emerald Publishing Limited.
- IDC (Hrsg.). (2020). *IDC Forecasts Strong 12.3% Growth for AI Market in 2020 Amidst Challenging Circumstances: Bd. IDC*. <https://www.idc.com/getdoc.jsp?containerId=prUS46757920>
- Jick, T.D. (1979). Mixing qualitative and quantitative methods: Triangulation in action. *Administrative Science Quarterly*, 24(4), 602–611. <https://doi.org/10.2307/2392366>
- Khodakarami, F., & Chan, Y.E. (2014). Exploring the role of customer relationship management (CRM) systems in customer knowledge creation. *Information & Management*, 51(1), 27–42. <https://doi.org/10.1016/j.im.2013.09.001>
- Khosravifar, B., Bentahar, J., Gomrokchi, M., & Alam, R. (2012). CRM: An efficient and reputation model for agent computing. *Knowledge-Based Systems*, 30, 1–16. <https://doi.org/10.1016/j.knosys.2011.01.004>
- Kumar, M., Singh, J.B., Chandwani, R., & Gupta, A. (2021). Locating resistance to healthcare information technology: A Bourdieusian analysis of doctors' symbolic capital conservation. *Information Systems Journal*, 32(2), 1–37. <https://doi.org/10.1111/isj.12357>
- Lapointe & Rivard. (2005). A multilevel model of resistance to information technology implementation. *MIS Quarterly*, 29(3), 461–491. <https://doi.org/10.2307/25148692>
- Levina, N., & Orlikowski, W.J. (2009). Understanding shifting power relations within and across organizations: A critical genre analysis. *Academy of Management Journal*, 52(4), 672–703. <https://doi.org/10.5465/amj.2009.43669902>
- Li, D., Tong, T.W., & Xiao, Y. (2021). Is China emerging as the global leader in AI. *Harvard Business Review*. <https://hbr.org/2021/02/is-china-emerging-as-the-global-leader-in-ai>
- Lincoln, Y.S., & Guba, E.G. (1985). *Naturalistic Inquiry*. SAGE Publications, Inc.
- Locke, K. (1996). Rewriting the discovery of grounded theory after 25 years? *Journal of Management Inquiry*, 5(3), 239–245. <https://doi.org/10.1177/105649269653008>

- Manley, A., & Williams, S. (2019). We're not run on numbers, we're people, we're emotional people': Exploring the experiences and lived consequences of emerging technologies, organizational surveillance and control among elite professionals. *Organization*, 1–22. <https://doi.org/10.1177/1350508419890078>
- Manyika, J., & Sneider, K. (2018). *AI, automation, and the future of work: Ten things to solve for*. McKinsey Global Institute. <https://www.mckinsey.com/featured-insights/future-of-work/ai-automation-and-the-future-of-work-ten-things-to-solve-for>
- Markus, M.L. (1983). Power, politics, and MIS implementation. *Communications of the ACM*, 26(6), 430–444. <https://doi.org/10.1145/358141.358148>
- McKinsey & Company. (2020). *The state of AI in 2020*. <https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2020>
- Milmo, D. (2022). *TechScape: How China became an AI superpower ready to take on the United States*. The Guardian. <https://www.theguardian.com/technology/2021/dec/08/techscape-china-ai-united-states>
- Morris, M., & Venkatesh, V. (2010). Job characteristics and job satisfaction: Understanding the role of enterprise resource planning system implementation. *MIS Quarterly*, 34(1), 143–161. <https://doi.org/10.2307/20721418>
- Orlikowski, W.J. (2000). Using technology and constituting structures: A practice lens for studying technology in organizations. *Organization Science*, 11(4), 404–428. <https://doi.org/10.1287/orsc.11.4.404.14600>
- Orlikowski, W.J. (2002). Knowing in practice: Enacting a collective capability in distributed organizing. *Organization Science*, 13(3), 249–273. <https://doi.org/10.1287/orsc.13.3.249.2776>
- Peltier, J.W., Zahay, D., & Lehmann, D.R. (2013). Organizational learning and CRM success: A model for linking organizational practices, customer data quality, and performance. *Journal of Interactive Marketing*, 27(1), 1–13. <https://doi.org/10.1016/j.intmar.2012.05.001>
- Schafheitle, S., Weibel, A., Ebert, I., Kasper, G., Schank, C., & Leicht-Deobald, U. (2020). No stone left unturned? Toward a framework for the impact of datafication technologies on organizational control. *Academy of Management Discoveries*, 6(3), 455–487. <https://doi.org/10.5465/amd.2019.0002>
- Schmidt, P., Biessmann, F., & Teubner, T. (2020). Transparency and trust in artificial intelligence systems. *Journal of Decision Systems*, 29(4), 260–278. <https://doi.org/10.1080/12460125.2020.1819094>
- Schultze, U., & Boland, R.J. (2000). Knowledge management technology and the reproduction of knowledge work practices. *Journal of Strategic Information Systems*, 9(2–3), 193–212. [https://doi.org/10.1016/S0963-8687\(00\)00043-3](https://doi.org/10.1016/S0963-8687(00)00043-3)
- Siggelkow, N. (2007). Persuasion with case studies. *Academy of Management Journal*, 50(1), 20–24. <https://doi.org/10.5465/amj.2007.24160882>
- Soltani, Z., & Navimipour, N.J. (2016). Customer relationship management mechanisms: A systematic review of the state-of-the-art literature and recommendations for future research. *Computers in Human Behavior*, 61, 667–688. <https://doi.org/10.1016/j.chb.2016.03.008>
- Strich, F., Mayer, A.S., & Fiedler, M. (2021). What do I do in a world of Artificial Intelligence? Investigating the impact of substitutive decision-making AI systems on employees' professional role identity. *Journal of the Association for Information Systems*, 22(2), 304–324. <https://doi.org/10.17705/1jais.00663>
- Tsang, E.W. (2014). Case studies and generalization in information systems research: A critical realist perspective. *The Journal of Strategic Information Systems*, 23(2), 174–186. <https://doi.org/10.1016/j.jsis.2013.09.002>
- von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries*, 4(4), 404–409. <https://doi.org/10.5465/amd.2018.0084>
- Winograd, T. (2006). Shifting viewpoints: Artificial intelligence and human–computer interaction. *Artificial Intelligence*, 170(18), 1256–1258. <https://doi.org/10.1016/j.artint.2006.10.011>
- Yin, R.K. (2009). *Case study research: Design and methods*. Sage. (Bd. 5)
- Zuboff, S. (2015). Big other: Surveillance capitalism and the prospects of an information civilization. *Journal of Information Technology*, 30(1), 75–89. <https://doi.org/10.1057/jit.2015.5>

Appendix

Representative quotations	First order concept	Second order concept	Theoretical dimensions
<ul style="list-style-type: none"> <li>• “The system can automatically monitor the service quality of the human” (Manager, Alpha).</li> <li>• “The AI system can make the employees’ work more quantitative” (Manager, Alpha).</li> </ul>	AI provides influence to managers as they reduce after sales work to data being automatically recorded	Information asymmetry	Field
<ul style="list-style-type: none"> <li>• “To lift performance by decreasing the number of employees” (Manager, Alpha).</li> <li>• “AI can replace customer service representatives at the front-end and in steps toward self-service” (Manager, Alpha).</li> </ul>	The aim of the AI is the substitution of employees. The design was suggesting enhancement.	Diverging interest	
<ul style="list-style-type: none"> <li>• “To monitor the customer service employees. This includes the speed of speech, the attitude of the employees, and their emotions during the calls with the customers” (Manager, Alpha).</li> <li>• “Thanks to the AI, a part of the operations can be tracked” (Manager, Alpha).</li> </ul>	AI enables to assess automatically the performance of customer service representatives according to criteria defined by managers	Symbolic capital (The power to classify and evaluate)	Capital
<ul style="list-style-type: none"> <li>• “The AI requires for the moment a lot of manpower for training. We increase investment to meet the requirement of reducing the number of customer service representatives” (Manager, Alpha).</li> </ul>	Productivity and cost savings are more important than the skills of the workers	Economic capital over cultural capital	
<ul style="list-style-type: none"> <li>• “The system can automatically monitor the service quality of the human” (Manager, Alpha).</li> <li>• “KPI are created from the data collected from each customer service representative for the purpose of monitoring them” (Manager, Alpha).</li> </ul>	AI provides top functionalities to control in detail and track the work of customer service representatives	Workers monitoring, by managers	Habitus
<ul style="list-style-type: none"> <li>• “The objective is to reduce the dependence on customer service representatives to make up for the [customer] loss rate” (Manager, Alpha).</li> </ul>	The AI for management is based on a low value of human ability	Lack of consideration for workers by managers	

Figure 1. Data coding (Alpha case).

Representative quotations	First order concept	Second order concept	Theoretical dimensions
<ul style="list-style-type: none"> <li>• “If sales employees enter the data by themselves, there will be subjectivity. Now, Xiaomi records its customer conversations” (CEO, Suzuki retailer).</li> </ul>	The AI provides to managers visibility upon the salespersons	Information asymmetry	Field
<ul style="list-style-type: none"> <li>• “The system supervises the salespersons’ behaviors. Did they call or not? Did they follow the required process to talk to their customers?” (CEO, Suzuki retailer).</li> <li>• “The database is always related to the control process” (CEO, Real estate client).</li> </ul>	The AI increases management control upon the salespersons through standardization	Control through standardization of processes	
<ul style="list-style-type: none"> <li>• “The system can help the management staff to identify good sales employees” (CEO, Suzuki retailer).</li> </ul>	The AI contributes to the evaluation naming which employees are good performers	Symbolic capital (naming and classifying)	Capital
<ul style="list-style-type: none"> <li>• The key issue is to enter the customer information in the database to guard against the risk of the employee being hired by competitors” (CMO, Real estate client).</li> <li>• “The purpose is to forbid salespersons to leak their customers to the competitors” (CMO, Real estate client).</li> </ul>	The contact between salespersons and clients is a key asset	Social capital	
<ul style="list-style-type: none"> <li>• “The major merit of the system for me [the CEO] is that, within a few minutes, I know what happened and what the salespeople talked about (CMO, Suzuki retailer).</li> <li>• “The system is used for recording all phone calls, in-coming and out-coming. Our KPIs depend on this record” (CMO, Real estate client).</li> </ul>	AI enables managers to micro-monitor salespersons	Workers monitoring, and tracking by managers	Habitus
<ul style="list-style-type: none"> <li>• “The database will automatically provide assignments to the sales team and send reminders” (CMO, Real estate client)</li> <li>• “The system assigns the leads from customer calls to the salespersons” (CEO, Suzuki retailer).</li> <li>• “The automatic task assignment to each salesperson presents a real benefit” (CEO, Bentley retailer).</li> </ul>	AI contributes to structure and automatize the sales processes imposed on sales teams	Lack of consideration for workers by managers	

Figure 2. Data coding (Sennsee case).