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From worker empowerment to managerial control: The devolution of AI tools' intended positive implementation to their negative consequences

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A R T I C L E I N F O

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A B S T R A C T

AI tools are increasingly being deployed in organizations with the promise to support workers, enable faster and more accurate processes, and thus to contribute to enhanced organizational outcomes. However, in practice, the introduction of AI tools often fails to meet these expectations and results in negative consequences, such as worker resistance and dissatisfaction. Yet we have little understanding of the process of how and why initially positive design intentions of AI tools result in negative consequences. Building on a qualitative in-depth case study of a Chinese firm introducing an AI tool in sales, we found that whereas the AI tool's initial design seemingly intended to lead to salespeople's empowerment and first achieved respective outcomes, over time the tool was appropriated for managerial control. We show that this devolution emerged organically from a growing managerial awareness of the affordances that the AI tool offered managers to perform their work better. Our study contributes to the literature on AI by highlighting the potential dangers of AI tools and emphasizing the importance of including workers in the AI tool's design and implementation phases.

1. Introduction

With rapid technological advancement, organizations increasingly introduce artificial intelligence (AI) tools across a wide spectrum of areas and tasks, including customer service (e.g., Nicolescu & Tudorache, 2022; Xu, Shieh, van Esch, & Ling, 2020), human resources (e.g., Van den Broek, Sergeeva, & Huysman, 2021), marketing (e.g., Jain & Aggarwal, 2020), and cybersecurity (e.g., Sarker, Furhad, & Nowrozy, 2021). AI tools rely on algorithms that harness statistical models to predict outcomes through the analysis of large and complex datasets (Berente, Gu, Recker, & Santhanam, 2021). In contrast to traditional information systems, AI tools are characterized by their ability to learn, to autonomously perform tasks, and to make decisions that previously required human expertise and input (Benbya, Davenport, & Pachidi, 2020; Berente et al., 2021; Faraj, Pachidi, & Sayegh, 2018).

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Based on these unique characteristics, AI tools promise novel benefits for organizations by providing more efficient, accurate, and objective processes and decisions (Agrawal, Gans, & Goldfarb, 2018; Davenport & Kirby, 2016; Raisch & Krakowski, 2021). Moreover, AI tools are associated with various benefits for workers, such as the empowerment and emancipation of employees (e.g., Strich, Mayer, & Fiedler, 2021), the relief from simple and repetitive tasks (e.g., Acemoglu & Restrepo, 2018), and the opportunity to provide enhanced customer service by gaining superior insights into customers' needs (e.g., Mayer, Strich, & Fiedler, 2020).

Despite AI's potential and associated benefits, prior research has pointed at serious issues that have often occurred as unintended consequences of organizations' goals to augment employees' work with AI. Prominent examples of such negative consequences include workers' loss of autonomy (e.g., Mayer et al., 2020), the undermining of professional expertise (e.g., Anthony, 2021; Lebovitz, Lifshitz-Assaf, & Levina, 2022), and attempts by workers to outsmart the AI tool (e.g., Strich et al., 2021). Interestingly, in some cases positive and negative consequences have seemed to occur simultaneously. For instance, Strich et al. (2021) showed how the same AI tool caused the deskilling and degradation of highly skilled loan consultants while simultaneously empowering low-skilled employees.

These opposing and sometimes even paradoxical findings emphasize that despite the often positive intentions when designing a technology, the actual use of a technology in organizations may result in varying outcomes (DeLone & McLean, 1992; DeSanctis & Poole, 1993; Petter, DeLone, & McLean, 2008). For instance, while AI tools in customer service are designed to relieve workers from simple and repetitive tasks (Acemoglu & Restrepo, 2018), their use may result in the increased dissatisfaction of workers, as tasks become more monotonous and mechanical (Umair, Conboy, & Whelan, 2019; Van Nimwegen, Burgos, van Oostendorp, & Schilf, 2006). However, whereas an extensive stream of literature has emphasized that the gap between a technology's intended design goals and its actual use is a major trigger for unintended consequences (e.g., Bailey & Barley, 2020), we know little about the process of how and why initially positive design intentions of AI tools result in negative consequences. Moreover, we have little understanding to what extent these tensions between positive and negative consequences may be reconciled. These questions are critical to gain more in-depth insights into the implications of AI tools in organizations and to enhance our understanding of how potential negative consequences may be prevented. Our study therefore seeks to explore the following research questions: *How and why do positive intentions of AI tool implementations have negative consequences? How and to what extent might tensions between AI's positive and negative consequences be reconciled in practice?*

To explore these research questions, we conducted an in-depth case study of a large Chinese firm that introduced an AI sales assistant, i.e., an AIA, in its customer service (CS) unit to support salespeople's work. Whereas salespeople were previously responsible for handling all customer requests and inquiries on their own, they are now supported by an AIA that is able to generate answers to customer requests and questions autonomously. Moreover, the AIA is able to generate novel insights about customers, which promises to help salespeople in providing more accurate and individualized services to their customers. Building on extensive archival data and 36 interviews with CS managers, we show that while the AIA was designed to support CS salespeople through automation and augmentation, in practice it devolved into a tool to control and manage them to a greater extent.

2. Theoretical background

2.1. AI in organizations

AI tools have emerged as a transformative force reshaping the landscape of organizations across industries and domains. With increasing technological advancement, AI tools have been introduced for a wide range of domains and tasks, including critical decision-making in hiring (Van den Broek, Sergeeva, & Huysman, 2021), legal matters (Christin, 2020), policing (Brayne, 2017), and medical diagnoses (Lebovitz et al., 2022). AI refers to the simulation of human tasks and decision-making practices by machines (Berente et al., 2021), including learning, reasoning, and problem-solving. Building on learning algorithms, AI tools are able to process large amounts of data, recognize patterns, and adapt their responses based on historical behavior and experiences (Benbya et al., 2020; Faraj et al., 2018). This learning capability sets AI apart as a tool that amplifies human capabilities instead of merely automating routine tasks (Berente et al., 2021).

AI tools can be introduced either to automate human work by keeping the human worker out of the loop or to augment human work by using AI tools to support and assist workers in their tasks and decision-making practices (Lebovitz et al., 2022; Raisch & Krakowski, 2021). Whereas initial predictions suggested that the advancement of AI tools will replace many jobs, prior research indicates that AI tools are primarily introduced to augment professional work and, thus, to combine human and machine capabilities (Benbya et al., 2020; Benbya et al., 2021).

2.2. Benefits of AI

The use of AI tools for augmenting professional work promises to derive several benefits for organizations and workers. On an organizational level, AI tools have the potential to enhance the efficiency, accuracy, and objectivity of processes and decision-making practices (Jarrahi, 2018). As a result, organizations aim to save costs (Li, Bonn, & Ye, 2019; Nam, Dutt, Chathoth, Daghfous, & Khan, 2021), gain competitive advantages (Makridakis, 2017), and increase customer satisfaction (Prentice, Dominique Lopes, & Wang, 2020). On an individual level, AI tools are associated with the promise to enhance human capabilities by "combining computational potential of human beings and computers" (Tegmark, 2017, p. 1) with a superior outcome that would be impossible if either humans or computers worked independently. The AI discerns patterns in the data, which are not necessarily apparent to the worker (Kellogg, Valentine, & Christin, 2020), and suggests actions in response to these patterns (Rosenblat, 2018). This approach is what Citron and Pasquale (2014) referred to as "human-in-the-loop," where the AI identifies patterns and produces recommendations out of those patterns, but the human implements the recommendations only if the recommendations are deemed appropriate. This human-AI collaboration is essential to ensure that the AI's recommendations are accurate (Wilson & Daugherty, 2018). Citron and Pasquale (2014) used AI-derived credit scoring as an example of necessary human oversight. They dealt with a case where algorithms utilized to calculate credit scores are granted undue weight, thereby creating confusion and uncertainty about how the credit scores are calculated or how to address the credit scores' inconsistencies.

Moreover, AI tools promise to relieve workers from repetitive and simple tasks, thereby enabling the workers to focus on more complex and creative tasks (Zanzotto, 2019). At the same time, with rapid technological advancement, AI tools are also increasingly capable of performing complex decisions and tasks that require emotional intelligence and creativity (Brynjolfsson & Mitchell, 2017). As a result, prior studies have emphasized that AI tools can contribute to the upskilling and empowerment of low-skilled workers who are enabled by the AI tool to work in more prestigious jobs that previously required specialized expertise (e.g., Jarrahi, 2018; Mayer, Strich, & Fiedler, 2020). For instance, Jarrahi (2018) showed that AI tools can support humans in their decision-making such that workers can process highly complex data under conditions of extreme uncertainty.

2.3. Downsides of AI

Extant literature indicates that the introduction and use of AI in organizational settings also come with potential dangers, and therefore have a negative side (e.g., Faraj et al., 2018; Giermindl et al., 2022; Mayer et al., 2020). On an organizational level, these potential dangers often relate to ethical dilemmas caused by AI's opacity and, thus, a lack of explainability (Burrell, 2016; Hafermalz & Huysman, 2019), unintended biases and discrimination (Mayer et al., 2020), and employee resistance to use AI tools (e.g., Van den Broek, Sergeeva, & Huysman, 2021). On an individual level, potential negative aspects of AI are often associated with the process of decoupling. Decoupling, i.e., the transformation of tasks into more simplified units, has been witnessed over and over since the advent of Taylorism in the early 20th century and now has dramatic ramifications in the interactions of intelligent machines and employees. As Braverman (1998) noted:

> The mass of workers gain nothing from … the decline in their command over the labor process … [and] the increasing command on the part of managers and engineers. On the contrary, not only does their skill fall in an absolute sense ([losing] craft and traditional abilities without gaining new abilities adequate to compensate the loss), but it falls even more in a relative sense. The more science is incorporated into the labor process, the more sophisticated an intellectual product the machine becomes, the less control … the worker has (pp. 294–295).

In decoupling the worker from the larger unit of work, the worker becomes more fungible (Berente et al., 2021). At the same time, since the work is transformed into smaller units, it requires more focused skill sets, and consequently, workers become more replicable and portable (Robert et al., 2020). This shift comes about because the task becomes more important than the worker. In addition, due to this emphasis on the task instead of the person, organizational indifference to the worker becomes institutionalized such that workers are made legible, controllable, and available on demand (Kellogg et al., 2020).

Moreover, an associated danger of AI tools is often related to AI's opacity, which hinders workers and sometimes even developers from understanding how the AI tools have derived a certain outcome (Burrell, 2016). This opacity often results in workers questioning their expertise (e.g., Lebovitz et al., 2022), blindly following an AI output (e.g., Anthony, 2021) or, conversely, utterly rejecting and ignoring that output (e.g., Lebovitz et al., 2022). The use of AI tools therefore poses a risk in undermining workers' expertise (Pakarinen & Huising, 2023).

Finally, the use of AI tools can further pose a danger to workers through domination and control, which is apparent in such activities as tracking and tailoring workers' behavior (Kellogg et al., 2020). In tracking workers, AI tools use learning algorithms to break down tasks that employees perform and then re-compose those tasks into a working whole. The algorithms subsequently assign work by matching expertise to tasks and by flagging individuals whose work causes bottlenecks or does not live up to expectations (Faraj et al., 2018). Algorithms make work more visible to co-workers through surveillance, sending reminders to slow or inadequate performers (Faraj et al., 2018; Schildt, 2017). Similarly, in tailoring the behavior of workers, workers who are knowledgeable in a narrow expertise domain are likely to become confined to a limited way of thinking and reasoning since this scrutiny of work segments focuses on the minutiae of tasks. This siloing of task scope can also limit innovation and prevent employees from gaining an understanding and appreciation of other epistemic viewpoints that might give rise to novel knowledge combinations (Faraj, von Krogh, Monteiro, & Lakhani, 2016).

3. Research methodology

We employed an in-depth case study approach to explore a fairly novel phenomenon and to understand relevant underlying mechanisms and relationships (Eisenhardt, 1989; Gioia, Corley, & Hamilton, 2013). Building on insights from a large, leading service company in China that introduced an AIA in their CS unit, we shed light on how and why the AIA's initially positive intentions turned into negative consequences over time.

3.1. AIA in customer service

Organizations introduce AIAs in their CS units to enhance efficiency and accuracy in handling customer requests and, thus, to contribute to an overall improved customer experience (Nicolescu & Tudorache, 2022; Xu et al., 2020). In contrast to AI chatbots that are directly used by customers but often lack personalized answers or accuracy in providing information (Ben Mimoun, Poncin, & Garnier, 2017; Etemad-Sajadi & Ghachem, 2015), AIAs are designed to augment CS salespersons' work by combining benefits of human and AI capabilities. Thus, whereas AI chatbots often automate CS work and replace CS jobs, AIAs are presumably used to augment the work of CS salespersons by helping them better serve customers (Xu et al., 2020).

AIAs streamline customer queries and requests, develop and maintain comprehensive customer records, and assess data repositories to anticipate and predict customer needs and interests (Guenzi & Habel, 2020; Singh et al., 2019). Many responsibilities of salespeople can be automated through AIAs, such as generating leads (Chatterjee et al., 2020), making recommendations, handling customer complaints (Singh et al., 2019), forecasting sales (Saura, Ribeiro-Soriano, & Palacios-Marqués, 2021), and assigning accounts (Zoltners et al., 2021). In addition, by digitizing individual salesperson's knowledge sets, it is possible to build a highly useful organization-level repository (Hofacker & Corsaro, 2020; Singh et al., 2019). Hence, AIAs are associated with various benefits for organizations and salespeople, such as increased productivity and efficiency (Zoltners et al., 2021), more salesperson support, better customer relationships (Alavi & Habel, 2021), and greater competitive advantage (Graca, Barry, & Doney, 2014).

3.2. Case description

Our case company, Alpha (pseudonym), is a large company in China that provides technological services. The company is state owned, employs more than 100,000 people, and is located in all main cities of China.

Traditionally, Alpha's CS department relied only on human call centers, i.e., on outsourced human CS salespeople. However, under this regime call centers were poorly administered, producing hundreds of thousands of errors per day. Alpha therefore launched the AIA in 2015 to "improve customer satisfaction and reduce costs" (Interview, AIA Project Development Manager (PDM)). The AIA used natural language processing (NLP) to solve customer issues through human-machine interactions via chatbots. In 2016, the AIA was embedded in a new online platform devoted to solving customer questions and complaints. In October 2018, the AIA went live in firm branches in eleven provinces. The AIA includes a cloud platform built on natural language understanding, a sub-technology of NLP; it further includes speech recognition, text-to-speech technology, and an AI-assisted training and authorization system by tier, vendor management, and service policy management. Fig. 1 gives an overview of the AIA.

3.3. Data collection

We collected our data between September 2018 and July 2020. We chose our case company, as it represents a real use case where AI had been actively utilized in CS for a significant period of time. During our research, we had access to the IT team that designed the AI and to the CS managers.

Informants were chosen according to standard guidelines for purposive sampling (Lincoln & Guba, 1985; Trochim, Donnelly, & Arora, 2016). Informant status included different hierarchical levels in both the company and CS departments. Unfortunately, we could not interview any CS salespeople because the CS task had been outsourced to another company and Alpha managers would not permit access to this source. Directly accessing CS salespeople was therefore infeasible.

Not having access to CS salespeople was a major limitation in the purposive sampling; it constrained our ability to distinguish clearly between the ideas and intentions of managers, salespeople, and designers. However, in spite of the research team's lack of direct access to the CS salespeople, extensive information about the impact on the CS salespeople's work practices was de facto available. The CS managers provided information about the current practices and were open about their future plans. Furthermore, the AIA designers and the technical documentation about initial system goals demonstrated a user-oriented design approach such that salespeople's welfare was well represented in the case data. We therefore felt strongly that we discovered substantial enough salient discrepancies between the AIA design and the executive users' use of the tool to justify a thorough exploration of our research questions. The data that was revealed as evidence for these discrepancies included semi-structured face-to-face interviews, follow-up interviews via phone and Wechat (text messages), and extensive archival documentation about the AIA development projects.

Based on the analysis of the archival documentation, we developed interview guides for conducting semi-structured, face-to-face interviews with the AI tool design team at the Alpha headquarters in September 2019. Preparatory interviews were telephonically

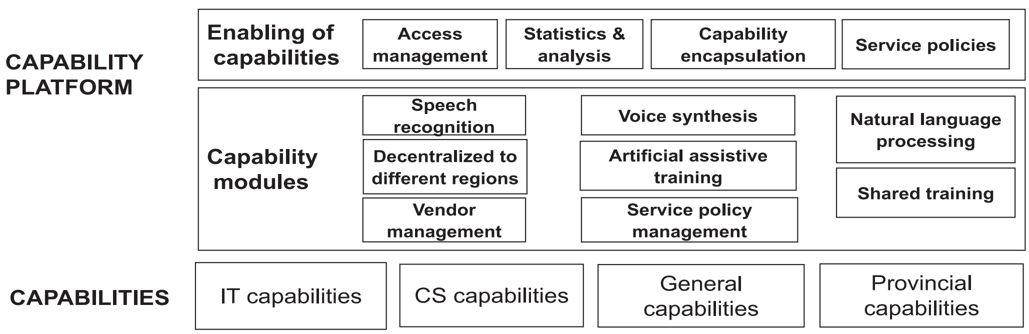

Fig. 1. Overview of the AIA (Technical Document, 2018).

conducted with the AI PDM six months before data collection, and closing interviews followed in the ten-month period after the on-site headquarters visit.

In late 2019 and early 2020, interviews with CS managers were conducted by telephone and Wechat, with a duration between one and three hours. We relied on the designed interview guide that had been tested with academic colleagues, and subsequently modified during the research process. The initial interview used a largely standardized interview guide for all informants, though it included two distinct guides for the design team and for the CS managers. Subsequent managerial interviews (i.e., those by telephone and Wechat) became progressively more structured as themes emerged from the data, such as the lack of worker empowerment and the focus on managerial control. This thematic focusing progressively prompted more targeted data collection to identify patterns across informants and (in)consistencies between the system's design and its actual use, as well as tentative relationships among concepts.

In sum, we conducted 36 interviews. With the respondents' permission, the interviews were recorded and transcribed verbatim. Table 1 provides an overview of the interviewees.

Based on the same interview guide, different members of the research team conducted the interviews in order to benefit from diverse perspectives. After each interview, the team discussed their impressions and shared ideas on possible adjustments to the interview guide and the way of conducting the interviews.

In addition to interviews, the study relied on archival data, such as Alpha's internal technical documents. This document described the AI technologies used, the projected timelines, and each sub-project objective. It included tool artifacts, namely representations of the tool's potential benefits, and image artifacts, such as the tool architecture and required infrastructure. Documentation also included electronic documents concerning strategic and operational aspects of the company, and marketing materials.

Although documentation is often considered to be a supplemental data source (Jick, 1979), in this study it became a key data source due to the pivotal role it played as a tool in designing the interview guides and engaging informants regarding the AIA objectives. In the research process, discrepancies between these archival sources, on the one hand, and the interviews, on the other hand, became wider and wider. These discrepancies were especially visible with regard to the aforementioned goal conflict between worker empowerment and managerial control. This particular conflict was not articulated in the archival sources, but both the design team and the CS managers subsequently claimed it.

We made further adjustments to data collection instruments, such as adding questions related to these emerging themes to the interview guide (Eisenhardt & Graebner, 2007). Overall, principles developed during the earlier data collection co-determined the sampling and content focus of the later data collection we did via follow-up telephone and Wechat interviews and in the comparative archival documentation analysis. Moreover, these principles provided the basis for clearly delineating themes and aggregate dimensions related to the potential benefits and adverse impacts of AI in the actual use of the system, which were not obvious in the archival documents.

3.4. Data analysis

Following Gioia et al. (2013), our detailed data analysis consisted of three steps: (1) identifying first-order codes, (2) defining theoretical subcategories and categories, and (3) aggregating theoretical dimensions. In a first step, every author coded the data independently and then, in a second step, they discussed and revised their coding until all agreed on the codes and their allocation. First-order codes consisted of statements and descriptions drawn from the archival documentation and interview transcripts. These included the identification and categorization of initial concepts (Locke, 2001; Van Maanen, 1979). During the initial stage, the focus was on finding consistency in issues, relationships, and other themes (Corley & Gioia, 2004). This technique is similar to open coding, relying as often as possible on the language the informants used or on a simple descriptive phrase when an in-vivo code was not available (Glaser & Strauss, 1967). From this step, tentative themes, concepts, and possibly even relationships between codes began to

Table 1
Overview of interviewees.

Interviewee position	No. of face-to-face interviews	No. of Telephone, WeChat, WeChat video, and informal communications
AIA Project Development Manager (PDM)	1	1
AIA Operation Manager	1	
AIA Implementation Project Manager (AIA IPM)	1	1
SMS Robot PDM	1	1
SMS Robot IPM	1	1
Physical Robot PDM	1	
Physical Robot IPM	2	2
Text analysis PDM	1	
Text analysis IPM	1	
IVR (Intelligent Voice Recognition) PDM	1	1
IVR IPM	2	
Semantic analysis PDM	1	
Semantic analysis IPM	1	
AR VR / active service PDM	1	1
AR VR / active service IPM	1	
CS manager	6	5
Sub-total	**23**	**13**
Total	**36**	

emerge through axial coding (Strauss & Corbin, 1990).

The next step of this iterative process was to categorize the emergent first-order concepts into second-order themes. In doing so, we moved back and forth between the emerging themes and the literature on AI. For instance, we summarized statements that described how the AIA initially aimed to provide customers with faster answers to their requests and to receive more accurate responses to create the second-order theme *enhanced customer support*.

Finally, we aggregated the derived second-order concepts into overarching dimensions. This process was not linear, but, instead, a non-recursive, process-oriented, analytic procedure (Locke, 2001) that continued until the emerging theoretical relationships and additional interviews no longer revealed new data relationships (Corley & Gioia, 2004). Overall, we employed an iterative research process and data analysis, which involved frequent backward and forward iterations between steps.

4. Findings

Our analysis revealed that the AIA was initially designed to augment salespeople's work and, thus, to generate novel benefits for the organization and salespeople. These associated benefits were realized in the beginning of the AIA introduction. However, over time, managers' thinking and behavior overshadowed these positive outcomes, triggering a shift from positive to negative consequences of the AIA.

4.1. The AIA's intended benefits

The intention of the AIA design was to augment CS salespeople's work by supporting them in their daily tasks and processes. As a result, the organization hoped to benefit from the following potentials, which were realized in the very early stages of implementation: enhanced (1) customer support, (2) sales, and (3) customer satisfaction. First, the AIA was designed to enhance customer support by providing salespeople with in-depth insights on customers' profiles, preferences, and behaviors:

> "As soon as the customer is connected to the CS salesperson, the AI provides [the salesperson with] all the customer's demographic data, historical purchases, and consumption behavior."
>
> (Interview, AIA PDM)

By having all necessary details concerning the context and interaction required for each customer situation, this information helped CS salespeople understand customers' needs and interests better. For instance, based on customers' detailed demographic data, the AIA could immediately decide in which language customers' requests should be answered or which pronoun of address (e.g., first or last name) customers preferred:

> "The AI suggests responses to customers' inquiries and additional promotions on current products and services. Then, the AI provides the CS salespeople with information about available products if she or he clicks a button."
>
> (Interview, AIA PDM)

Similarly, the official CS technical documentation defined the AIA's "service target" as:

> "Intelligent services such as service reminders and service recommendations are provided to the Customer Service salespeople through phonetic and semantic recognition technologies, in the hope of boosting our staff efficiency while securing high-quality services for our customers."
>
> (Technical Document, 2018, p. 9)

As a result, CS salespeople were able to provide more individualized answers to customers' requests and inquiries, thereby enhancing their support to customers.

Second, the AIA was designed to enhance sales by providing salespeople with individual product recommendations and predictive insights on customers' purchase preferences. These insights were intended to help CS salespeople determine more easily which services and products might be of interest to the customer:

> "From the data about the customer, the AI provides predictions about the customer's potential purchasing behavior"
>
> (Interview, AIA PDM)

Moreover, the AIA was designed to convert the voices of the customer and the CS salesperson into text, and to relate the text of the conversation to existing knowledge about company products and services. Thereby, CS salespeople could gain additional insights into customers' preferences:

> "Here is the screen used by the CS [salesperson]… Here you can see the question asked orally by a customer and converted into text by the AI. This text is often incomplete. So, the AI will complete it. The AI then identifies key words in the customer's text and relates them to the company's products."
>
> (Interview, AIA PDM)

As a result of this individualized and customer-specific target approach, the organization hoped to increase CS salespeople's sales.

Third, the AIA was designed to increase CS salespeople's efficiency in answering customer requests and inquiries faster and more accurately, which aimed to enhance customer satisfaction. The technical document claimed, for example, that "[t]he objective of the

AI Assistant is to boost CS salespeople's efficiency" (Technical Document, p. 8); the company's marketing information states that the AIA would support the service target of "efficient frontline support."

The underlying idea was to relieve CS salespeople from simple and repetitive questions and tasks and thus to help them in focusing on more complex issues. As the AIA PDM emphasized:

> "The AIA covers the frequently asked questions, allowing CS salespeople to focus on higher complexity cases and product recommendations."

Moreover, the AIA was intended to help salespeople have more time to focus on customers' individual demands and to provide services of higher quality:

> "Another objective of the AI was to secure high-quality services for customers through both the AI and the CS salespeople."
> (Interview, AIA PDM)

4.2. The emergence and domination of the AIA's negative consequences

Although the AIA tool's design process focused on the organization's intended goal to enhance CS salespeople's work, the situation reversed itself shortly after implementation, as the features of the AIA sparked CS managers' interest in using the AIA to control and monitor salespeople. This downstream interest emerged after the AIA had been implemented and CS managers could explore and test the AIA's features. In this process, CS managers realized that the AIA is useful not only in terms of enhancing salespeople's work but also to enhance their own work, in that the AIA makes sure that salespeople perform well. As a result, managers started to take advantage of the AIA's features that supported greater control over the salespeople, leading to a shift from the initial positive consequences to the dominance of the AIA's negative consequences. These negative consequences involved the misuse of (1) coordination, (2) power, and (3) embedded biases over the salespeople. In the following, we elaborate on each negative consequence and emphasize how managers' thinking and behavior contributed not only to the AIA's negative consequences overtaking the positive consequences, but also to the retreat and ultimate dissolution of the initially realized positive ones.

The first misuse of the AIA involved coordination. The CS managers struggled with high costs in their unit, which were mainly caused by employee salaries. Since the AIA was able to automate many tasks that were previously performed by salespeople, CS managers tried to replace some salespeople with the AIA after they had realized how efficiently and accurately the tool performed tasks. As a CS manager admitted:

> "[The AIA can be used to] lift performance by decreasing the number of employees."

With the AIA in the hands of CS managers, it seemed that, in their minds, human ability and character were easily replaceable. One of the CS managers explained:

> "The objective is to reduce dependence on CS salespeople to make up for [CS salespeople] losses [i.e., to make up for the turnover]."

The underlying logic appears to have been that work and worker need to be decoupled such that, in the interest of the greater efficiency the AIA could provide, it would be possible to reduce the workforce.

This goal to save costs by replacing salespeople with the AIA escalated over time. In the beginning, CS managers stated that the AIA can take over tasks that are "simple and have clear rules," and that it can also take over "basic query services, and functional reporting services," "basic interactive guidance and simple business handling," "complaint recording," and "problem detection in fault and accounting and other scenarios service." However, in later interviews, CS managers emphasized their ultimate goal, namely, to have the AIA take over all CS processes and, thus, to fully automate salespeople's work. One of the CS managers, for example, said that "[i]t will take some time for the AIA to fully cover all human operations," strongly insinuating that the AIA would, in fact, finally and completely take over from human salespeople. That salespeople are still employed, therefore, seemed to be simply due to the implementation lag. However, in the final stage of this transformation, the workforce is intended to be fully decoupled from the organization:

> "[F]or the moment, the AIA requires a lot of manpower for training. We increase investment in AI development to meet the requirement of reducing the number of CS salespeople."
> (CS manager)

The two contradictions of this situation were: (1) that the CS salespeople were essential in training the AIA that would replace them and (2) that management, while they openly admitted to fewer employees as the goal of the AIA, hid this goal in their discourse. In order to cut the workforce and move CS to the AIA, the CS salespeople had to do more work:

> "Yes, there will be a lot of data precipitation in the process of using an AI tool. Employees need to analyze these data and utilize the value of these data, for example, capturing new demands of users, analyzing the service effect of existing service schemes, focusing on the change of service proportion, etc. All the analysis results will also be used to optimize our AI tool."
> (Interview, CS manager)

Moreover, in order to use the AIA, the employees needed to be trained:

> "Employees have to learn the process design of the AIA, and also routine training and other maintenance work for AI applications."
>
> (Interview, CS manager)

For instance, the AIA required an extensive training set for machine learning's predictions in order to update those predictions over time. Thus, CS managers intentionally used their power to make salespeople contribute to their own replacement—without the salespeople being aware of this situation. CS managers used this approach to fulfil their own goals—which saved costs and enhanced the efficiency of CS processes.

In recognizing the irony of this situation where employees train the system and learn new skills, managers muted the harshness of the future outcomes by making it appear that the job loss could mean freedom for the employees, as suggested by CS managers in interviews:

- "Part of the workload of employees can be liberated and those employees can be assigned to other tasks."
- "The ultimate goal of AI applications is to free up people and put more humans into complex and challenging jobs."

The second negative consequence of the AIA was the misuse of power, seen in this case through enhanced surveillance. Surveillance involved the monitoring and tracking of salespeople's behavior. Traditionally, CS managers struggled with measuring and monitoring salespeople's work quality in a qualitative environment, which forced managers to rely on judgement calls with regard to how well their CS salespeople handled customers. The AIA allowed CS managers to:

> "monitor the CS salespeople…, includ[ing] their speed of speech, their attitudes, [and] their emotions during calls with the customers."
>
> (Interview, CS manager)

For instance, the AIA would assess the level of tension in the CS salespeople's interactions with customers. In order to do so, it would measure the speed of the people's voices to gauge attitude and emotion in the communication. When the AIA would identify moments of tension, it would alert the CS salespeople to speak more slowly. As a CS manager said:

> "Thanks to the AIA, a part of the operations can be tracked. If a CS salesperson's attitude is not good in all respects, the AIA can send the person a warning in real time."

The attitude referred to is a metric created by combining the CS salesperson's voice speed with semantic indicators of her/his emotional presence during a call.

Moreover, we found that surveillance was not just monitoring what the workers did, but also assessing the quality of their work. Traditionally, CS managers often did not know who performed well and who did not. Even if they suspected someone of weak performance, many CS managers did not dare to confront salespeople with their impressions because they did not have any clear evidence. Now, the AIA assessment phase flagged those CS salespeople that the AIA identified as weaker, not just in productivity but also in their attitudes. Moreover, all those assessments are delivered to the CS manager:

> "They are displayed on [her/his] dashboard. Key performance indicators (KPIs) are created from the data collected from each CS salesperson for the purpose of monitoring."
>
> (CS manager)

Up-to-date and regularly refreshed data on workers' attitudes place workers under constant scrutiny, obligating them to suppress their emotions so as to avoid triggering the system's warnings and alerts.

Overall, the AIA allowed CS managers to make the salespeople themselves and their work more visible. As a result, CS managers could use the AIA to confront salespeople who caused bottlenecks and whose work did not live up to expectations, and to take respective actions.

The third negative consequence of the implementation of the AIA that emerged was the embedded bias of the managers. In order to maintain the subordination of the workers, they maintained a system of inequity and opacity. In this situation, inequity ensures that workers have less access to detailed knowledge than either the AIA or CS managers. While the design goal was for employees to have "a general understanding of each module" (Cs manager), and while CS managers know everything relevant to CS processes, salespeople are limited to the knowledge of their particular task or subtask. Managers also have greater access to and understanding of the AIA. In fact, Alpha's CS salespeople have so little access to the system that other humans train them to use it; the trainers therefore serve as an additional barrier to the system itself, reinforcing its opacity. One of the CS managers put it as follows:

> "To teach the robots, we use a human-machine model. To monitor CS salespeople, we use a human-human model."

A human-human model devalues employee consensus-building processes because the employees are presented with the system as it is, without the opportunity or ability to understand how the system functions. In this case, experts who are not workers set the norms for the workers, without any interaction with or validation from them.

The managers seemed to realize quite clearly that if salespeople could overcome their own reluctance, AIAs could improve the customer experience dramatically. Indeed, over the implementation periods, as one CS manager said:

"[E]mployees begin to understand the application of data and that communication is actually the exchange of data. Through the opportunity of AI application, users began to think about how to better serve users and transform the old service methods. It was no longer a regular system service thinking, but a case of thinking from the user's point of view. The optimization scheme based on this is also more in line with the service effect expected by the user."

In fact, the CS manager knew that:

"there is employee resistance. There may be some reasons [for this]. First, they don't have enough perception and understanding, and they don't use tools very often. Second, they feel the crisis arising from artificial intelligence. Third, the bugs generated by the AI cause them an extra burden."

Managers did not only have access to the same knowledge as they had before the AIA implementation; they actually ended up gaining more operational knowledge than before. On the one hand, Alpha's AIA offered managers new affordances, while, on the other hand, it restricted the knowledge and actions available to workers. As emphasized earlier, managers could gain access to negative information that denigrates current (or even prospective) employees, but since the AIA rules the scene, workers could not negotiate practices associated with their work (Ajunwa & Greene, 2019).

In our CS managerial interviews, management disclosed that this disparity in knowledge generated some resistance to the AIA implementation. As another manager mentioned:

"There is employee resistance, because they don't have enough insight and understanding."

Yet another interviewee disparaged the sales people in saying that:

"Resistance depends on the employees' understanding of AI. If they don't know enough about AI, they can't [appreciate it], but [this is] not necessarily caused by the AI. The difficulty could lie in the difference between the users' ability and their hierarchical level."

A third interviewed CS manager suggested that this knowledge inequity could be addressed:

"(1) to make up for the lack of perception and cognition, (2) to make up for technical deficiencies through strategies to improve AI service capability, [and] (3) to enhance employees' sense of gain."

In spite of those insights, in the final analysis the CS managers generally remained in favor of replacing all salespeople with computers.

5. Discussion

Our case study illustrates how an AI tool, which was designed with the intention to support workers in their work by providing enhanced insights on customer needs and interests and relieving workers from simple and repetitive tasks, was eventually used to surveil and ultimately replace their work. As a result of this replacement, managers realized after implementation that AI's unique characteristics, such as the ability to analyze and measure human behavior and autonomously make predictions about it, can be used not only to enhance workers' work and increase customer satisfaction, but also to control and monitor them. These opportunities helped managers in fulfilling their own goals and needs, such as reducing staff costs and increasing workers' output. The managers' initial focus during the AI design phase on supporting workers therefore shifted after the AI implementation toward supporting the goals and needs of the managers themselves. Importantly, managers concealed their shift in thinking and behavior from the workers, and let them believe that the AI tool was introduced only to help them. This tactic was important to managers to ensure that workers would continue to use the AI tool and feed it with the necessary data. Overall, this extreme case illustrates how the implementation of an AI tool was designed with positive intentions to support workers' work and that, although these positive outcomes were first realized, they shifted over time to a domination by AI's negative consequences.

Our study makes the following contributions to the literature on AI. First, our paper contributes to prior research that emphasized the importance of studying the design and use of technologies holistically, AI tools in particular (e.g., Bailey & Barley, 2020; Waardenburg & Huysman, 2022), in order to cross what Leonardi (2009) referred to as the "implementation line." Empirical research has shown that managers and workers should be involved in the design phase of the AI tool to better situate associated promises and goals with the AI implementation (e.g., Mayer et al., 2020; Van den Broek, Sergeeva, & Huysman, 2021). Thereby, these studies argue, it becomes possible to reduce the gap between intentions in the design phase and actual use after implementation. As our case shows, because the only stakeholders involved in the design phase were managers, a natural result in the implementation phase was the emergence of AI's negative consequences. Managers could take advantage of the AI tool to fulfil their own goals and interests, because only they were aware of the AI's characteristics and the resulting affordances.

Second, our research expands the discussion of how bias impacts an AI tool's design and use (Forsythe, 2001). Implicit in this design and explicit in its implementation are the managers' embedded beliefs and ideologies that workers need to be kept in their place as subordinates and that the system needs to support that subordinated position. This subordination is evident in at least two ways in this AIA system: through inequity and through opacity. From this case study it is clear that the opacity of AI's "black box" not only makes it impossible for AI users to make sense of the AI outcome (e.g., Lebovitz et al., 2022; Strich et al., 2021; Waardenburg & Huysman, 2022), but the AI users' lack of comprehension leads to resistance to the tool itself. The inequity of the tool derives partly from the contrast between those who do understand the tool and those who do not, and also from the distinction between those who are being dominated through surveillance and monitoring and those who carry out those surveilling and monitoring activities. Surveillance affordances, in particular, have proved to reinforce inequity and to mask that feature in the tool's "objective" nature (Brayne, 2017). As such, this finding also moves research toward a greater understanding of the importance of power in the discussion around the design and use of technology (Bailey & Barley, 2020). This is because managers used their position and power to deploy the AI tool in order to support their own interests, not simply in terms of increased efficiencies, but also in terms of the maintenance of hierarchies, a structure at risk in instances of emerging technology (Barrett et al., 2012).

What is fascinating and also novel about the findings in our case study is that managers did not appear to fully understand the extent to which the AIA could not only replace humans in the sales equation, but also enhance their own ability to control the overall sales setting. As time went on, managers' attitudes seemed to change, moving away from the original design and focusing more on their enhanced control. What at first was a healthier respect for worker empowerment, eventually morphed into a scenario of tightened managerial control.

Third, our research extends the discussion around organizational coordination in the context of AI, in particular, augmentation and automation (Raisch & Krakowski, 2021). Previous work has emphasized that it is important to uphold the paradox between augmentation and automation (Raisch & Krakowski, 2021) in order to maintain the benefits of each while avoiding their drawbacks. Equally important is the need to maximize such positive outcomes, for example, efficiency and customer satisfaction, while minimizing error and cost. Instead of dealing with this paradox through a balanced approach, managers reconciled the tension between AI's potential to support as well as harm workers by using workers to enhance the AI tool and then to ultimately automate their work and replace their jobs with the improved AI tool.

Our research also yields important practical implications. First, the design of AI tools should include all stakeholders (Monod et al., 2022). This approach would ensure that the goals of any AI tool would be implemented according to a balanced design. In the case of the AIA studied here, the design phase gave evidence of support for performance enhanced by AIA assistance, and of greater worker empowerment. This indicates that the goals may have been well intentioned to start with but became more duplicitous over time as managers stopped sharing their evolving intentions. It is deceptive to offer workers hope that a new AI tool will aid them in doing a better job while simultaneously planning to retrench and increase surveillance. Therefore, an attendant practical implication is that design principles should extend across the AI tool's implementation and even across its lifetime, as proposed by value-sensitive design, whereby stakeholders representing all factions within the organization are active participants in the evaluation and modifications of the system over time.

Efforts should therefore be made to recognize the contradictions inherent in AIA implementations. The lesson this study holds for managers who have begun or who plan to implement an AIA at this moment of the "sales renaissance" in AI (Syam & Sharma, 2018) is that they will need to address these conundrums. Most starkly, the managerial choices would be between: (1) workforce reduction or worker empowerment, (2) higher performance through job satisfaction or intensive maximizing of efficiency, (3) innovation outsourcing or online community building, and (4) top-down or user-oriented change. It hardly bears mentioning that researchers should determine which of these stark choices would lead to a more equitable workplace where organizations value human effort at all hierarchical levels and reward symbiotic partnerships that make the most of the differing human and digital technology strengths (Gal, Jensen, & Stein, 2020).

Having identified this set of options, we caution that there might be ways to combine the two intelligently or use them as tensions to be resolved (Ciriello, Richter, & Schwabe, 2019) or maintained in irresolution (instead of mutually exclusive choices as shown in organizational justice theory (Robert et al., 2020)). For example, a balance between augmentation and automation should be maintained. As appealing as automation might be to a manager, in its reduction of repetitive and low-level tasks, too much emphasis on automation might lead to the AI tool completely replacing the workers. Alternatively, while augmentation is equally appealing in its ability to support and enhance a worker's more complex activities, it will lead to higher overhead costs because of the system's need to learn constantly, resulting in persistent and niggling changes across the platform (Raisch & Krakowski, 2021).

Since managers in this case concealed their true interests and also the affordances of the AI system that focused on surveillance, workers continued working with the system, believing that it would be used to support their work. Thus, our research emphasizes the crucial need to unpack AI's black box—not only for workers to work effectively with the AI system, but also to help them in protecting personnel rights and preventing AI's misuse. In this context, this research adds to recent discussions around AI regulations and the importance of ethical guidelines when implementing AI technologies (e.g., Regulation, 2023).

6. Conclusion

Our study provides an important case that illustrates how the introduction of AI tools can cause serious harm to workers. Although the AI tool was designed to empower workers, the study's findings suggest a disconnect between potential benefits and managerial unwillingness to cede some control. Whereas the justification of the AI tool was the admirable goal of worker empowerment and job enrichment, it was eventually only used for greater management domination and oversight. These insights contribute to debates around AI tools and their implications for organizations, workers, and the wider society.

CRediT authorship contribution statement

Emmanuel Monod: Conceptualization, Methodology. **Anne-Sophie Mayer:** Writing – original draft, Writing – review & editing. **Detmar Straub:** Writing – original draft, Writing – review & editing. **Elisabeth Joyce:** Writing – original draft, Writing – review & editing. **Jiayin Qi:** Conceptualization, Methodology, Data curation.

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