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Responding to Paradoxical Organisational Demands for AI-Powered Systems considering Fairness

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Short Paper

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Abstract

Developing and maintaining fair AI is increasingly in demand when unintended ethical issues contaminate the benefits of AI and cause negative implications for individuals and society. Organizations are challenged by simultaneously managing the divergent needs derived from the instrumental and humanistic goals of employing AI. In responding to the challenge, this paper draws on the paradox theory from a sociotechnical lens to first explore the contradictory organizational needs salient in the lifecycle of AI-powered systems. Moreover, we intend to unfold the responding process of the company to illuminate the role of social agents and technical artefacts in the process of managing paradoxical needs. To achieve the intention of the study, we conduct an in-depth case study on an AI-powered talent recruitment system deployed in an IT company. This study will contribute to research and practice regarding how organizational use of digital technologies generates positive ethical implications for individuals and society.

Keywords: Artificial Intelligence, algorithmic fairness, paradox, organizational use

Introduction

Artificial intelligence (AI) has garnered significant global attention in recent years. The introduction of AI expedites the replacement of information systems in organizational management. AI-powered systems that capitalize on big data captured through digital technologies and robust computing capabilities facilitate the complete automation of specific tasks and the synergistic collaboration between technology and human knowledge (Benbya et al., 2020; Borges et al., 2021). This transformation affords substantial instrumental value to organizations, including enhanced organizational efficiency and capability to deliver superior products and services to consumers and society (Stahl et al., 2021). A global survey conducted by McKinsey (2022) identify that 63% of adopters of AI solutions across industries observed an increase in revenues, while 32% experienced a reduction in costs.

Given the growing permeation of AI deployment in organizational management, the multifaceted implications of AI for humanistic values, such as justice, well-being, and freedom, have increasingly drawn people's attention (Gal et al., 2022). One the one hand, AI dysfunctions arise from the use of AI. It is a phenomenon reflecting the intensified tension between technological competence and human social structures where technologies inhabit considering the ethical implications of AI (Benbya et al., 2020). One of the most crucial ethical concerns related to the use of AI is unfairness, which challenges the assumption of technologies that bring advantages to humankind overall (Majchrzak et al., 2016). Stakeholders of AI-powered systems frequently experience discrimination during their interactions with the systems. For example, cutting-edge face recognition algorithm packages have much poorer performance in assessing females and people of color than male white people (Grother et al., 2019). These undesirable impacts of deploying AI are likely to counterbalance or even surpass the benefits of AI.

On the other hand, AI can be used for fostering social good. For instance, lending infrastructures empowered by machine learning algorithms assist the subpopulations who are marginalized in smooth access to loans (Tantri, 2021). The positive implications for stakeholders are more likely to drive their active interactions with and feedback on the system, which recursively promotes the achievement of the system's instrumental goals (Grover et al., 2009). Therefore, it is possible for organizations to grasp the AI-enabled benefits and contribute to social equality by conscientiously managing the entire lifecycle of AI-powered systems, including the stage of design, implementation, and use in practice (Mikalef et al., 2022).

Organizations confront with divergent needs and values from diverse interdependent stakeholders at each stage of a fair AI-powered system's lifecycle. It creates a challenge for organizations to simultaneously consider the needs to satisfy the instrumental and humanistic objectives of deploying AI. Organizations are prone to exploit the efficiency of AI-powered systems at the cost of concerning the requirement of flexibility by making a choice between these needs (Marabelli et al., 2021). For instance, management can face a tension emerging from the contradictory needs from management and users of the AI-powered system at the AI implementation stage. Users require algorithms to be explainable by knowing important criteria as a prerequisite of fairness, but management needs to protect intellectual property and prevent potential speculative behaviors of users by retaining the opaqueness of algorithms. In response to the contradiction, management is commonly inclined to either one in pursuit of the system's efficiency (Hermann, 2021). This contradiction is not the only one related to fair AI-powered solutions identified by scholars. At the design stage, Binns (2020) find that organizations confront with the contradictory demands for ensuring consistency between cases and judging each case based on its own merits. This salient tension is associated with another tension emerging at the use stage. Organizations need to balance between delegating the task to the system and involving humans to augment the system (Raisch & Krakowski, 2021).

However, previous research has not holistically identified the contradictions emerging in the lifecycle of an AI-powered system and not sufficiently developed instrumental and practicable mechanisms to help organizations correctly understand and manage these contradictions. Some scholars have endowed these contradictions with a mutually exclusive "either/or" ontology (e.g., Marabelli et al., 2021). The ontology is questionable because the emphasis on one side will intensify the tension and trigger the need for the other side. In other words, organizations cannot simply retain one need and abandon the other. The incomprehensive ontology of the contradictions related to fair AI engenders proposals of static mechanisms for addressing tensions in most prior literature. Static mechanisms include the mechanisms based on contingency theory (Galbraith, 1973) and the general guidelines obscuring the management process and the role of AI and social actors (Leicht-Deobald et al., 2019). They cannot assist organizations in managing both demands simultaneously. Furthermore, they cannot adapt along with organizations' constant shift between two needs in response to internal and external impetus (Smith & Lewis, 2011).

Another group of scholars acknowledge that the ontology of contradictory demands should be perceived as "both/and". However, they do not emphasize the ethical implications of AI (van den Broek et al., 2021), and they largely delve into a single phase of the lifecycle of AI-powered systems, such as implementation and use in practices (e.g., Stohl et al., 2016). Scholars call for extending the investigation scope of algorithmic fairness from one stage to the whole lifecycle of AI (Dolata et al., 2021). We intend to address the gaps by answering what contradictions are salient in the lifecycle of AI-powered systems considering fairness and how the organization responds to the contradictions.

We present an in-depth case study of an AI-powered talent recruitment system that has been developed and implemented in an IT company. It provides an opportunity to explore the lifecycle of AI-powered

systems and the contradictory yet interdependent needs that arise in the lifecycle. We draw on paradox theory through a sociotechnical perspective to study algorithmic fairness. This study will speak to the conversation about information systems (IS) and management by identifying paradoxes that arise in the context of fair AI and developing process models that depicting the possibly interwoven paradoxes and the ongoing management process in the lifecycle of an AI-powered system.

Background Literature

Algorithmic fairness

Algorithmic fairness is defined as sociotechnical strategies that prevent AI-powered decision-making from harming or benefiting different subgroups (Barocas & Selbst, 2016). Previous literature has primarily focused on the technical perspective and the social perspective of algorithmic fairness. The technical perspective aims to improve algorithmic outcomes based on the mathematical formalization of fairness (Dolata et al., 2021). Group-level fairness and individual fairness consider different aspects of the coherent moral principles. They are distinguished by technical expression and based on different world views (Binns, 2020). The normative conflicts between the two types of fairness measures in practice require users to identify the type of unfairness that is salient and develop an accountable process of deciding the assumptions and fairness metrics to use (Binns, 2020).

Algorithmic fairness from a social perspective provides social discourses assuming that algorithmic fairness cannot be fully achieved by mathematical formalisation. Researchers from social disciplines identify sources of algorithmic unfairness beyond technical artifacts, such as the inheritance of coloniality in social structures (e.g., Mohamed et al., 2020). They also develop strategies for coping with algorithmic unfairness from theoretical lenses in other disciplines beyond computer science; for example, Fazelpour and Lipton (2020) draw on the concept of ideal and non-ideal theorising modes to guide the formalisation of fairness in algorithms. Treating algorithmic fairness as socially constructed enables more dynamic and more comprehensive investigation than the technical perspective of algorithmic fairness that are assumed to be independent of contexts (Dolata et al., 2021). However, some problematic assumptions underlie the social perspective, such as ignoring the difference between fairness metrics. By problematising those premises underlying two perspectives of algorithmic fairness, the sociotechnical perspective of algorithmic fairness is increasingly recommended by researchers (e.g., Holstein et al., 2019; Lambrecht & Tucker, 2019).

Sociotechnical Perspective and AI

The sociotechnical perspective is regarded as a bridge connecting social analysis and technical-oriented approaches to organizational challenges (Davis & Olson, 1985). The sociotechnical perspective is regarded as the central principle of IS that ensures the distinctiveness of IS and differentiates it from other technological-relevant fields, such as software engineering. It enables the creation of problem-portable knowledge that is not constrained to one specific IS problem but can be utilized to answer a set of problems or phenomena associated with the discipline (Abbott, 2010; Sarker et al., 2019). IS scholars are encouraged to involve different proportions of social and technical elements and examine various social-technical relationships (Sarker et al., 2019).

Research on AI implementation in the organizational context and AI-related ethical issues particularly welcome this approach because organizational application of AI warrants a notable portion of collaboration and mutual acclimation between organizational structures and AI considering both humanistic and technical consequences (Pääkkönen et al., 2020). For example, Asatiani et al. (2021) explore a sociotechnical envelopment approach to balance the advantages and the risks of implementing inexplicable AI in organizations. Algorithmic fairness involves technological artifacts, social agents, and their interplays and requires organizations to contemplate instrumental and humanistic goals. Based on the sociotechnical perspective, Dolata et al. (2021) propose that research on algorithmic fairness need to use information to direct the complex association between technical and social constituents, consider interconnected and divergent outcomes more than fairness, and involve IS into dynamic and reciprocal interactions with the context. Our adoption of the sociotechnical perspective is due to its fit with algorithmic fairness, and besides, this perspective enables us to incorporate novel and appropriate perspectives from reference disciplines (Rai, 2017).

Paradox Theory

The definition of paradox has been adapted as "persistent contradiction between interdependent elements" in organizational studies (Schad et al., 2016). This definition indicates the dynamic relationship between two divergent elements and a latent process ontology of paradox that entails a dynamic strategy for balancing two poles. Paradox theory has a long history of being applied in organizational studies where scholars have explored the nature of, measures for, and impacts of paradox (Schad et al., 2016). For example, Smith and Lewis (2011) identified four categories of organizational paradox, including learning, organizing, belonging, and performing paradox, while Papachroni et al. (2016) put forward a path-dependent process as a coping strategy for organizational ambidexterity that organizations pursue exploration and exploitation simultaneously.

Previous IS research has also studied the nature of, approaches to, and outcomes of paradoxes that were salient in technological-relevant phenomena. We identify the most prevalent paradoxes mentioned in IS literature and illustrate the impact of the emergent AI context on the paradoxes. We use paradoxical tensions that are differentiated from the dilemma-like tensions and paradox interchangeably as previous paradox literature suggests (Mini & Widjaja, 2019; Putnam et al., 2016).

The first most explored paradoxical tension is between control and empowerment. For example, Ciriello et al. (2019) identify that digital artifacts simultaneously provide users with freedom and restrain users' innovation practices. Organizations deploying AI-powered systems also face the paradoxical tension between empowering and constraining users (Marabelli et al., 2021; Meijerink & Bondarouk, 2021). This paradoxical tension is intimately associated with ethical concerns such as fairness and users' well-being (Deng et al., 2016; Wiener et al., 2021). However, AI-powered systems are differentiated from traditional IS because of AI's inherent self-learning ability that causes a reinforced cyclical relationship between algorithmic outcomes and the context. This characteristic of AI-powered systems can further exacerbate unfairness (Barocas & Selbst, 2016). Controlled users' responses to the paradoxical tension can be fed back to the system and trigger the adaption to new inputs, such as building up the degree of controls when individuals perform resistances (Meijerink & Bondarouk, 2021). Therefore, the knowledge of how to manage the paradoxical tension becomes more critical because inclining to one side may result in intensified problems of unfairness.

The other prevalent paradoxical tension associated with both traditional IS and AI is between dependence and independence, yet the context of applying traditional IS is different from that of AI. Independence related to traditional IS is from the perspective of humans. It indicates that humans are provided freedom in relation to space, time, and co-workers (Lang & Jarvenpaa, 2005). Conversely, independence in the context of AI is from the perspective of AI-powered systems. The system can be independent of human's expert knowledge and completes missions automatically (van den Broek et al., 2021). This difference explicates the necessity for investigating AI-relevant paradoxes.

Previous research in the IS field that focused on paradox emerging from technological-related phenomena has tended to view paradox as "a noun, a concrete, discernible tension between distinct elements" (Schad et al., 2016). These studies identify paradoxical tensions associated with technologies based on the definition of paradox. For example, Mazurova et al. (2022) unearth paradoxical tensions existing in the use of an AI-powered evaluation system in competitive sports. However, there are relatively fewer articles that regard paradox as a verb and emphasize the constant interplay between two divergent elements. One study is from van den Broek et al. (2021), who develop a process model to depict how organizations include and exclude human experts to manage the paradoxical tension between automation and augmentation. To gain insight into the process of managing paradoxes, it is important to recognize paradox as both a noun with identifiable characteristics and a verb with dynamics.

Paradox Theory through a Sociotechnical Perspective

Paradox theory through a sociotechnical lens indicates that we must consider the synergetic role of technical and social elements in engendering and responding to paradox, as well as the synergetic impacts that link humanistic and instrumental values. We present the key arguments of two perspectives and provide justification for why the integration of two perspectives is appropriate for studying our research questions in Table 1.

Table 1 Integration of Paradox Theory and the Sociotechnical Perspective

Key arguments of the paradox theory	Key arguments of the sociotechnical lens	References	Relations to our study
Paradox is contradictory but interdependent elements that present concurrently and persistently.	Interdependent contradictions can emerge in the process of managing algorithmic fairness.	Smith and Lewis (2011), Dolata et al. (2021)	We can unearth the paradoxical tensions existing in the lifecycle of an AI-powered system considering the interplays between technical and social components in a system.
The socio-technical interplays render latent paradoxical tensions embedded in the system salient. Socially constructed paradoxical tensions are tensions from actors' perceptions.	Some tensions embedded into the sociotechnical system and actualized by the interplays between stakeholders and AI, such as the tension between transparency and opaqueness; some others are constructed through stakeholders' perceptions, such as the tension between personal integrity and compliance with algorithmic decisions.	Schad and Bansal (2018), Leicht-Deobald et al. (2019)	We can discriminate system-inherent tensions and socially constructed tensions. We are also conscious that coping strategies need to assist in stakeholders' cognitive changes and behavioural changes.
The collective management strategy of paradoxical tensions emphasises the dynamism of attention between opposing needs.	The sociotechnical lens deems that achieving algorithmic fairness is an ongoing process considering mutual accommodation between components in a system.	Schad et al. (2016), Dolata et al. (2021)	We can uncover the ongoing management process that engages both technical and social factors in response to paradoxical tensions associated with an AI-powered system.
Managing paradoxical tensions need to involve stakeholders into intense and systematic information processing of opposing elements and their interdependence.	Information is the core that directs the interplays between technical and social components in a system.	Miron-Spektor et al. (2022), Dolata et al. (2021)	We can take information of data and models that impacts algorithmic fairness of an AI-powered system into account when we explore how stakeholders process information to attend to contradictory needs.

Research Design

Our purpose is to identify the paradoxical tensions emerging in the lifecycle of an AI-powered system implemented in an organization and unearth how the organization manage the tensions. A case study method is the most appropriate to answer exploratory "what" and "how" questions. This method can help us open the black box in terms of the dynamic relationships between opposing needs and unfold the process of balancing paradox. We will apply a single-case design that permits several units of analysis to avoid an improperly abstract level of analysis (Yin, 2003).

Case Description

Our case is an AI-powered talent recruitment system developed and implemented in an IT company. There are three reasons for focusing on AI applied to human resource management (HRM). First, the role of HR is associated with the internal implementation of business strategy and the achievement of external social responsibilities. The core of HRM has converted from administrative tasks to active participation in the

development and implementation of organizational strategy (Lawler III, 2005). With the extension of HR's functions, the commitments made by current and future HR involve producing social good to external stakeholders such as the community (Ulrich & Dulebohn, 2015) and offering equal job opportunities to individuals, which is essential (Derous & Ryan, 2018).

Second, the challenges of maintaining equality in the recruitment process have changed due to the use of AI. Before introducing AI to HRM, unfairness of traditional HRM largely results from human bias (Derous & Ryan, 2018). Human bias is expected to be mitigated by applying a more objective and superior AI-powered system (Giermindl et al., 2021). However, the reality indicates that the use of AI has multifaceted implications that display new challenges for organizations. They should consider both the social components that already exist in traditional HRM and the nascent technical components to ensure a fair talent recruitment process.

The system imitates the traditional talent recruitment process involving talent portrait through the analysis of curriculum vitae (CV), talent screening through automatic CV filtering, and customized examination based on job requirements, and talent matching. Different from those outsourcing AI-powered systems adopted in companies, this system is developed by the AI team entrenched in the HR department, which is specialized in developing algorithms to help HRM. This mode permits HR members' participation in each stage of the system's lifecycle. It provides us with an opportunity to identify paradoxical tensions between people from different roles who may prioritize divergent values and goals. The team is hierarchical with a main team leader who manages the overall development strategy of the AI-powered system and communicates with the management in the company. Under the leader, there are primarily three types of positions: product manager, algorithm designers, and system designers in the team. The product manager bridges AI team with other departments regarding the demands of business operations and the AI team's needs. The product manager also plays a critical role in coordinating the opinions of the AI specialists and members from other departments.

Data Sources and Collection Methods

The data collection is expected to be longitudinal. Because the company has implemented the system, we will utilise archives, such as meeting notes and the published papers of the AI team, to help probe the design and the implementation stage. The sample of interviewees will include designers in the AI team, product managers, employees from the HR department who routinely use the system, employees from other departments who use the system when recruiting new members, and job candidates who interact with the system. We will use the snowball sampling strategy that permits each interviewee to recommend other members of the company who could offer insights.

The interview will primarily consist of questions that are pertinent to 1) the role related to the system and the background of the interviewee, 2) their experience with the system, and 3) the discrepancy between the current system and their expectations. Based on Jarzabkowski and Bednarek (2018) advice on unearthing salient and latent paradox, we also focus on interviewees' emotions that can be reflected by tone of voice, facial expressions, and movements. They are important real-time information that indicate salient tensions that stakeholders are experiencing.

Prospective Data Analysis

We follow the qualitative data analysis guideline of investigating intraorganizational paradox created by Jarzabkowski et al. (2013). First, we will write chronological case stories of each phase of the lifecycle of the system. These case stories help us capture a fuller picture of each phase and the interactions between stakeholders. Second, we identify paradoxical tensions from the case stories with the original qualitative data at hands. The identification is primarily based on narratives. Narrative method focuses on language and discourse that suggest the manifestation of paradoxical tensions from stakeholders' perceptions. Previous paradox studies pay attention to some words, such as tension, conflict, discord, and challenge (Jarzabkowski et al., 2019). Paradox scholars also find that humour and irony are clues of paradoxical tensions because they reveal contradictory feelings (Lewis, 2000). We will zoom into the socially constructed paradoxical tensions to uncover the underlying dominant tensions that impact the primary resources in the sociotechnical system (Schad & Bansal, 2018). Third, we will move back and forth between the identified paradoxical tensions at each phase of the lifecycle of the system and literature by the attempt

to match the paradoxical tensions with the predetermined categories in literature, such as organising, performing, belonging, and learning paradox (Smith & Lewis, 2011). The unmatchable tensions can be the unique ones to our context. We further examine the relationship between paradoxical tensions within a phase and across phases to construct the process model.

Fourth, we will inductively code the qualitative date to identify stakeholders' responses to the identified tensions at each phase of the lifecycle of the system. Exploring the associations between paradoxical tensions and responses within a phase and across phases and the impact of these associations on achieving fairness is important for capturing the comprehensive picture of how organizations handle paradoxical tensions. Lastly, we intend to examine the process model that describing paradoxical tensions and stakeholders' responses over time. We may identify variations of tensions, responses, or their relationships in the ongoing process. The reasons underlying the variations could indicate the things that organizations should pay attention to in the long run.

Implications and Future Research

Theoretical and Practical Implications

Through this study, we will theoretically contribute to the literature on IS and management. Embracing a sociotechnical perspective that considers both technologies and societal actors is central to the IS discipline and can broaden its scope, as well as enabling contributions to other related domains (Briggs et al., 2010; King, 2013). With drawing on this perspective, our research questions frame both social and technical facets and consider the humanistic impact resulting from the interaction between social agents and AI technology. By answering these questions, we intend to discover paradoxical demands that emerge in the lifecycle of an AI-powered system embedded with a notion of fairness and explore how organizational members can attend to these demands to seek sustainability rather than short-term achievement with AI technology. This can add empirical knowledge to research on digital technologies and social justice. Another important contribution to IS literature is that we conceptualize and explore these paradoxical tensions through the lens of paradox theory. Furthermore, by adopting this perspective, we overturn the deterministic lens through which researchers were used to study algorithmic decision-making that implies a predetermined consequence of employing AI in organizations (Parent-Rocheleau & Parker, 2021).

Drawing on the paradox theory through a sociotechnical lens enables us to explore the mechanism of balancing nested paradoxes by unfolding the process of social-technical interplay. Therefore, we can respond to the call from paradox researchers who have appealed for more studies on how one paradox or approaches to the paradox induce another paradox (Schad et al., 2016). In addition, more possibilities of the relationship between paradoxes and spill-over of tensions are expected to be identified in this study, which extends the pair-matched relationship proposed by Smith and Lewis (2011).

Practically, we identify the roles of social agents and technical artifacts in the process of developing, implementing, and maintaining a fair AI-powered system. Managers can become aware of the dynamic process of balancing and equipped with the knowledge regarding how to manage paradoxes associated with a fair AI-powered system; employees and AI designers can recognize their roles in the process and learn how to manage the paradoxical needs emerging out of their positions so that a virtuous cycle can be spurred.

Future Research

Data collection is ongoing, and the collected data is analysed.

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